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Measuring Risk Attitudes among Mozambican Farmers

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ABSTRACT

Although farmers in developing countries are generally thought to be risk averse, little is known about the actual form of their risk preferences. In this paper, we use a relatively large field experiment to explore risk preferences related to sweet potato production among a sample of farmers in northern Mozambique. We explicitly test whether preferences follow the constant relative risk aversion (CRRA) utility function and whether farmers follow expected utility theory or rank dependent utility theory in generating their preferences. We find that we can reject the null that farmers' preferences follow the CRRA utility function in favor of the more flexible power risk aversion preferences. In a mixture model, we find that about three-fourths of farmers in our sample develop risk preferences by rank dependent utility. We also find that by making the common CRRA assumption in our sample, we poorly predict risk preferences among those who are less risk averse.

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CONTENTS

I. INTRODUCTION

Although it is generally assumed that farmers in rural areas of developing countries are risk averse, little is known about the actual form of their risk preferences. When economists attempt to measure risk preferences, they typically assume that risk preferences follow the constant relative risk assumption (CRRA) utility function (see Cardenas and Carpenter (2008) or Hurley (2010) for recent reviews of the literature). However, the consequences of simply making this assumption without testing it are unclear. Few studies actually test risk preferences in the field without making the CRRA assumption. An important exception is Holt and Laury (2002) who consider a more flexible parameterization of the utility function, although they do so in a laboratory experiment setting.

Furthermore, it is likely that risk preferences among farmers in developing countries are important constraints that keep farmers from reaching their productive potential. Smallholders in developing countries face risk at several points in the production process. Dercon and Christiaensen (2011) explicitly show that Ethiopian farmers are constrained in technology adoption by risk. Furthermore, Boucher et al. (2008) argue theoretically that a class of farmers is risk rationed in Peru; that is, due to risk, some farmers will not try to access the formal credit market, even if it would raise their productivity and income levels. Overcoming such barriers to risk, then, could help farmers in developing countries improve their livelihoods along several dimensions.

Understanding the heterogeneity of risk preferences and the implications of making specific assumptions about the form of risk preferences may have consequences as programs are designed to help farmers in developing countries overcome several different potential sources of risk. For example, in several countries, weather insurance pilot projects have begun (e.g., Giné and Yang 2009; Hill and Viceisza 2010). However, such projects may be unsuccessful without a proper understanding of the risk preferences of farmers. Additional information about the type and distribution of risk preferences among farmers can be important information in informing intervention design.

In this paper, we use experimental data collected in rural Mozambique to elicit risk preferences of farmers participating in an agricultural program that promoted orange-fleshed sweet potatoes (OFSP). The data were collected in the final survey of a randomized evaluation of an intervention that provided farmers with OFSP vines and information on how to grow OFSP and the relative nutritional benefits of consuming orange rather than white sweet potatoes, particularly for women of childbearing age and children under five years old.

The experiment to elicit risk preferences was framed around the adoption of sweet potato varieties and consisted of presenting a menu of ordered lottery choices over hypothetical gains to the farmers. The experiment was conducted with 682 farmers. We used the data to consider and test several models of risk preferences against one another. We initially compared two contending models of choice under uncertainty, Expected Utility Theory (EUT) and Rank Dependent Utility (RDU). We then considered a general class of value functions that explicitly allows for variation in relative risk aversion, extending the assumption of constant relative risk aversion (CRRA) that is often made in the literature.

Our primary contribution to the literature is that we used experimental data collected in the field to nest different potential models of risk preferences, and we developed and tested these models against one another. We further constructed a model that allows for heterogeneity in the theoretical basis for risk preferences—namely, EUT or RDU. In general, we found that the RDU dominates EUT, and we generally reject the CRRA hypothesis, regardless of the form of preferences. We then showed the magnitude of errors that takes place if one assumes CRRA preferences. We found that farmers who are less risk averse are more susceptible to mischaracterization under the CRRA assumption than more risk-averse farmers, based on the results of our model.

The paper will proceed as follows. The next section will discuss the literature on the measurement of risk preferences, both in the laboratory and in field experiments. The third section describes the setting in which the data collection and field experiment took place, as well as more details about the data collection effort and field experiment. The fourth section presents and discusses the results, and the final section concludes.

II. MEASURING RISK PREFERENCES IN DEVELOPING COUNTRIES

A large body of literature characterizes risk preferences among residents of developing countries. In most cases, the EUT is used as a conceptual framework to frame risk preferences; although more recently, some authors have also considered alternative utility frameworks for choice under uncertainty. Previous work on the characterization of risk preferences has been based on either the use of experimental lotteries or the analysis of production decisions collected from household survey data. We will focus on the first line of work since this paper also

[1] See Hurley (2010) for a recent and more exhaustive review.

uses experimental lottery data from the field. Here, we only summarize papers that are directly relevant to our analysis.

Binswanger (1980, 1981)'s studies are among the first to provide formal tests of risk aversion among farmers in a developing country. The papers describe both hypothetical and real payoff lotteries to Indian farmers in which the outcome probabilities were fixed, but the payoffs of the lotteries varied. These studies found that most Indian farmers in the study were risk averse and that the degree of risk aversion increased with the monetary payoff of the lotteries. Overall, these results suggest that farmers' choices were consistent with increasing relative risk aversion (IRRA) and decreasing absolute risk aversion (DARA).

Using similar procedures, Miyata (2003) and Wik et al. (2004) studied Indonesian and Zambian villagers, respectively. Confirming Binswanger (1980, 1981)'s findings, they also found that farmers preferences are characterized by extreme to moderate degrees of risk aversion, by DARA, and by nonincreasing or decreasing relative risk aversion.

Mosley and Verschoor (2005) studied three different countries (Ethiopia, India, and Uganda) and combined choices over lottery pairs with hypothetical certainty equivalent questions. Similar to Binswanger (1980, 1981), they found no significant relationship between risk aversion and respondents characteristics such as age, gender, literacy, income, or wealth. Responses obtained from the hypothetical certainty equivalent questions, however, do correlate significantly with the data collected through real payoff lottery choices. Contrary to results found by other authors, Yesuf and Bluffstone (2009) used a dataset collected in northern Ethiopia and found that risk aversion is significantly correlated with respondents' characteristics, such as household composition, income, and wealth.

Hill (2009) relied on stated preferences and beliefs to identify the effect of risk aversion on production decisions for a sample of Ugandan coffee growers. Using both nonparametric and regression analysis, she found that higher risk aversion translates into a lower allocation of labor toward a risky perennial crop such as coffee. This effect dissipates among wealthier farmers. This result underscores the importance of understanding risk preferences for measuring specific farmer-level outcomes.

More recently, Liu (2008), Tanaka et al. (2010), and Harrison et al. (2010) departed from the previously cited work in that they considered an alternative utility framework to EUT by considering Prospect Theory (PT) or RDU models. These studies also contrast with previous work in the way lottery choices are elicited. Instead of fixing the outcome probabilities and varying the lottery stakes (as was proposed by Binswanger (1980)), they followed Holt and Laury (2002) and used multiple price lotteries (MPL) where the lottery payoffs are fixed in each choice task, and the outcome probabilities are varied. While Liu (2008) and Tanaka et al. (2010) analyzed the PT framework over the full range of gains and losses, Harrison et al. (2010) focused on the gain domain only, and they compared EUT to RDU by testing

Table 1: Risk Preferences, Perception Framework, and Utility Functions

Study	Country	Lottery Type	Perception Framework	Utility Function
Binswanger (1981)	India	Hypothetical and real	EUT	CRRA
Holt and Laury (2002)	USA	Hypothetical and real	EUT	CRRA and Power
Miyata (2003)	Indonesia	Real	EUT	CRRA
Wik et al. (2004)	Zambia	Real	EUT	CRRA
Mosley and Verschoor (2005)	Ethiopia, India, Uganda	Real and hypothetical	EUT	CRRA
Liu (2008)	China	Real	EUT and CPT	CRRA
Hill (2009)	Uganda	Hypothetical	EUT	CRRA
Yesuf and Bluffstone (2009)	Ethiopia	Real	EUT	CRRA
Tanaka et al. (2010)	Vietnam	Real	EUT and CPT	CRRA
Harrison et al. (2010)	Ethiopia, India, Uganda	Real	EUT and RDU	CRRA

the nonlinearity of the probability weighting function. Harrison et al. (2010) also estimated finite mixture models, allowing both EUT and RDU to explain some proportion of respondents' choices over risky lotteries. In this paper, we extend Harrison et al. (2010) by relaxing the CRRA assumption in the utility function, while also estimating a finite mixture model.

In Table 1 we summarize some essential characteristics of the work cited above. As can be seen in this table, most of the previously mentioned studies relied exclusively on CRRA utility functions to compute coefficients of relative risk aversion. Under EUT, CRRA utility functions are convenient to work with because they summarize attitudes toward risk in a single parameter that is related to the curvature of the utility function. This simplicity in the functional form comes at the cost of generality since there is no reason to believe a-priori that risk attitudes should be characterized by increasing relative risk aversion. Holt and Laury (2002)'s research using US students' responses from laboratory experiments is the only work we are aware of in this literature that relaxes the CRRA assumption. They notice that respondents' choices are actually more consistent with IRRA than with CRRA, so they consider a power utility function allowing the relative risk aversion coefficient to be decreasing, constant, or increasing. In this paper, we build on the previous literature by considering a general utility specification, which allows us to test altogether EUT against RDU and CRRA against a more general valuation function.

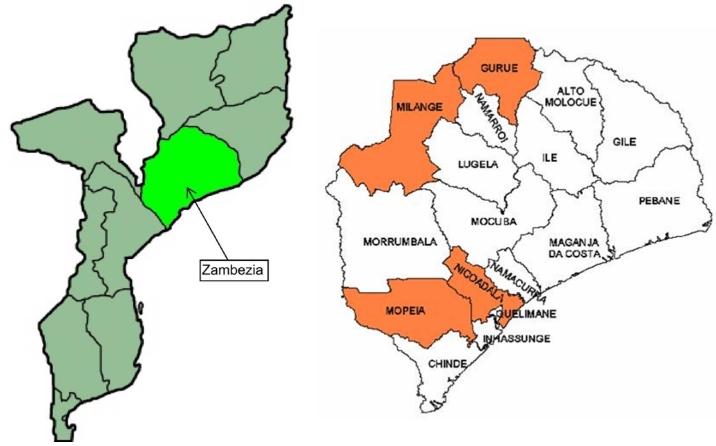
III. THE FIELD EXPERIMENT

The field experiment we discuss was conducted as part of the final survey in the impact evaluation of the HarvestPlus Reaching End Users (REU) project in Zambézia Province of northern Mozambique. The REU was an integrated biofortification project with the goal of reducing vitamin A deficiency among young children and women of childbearing age. Vitamin A was introduced through OFSP; vines were distributed to households at the beginning of the project and annually thereafter. The project then worked to increase adoption and consumption of OFSP by combining agricultural extension on OFSP cultivation and propagation, nutrition education on the health benefits of vitamin A-rich OFSP, and a marketing component.

III.1 The REU Project in Zambézia

The REU project took place between 2006 and 2009 in four districts of Zambézia (Figure 1). The program was implemented within farmers' groups in 144 communities in Milange, Gurué, Mopeia, and Nicoadala districts of

Figure 1: Survey Location Maps



Zambézia. Because existing community organizations are quite scarce in Mozambique, the project worked with communities to identify existing organizations, usually church groups, and then expanded or combined groups to include roughly 100 farmers on average.[2] The project ran for three growing seasons, from the 2006–2007 season to the 2008–2009 season.

The impact evaluation was designed in collaboration with the implementing agencies. Prior to the intervention, a set of communities was randomly divided into three groups: an intensive treatment group (Model 1), a less intensive treatment group (Model 2), and a control group. Randomization took place within three strata, Milange district, Gurué district, and two southern districts (Mopeia and Nicoadala, referred to in this paper as the South), to ensure that regional or language effects would not dominate any estimated impacts. The sample for this paper was collected in all three strata.

III.2 Data Collection

It is Important to note that the impact evaluation collected socioeconomic data prior to implementation of the REU in October and November of 2006 and in mid-2009 after the REU had been implemented for three seasons. The socioeconomic surveys elicited information about: household demographics and human capital, production of sweet potatoes and other crops, food and nonfood consumption and expenditures, assets, and shocks. The 2009 survey returned to exactly the same households as were interviewed in 2006, so we can match information about the individuals and households participating in the experiment prior to the intervention with data from the risk perception experiment detailed below. We report descriptive statistics for the sample in Table 2.

[2] More details on the project and site selection are available in de Brauw et al. (2010).

Table 2: Summary Statistics

	Sample Mean	Std. Dev.
Gender (% male respondents)	38.8	48.8
% of respondents below 30	35.6	47.9
% of respondents above 50	4.5	20.8
% of respondents in Milange	57.6	49.4
% respondents in Gurue	23.9	42.7
% responents in South	18.5	18.5
% who can speak Portuguese	49.6	50.0
% with wage earner in household	24.5	43.0
% with experience in sweet potato (> 5 years)	87.7	32.9
Total food expenditures per capita per day (USD)	0.27	0.13
% Reporting severe income shock	6.3	24.3
% Reporting severe asset shock	3.3	18.0
# enumerators	10	-

Table 3: Payoff Matrix

$P(A_1)$	A_1	$P(A_2)$	A_2	$P(B_1)$	B_1	$P(B_2)$	B_2	$E[A]$	$E[B]$	$E[A] - E[B]$
0.1	50	0.9	40	0.1	95	0.9	5	8.2	3.8	4.4
0.2	50	0.8	40	0.2	95	0.8	5	8.4	5.6	2.8
0.3	50	0.7	40	0.3	95	0.7	5	8.6	7.4	1.2
0.4	50	0.6	40	0.4	95	0.6	5	8.8	9.2	-0.4
0.5	50	0.5	40	0.5	95	0.5	5	9.0	11.0	-2.0
0.6	50	0.4	40	0.6	95	0.4	5	9.2	12.8	-3.6
0.7	50	0.3	40	0.7	95	0.3	5	9.4	14.6	-5.2
0.8	50	0.2	40	0.8	95	0.2	5	9.6	16.4	-6.8
0.9	50	0.1	40	0.9	95	0.1	5	9.8	18.2	-8.4
1.0	50	0.0	40	1.0	95	0.0	5	10	20	-10

Table 4: Pattern of Responses by Gender

N = 682	All	Male	Female
Stick to A (safe choice)	69	31	38
Stick to B (risky choice)	26	11	15
Shift once from A to B	587	223	364
Shift more than once	1	0	1

III.3 The Risk Perception Experiment

Following Holt and Laury (2002), we designed a hypothetical experiment to elicit the attitudes of the respondents toward uncertainty specifically related to sweet potato production. A subsample of 439 households was randomly selected from the overall sample to participate in this experiment. Whenever possible, we tried to perform the experiment on both the household head and the spouse. For 243 households, two respondents were available for the interview; in all of these cases, respondents were separated to avoid one influencing the other's responses. In all other cases, either a spouse did not exist, or the spouse was not present. Overall, a total of 682 respondents participated in the experiment and made choices from a menu of ordered lotteries. In the experiment, the respondent was asked to choose between two varieties of sweet potatoes. One of these varieties (variety A) would yield a higher output (50 50-kg bags per acre) under good rainfall conditions but a slightly lower output (40 50-kg bags per acre) under bad rainfall conditions. The other variety (B) had more variable hypothetical yields. With good rainfall, yields were quite high (95 50-kg bags per acre), but with poor rainfall, the yield would be quite low (5 50-kg per acre). The respondent had to make choices between these two varieties under 10 different rainfall scenarios, as the probability of good rainfall gradually increased from 10 percent to 100 percent. We include the protocol for the experiment, translated into English, in the Appendix.

For each distinct probability of good rainfall, the respondent was asked to choose between variety A, a less risky variety of sweet potato, and variety B, a more risky variety (Table 3). The net expected value of each choice task (not shown to the respondent) is computed as

$$E\,[A] - E\,[B] = \sum_{s=1}^{2} P\,(A_s)\,A_s - \sum_{s=1}^{2} P\,(B_s)\,B_s$$

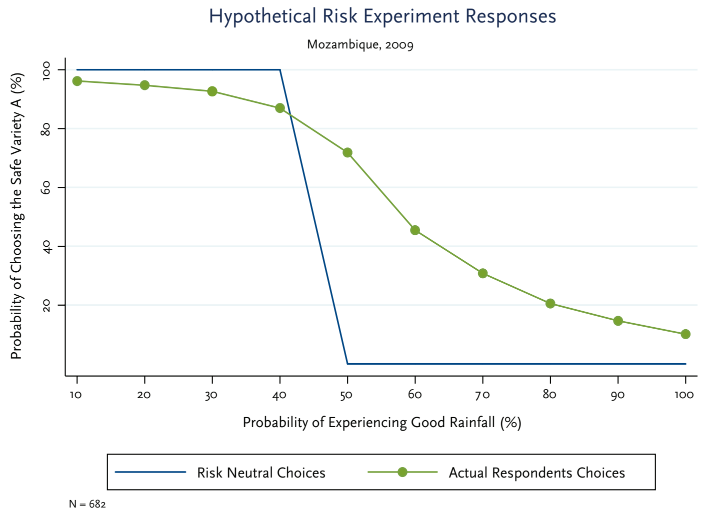
where for each variety (A or B), $s = 1$ indicates the more favorable state of nature, i.e., good rainfall, and $s = 2$ indicates the less favorable scenario, i.e., poor rainfall and therefore lower sweet potato yields. As observed in Table 3, the expected payoff for variety B was higher than variety A for all probabilities of good rainfall of 40 percent and above.

We next examine response patterns by gender (Table 4). The majority of respondents (86 percent) began the experiment by choosing the safer variety (A) under unfavorable rainfall scenarios and then shifted to the more risky variety (B) as the probability of experiencing good rainfall increased. A minority of respondents (10 percent) chose the safe variety throughout all rainfall scenarios, even when presented with certainty of good rainfall. Fewer respondents chose the risky variety from beginning to end (4 percent), while only one respondent chose to change her preferred variety more than once. As a result, it is clear that almost all respondents understood the experiment quite well.

We next compare the average choices by respondents with the risk neutral choices (Figure 2) by reporting the proportion of respondents that chose the safer variety, variety A, by the probability of experiencing good rainfall in the experiment. We note that the proportion of risky variety choices increases monotonically as the probability of experiencing good rainfall increases. However, it does so at a substantially slower rate than would be expected if all respondents were risk neutral. Therefore, we can conclude that at least with respect to sweet potato varieties, the average farmer in our sample is risk averse.

Although we can conclude that, on average, our sample

Figure 2: Risk Experiment Responses



is risk averse, we have not yet characterized preferences theoretically. We present a standard conceptual framework about choice under uncertainty in the next section. The standard framework will be the basis of our empirical analysis of risk attitudes.

IV. METHODOLOGY AND RESULTS

IV.1 Methodology

IV.1.1 Conceptual Framework

We assume that utility $U\,(\sum_j \omega\,(p_j)\,x_j) = \sum_j \omega\,(p_j)\,U\,(x_j)$ is formed over risky lottery outcomes x_j, $j \in \{1,2\}$, weighted by their subjective probability of occurrence $\omega\,(p_j)$ with $p_j \geq 0$ and $\sum \omega\,(p_j) = 1$. In this paper, the lotteries are related to choices of sweet potato varieties with different yields under alternative rainfall scenarios. Therefore, we restrict our attention to the gain domain, i.e., $x_j > 0$.

Under Expected Utility Theory (EUT) (Bernoulli 1738; von Neumann and Morgenstern 1944), the subjective probabilities are identical to the objective probabilities, and the probability weighting function is thus defined by $\omega\,(p_j) = p_j$. In this case, the most commonly adopted measures of risk aversion are given by the coefficient of absolute risk aversion $ARA(x) = -\frac{U''(x)}{U'(x)}$, or by the coefficient of relative risk aversion $RRA(x) = x\,ARA(x)$ (Pratt 1964; Arrow 1965).

Quiggin (1982, 1993) has proposed a Rank Dependent Utility (RDU) framework that can be seen as a generalization of EUT. Under RDU, subjective probabilities are not constrained to be equal to objective probabilities as in EUT. Instead, agents are allowed to make their choices under uncertainty according to a nonlinear probability weighting function. Under this framework, the extent to which agents are risk averse is not only captured by some measure of the curvature of the utility function (such as $ARA(x)$ or $RRA(x)$) but also by the nonlinearity of the probability weighting function. We will consider both theoretical approaches.[3]

In this paper, we assess the extent to which the choices made by the respondents are consistent with EUT by testing, whether or not the probability weighting function is linear. We also look at different nested specifications of the valuation function $U(.)$, and this allows us to determine the shape of risk preferences, which is more consistent with the data.

IV.1.2 Utility Functions

Power Risk Aversion Utility We start by considering a general parameterization of the utility function that allows $RRA(x)$ to be decreasing, increasing, or constant. A parsimonious specification allowing such degree of generality is proposed by Xie (2000) with the Power Risk Aversion (PRA) utility function. The PRA valuation function is given by

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

The coefficient of absolute risk aversion is now nonincreasing in x and given by

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

while the coefficient of relative risk aversion can be written as

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

Constant Relative Risk Aversion Utility When $\gamma = 0$, the PRA reduces to the CRRA utility function, which is the most commonly assumed specification in studies of risk aversion. It can be written as:

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

Under this parameterization, the coefficient of relative risk aversion is equal to σ, and the coefficient of absolute risk aversion is assumed to be decreasing ($ARA^{CRRA}(x) = \sigma/x$).

IV.1.3 Regression model

We assume that farmers in our sample choose the sweet potato varieties that deliver the highest expected utility under each rainfall scenario. This setup is similar to a random utility model where U_A^* and U_B^* are unobserved single period utility levels associated with the choice of variety A and B. For any given rainfall scenario, we assume that the difference $\Delta U^* = U_A^* - U_B^*$ is a latent variable that depends on a set of explanatory variables X and on parameters $\sigma, \gamma, \mu, \beta$. More specifically, we assume that

$$U_j = \sum_s \omega(p_{sj})\, U(y_{sj}; \sigma, \gamma) \tag{5}$$

$$\omega(p_{sj}) = p_{sj}^{\mu} / [\, p_{sj}^{\mu} + (1-p_{sj})^{\mu}]^{1/\mu} \tag{6}$$

$$\Delta U^* = U_A^* - U_B^* = f(X; \sigma, \gamma, \mu, \beta) + \varepsilon \tag{7}$$

$$\varepsilon \sim N(0,1) \tag{8}$$

$$y_A = 1[y^* > 0] \tag{9}$$

where $s = 1, 2$ denotes the bad rainfall/good rainfall states, $j = A, B$ is the index for the two varieties of sweet potato, and $1[y^* > 0]$ is an indicator function equal to 1 if $y^* > 0$ and 0 otherwise. We include a set of explanatory X variables to control for observable heterogeneity in σ, which is the coefficient of relative risk aversion under the CRRA utility. This approach is similar to the estimation of a random parameter model where the estimated parameter $\hat{\sigma}$ is assumed to vary across observations according to $\hat{\sigma}_i = f(X_i\, \beta) = \alpha + \beta X_i + u_i$ where $u_i \sim N(0, 1)$. The variable y_A represents the choice of variety A, and $\sigma, \gamma, \mu, \beta$ are the parameters to be estimated. In equation (8), we assume that the error term ε is normally distributed with variance 1 and is identically and independently distributed between respondents. However, when we estimate parameters, we allow choices to be correlated within respondents.

The likelihood function for the discrete choice model described in equations (5) through (9) is:

$$L(\sigma, \gamma, \mu, \beta \mid X_i, y_{Ai}) = \prod_{i=1}^{N} [\Phi(\Delta U^*(X_i; \sigma_i, \gamma, \mu, \beta))]^{y_{Ai}} \times [1 - \Phi(\Delta U^*(X_i; \sigma_i, \gamma, \mu, \beta))]^{1-y_{Ai}} \tag{10}$$

where $\Phi(.)$ is the cumulative standard normal distribution. We obtain estimates of the parameters by maximizing the logarithm of equation (10).

IV.1.4 Finite Mixture Model

Following Harrison et al. (2010), we also estimate a mixture model where we allow both EUT and RDU to explain observed choices under uncertainty by Mozambican farmers. The likelihood function for this model is given by

[3] Kahneman and Tversky (1979) and Tversky and Kahneman (1992) further generalize EUT by assuming that subjective and objective probabilities are not identical, as in RDU, but also by assuming that the way agents valorize risky lotteries varies according to whether the outcomes of the lotteries lie in the loss or in the gain domain (Cumulative prospect Theory, or CPT). Since our experiment is restricted to the gain domain by design (sweet potato yields are defined only over the gain domain), we cannot empirically test whether EUT or RDU hold against CPT.

Table 5: Regression Results

	PRA			CRRA		
	(1)	(2)	(3)	(4)	(5)	(6)
σ	0.33***	0.41*	0.45**	0.74***	0.83***	0.92***
	(0.05)	(0.25)	(0.21)	(0.01)	(0.10)	(0.13)
Male		0.09	0.01		-0.05	0.03
		(0.07)	(0.06)		(0.04)	(0.04)
Age < 30		0.13**	0.14**		0.04	0.00
		(0.07)	(0.06)		(0.04)	(0.03)
Age > 50		0.10	0.00		-0.06	-0.11*
		(0.12)	(0.07)		(0.08)	(0.06)
Gurue District		-0.16	-0.13		-0.14***	-0.11*
		(0.15)	(0.12)		(0.05)	(0.07)
South District		0.17*	0.28**		0.08	0.14*
		(0.10)	(0.13)		(0.06)	(0.08)
Education (Speaks Portuguese)		-0.06	-0.55*		-0.02	-0.02
		(0.05)	(0.03)		(0.02)	(0.02)
Wage in Household		-0.10	-0.09		-0.03	0.06
		(0.07)	(0.06)		(0.04)	(0.03)
Experience with Sweet Potato (>5 years)		-0.04	-0.05		0.02	-0.07
		(0.08)	(0.08)		(0.06)	(0.06)
Total Food Expenditure per Capita		-0.09	-0.13**		0.03	0.03
		(0.08)	(0.05)		(0.04)	(0.03)
Severe Shock to Income		0.19	0.15		0.09	0.06
		(0.13)	(0.10)		(0.08)	(0.07)
Severe Shock to Assets		0.11	-0.07		0.07	0.10
		(0.15)	(0.10)		(0.10)	(0.12)
Village and Enumerator Dummies	No	No	Yes	No	No	Yes
μ	1.37***	1.24***	1.22***	1.15***	1.13***	1.08***
	(0.06)	(0.11)	(0.09)	(0.02)	(0.02)	(0.01)
$F-stat\ (H_o : \mu = 1)$	42.3***	5.20**	6.30***	75.10***	48.44***	36.00***
$p-value$	(0.00)	(0.01)	(0.01)	(0.00)	(0.00)	(0.00)
γ	0.16***	0.13***	0.09***	–	–	–
	(0.01)	(0.03)	(0.01)			
N	6820	5700	5700	6820	5700	5700
Log-Likelihood	-2867.6	-2346.1	-2195.5	-2916.9	-2371.2	-2233.2

Maximum likelihood estimates. ***, **, and * denote statistical significance level of 1%, 5%, and 10%, respectively.

$$L(\sigma_i, \gamma, \mu, \beta, \pi \mid X_i, y_{Ai}) = \prod_{i=1}^{N} \pi\, [\Phi(\Delta U^*_{EUT}(X_i; \sigma_i, \gamma, \mu, \beta))]^{y_{Ai}} \quad \text{x}\ (1-\pi)\,[1-\Phi(\Delta U^*_{RDU}(X_i; \sigma_i, \gamma, \mu, \beta))]^{1-y_{Ai}} \tag{11}$$

where π is the parameter determining the proportion of respondents behaving according to EUT (μ=1).

IV.2 Results

IV.2.1 Homogenous Preferences

We want to learn about which form of risk preferences best characterizes the preferences of farmers in our sample, with respect to the two hypothetical varieties of sweet potatoes posed to them. Since RDU is a generalization of EUT over the gain domain and since the

CRRA form is a special case of the PRA utility function, all the specifications considered here are nested within the PRA utility function under the RDU framework.[4]

We begin by estimating the model described by equations (5) through (9) (Table 5). We initially estimate a general model in which the parameters are common across respondents (column 1). The two parameters of the PRA utility function (1) are positive and significantly different from zero: $\hat{\sigma} = 0.33$ and $\hat{\gamma} = 0.16$. Recall that the parameter γ represents the difference between the PRA and the CRRA; if $\gamma = 0$, then PRA preferences collapse to CRRA preferences. As we can reject the null hypothesis that if $\hat{\gamma} = 0$ at the 1 percent significance level, we conclude that preferences do not, on average, follow the CRRA in favor of PRA preferences.

Constant relative risk aversion is a convenient assumption to impose because of the simplicity of the implied utility function. Under CRRA utility, relative risk aversion (and the curvature of the utility function) is summarized in only one parameter (σ). Under PRA utility, however, the coefficient of relative risk aversion is now determined by two parameters, σ and γ, each of which influences the curvature of the utility function. We depict the relative influence of these two parameters on the shape of the utility function in Figure 3 by plotting the utility function for different values of σ and γ at estimated parameter values. With this set of parameter values, we observe that absolute risk aversion (2) is decreasing, but relative risk aversion (3) is increasing. We demonstrate this point in Figure 4, which illustrates that relative risk aversion is increasing for all values of X at the estimates' parameter values.

A further parameter of interest is 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 (equation 6). Note that EUT is consistent with $\mu = 1$, and equation (6) collapses to $\omega(p) = p$ if $\mu = 1$. Therefore, in this framework, we can test the null hypothesis that $\mu = 1$ against the alternative that it is not ($\mu \neq 1$), which is equivalent to testing the null hypothesis that preferences behave as in EUT against the alternative that preferences follow the RDU.

We report the $F-statistic$ of this hypothesis test in Table 5, and in all specifications, we strongly reject EUT in favor of RDU. Since we find that $\hat{\mu} > 1$ under each specification, the respondents' probability weighting function is S-shaped. Respondents tend, therefore, to underweight small probabilities relative to the objective and overweight larger probabilities. In the top graph in Figure 4, we plot the nonlinear probability weighting function against the identity function that is imposed if we assume EUT. Note that only around a probability of the good rainfall state of 0.6 do farmers begin to overweight subjective probabilities; before that point, they underweight objective probabilities.

We also model σ as a function of observable

Figure 3: Power Risk Aversion Utility Function

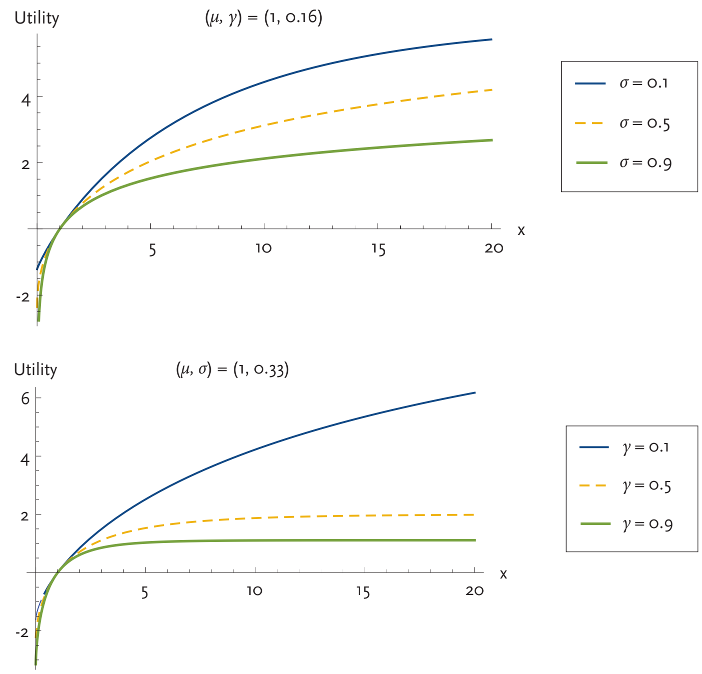
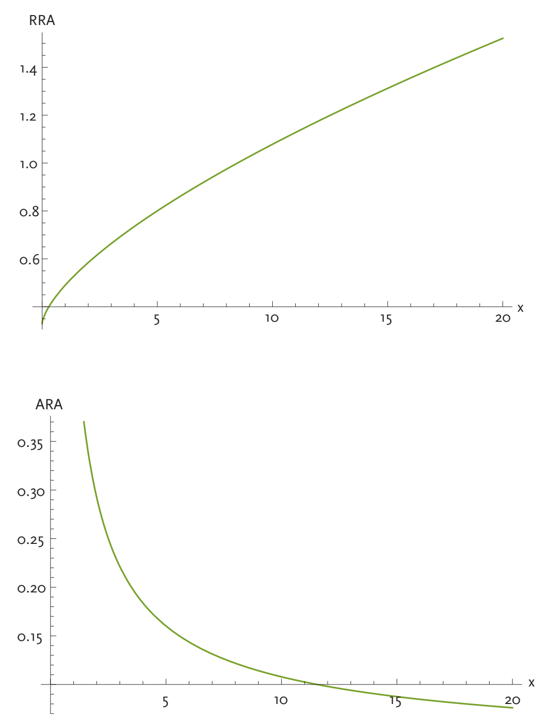


Figure 4: Absolute and Relative Risk Aversion [(μ, γ, σ) = (1, 0.16, 0.33)]



[4] In our specification, (6) implies that the valuation function is consistent with EUT only if μ=1.

characteristics about respondents (Table 5, columns 2–3 and 5–6). We focus on measuring σ as a function of observables rather than γ, specifically so that we can compare the effect of observables on the curvature of both the CRRA and PRA utility functions. We include variables measured in the baseline socioeconomic survey, including the age, gender, and education level of the respondent, total household expenditures, and previous household experience with growing sweet potatoes. Moreover, we include contemporaneous variables capturing self-reported shocks to income and asset holdings in the past 12 months, as well as an indicator of whether a member of the household is a wage earner. Finally, we include village-dummy variables to account for community-specific characteristics like agroecological conditions, for example, and we control for enumerator effects during the interview.

For PRA preferences, the conditional estimates are reported in columns 2 and 3 of Table 5.[5] We find that only a few variables have a statistically significant influence on risk aversion. For example, the estimated coefficient among younger respondents (less than 30 years old) suggests that they are more risk averse than respondents age 30 to 50. The gender of the respondent does not appear to influence risk aversion. Moreover, we find that respondents located in the southern districts of Zambézia are also more averse to risks related to sweet potato yields. In the southern districts, farmers prefer to plant sweet potato after they harvest the primary rice crop, so the sweet potato growing season is shorter. As a result, farmers could be more risk averse, particularly with respect to poor rainfall, due to the short season. Respondents who experienced shocks to income or assets in 2009 do not seem to answer differently than respondents who did not experience such shocks. After taking into account village and enumerator effects, higher education and higher level of food expenditures are also associated with lower risk aversion. Finally, it is important to note that including control variables to condition σ does not alter the main results. Even when controlling for individual and household characteristics, we still reject CRRA in favor of PRA ($\hat{\gamma} \neq 0$), and we still reject EUT in favor of RDU ($\hat{\mu} \neq 1$).

An open question is how badly one predicts risk preferences if using the common assumption of CRRA preferences. First, we predict the distribution of relative risk aversion under the PRA and CRRA utility functions, conditioning on individual and household characteristics (Figure 5). We find that under the PRA, individuals are predicted to be more risk averse, though the variation in relative risk aversion is larger. Yet it could be that the two

[5] Information on total food expenditure was not collected for a small part of our sample, so the total number of observations for the conditional analysis is 5700 instead of 6820.

Figure 5: Estimated σ Distribution for PRA and CRRA

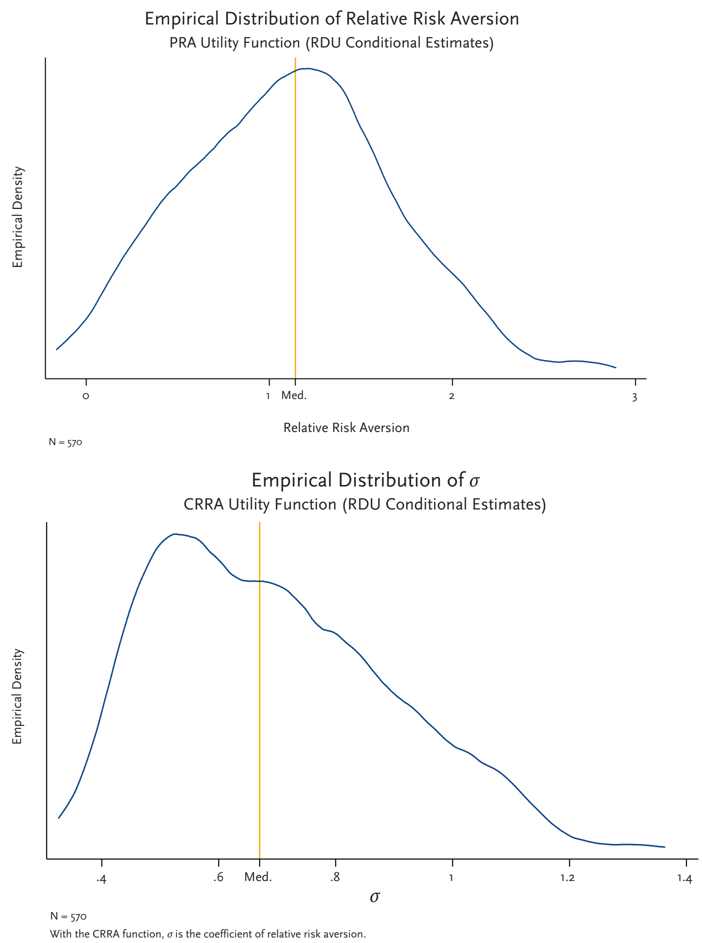
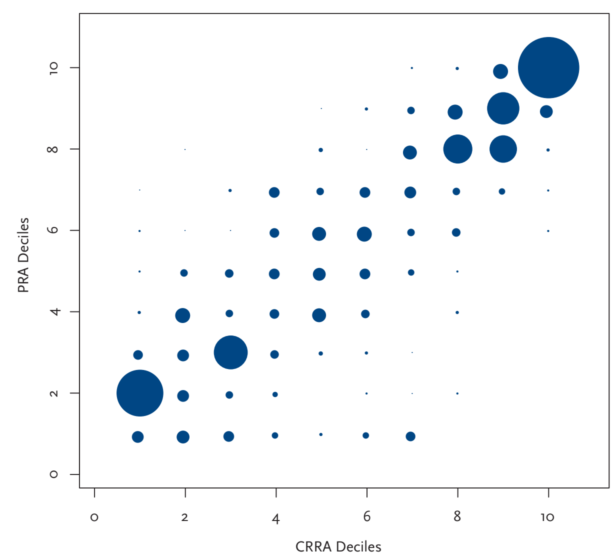


Figure 6: Bubble Plot for RRA (x) Distribution of PRA vs CRRA



utility functions predict essentially the same relative risk ranking. To measure this, we assigned the predictions under both utility functions into deciles, with relative risk aversion increasing by decile rank. We then plotted

Table 6: Regression Results, Mixture Model

	Estimate	Standard Error
Mixing Parameters		
π^{EUT}	0.278***	(0.059)
π^{CPT}	0.722***	(0.059)
EUT Parameters		
σ	0.000	(0.001)
γ	0.081***	(0.003)
CPT Parameters		
σ	0.164	(0.356)
γ	0.308***	(0.065)
μ	0.571**	(0.260)
N	6820	
Log-Likelihood	-2847.2	

Maximum likelihood estimates. ***, **, and * denote statistical significance level of 1%, 5%, and 10%, respectively.

farmers by PRA decile on the y-axis and by CRRA decile on the x-axis in a bubble plot, where the size of the bubble represents the number of farmers falling into each decile cell (Figure 6). If PRA and CRRA preferences ranked farmers similarly, we would find 10 large bubbles along the 45 degree line. Instead, we find a significant number of farmers who fall into different deciles under PRA preferences than under CRRA preferences, as evidenced by the size and number of bubbles off of the 45 degree line. If one assumes CRRA, a similar group of farmers are the most risk averse as under PRA preferences, but as farmers are predicted to be less risk averse, the rankings diverge. In fact, many of the farmers characterized as in the least risk-averse decile under CRRA end up in the second decile under PRA, and the least risk-averse farmers under PRA are found in every decile up to the 7th under CRRA preferences. In general, the figure indicates that if we had made the CRRA assumption, the relative ranking of risk aversion among farmers in our sample would be dramatically different than under PRA preferences. If we remain conservative and consider that our estimated σ coefficients classified +/- 1 decile apart are similar, we still find that close to 33 percent of farmers are misclassified under CRRA parameter estimates relative to PRA parameters.

IV.2.2 Preference Heterogeneity

In the previous subsection, we imposed a single utility framework on the data (either EUT or RDU). We next relax this assumption by allowing a proportion of farmers to respond according to EUT and the remaining farmers to respond according to RDU. Harrison and Rutström (2009) and Harrison et al. (2010) have recently shown that preference heterogeneity is potentially a relevant factor to account for in experimental data related to risk attitudes. Therefore, we base the next set of results on the likelihood function in equation (11), which is similar in spirit to a regime switching model.

Among our sample, neither EUT nor RDU fully explains observed attitudes toward risk related to sweet potato yields in Zambézia (Table 6). We find that the estimated parameter on the share of farmers behaving according to EUT is significantly different from zero (28 percent). However, the percentage is not large; the majority of farmers still behave according to RDU according to the finite mixture model (72 percent).

Interestingly, by relaxing the assumption made on homogenous preferences, the way RDU farmers discount objective probabilities changes. The estimated parameter characterizing the probability weighting function is now $\hat{\mu} = 0.57$, which implies that RDU farmers actually over-weight small probabilities and under-weight larger probabilities. This finding is more consistent with typical weighting functions from RDU, so estimating risk preferences in a mixture model appears to be more realistic.

V. CONCLUSION

In this paper, we have used experimental data that was collected in combination with data from an impact evaluation of an agricultural biofortification intervention that used OFSP as the delivery mechanism for additional vitamin A. As the intervention involved growing OFSP, we framed our experiment around growing sweet potatoes. We conducted the experiment among a subsample of farm households (682 respondents) included in the final impact evaluation survey.

When we estimated risk preferences in a general form that nested more restrictive forms of preferences typically used in the literature, we found that we could strongly reject the hypotheses that farmers follow CRRA preferences. We also found that by averaging across the whole sample, we could reject the null hypothesis that preferences follow EUT, accepting the alternative hypothesis that preferences follow RDU. We also estimated the proportion of farmers whose preferences follow EUT by estimating a mixture model; the point estimate was 0.278, suggesting that for about one-fourth of farmers, the objective probabilities of states coincide with their subjective probabilities.

We finally demonstrated how the assumptions of CRRA preferences affect the characterization of risk preferences. Relative to PRA preferences, CRRA preferences do reasonably well at describing the preferences of more risk-averse farmers but appear to poorly describe the risk preferences of less risk-averse farmers. Therefore, making the CRRA assumption is not without cost; more flexible forms of risk preferences certainly lead to a different ranking of individuals with respect to risk aversion, at worst badly mischaracterizing risk preferences among sampled individuals.

Therefore, we suggest that researchers use caution before making the CRRA assumption in empirical applications. One potential concern with our application, however, is that we asked about risk preferences in a narrowly defined hypothetical context and that risk preferences in growing sweet potatoes might be different than in other contexts. We believe that it might be worthwhile to replicate this analysis with an experiment that either more broadly defines the risk domain, includes real payouts, or both.

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APPENDIX

RISK PERCEPTIONS MODULE

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: "Scientists are working to find varieties of sweet potato that are better than what you are used to at present. The following choices are hypothetical but can help provide some input to their research. Assume there are two varieties being planned that have different yield potential depending on how much it rains. Below you will 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 the new 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 50 kg bags. Once again, the two varieties only differ in how they perform under different rainfall conditions. Variety B performs extremely well under very good rainfall conditions, yielding 95 bags. But it does not perform that well if rainfall is moderate; with moderate rainfall, Variety B yields only 5 bags. On the other hand, Variety A gives more consistent yields: if there is very good rainfall, it yields 50 bags, and if there is moderate rainfall, it will yield 40 bags. So Variety B is more risky than Variety A. Again, if there is very good rainfall, Variety B will yield 95 bags while Variety A will yield 50 bags. If there is moderate rainfall, Variety B will yield only 5 bags, while Variety A will yield 40 bags. 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% to 100%. So we will ask you: if the chance of very good rainfall is 1 out of 10 and that of moderate 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 if you if the chance of good rainfall is now two out of ten, and the chance of moderate 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 moderate rainfall. For example, over the next ten-year period, the chance of very good rainfall being 2 out 10 means over the next ten year period there is likely to be very good rainfall in 2 years. And so on.

Please note once again that both varieties would command the same price in the market."

Enumerator: Please ensure that the respondent understands what is meant by asking them to repeat back to you the structure of the choices. Please don't 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've understood. Writing out the yields for the two varieties (on the ground) may be useful. You may want to use sticks to represent five bags and thus demonstrate the 95, 5, 50, and 40 bags for those who are not literate. Once you are convinced they've understood the set up, you can proceed to the choices. A common misunderstanding is to interpret higher chance of rain as 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, please ensure that the two respondents from the household do not observe each other's answers.