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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 lab-in-the-field experiment to explore risk preferences related to sweet potato production among a sample of farmers in northern Mozambique. A unique feature of this experiment is that it includes a large subsample of husband and wife pairs. After exploring correlations between husband and wife preferences, 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 reject the null hypothesis that farmers' preferences follow the CRRA utility function, in favor of the more flexible power risk aversion preferences. If we make the common CRRA assumption in our sample, we poorly predict risk preferences among those who are less risk averse.

1. 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), Delavande et al. (2011) 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. Several impact evaluations have recently been conducted on pilot projects related to weather insurance, with mixed success. Cole et al. (2013) test the importance of the insurance contract price on take up in India by randomizing price offers, and find that average take up in participating villages is around 25%, though almost no one takes up insurance in neighboring villages that did not receive a visit from insurance agents. Hill and Robles (2011) find similar take up (27%) in a pilot project in southern Ethiopia that offered small amounts of insurance, rather than attempting to insure the farmer's entire production. Additional information about the type and distribution of risk preferences among farmers might be important in informing the design of weather insurance contracts, to improve take up.

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 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 data were collected in the final survey of a randomized evaluation designed to evaluate an intervention that provided farmers with OFSP vines, information about how to grow OFSP, and the relative nutritional benefits of consuming orange rather than white sweet potatoes, particularly for women of child bearing age and children under five years old. One unique aspect of the experiment is that it was conducted separately

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with both the household head and spouse when both were present. It was therefore conducted with 682 farmers from a total of 439 households. Within households in which both head and spouse were present, we examine the correlation between the husband's and the wife's preferences.

We use the data to consider and test several models of risk preferences against one another. We initially compare two contending models of choice under uncertainty, Expected Utility Theory (EUT) and Rank Dependent Utility (RDU). Quiggin (1982, 1993) have proposed a Rank Dependent Utility (RDU) framework that can be considered 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.[1] We then consider 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.

Our primary contribution to the literature is that we use data collected in a lab-in-the-field experiment to nest different potential models of risk preferences, and then we develop and test these models against one another. We are also able to examine risk preferences among the head and the spouse, and to consider whether they predict one another's risk preferences within this hypothetical context. We further construct a model that allows for heterogeneity in the theoretical basis for risk preferences; namely, EUT or RDU. Our experiment is related to the lab experiment conducted by Andersen et al. (2010), who conduct a lab experiment among 150 subjects and elicit both risk preferences and subjective probabilities, using real payoffs. In general, our finding is relatively consistent with both Kahneman and Tversky (1979) and Andersen et al. (2010); we find that the RDU dominates EUT, and we generally reject the hypothesis of CRRA, regardless of the form of preferences. We then show the magnitude of errors that take place if one assumes CRRA preferences. We find 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. Furthermore, we find that the risk premium implied by RDU is substantially higher than that of EUT, suggesting that one explanation for low take ups of rainfall insurance in developing countries may be a mischaracterization of risk preferences.

The paper proceeds 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 both. The fourth section presents and discusses the results, and the final section concludes.

2. 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 (Harrison et al., 2010; Liu, 2013; Tanaka et al., 2010). Previous work on characterizing risk preferences has been based either on the use of experimental lotteries or on the analysis of production decisions collected from household survey data. We will focus on the first line of work since this paper also uses experimental lottery data from the field. Here, we only summarize papers that are directly relevant to our analysis.[2]

Binswanger (1980, 1981) are among the first studies 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 suggested 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 non-increasing 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 find no significant relationship between risk aversion and respondent 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. In contrast with the results found by other authors, Yesuf and Bluffstone (2009) used a data set collected in northern Ethiopia, and found that risk aversion is significantly correlated with respondent 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 finds that higher risk aversion translates into a lower allocation of labor towards 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 (2013), Tanaka et al. (2010), and Harrison et al. (2010) depart from the previously cited work to consider an alternative utility framework to EUT, in the form of 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 proposed by Binswanger (1980), they follow Holt and Laury (2002) and use multiple price lotteries (MPL) in which the lottery payoffs are fixed in each choice task, and the outcome probabilities are varied. While Liu (2013) and Tanaka et al. (2010) analyzed the PT framework over the full range of gains and losses, Harrison et al. (2010) focused only on the gain domain, and they compared EUT to RDU by testing the non-linearity of the probability weighting function. Harrison et al. (2010) also estimated a finite mixture models allowing both EUT and RDU to explain some proportion of respondents' choices over risky lotteries.

In a similar experiment, Andersen et al. (2010) use an MPL and elicit subjective probabilities experimentally among 150 participants in a lab experiment, similarly estimating a mixture model and finding the RDU dominates the EUT. This paper differs from Andersen et al. (2010) in several ways. First, Andersen et al. (2010) use a weighting function not typically found in the literature. Second, whereas Andersen et al. (2010) conduct a lab experiment, this paper uses a lab-in-the-field experiment with a larger sample and radically different conditions under which the experiment took place. Finally, in this paper two members of the same household often participated in the experiment, whereas in a lab experiment individuals are not likely to be related.

In Table 1, we summarize some essential characteristics of the work cited above. Most of the previously mentioned studies rely 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 towards risk in a single parameter,

[1] RDU is related to prospect theory (PT) which further postulates that agents value risky lotteries differently in the gain and loss domain (Kahneman and Tversky, 1979). Since the experiment presented in this paper only takes place in the gain domain, we cannot empirically test EUT or RDU versus PT.

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

Table 1
Risk preferences, perception framework and utility functions.

Study	Country	Lottery type	Perception framework	Utility function	Probability weighting	Estimated parameter
Binswanger (1981)	India	Hypothetical + real	EUT	CRRA	Linear	
(Holt and Laury, 2002)	USA	Hypothetical + real	EUT	CRRA + Power	Linear	
Miyata (2003)	Indonesia	Real	EUT	CRRA	Linear	
Wik et al. (2004)	Zambia	Real	EUT	CRRA	Linear	
Mosley and Verschoor (2005)	Multiple	Real + hypothetical	EUT	CRRA	Linear	
Liu (2013)	China	Real	EUT + CPT	CRRA	$\omega(p) = exp[-(-lnp)^{\mu}]$	$\hat{\mu} = 0.69$
Hill (2009)	Uganda	Hypothetical	EUT	CRRA	Linear	
Yesuf and Bluffstone (2009)	Ethiopia	Real	EUT	CRRA	Linear	
Tanaka et al. (2010)	Vietnam	Real	EUT + CPT	CRRA	$\omega(p) = 1/\exp[ln(1/p)]^{\mu}$	$\hat{\mu} = 0.74$
Harrison et al. (2010)	Multiple	Real	EUT + RDU	CRRA	$\omega(p) = p^{\mu}/[p^{\mu} + (1-p)^{\mu}]^{1/\mu}$	$\hat{\mu} = 1.38$
This paper	Mozambique	Hypothetical	EUT + RDU	CRRA + PRA	$\omega(p) = p^{\mu}/[p^{\mu} + (1-p)^{\mu}]^{1/\mu}$	$\hat{\mu} = 1.37$ e

Notes: Mosley and Verschoor (2005) and Harrison et al. (2010) use data from Ethiopia, India and Uganda.

which is related to the curvature of the utility function. Simplicity in the functional form comes at the cost of generality, since a priori there is no reason to believe that risk attitudes should be characterized by constant relative risk aversion. Holt and Laury (2002), who used responses by US students 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 CRRA, so they consider a power utility function allowing the relative risk aversion coefficient to be either 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.

3. 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 a goal of reducing vitamin A deficiency among young children and women of child bearing age. Vitamin A was introduced through OFSP, which have more vitamin A than traditionally grown white or yellow flesh sweet potatoes. OFSP vines were distributed to households at the beginning of the project and annually thereafter. The project then provided agricultural extension focused on OFSP, nutrition extension focused on vitamin A benefits and consumption, and marketing information on OFSP to participating households.

3.1. The REU project in Zambézia

The REU project took place between 2006 and 2009 in four districts of Zambézia (Fig. 1). The program was implemented within farmers' groups in 144 communities in Milange, Gurué, Mopeia, and Nicoadala districts of Zambézia. Because existing community organizations are scarce in northern 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. [3]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 deemed suitable for the intervention was randomly selected 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 the two southern districts (the South), to ensure that regional or language

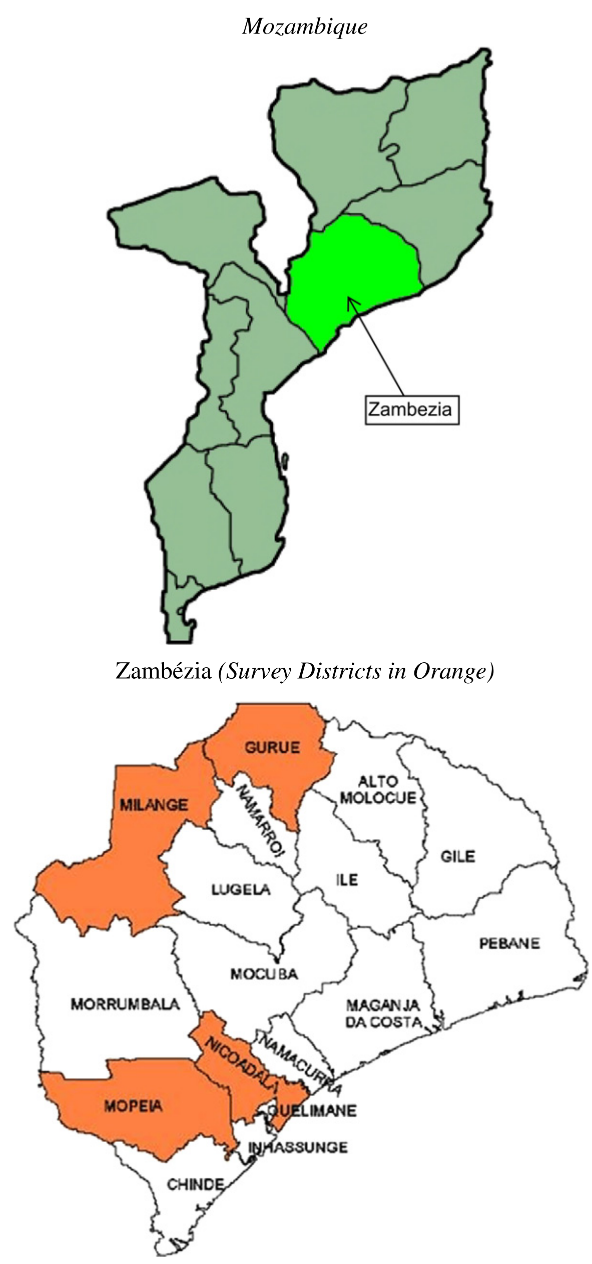


Fig. 1. Survey location map. Mozambique. Zambézia (surveyed districts in orange).

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

Table 2
Descriptive statistics, by number of household respondents.

	(1)	(2)	(3)	(4)	(5)
	Whole sample	Single headed households	Households with 1 resp.	Households with 2 resp.	p-Value H_0: (3) = (4)
% resp. in HH with 2 respondents	71.3	0.0	0.0	100.0	–
% resp. in single headed HH	4.3	100.0	0.0	0.0	–
Gender (% male respondents)	38.9	6.9	12.0	50.0	0.00
% of respondents below 30	35.6	41.4	40.7	33.5	0.10
% of respondents above 50	4.5	3.4	1.2	5.8	0.00
% respondents in treated villages	68.8	79.3	67.1	68.7	0.69
% of respondents in Milange	57.6	62.1	80.8	49.4	0.00
% respondents in Gurué	23.9	24.1	8.4	29.2	0.00
% respondents in South	18.5	13.8	10.8	21.4	0.00
% resp. who can speak Portuguese	28.6	17.2	13.8	34.4	0.00
% resp. with wage earner in household	24.5	31.0	24.0	24.3	0.93
% resp. with self employed member in household	30.6	13.8	19.8	35.4	0.00
# plots owned	3.7	3.0	3.6	3.8	0.03
Share of OFSP over SP	44.0	42.5	42.3	44.7	0.53
% resp. with experience in sweet potato (>5 years)	87.7	82.8	91.0	86.8	0.12
Total food expenditures per capita per day (USD)	0.27	0.29	0.26	0.28	0.15
Quintile 1 (poorest)	20.0	23.1	17.6	20.6	0.45
Quintile 2	20.0	30.8	25.0	17.6	0.08
Quintile 3	20.0	3.8	25.7	19.1	0.12
Quintile 4	20.2	26.9	19.1	20.1	0.80
Quintile 5 (richest)	19.8	15.4	12.5	22.5	0.00
% reporting severe income shock	6.3	3.8	5.1	6.9	0.45
% reporting severe asset shock	3.3	3.8	2.9	3.4	0.77
Number of respondents	682	29	167	486	–

Notes: the fifth column reports p-values for two-sample tests of equal proportions between 1-resp and 2-resp households.

effects would not dominate any estimated impacts. The sample for this paper was collected in all three strata.

3.2. Data collection

Important for this paper, the impact evaluation collected socioeconomic data both prior to implementation of the REU in October and November of 2006 and after the REU had been implemented for three seasons, in mid-2009. The socioeconomic surveys were designed to elicit information about several aspects of the household, including its demographics, agricultural production, landholdings, experience growing sweet potatoes, non-agricultural income sources, and household expenditures. The 2009 survey returned to exactly the same households as were interviewed in 2006, so we can match information about the individuals participating in the experiment and about the household prior to the intervention with data from the risk perception experiment detailed below. We specifically construct variables from the baseline survey including respondent demographic characteristics, the respondent's education level, household experience growing sweet potatoes, and per capita food expenditures. We measure negative shocks to the household between baseline and final surveys using the final survey, as well as constructing enumerator dummy variables.

3.3. The risk perception experiment

Following Holt and Laury (2002), we designed a hypothetical experiment to elicit the attitudes of the respondents towards 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 the other 196 households, 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.

Whereas our sample is relatively unique in that it attempted to include the household head and the spouse, this feature led to some selection of households in which we could conduct the experiment with both partners. To illustrate, we initially examine average observable characteristics between households with two respondents and households with one respondent (Table 2).[4] We were more likely able to find two respondents in Gurué and the two southern districts, among households with older household heads, and we were less likely to find richer households in terms of baseline asset holdings, and more likely to find poorer households. Consequently, we further study correlations between choices made by the head and spouse.[5] If the way husbands (wives) form risk preferences with respect to our framed experiment depends heavily on the way their partner forms risk preferences, then we need to explicitly take the selection process into account. If, on the other hand, we observe that husbands and wives make choices observationally independently of one another, then selection should not play a role in our preference parameter estimates. We return to this idea in the next subsection.

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) under good rainfall conditions, but a slightly lower output (40 50 kg bags) under bad rainfall conditions.[6] The other variety (B) had more variable hypothetical yields. With good rainfall, yields were quite high (95 50 kg bags), but with poor rainfall, the yield would be quite low (5 50 kg bags). 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% to 100%.[7] 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.

[4] We also report descriptive statistics for the overall sample in Table 2.

[5] During the interview, the enumerators were instructed to conduct the risk experiment separately for husbands and wives in households where both agreed to participate. One could nonetheless expect that because husbands and wives share common information and are exposed to a similar environment, their risk preferences are potentially aligned.

[6] Farmers in Zambézia frequently measure crop production in terms of bags designed to hold 50 kg of dry maize. A 50 kg bag holds approximately 60 kgs of sweet potatoes, and we designed the experiment to only propose plausible hypothetical yields to farmers.

[7] We include the protocol for the experiment, translated into English, in the Appendix A.

We initially describe the payoff matrix of the experiment (Table 3). For each line in the table, the respondent was asked to choose between the less risky variety (variety A) and the more risky variety (variety B). 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 shown in Table 3, in expected terms the expected yield was higher for variety B than variety A for all probabilities of good rainfall of 40% and above.

We next examine response patterns by gender (Table 4). The majority of respondents (86%) 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%) chose the safe variety throughout all rainfall scenarios, even when presented with certainty of good rainfall. Fewer respondents chose the risky variety from the beginning to the end (4%), while only one respondent chose to change her preferred variety more than once. As a result, it seems that almost all respondents clearly understood the experiment quite well.

We next compare the average choices by respondents with the risk neutral choices (Fig. 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.

3.4. Preferences among husbands and wives

As discussed in the previous section, there is some selection of households in which we have two rather than one respondent. Therefore, it is important to consider whether their choices were correlated or not, and if they are correlated, whether or not including both partners in estimating risk preferences would affect the estimates themselves. In this subsection, we explicitly study the subsample of husbands and wives who were both in the sample.

Among husbands and wives who both participated in the experiment, the overall correlation between responses was 0.79. However, we would expect responses to be the same in the distribution tails, since choices were the same among most respondents. The correlation between pairs' responses would be a concern if they were the same in the middle of the distribution, around the choice when the risk neutral choice switches from A to B. Specifically, if the correlation was high for scenarios 4 to 7, our risk parameter estimates based on the entire sample would overweight the household head-spouse pairs, since they show up twice in the data set whereas households in which we only interviewed one partner show up once.

Table 3
Payoff matrix, hypothetical experiment.

$P(A_1)$	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

Therefore, we next plot whether or not the frequency with which the pairs' responses were the same, by scenario number (Fig. 3). As expected, pairs' responses are similar in the tails of the experiment. Choices diverge to the sixth scenario, which only matches 57% of the time, and then begin to increase as expected. Because husbands and wives share a great deal in common—environmental factors, agricultural shocks, and at least some forms of information, and as at least some decision making occurs jointly at the household level, one might expect a priori that risk preferences among household pairs would be more aligned than the preferences of any two individuals in the sample drawn at random. If, on the contrary, the intra-household correlation of responses is low, household selection would not likely affect parameter estimates.

To understand the degree to which risk preferences of household pairs are correlated, for each scenario we draw 100 random pairs of respondents within our data set, with replacement, and measure the percentage of same responses for each scenario. In Fig. 3, these percentages appear as lighter lines, whereas the household pairs appear as the darker line with points. For the first three rounds of responses, the percentage of matching responses between the household pairs falls well within the distribution of percentages of matching responses for the random pairs. However, for scenarios 4 through 8, the household pairs are on the upper end of the distribution of random pairs before falling back to the middle of the distribution for scenarios 9 and 10. That said, the difference between household pairs and random pairs is not dramatic, and for some random pairs the degree of matched responses is quite close to the percentage of matched responses observed within the household pairs.

To further assess whether the degree of intra-household similarity in risk preferences is such that we should be concerned about selection bias affecting our parameter estimates, we conduct the following experiment. For each scenario, we initially estimate the proportion of same responses from a sample of random pairs from the data set, which is equivalent to the sample size (243 pairs). Assuming this estimate is the true value for the population, we then conduct a t-test against the proportion of same responses from the true household pairs, for the null hypothesis that the two proportions are equal, and we save the associated p-value. We then repeat this procedure 1000 times, and produce box plots of the distributions of p-values from the tests (Fig. 4). The boxes represent the interquartile ranges of the p-value distribution, with the 75th percentile represented at the upper end of the rectangles, and the 25th percentile at the lower end, and the horizontal line inside the box representing the median of the distribution. If the responses were significantly more correlated among true household pairs than among random pairs of respondents, we would expect to observe much of the p-value distribution to fall below the 10 or 5% to be lower distribution fall below the 5% (or possibly 10%) significance level. In most cases (rounds 1, 2, 3, 5, 9 and 10), the interquartile range of the distribution lies completely above the 10% horizontal line. For rounds 4, 6, 7 and 8, the median of the interquartile range falls below the 10% line, but never below the 5% line, suggesting some selection. However, in all cases the median of the p-value distribution lies above the 5% significance line.

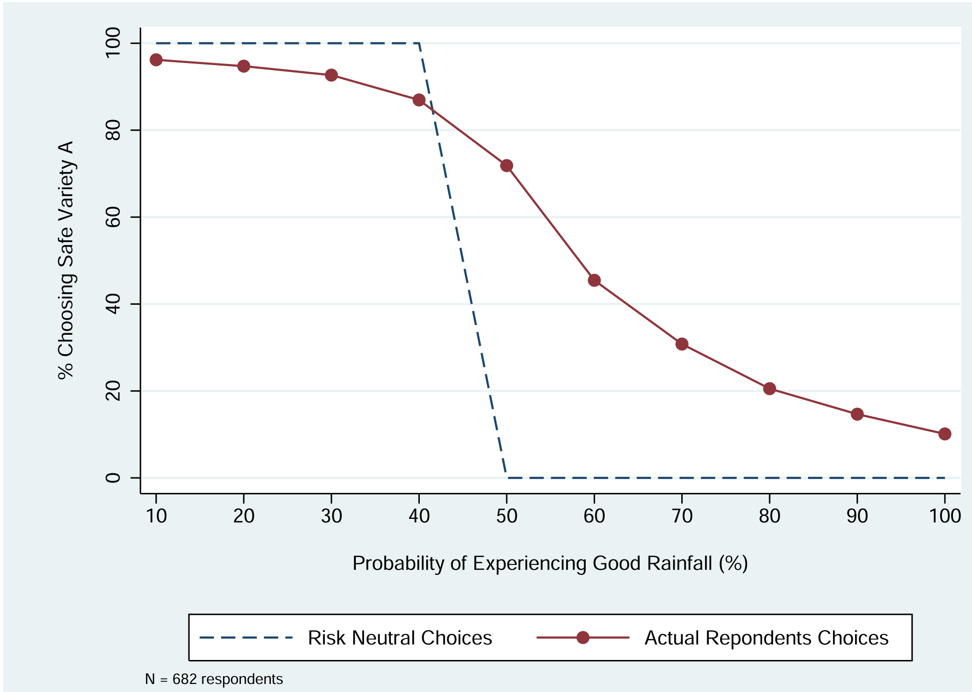
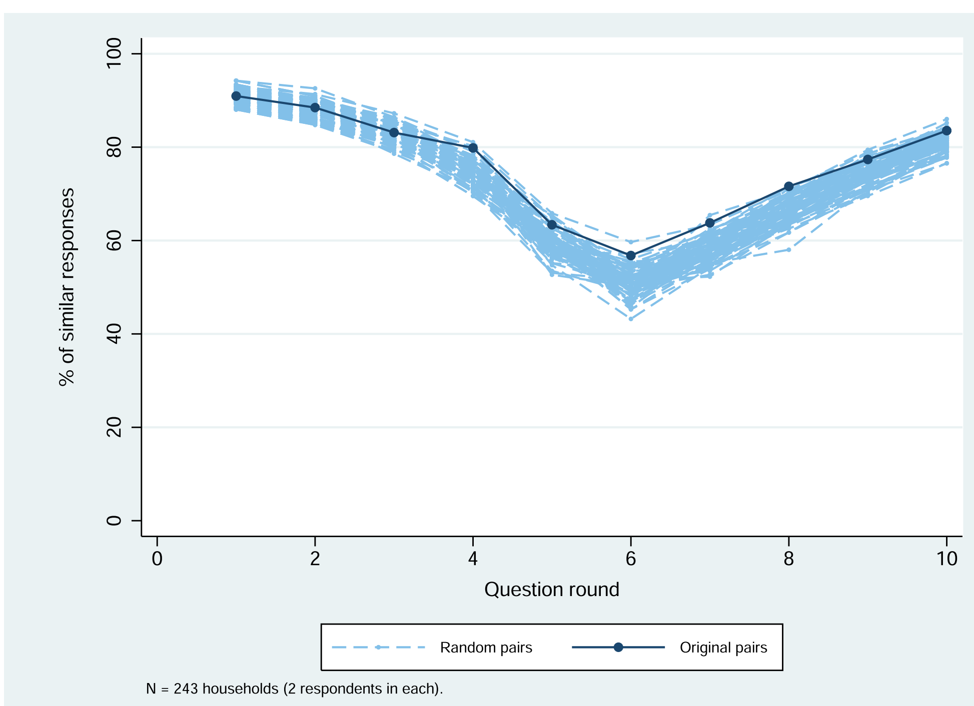


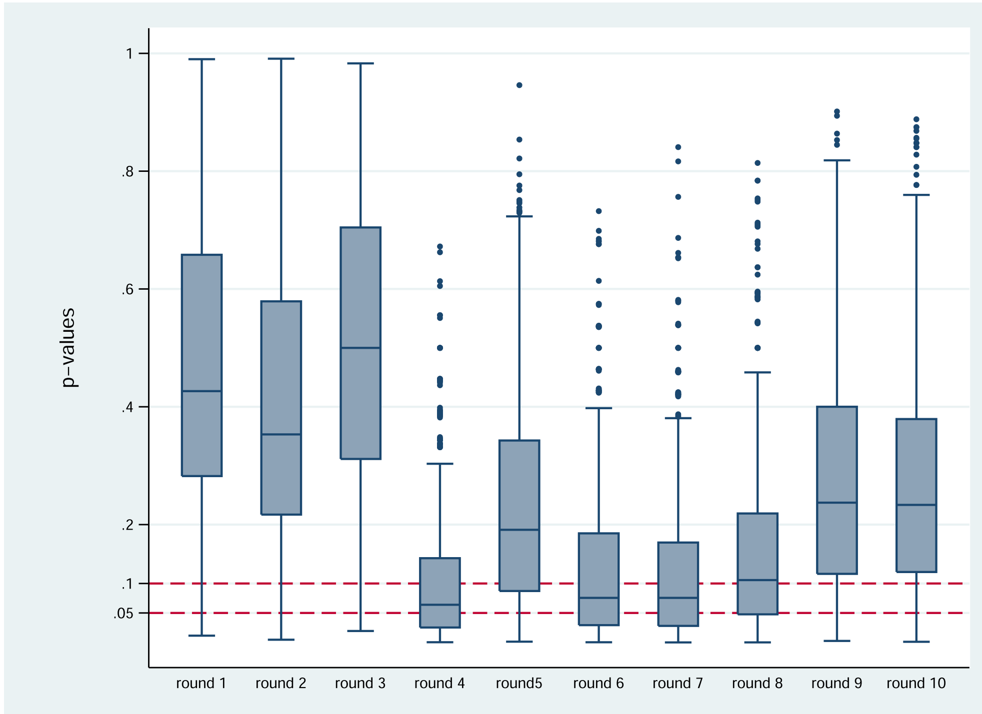
Fig. 2. Risk experiment responses.

We interpret these results as a sign that the degree of similarity between husbands and wives' preferences as revealed by the experiment is not significantly different than the degree of similarity in preferences that we would observe among any other random pair of respondents. The high observed degree of similarity is largely, but not completely, driven by similarity in responses between households, rather than



Note: This figure shows the percentage of similar responses across respondent pairs for households with two respondents (solid dark blue line) and for 100 randomly generated pairs of respondents (dashed light blue lines).

Fig. 3. Proportion of similar choices between husbands and wives.



Note: This figure shows the p-value distribution for round-specific tests of equal proportion in response similarity between true household pairs and random respondent pairs. For each question round, 1000 random pairs were generated and a one-sided t-test for $H_0 : P_{true} = P^i_{random}$, $(i = 1, ..., 1000)$ was generated, where P_{true} is the round-specific proportion of same responses for true household pairs, and P_{random} is the proportion of same responses between random pairs of respondents. P-values above the 5% (10%) threshold indicate that we cannot reject the hypothesis that choices made by husbands and wives within households would have been similar had any one of the respondent been paired with another randomly selected respondent in our sample at a 95% (resp. 90%) confidence level.

Fig. 4. Similarity of responses within households, by response round.

within households. Consequently, whereas there is selection in households for which both partners could be found, that selection will not greatly affect the characteristics of risk preferences in the general sample with respect to growing sweet potatoes.

4. Methodology and results

Although we can conclude that on average our sample 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.

4.1. Methodology

4.1.1. Conceptual framework

We assume that utility $U(\sum_j \omega(p_j) y_j) = \sum_j \omega(p_j) U(y_j)$ is formed over risky lottery outcomes $y_j, j \in \{1, 2\}$, weighted by their subjective probability of occurrence $\omega(p_j)$ with $p_j \geq 0$ and $0 \leq \sum \omega(p_j) \leq 1$.[8] 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. $y_j > 0$.

Under 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 $ARA(y) = -\frac{U''(y)}{U'(y)}$, or by the coefficient of relative risk aversion $RRA(y) = xARA(y)$ (Arrow, 1965; Pratt, 1964). The extent to which agents are risk averse is captured not only by some measure of the curvature of the utility function (such as $ARA(y)$ or $RRA(y)$), but also by the non-linearity of the probability weighting function. In this paper, we will consider both theoretical approaches. 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 $U(.)$ allowing us to determine the shape of risk preferences consistent with the data.

4.1.2. Utility functions

4.1.2.1. Power risk aversion utility. We start by considering a general parameterization of the utility function that allows $RRA(y)$ to be either decreasing, increasing, or constant. A parsimonious specification allowing

[8] 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 subcertainty overall (Gonzalez and Wu, 1999; Kahneman and Tversky, 1979).

such degree of generality is proposed by Xie (2000) with the "Power Risk Aversion" (PRA) utility function.[9] The PRA valuation function is given by

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

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

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

while the coefficient of relative risk aversion can be written as

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

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

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

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 ($ARA^{CRRA}(y) = \sigma/y$).

4.1.3. 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 σ, γ, μ, and β. More specifically, we assume that

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

$$\omega\left(p_{sj}\right) = p_{sj}^{\mu} / \left[p_{sj}^{\mu} + \left(1-p_{sj}\right)^{\mu}\right]^{1/\mu} \quad (6)$$

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

$$\varepsilon \sim N(0, 1) \quad (8)$$

$$y_A = 1\left[y^* > 0\right] \quad (9)$$

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 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 σ, γ, μ, and β are the parameters to be estimated. In Eq. (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 Eqs. (5) through (9) is:

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

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

4.1.4. Finite mixture model

Following Harrison et al. (2010) and Andersen 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

$$\begin{aligned} L(\sigma_i, \gamma, \mu, \beta, \pi | X_i, y_{Ai}) \quad = \quad & \prod_{i=1}^{N} \pi \left[\Phi\left(\Delta U_{EUT}^*(X_i; \sigma_i, \gamma, \mu, \beta)\right)\right]^{y_{Ai}} \\ & \times (1-\pi)\left[1 - \Phi\left(\Delta U_{RDU}^*(X_i; \sigma_i, \gamma, \mu, \beta)\right)\right]^{1-y_{Ai}} \end{aligned} \quad (11)$$

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

4.2. Results

4.2.1. Homogenous preferences

We want to learn about which form of risk preferences best characterize 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.[10]

We begin by estimating the model described by Eqs. (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 $\hat{\gamma} = 0$ at the 1% significance level, we conclude that preferences do not, on average, follow the CRRA in favor of PRA preferences.[11]

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. In general, while the curvature of the utility function increases both with γ and with σ, the effect of these two parameters on the coefficient of relative risk aversion is different. Relative risk aversion always

[9] An alternative general functional form allowing different shapes in risk aversion coefficients is presented in Saha (1993). The proposed that functional form does not include CRRA as a special case, which is why we prefer working with the Xie (2000) function.

[10] In our specification, (6) implies that the valuation function is consistent with EUT only if $\mu = 1$.

[11] Although based on the analysis in Section 3.4 we are comfortable ignoring selection in these results, nonetheless we re-estimated all models presented in the paper, while randomly selecting either the husband or wife among households with two respondents. Results (available from the authors) did not qualitatively differ from the results presented.

Table 5
Maximum likelihood estimates, PRA and CRRA models.

	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 ($H_0: \mu = 1$)	42.3***	5.20**	6.30***	75.1***	48.44***	36.0***
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

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

increases with γ, but changes in σ have an ambiguous effect on $RRA(x)$ when $\gamma \neq 0$. This point is clearly illustrated in Eq. (3).

We depict the relative influence of these two parameters on the shape of the utility function in Fig. 5 by plotting the utility function for different values of σ and γ at estimated parameter values. With this specific set of parameter values, we observe that absolute risk aversion is decreasing (as in Eq. (2)), but relative risk aversion is increasing (as in Eq. (3)). We demonstrate this point in Fig. 6, 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 (Eq. (6)). Note that EUT is consistent with $\mu = 1$, and Eq. (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 left-hand graph depicted in Fig. 7, we plot the non-linear 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 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 conditional estimates of PRA preferences, we find that only a few variables have a statistically significant influence on risk aversion (Table 5, columns 2 and 3).[12] For example, the estimated coefficient among younger respondents (less than 30 years old) suggests that they are more risk averse than the respondents of 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 in southern districts prefer to plant sweet potato after they harvest the primary rice crop, so the 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

[12] Information on total food expenditures 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.

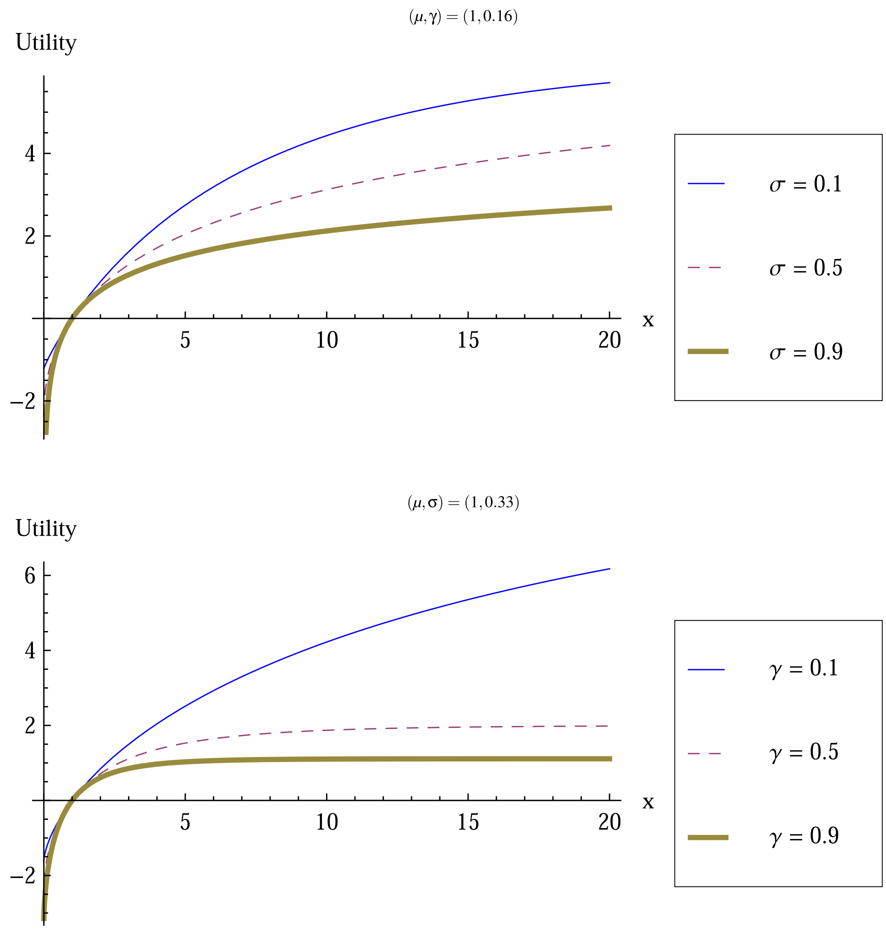


Fig. 5. Power risk aversion utility function. $(\mu, \gamma) = (1, 0.16)$. $(\mu, \sigma) = (1, 0.33)$.

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, assuming that PRA preferences correctly characterize risk preferences. To examine this question, we compare the empirical distribution of relative risk aversion parameters under CRRA and under PRA (Fig. 8). While it is misleading to directly compare the relative risk aversion coefficients, Fig. 8 demonstrates that the shape of the relative risk aversion distribution differs according to which preference environment is assumed. Therefore, the level of risk aversion among those who are risk averse is mischaracterized when the CRRA is assumed.

To further illustrate problems that can occur under the assumption of CRRA, we next consider the relative ranking of risk preferences under both preference relations. If the relative ranking is the same, then at least the CRRA assumption gets the relative ranking right within the data, if not the degree of risk aversion among the most risk averse. To measure the relative ranking, we first predicted relative risk aversion under both PRA and CRRA, and then assigned the predictions into deciles, with relative risk aversion increasing by deciles. We then plotted 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 (Fig. 9). If PRA and CRRA preferences ranked farmers similarly, we would find 10 large bubbles along the 45° line. Instead, we find significant numbers 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° 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 CRRA and PRA farmers diverge. In fact, many of the farmers characterized as least risk averse 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% of farmers are misclassified under CRRA parameter estimates relative to PRA parameters.

Another way to assess the implications of misrepresenting farmers' preferences is to consider a simple crop insurance example where farmers have to choose between a risky lottery or an insurance contract against the payment of a risk premium. We set up an example in which the farmer receives a payment of 200 under the good outcome, and 100 under the bad outcome, with each occurring with equal probability, making the expected value of the lottery 150. We then compute the certainty equivalent and the risk premium under the four different preference specifications examined above, using the parameter estimates from Table 5. For this specific example (Table 6), it appears that making the wrong assumption about the shape of the utility function alone (CRRA vs PRA) implies that the risk premium is substantially underestimated (3.9 units vs 15.2

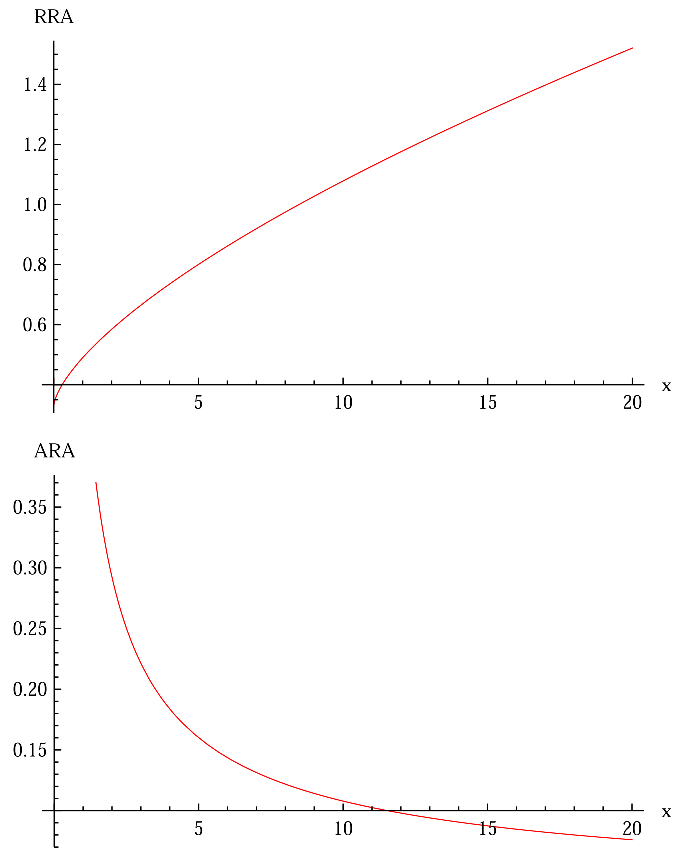


Fig. 6. Absolute and relative risk aversion $[(\mu, \gamma, \sigma) = (1, 0.16, 0.33)]$.

units). Making an incorrect assumption about the underlying choice framework (EUT vs RDU) implies a further underestimate of the risk premium. Assuming both CRRA under EUT rather than PRA under RDU translates into an estimated risk premium that is underestimated by nearly an order of magnitude. Therefore, differences in risk premia implied by assuming alternative preferences are substantial. We further vary the risk faced by the farmer by increasing the spread of the risky lottery (while preserving the expected mean), and illustrating implied differences in risk premia in Fig. 10. The difference in risk premium between CRRA-EUT and PRA-RDU widens as the risk associated with the lottery increases. In an agricultural context, the primary risks are likely to be small relative to a coin flip, but even under such conditions and with these parameters the risk premium still appears underestimated.

4.2.2. Preference heterogeneity

In the previous subsection, we have 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 Eq. (11), which is similar in spirit to a regime switching model.

Among our sample, neither EUT nor RDU fully explains observed attitudes towards risk related to sweet potato yields in Zambézia (Table 7). We find that the estimated parameter on the share of farmers behaving according to EUT is significantly different from zero (28%). However, the percentage is not large; the majority of farmers still behave according to RDU according to the finite-mixture model (72%).

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 (Fig. 11).

5. 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 included in the final impact evaluation survey, and the experiment included 682 respondents.

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 0.728, suggesting that for about one-fourth of farmers, the objective probabilities of states coincide with their subjective probabilities.

We finally demonstrate 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

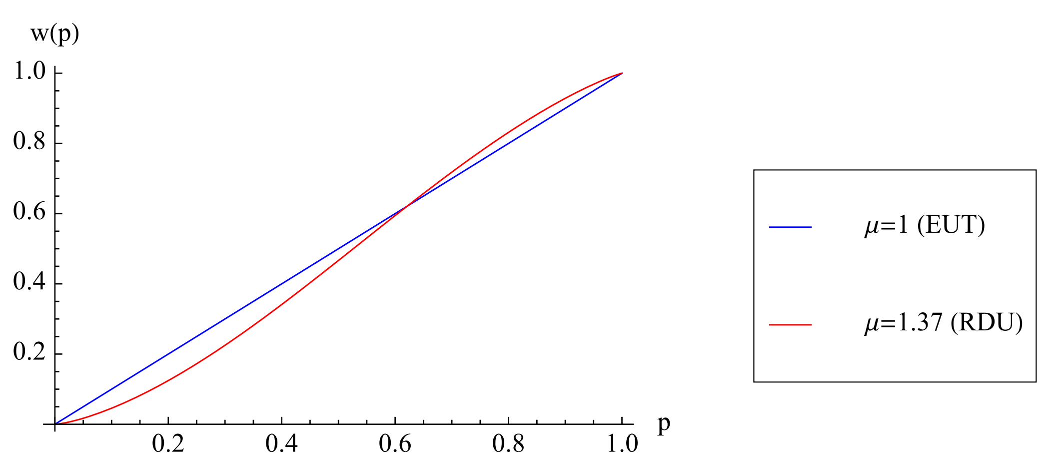
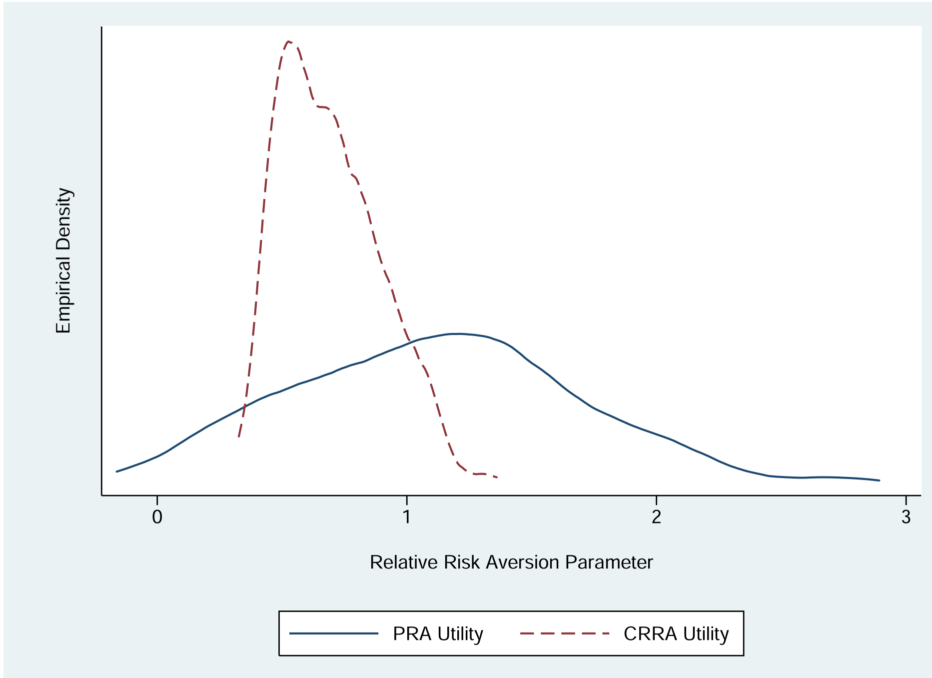


Fig. 7. Weighting function for the PRA utility. RDU only.



Note: This figure shows the distribution of the estimated relative risk aversion parameter ($\hat{\sigma}$). Only under CRRA utility is this parameter identical to the coefficient of relative risk aversion. Under PRA utility, the coefficient of relative risk aversion is a nonlinear function of $\hat{\sigma}$: $\hat{RRA}^{PRA}(y) = \hat{\sigma} + \hat{\gamma} y^{1-\hat{\sigma}}$

Fig. 8. Estimated distribution of relative risk aversion for PRA and CRRA, RDU conditional estimates.

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.

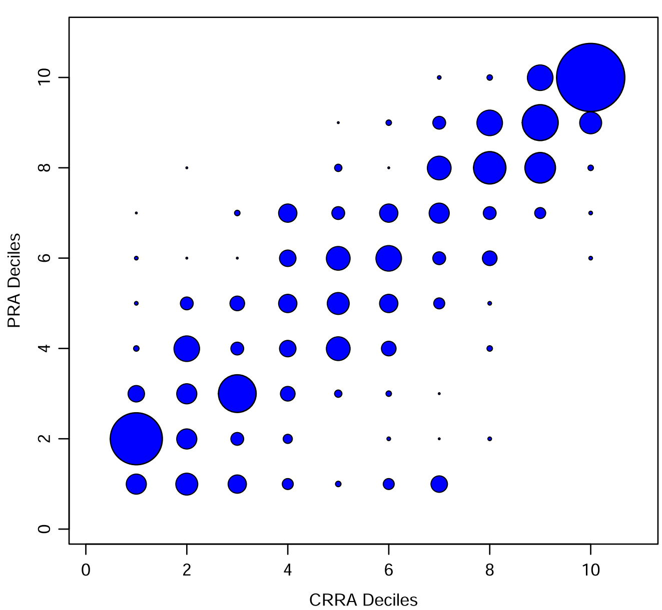


Fig. 9. Bubble plot for *RRA*(x) distribution of PRA vs CRRA.

Appendix A

Q. 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

Table 6
Risk premium for a lottery with an expected value of 150.

		EUT		RDU	
	Risk neutral	CRRA	PRA	CRRA	PRA
Certainty equivalent	150	146.1	134.8	139.5	114.3
Risk premium	0.0	3.9	15.2	10.5	35.7

Note: the certainty equivalent and the risk premia are calculated based on the estimated parameters for the respective utility functions.

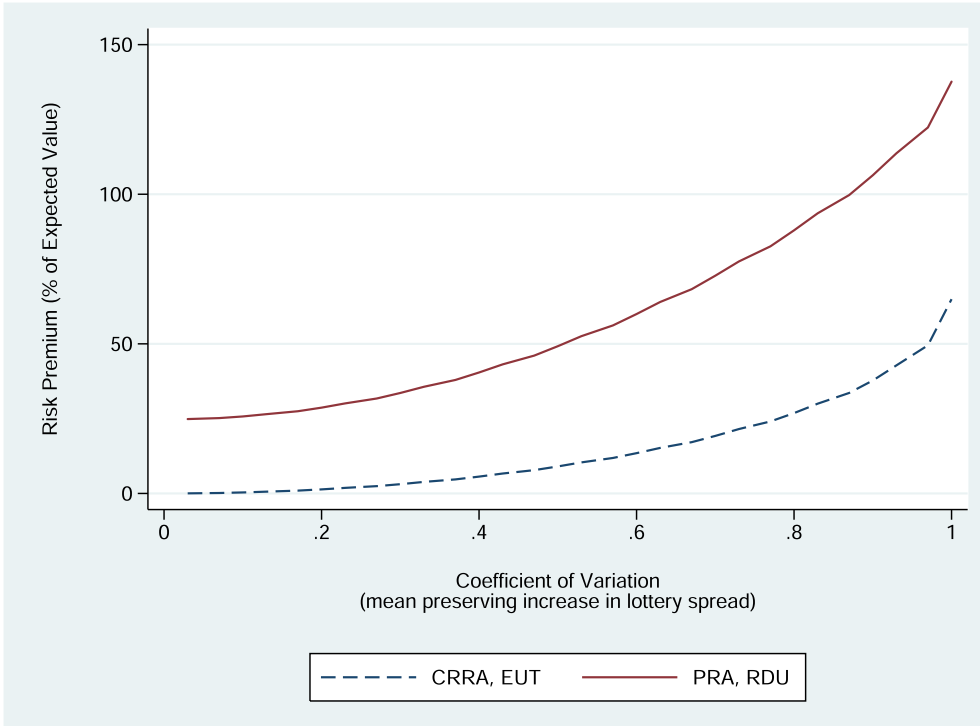


Fig. 10. Differences in implied risk premia.

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.

Table 7
Maximum likelihood estimates, mixture model.

	Estimate	Standard error
Mixing parameters		
π^{EUT}	0.278***	(0.059)
π^{RDU}	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	

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

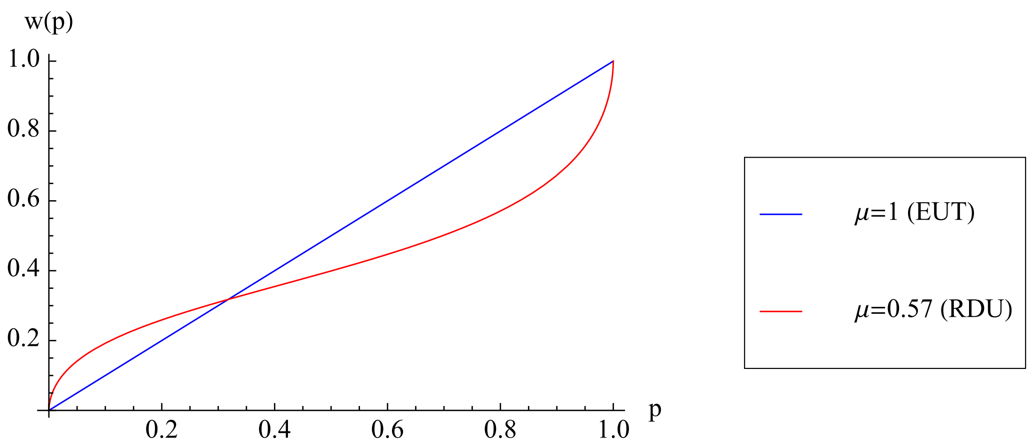


Fig. 11. Weighting funtion for the PRA utility (mixture model). Mixture model ($\pi^{EUT} = 0.28$).

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