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Drought risk attitudes in pastoral and agro-pastoral communities in Kenya

Teun Schrieks [a,*], W.J. Wouter Botzen [a,b], Toon Haer [a], Jeroen C.J.H. Aerts [a]

[a] *Institute for Environmental Studies (IVM), Vrije Universiteit Amsterdam, De Boelelaan 1111, Amsterdam 1081HV, the Netherlands*
[b] *Utrecht University School of Economics (U.S.E.), Utrecht University, Kriekenpitplein 21-22, Utrecht 3584 EC, the Netherlands*

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ABSTRACT

Pastoral and agro-pastoral communities are amongst the most vulnerable groups in the world to increased drought risk caused by climate change. Risk preferences play a key role in drought adaptation decisions, but little research has been done on risk preferences in (agro-)pastoral communities. This study therefore examines risk attitudes amongst Kenyan (agro-)pastoralists, which can inform the development of effective adaptation policies. A hypothetical multiple price list experiment, framed as farming decisions under drought-risk scenarios, is employed to measure utility curvature and probability weighting. Varying rainfall scenarios are presented to assess changes in risk-taking behaviour if climate change increases the probability of drought. We included three psychological factors and several socioeconomic variables in the analysis to understand variations in risk attitudes between individuals. The respondents are, on average, risk-averse and overweight high probabilities. An increased drought risk due to climate change is expected to amplify risk-averse behaviour. An internal locus of control and high drought-risk perceptions are associated with risk-averse behaviour, whereas receiving emergency drought support is associated with less risk-averse behaviour. Policies promoting anticipatory risk-reducing behaviour could emphasise the effectiveness of individual actions, increase awareness of the problem, and minimise reliance on emergency assistance.

1. Introduction

The frequency and severity of droughts are expected to increase because of climate change (CRED & UNDRR, 2020). Among the most vulnerable groups in the world to these climate change induced droughts are pastoral and agro-pastoral communities (Herrero et al., 2016; Thornton, van de Steeg, Notenbaert, & Herrero, 2009). Climate change adaptation is important to reduce the vulnerability of these communities (Herrero et al., 2016). Household level adaptation strategies involve risky investments, which means that risk preferences play a key role in the decision to implement adaptation strategies (Freudenreich & Musshoff, 2022; Holden & Quiggin, 2017; Ward & Singh, 2015). Sub-Saharan Africa alone, is inhabited by 100 million pastoralists (Notenbaert et al., 2009), but little research has been done on risk attitudes in pastoral communities. We conducted a framed field experiment, included in a household survey, in pastoral and agro-pastoral communities in the Kenyan drylands. The population in the Kenyan drylands comprises many (agro-)pastoralists and at the same time it is located in one of the most drought-prone regions in the world (Gbegbelegbe et al., 2018; ICPAC/WFP, 2018; Liebmann et al., 2014; Lyon & DeWitt, 2012). The aim of this paper is to assess risk attitudes in the specific context of agricultural drought risk for (agro-)pastoral communities and to analyse the influence of psychological factors and several socioeconomic variables on risk attitudes to understand variations in risk attitudes between individuals. Understanding the risk attitudes of (agro-)pastoralists in the context of droughts can inform the development of effective adaptation policies, from which lessons can be drawn for pastoral communities in other regions.

We used a Holt and Laury (2002) type *multiple price list* (MPL) lottery to elicit risk attitudes. Since we are interested in risk-taking behaviour in the specific context of drought risk for (agro-)pastoralists, we framed the MPL as an agricultural decision under different drought scenarios. The majority of our sample is involved in livestock keeping, but we also have respondents who practice small-scale crop farming. To make sure that all respondents make decisions in a context that they are familiar with, we developed both a crop version and a livestock version of the experiment. In the version for crop farmers, the lotteries are framed as a decision between two types of maize crops, similar to the work by De

* Corresponding author.
E-mail address: teun.schrieks@vu.nl (T. Schrieks).

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Brauw and Eozenou (2014) and Holden and Quiggin (2017). The livestock version is framed as a decision about the number of cows to hold. To the best of our knowledge, we are the first to develop a framed MPL specifically for pastoralists.

The Holt and Laury (2002) MPL method is an often applied method in which participants receive a list of paired binary lottery choices (Charness et al., 2013). Applications of the Holt and Laury (2002) experiment often keep instructions abstract to avoid the possibility that the context influences behaviour because of induced values (Alekseev et al., 2017; Smith, 1976). However, applications in the field, especially with farmers in low- and middle-income countries, reveal that many people find abstract MPL choices difficult to comprehend, leading to high rates of inconsistent choices (Charness & Viceisza, 2016; Estepa-Mohedano & Espinosa, 2023; Hirschauer et al., 2014). Providing context to the participants can reduce confusion, resulting in more reliable choices (Alekseev et al., 2017). Furthermore, several studies have found that risk-taking behaviour can be domain-specific (Ioannou & Sadeh, 2016; Weber et al., 2002). Verschoor et al., (2016) compare risk aversion levels from a framed experiment with the actual risk-taking behaviour of farmers in Uganda. They only find a correlation between the experiment results and risk-taking behaviour in one domain, similar to the context of their experiment, but do not find a correlation between the experiment results and risk-taking in other domains. Therefore, an experiment framed as farming decisions, instead of a neutral lottery, is more likely to represent actual real-life risk-taking behaviour in that context. A reason why the Holt and Laury MPL lottery is a suitable type of lottery for our context is that it allows for some level of uncertainty in both the risky and the safe alternatives. In farming decisions, there is always some difference in outcomes caused by fluctuations in the weather, the Holt and Laury setup is therefore more realistic than a lottery setup with a risky lottery and a certainty equivalent.

Another challenge with conducting a field experiment in rural communities in low- and middle-income countries, is that these respondents often have trouble understanding probabilities. Providing contextual aids to present probabilities can significantly reduce choice inconsistencies (Estepa-Mohedano & Espinosa, 2023). We, therefore, use contextual aids in the form of pictures that represent either a good or failed rainy season to present the probability of a drought. Lab experiments on risk aversion generally provide monetary incentives to mitigate a potential hypothetical bias (Harrison & Rutström, 2008). In a field experiment, it is much more complicated to provide monetary incentives than in a controlled lab experiment with students at the university. We conducted a framed experiment in a rural setting in a low-income region. In such a context it can be unsafe for researchers to carry monetary rewards and it can be perceived as unfair by participants if some people receive rewards and others do not (Brañas-Garza et al., 2021). We therefore did not provide monetary incentives. The answers in a hypothetical experiment are potentially less reliable and several lab experiments that compare hypothetical and real incentives indeed find evidence for a hypothetical bias (Harrison & Rutström, 2008). Applications in field experiments in rural areas in low- and middle-income countries by Brañas-Garza et al. (2021) and Jacobsen and Petrie (2009) do, however, not find significant differences in risk preferences between hypothetical and incentivised experiments, which is why we trust that our hypothetical experiment also provides reliable results.

We measure risk attitudes for the expected utility theory (EUT) and rank dependant utility theory (RDU). Risk attitudes in EUT are represented by the curvature of the utility function, whereas risk attitudes in RDU are a combination of both utility curvature and probability weighting (Diecidue & Wakker, 2001; Machina, 2008; Quiggin, 1982; Von Neumann & Morgenstern, 1947). In the context of climate change, it is relevant to include probability weighting because it is important to assess how people evaluate the increasing probabilities of natural hazards (Robinson & Botzen, 2020). By presenting choices to the respondents with varying probabilities, we can also implicitly elicit how an increased probability of drought caused by climate change can influence risk-taking behaviour.

Several previous studies account for demographic variables, such as age, gender, income, and education level, in the analysis of the experiments (e.g. De Brauw & Eozenou 2014; Estepa-Mohedano & Espinosa 2023; Harrison et al., 2010), but few studies include perceptions and biases as explanatory variables. However, Robinson and Botzen (2019, 2020) found that psychological factors, such as internal locus of control, worry, and threshold level of concern, influence the risk-taking behaviour of Dutch homeowners in a flood-risk insurance experiment. It is important to better understand the influence of these perceptions and biases on risk-taking behaviour in the context of drought in East Africa to inform adaptation policies. We identified three different psychological factors that are found to influence risk attitudes in previous studies: 1) locus of control,[1] which refers to individual's beliefs in how much they have control over the outcomes of their lives (Antwi-Boasiako, 2017; Botzen et al., 2019; Robinson & Botzen, 2020; Rotter, 1966), 2) worry about future drought (Lerner & Keltner, 2001; Schade et al., 2012), and 3) drought-risk perceptions (Villacis et al., 2021). Previous studies have found that people with a higher locus of control are more likely to take measures to reduce the risks of natural disasters (Antwi-Boasiako, 2017; Botzen et al., 2019), people who worry more make more risk-averse choices (Lerner & Keltner, 2001; Schade et al., 2012) and that climate change risk perceptions and experience of natural hazards shocks are positively correlated with risk aversion (Freudenreich & Musshoff, 2022; Reynaud & Aubert, 2020; Villacis et al., 2021), but we are not aware of studies that assess these factors in the context of drought risk. We aim to fill this gap by assessing how these factors influence risk attitudes in the context of agricultural drought risk in (agro-)pastoral communities, which can inform drought risk adaptation policies.

The next section provides a more detailed explanation of the experimental design and details the data analysis. Then, Section 3 presents the results. Next, Section 4 discusses the research, and Section 5 concludes the work.

2. Methods

2.1. Experimental design

This section summarises the crop and livestock versions of the experiment (adapted from Schrieks et al., in press). The participant instructions for the experiment can be found in Appendix A. The crop version of this experiment is based on previous experiments by De Brauw and Eozenou (2014) and Holden and Quiggin (2017), who conducted similar experiments with crop farmers in Mozambique and Malawi, respectively. In our experiment, the crop farmers were asked to choose between two varieties of maize, one of the most common crops in this region. Participants had to imagine having one acre of land on which they could plant only one maize crop. Variety A is a safe choice yielding 20 bags of maize (50 kg per bag) in a rainy season with normal rains and a slightly lower yield of 16 bags in a bad rainy season with little rainfall. Variety B is a riskier choice, with a much higher yield of 36 bags in a good rainy season but a low yield of only two bags in a bad rainy season (Fig. 3).

In the livestock version, participants chose the number of cows to hold on a piece of land. If the rains are good, all cows survive, but if the rains are bad, some cows die because of a lack of pasture and water. Option A involves fewer cows than Option B, resulting in lower payoffs in a good season but more cows that survive in a bad season (Fig. 2).

[1] People with an internal locus of control believe that outcomes depend on their own efforts, whereas people with an external locus of control believe that outcomes depend on outside factors on which they have little influence (Rotter, 1966). In this study, we focus on the internal locus of control, so if we refer to a high locus of control, we mean that a person has a high internal locus of control.

In all choices in both versions, Option A has moderate payoffs in both good and bad seasons, whereas Option B is the risky choice with high payoffs in good seasons but low payoffs in bad seasons. Probabilities were framed as rainfall scenarios, with probability p for a bad rainy season and probability 1-p for a good rainy season (De Brauw & Eozenou, 2014). As visual aids to present the probabilities, we depicted sacks with ten balls, each representing either a bad or good rainy season (Fig. 1). Further, we used visual aids to present the outcome of each scenario, with pictures of bags of maize in different sizes in the crop version (Fig. 3) and pictures of cows in the livestock version (Fig. 2).

To measure both the probability weighting and utility curvature, we provided each participant with two sets of nine paired lotteries (Drichoutis & Lusk, 2016). We used the standard Holt and Laury approach with varying probabilities and fixed payoffs in the first set. In the first choice of this set, there is a probability of 0.9 for a bad rainy season and 0.1 for a good rainy season. In every consecutive choice, the probability of a bad (good) rainy season decreases (increases) by 0.1 until there is a 0.1 probability of a bad rainy season and a 0.9 probability of a good rainy season in the last choice. With the varying probabilities in this choice set, we can implicitly assess how choices change if the probability of drought changes because of climate change. In the second set, we keep the probabilities constant at 0.5 but vary the payoffs of the lotteries. The constant probability set is better suited to measuring the curvature of the utility function, whereas the varying probabilities set is better suited to measuring probability weighting (Drichoutis & Lusk, 2016).

Table 1 to 4 list the payoffs for all lottery pairs in both sets for both experiment versions. Option A has the highest expected payoff in the first choices in both sets. In every consecutive choice set, Option B becomes more attractive. Most people are expected to select Option A in the first choice and switch to Option B in one of the later choices. The later people switch from A to B, the more risk-averse they are. We can estimate the utility curvature and probability weighting parameters based on the switching points. The last columns in Tables 1–4 display the range of the utility curvature parameter (constant relative risk aversion, CRRA) if the subject switches from A to B in that choice, assuming EUT (no probability weighting).

Based on discussions with local experts, we keep the maize yields and number of cows within certain bounds to stay close to reality. A larger variation in payoffs would theoretically allow to measure a larger variation in risk attitudes but would result in unrealistic choices. We also kept the relative differences in payoffs in both versions the same (same CRRA intervals) to allow for a comparison between the crop and livestock versions.

All choices in both versions of the experiments were hypothetical choices without monetary incentives. Participants did receive a small payment as compensation for their time for participating in the whole household survey, but this payment was the same for everyone and did not depend on their answers in the experiment.

Fig. 1. Visual aid for probabilities: Icons: Flaticon.com

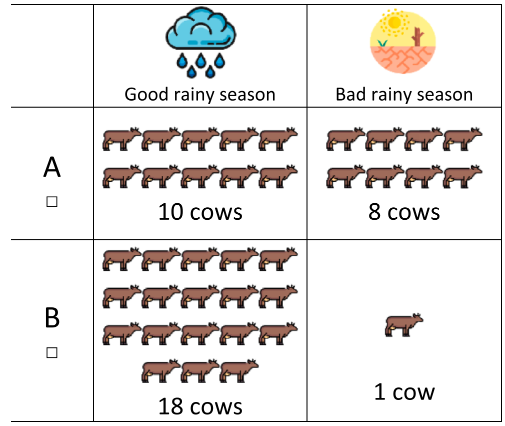

Fig. 2. Visual aids for livestock version. Icons: Flaticon.com

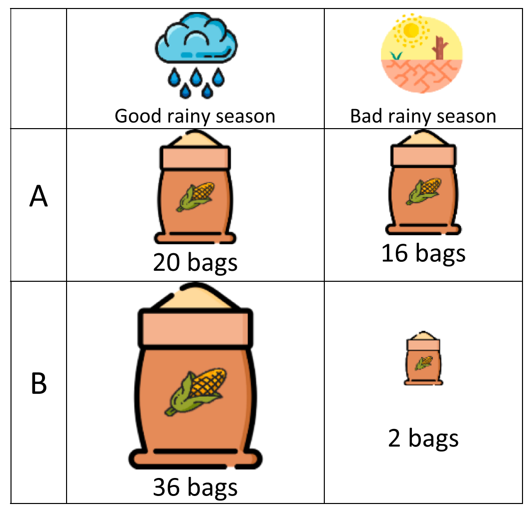

Fig. 3. Visual aids for crop version. Icons: Flaticon.com

2.2. *Data collection and survey design*

The experiment was part of a larger household survey that has been conducted in May 2022 in (agro-)pastoral communities in Oldonyiro Ward and Burat Ward in Isiolo County, Kenya (Fig. 4). This region consists of arid and semi-arid land with low and irregular rainfall (GoK, 2018; Quandt & Kimathi, 2017). Around 80% of the land is communally owned with pastoralism as the main livelihood activity, and some agro-pastoralism in the semi-arid zones (MoALF, 2018). A stratified sampling method was employed by dividing the population into sub-groups based on gender and age, with data from the Kenya Population and Housing Census of 2019 (Kenya National Bureau of Statistics, 2019). In total, we interviewed 502 individuals. We made sure that we interviewed only one person per household, and we gave clear instructions to our interviewers that they should try to find a quiet place where respondents would not be distracted by other household members. The participants were informed that the data would be anonymized and treated confidentially.

Besides the experiment, the household survey consisted of several other questions on, amongst others, the psychological factors that we included in our analysis and socio-economic and demographic characteristics. Table 5 provides descriptive statistics and a description of the questions for all independent variables that we used in our regression analysis.

The first five variables in Table 5 are measures for the psychological factors. We identified three different psychological factors that are

Table 1
MPL with varying probabilities for livestock version (payoffs in number of cows that survive).

P(A1)	A1	P(A2)	A2	P(B1)	B1	P(B2)	B2	EV[A]	EV[B]	EV[A] - EV[B]	CRRA interval for switch to B (EUT)
0.1	10	0.9	8	0.1	18	0.9	1	8.2	2.7	5.5	$\beta \leq -1.95$
0.2	10	0.8	8	0.2	18	0.8	1	8.4	4.4	4	$-1.95 \leq \beta \leq -1.11$
0.3	10	0.7	8	0.3	18	0.7	1	8.6	6.1	2.5	$-1.11 \leq \beta \leq -0.61$
0.4	10	0.6	8	0.4	18	0.6	1	8.8	7.8	1	$-0.61 \leq \beta \leq -0.22$
0.5	10	0.5	8	0.5	18	0.5	1	9	9.5	−0.5	$-0.22 \leq \beta \leq 0.11$
0.6	10	0.4	8	0.6	18	0.4	1	9.2	11.2	−2	$0.11 \leq \beta \leq 0.41$
0.7	10	0.3	8	0.7	18	0.3	1	9.4	12.9	−3.5	$0.41 \leq \beta \leq 0.72$
0.8	10	0.2	8	0.8	18	0.2	1	9.6	14.6	−5	$0.72 \leq \beta \leq 1.08$
0.9	10	0.1	8	0.9	18	0.1	1	9.8	16.3	−6.5	$1.08 \leq \beta \leq 1.57$
										Always A:	$\beta \geq 1.57$

Table 2
MPL with varying probabilities for crop version (payoffs in amount of 50 kg maize bags).

P(A1)	A1	P(A2)	A2	P(B1)	B1	P(B2)	B2	EV[A]	EV[B]	EV[A] - EV[B]	CRRA Interval for switch to B (EUT)
0.1	20	0.9	16	0.1	36	0.9	2	16.4	5.4	11	$\beta \leq -1.95$
0.2	20	0.8	16	0.2	36	0.8	2	16.8	8.8	8	$-1.95 \leq \beta \leq -1.11$
0.3	20	0.7	16	0.3	36	0.7	2	17.2	12.2	5	$-1.11 \leq \beta \leq -0.61$
0.4	20	0.6	16	0.4	36	0.6	2	17.6	15.6	2	$-0.61 \leq \beta \leq -0.22$
0.5	20	0.5	16	0.5	36	0.5	2	18	19	−1	$-0.22 \leq \beta \leq 0.11$
0.6	20	0.4	16	0.6	36	0.4	2	18.4	22.4	−4	$0.11 \leq \beta \leq 0.41$
0.7	20	0.3	16	0.7	36	0.3	2	18.8	25.8	−7	$0.41 \leq \beta \leq 0.72$
0.8	20	0.2	16	0.8	36	0.2	2	19.2	29.2	−10	$0.72 \leq \beta \leq 1.08$
0.9	20	0.1	16	0.9	36	0.1	2	19.6	32.6	−13	$1.08 \leq \beta \leq 1.57$
										Always A:	$\beta \geq 1.57$

Table 3
MPL with constant probabilities for livestock version (payoffs in number of cows that survive).

P(A1)	A1	P(A2)	A2	P(B1)	B1	P(B2)	B2	EV[A]	EV[B]	EV[A] - EV[B]	CRRA Interval for switch to B (EUT)
0.5	10	0.5	8	0.5	14	0.5	1	9	7.5	1.5	$\beta \leq -0.54$
0.5	11	0.5	8	0.5	16	0.5	1	9.5	8.5	1	$-0.54 \leq \beta \leq -0.28$
0.5	12	0.5	8	0.5	18	0.5	1	10	9.5	0.5	$-0.28 \leq \beta \leq -0.11$
0.5	13	0.5	8	0.5	20	0.5	1	10.5	10.5	0	$-0.11 \leq \beta \leq 0$
0.5	14	0.5	8	0.5	22	0.5	1	11	11.5	−0.5	$0 \leq \beta \leq 0.09$
0.5	15	0.5	8	0.5	24	0.5	1	11.5	12.5	−1	$0.09 \leq \beta \leq 0.16$
0.5	16	0.5	8	0.5	26	0.5	1	12	13.5	−1.5	$0.16 \leq \beta \leq 0.21$
0.5	17	0.5	8	0.5	28	0.5	1	12.5	14.5	−2	$0.21 \leq \beta \leq 0.26$
0.5	18	0.5	8	0.5	30	0.5	1	13	15.5	−2.5	$0.26 \leq \beta \leq 0.29$
										Always A:	$\beta \geq 0.29$

Table 4
MPL with constant probabilities for crop version (payoffs in amount of 50 kg maize bags).

P(A1)	A1	P(A2)	A2	P(B1)	B1	P(B2)	B2	EV[A]	EV[B]	EV[A] - EV[B]	CRRA Interval for switch to B (EUT)
0.5	20	0.5	16	0.5	28	0.5	2	18	15	3	$\beta \leq -0.54$
0.5	22	0.5	16	0.5	32	0.5	2	19	17	2	$-0.54 \leq \beta \leq -0.28$
0.5	24	0.5	16	0.5	36	0.5	2	20	19	1	$-0.28 \leq \beta \leq -0.11$
0.5	26	0.5	16	0.5	40	0.5	2	21	21	0	$-0.11 \leq \beta \leq 0$
0.5	28	0.5	16	0.5	44	0.5	2	22	23	−1	$0 \leq \beta \leq 0.09$
0.5	30	0.5	16	0.5	48	0.5	2	23	25	−2	$0.09 \leq \beta \leq 0.16$
0.5	32	0.5	16	0.5	52	0.5	2	24	27	−3	$0.16 \leq \beta \leq 0.21$
0.5	34	0.5	16	0.5	56	0.5	2	25	29	−4	$0.21 \leq \beta \leq 0.26$
0.5	36	0.5	16	0.5	60	0.5	2	26	31	−5	$0.26 \leq \beta \leq 0.29$
										Always A:	$\beta \geq 0.29$

found to influence risk attitudes in previous studies: 1) locus of control (Antwi-Boasiako, 2017; Botzen et al., 2019; Robinson & Botzen, 2020), 2) worry about future drought (Lerner & Keltner, 2001; Schade et al., 2012), and 3) drought-risk perceptions (Villacis et al., 2021). Locus of control refers to individuals' beliefs in how much control they have over the outcomes of their lives. To measure (internal) locus of control, we used a question from the World Values Survey (Haerpfer et al., 2022). People with an internal locus of control believe that outcomes depend on their own efforts, whereas people with an external locus of control believe that outcomes depend on outside factors on which they have little influence (Rotter, 1966). In this study, we focus on the internal locus of control, so if we refer to a high locus of control, we mean that a person has a high internal locus of control.

We included one question on worry about future drought (How much do you worry about the impact of future drought on you and your family?) and three questions about risk perceptions, which are all based on questionnaires from studies on drought risk and adaptation (Arunrat et al., 2016; Gebrehiwot & Van der Veen, 2015; Grothmann & Patt, 2005; Keshavarz & Karami, 2016; Truelove et al., 2015; Van Duinen et al., 2015; Wang et al., 2019; Wens et al., 2021; Yazdanpanah et al., 2014). Most of these studies use Protection Motivation Theory to asses adaptation behaviour in which risk perceptions play an important role (Rogers,

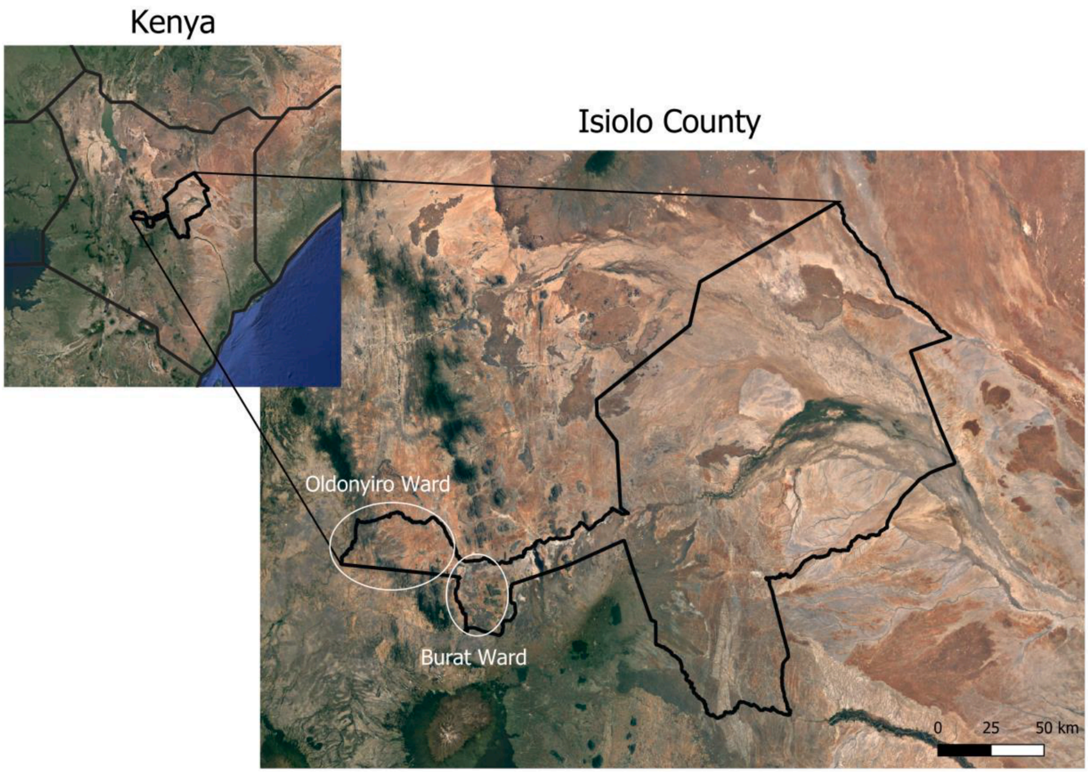

Fig. 4. Location of the case study areas, Oldonyiro Ward and Burat Ward, in Isiolo County and Kenya.

1983). The factor that measures risk perception in Protection Motivation Theory is called risk appraisal which consists of the perceived probability that a drought will occur and the perceived severity of a drought when it occurs. We created one variable on *risk appraisal* which is a combination of two survey questions: 1) 'Do you expect the frequency of droughts in the coming five years to decrease, increase, or stay the same in your region?' 2) 'Do you expect that the severity of droughts in the coming five years will decrease, increase, or stay the same in your region?' We also included another variable on perceived frequency, which we call *expected frequency,* based on the following question: 'How often do you expect a drought to occur in the region where you live?' And we included another variable on perceived severity, which we call *relative impact*, based on the following question: "If you compare your family situation to the rest of the community, do droughts affect you less or more than an average family?" This gives us three different variables for drought risk perceptions (risk appraisal, expected frequency and relative impact) which we all have included in our maximum likelihood analysis to assess how they influence risk attitudes.

In the Locus of Control question we used at 10-point Likert scale, based on the World Values Survey (Haerpfer et al., 2022), while in most other questions we use a 5-point Likert scale, based on other survey studies (Arunrat et al., 2016; Gebrehiwot & Van der Veen, 2015; Grothmann & Patt, 2005; Keshavarz & Karami, 2016; Truelove et al., 2015; Van Duinen et al., 2015; Wang et al., 2019; Wens et al., 2021; Yazdanpanah et al., 2014). We have tested the questions in a pilot study in March 2022, and we did not observe confusion amongst the participants about the different scales. The 5-point Likert scale questions and the 10-point Likers scale questions were placed in different parts of the survey, so people were not switching back and forth between the different scales.

2.3. Data analysis

We analysed the experimental data using maximum likelihood estimation of the utility functions (Harrison, 2008; Harrison & Rutström, 2008). We assumed constant relative risk aversion (CRRA) in the analyses, a common assumption in EUT and RDU models (Wakker, 2008).

First, we estimated the following EUT function with linear probabilities:

$$EU = \sum_{i=1}^{2} p_i \frac{x_i^{(1-\beta)}}{(1-\beta)} \tag{1}$$

where p_i is the probability of outcome i, x_i denotes the payoff of outcome i, and β represents the risk aversion parameter that will be estimated. People are risk-averse if $\beta > 0$, risk-neutral if $\beta = 0$, and risk-seeking if $\beta < 0$.

Second, we included a probability weighting function based on the work by Tversky and Kahneman (1992) to evaluate the RDU assumption of nonlinear probability weighting. For this RDU model, we used the following equations:

$$RDU = \sum_{i=1}^{2} w(p_i) \frac{x_i^{(1-\beta)}}{(1-\beta)} \tag{2}$$

$$w(p_1) = \frac{p_i^{\gamma}}{\left(p_i^{\gamma} + (1-p_i)^{\gamma}\right)^{\frac{1}{\gamma}}} \tag{3}$$

$$w(p_2) = 1 - w(p_1) \tag{4}$$

The weight of the probability for the high payoff outcome is $w(p_1)$ and the weight for the probability of the low payoff outcome is $w(p_2)$. The parameter γ is the probability weighting coefficient. With $\gamma = 1$, the RDU function collapses to the EUT function (linear probabilities), whereas $\gamma < 1$ means that people overweight low probabilities and underweight high probabilities, $\gamma > 1$ means that people underweight low probabilities and overweight high probabilities. We used a Wald test to determine whether γ is significantly different from 1. If we can reject the null hypothesis that $\gamma = 1$, then we can conclude that RDU performs better in explaining the experimental results than EUT.

Table 5
Descriptive statistics.

Variables	Questions/descriptions	Coding	Mean	Std. Dev.	N
Locus of control	Some people feel they have completely free choice and control over their lives, while other people feel that what they do has no real effect on what happens to them. On a scale from 0 to 10, How much freedom of choice and control do you feel you have over the way your life turns out?	No choice et all = 0 to a great deal of choice = 10	7.41	2.72	497
Worry future drought	How much do you worry about the impact of future drought on you and your family?	Not at all worried is 1 to verry worried = 5	4.62	0.61	501
Expected frequency	How often do you expect a drought to occur in the region where you live?	Once every 10 rainy seasons or less = 1 to every rainy season = 10	8.94	1.03	501
Risk appraisal	1) Do you expect the frequency of droughts in the coming five years will decrease, increase or stay the same in your region? 2) Do you expect that the severity of droughts in the coming five years will decrease, increase or stay the same in your region?	Decrease a lot = 1 to increase a lot = 5 (average of the two questions)	4.38	0.66	478
Relative impact	If you compare your family situation to the rest of the community, do droughts affect you less or more than an average family?	A lot less than others = 1 to a lot more than others = 5	3.16	0.69	502
Access to credit	To what extent do you feel that you have sufficient access to the following resources to cope with droughts? Loans	No access at all = 1 to more than sufficient access = 4	1.76	0.88	494
Access VSAL	To what extent do you feel that you have sufficient access to the following resources to cope with droughts? Village Savings and Loan Schemes (VSAL)	No access at all = 1 to more than sufficient access = 4	2.27	1.01	499
Access forecast info	To what extent do you feel that you have sufficient access to the following resources to cope with droughts? Forecast information and early warnings	No access at all = 1 to more than sufficient access = 4	1.84	0.90	488
Food Aid	Did you receive food aid from NGOs/Aid Agencies or the government to cope with a drought event?	1 = Yes 0 = No	0.38		502
Household head	Dummy for head of the household	1 = Yes 0 = No	0.71		502
Education level	What is your highest completed level of education?	No formal education = 0 to completed tertiary education = 6	1.77	1.72	502
Household size	How many members does your household have?	Number of household members	5.96	2.94	491
Age	How old are you?	Age	36.52	13.45	502
Gender	Gender respondent	Female = 1, Male = 0	0.52		502
Expenditure	Sum of yearly household expenditure on: (1) (crop) farming activities, (2) livestock related activities, (3) non-food items and (4) food?	Total yearly expenditures in 1000 Kenyan Shillings (KSh)	97.18	83.31	502
Livestock keeper	Dummy for livestock keeper	1= livestock keeper, 0 = no livestock keeper	0.71		502
Crop farmer	Dummy for crop farmer	1= crop farmer, 0 = no crop farmer	0.19		502
Burat Ward	Dummy for people living in Burat Ward	1 = Burat, 2 = Oldonyiro	0.54		502
Ethnicity dummies	Which ethnic group is the participant from?	Dummy variables for four most common ethnicities			502

To estimate the EUT and RDU model parameters we used a probit function following Harrison and Rutström (2008). For each lottery pair, the model first estimated the expected utility (EU) for a candidate estimate of β (and γ in the RDU model), and calculated the difference in EU between option A and option B:

$$\Delta \text{EU} = EU_B - EU_A \tag{5}$$

This estimated difference, ΔEU, is then linked to the observed choices using a standard cumulative normal distribution function, to estimate the likelihood of the choice for the given model specifications (Harrison, 2008; Harrison & Rutström, 2008). With maximum likelihood estimation we estimated the model parameters that maximize the likelihood of the observed choices. Standard errors are clustered at the individual level which allows responses from the same subject to be correlated due to unobserved individual effects (Harrison & Rutström, 2008).

2.4. Hypotheses

Studies that measure risk aversion in field experiment in low- and middle-income countries find that people are on average risk averse (Binswanger, 1980; De Brauw & Eozenou, 2014; Tanaka et al., 2010), which means that the utility curvature parameter is significantly larger than zero. Studies that also include probability weighting, find that the probability weighting significantly differs from one, which means that RDU performs better in explaining risk preferences than EUT (De Brauw & Eozenou, 2014; Harrison et al., 2010; Humphrey & Verschoor, 2004; Liu, 2013; Tanaka et al., 2010). To assess if our findings correspond with the existing literature, we test the following two hypotheses:

Hypothesis 1. People are on average risk averse, which means that the utility curvature parameter (β) is larger than 0.

Hypothesis 2. The probability weighting parameter (γ) is significantly different from one, meaning that RDU performs better in explaining risk preferences that EUT.

We also formulated hypothesis on the effect of three psychological factors on risk aversion. The first factor is Locus of control. Previous studies have found that people with a higher locus of control are more likely to take measures to reduce the risks of natural disasters (Antwi-Boasiako, 2017; Botzen et al., 2019). A plausible explanation for this relationship is that people who believe they can control the influence of unfavourable events are also more likely to pay attention to potential dangers (Robinson & Botzen, 2020). Based on these studies, we expect a positive relationship between the locus of control and risk aversion.

Hypothesis 3. People with a higher internal locus of control are more risk-averse.

The second psychological factor is worry about future drought.. People who worry more make more risk-averse choices (Lerner & Keltner, 2001; Schade et al., 2012), so we expect a positive effect of worry about future drought on risk aversion.

Hypothesis 4. People who worry more about drought effects are more risk-averse.

The third psychological factor is drought-risk perception.

Climate change risk perceptions are positively related to risk aversion (Villacis et al., 2021), and several studies have found people to be more risk-averse when they experience shocks from natural hazards

(Freudenreich & Musshoff, 2022; Reynaud & Aubert, 2020) and experiencing a natural hazard shock is positively correlated with risk perception (Gebrehiwot & van der Veen, 2021). Thus, we expect a positive effect of the drought-risk perception parameters on the level of risk aversion.

Hypothesis 5. People with a higher drought-risk perception are more risk-averse.

3. Results

3.1. Switching points and inconsistent choices

Out of the 502 participants, 474 respondents fully completed both choice sets. The 27 participants from whom we do not have complete answers were excluded from the analysis. We defined the switching points and inconsistencies in the answers for the remaining 474 respondents. According to theory, a choice pattern is consistent if the first choice is Option A and only one switch is made from A to B or if the same option is selected (either A or B) in all nine choices (Jacobson & Petrie, 2009). Switching from B to A is inconsistent with EUT and RDU, because the relative value of B increases in the choice set, indicating that a person who prefers Option B in an early choice should also prefer Option B in the later choices. Choice patterns are inconsistent if people switch more than once between A and B or switch in the wrong direction (from B to A).

In the sample, we observed ten inconsistent choice patterns in the first choice set (varying probability set) and 14 inconsistent choice patterns in the second choice set (fixed probability set). In total, we have 23 participants with inconsistent choices in at least one of the choice sets (one person was inconsistent in both sets). Thus, we have inconsistencies in 4.85% of the 474 respondents, a very low percentage compared to other studies (e.g. Charness & Viceisza, 2016; Hirschauer et al., 2014; Jacobson & Petrie, 2009). We excluded the inconsistent choices from our analysis, we have however also done an analysis in which we included the inconsistent choice with a Fechner error specification to account for mistakes in choices (Crosetto & Filippin, 2016; Harrison & Rutström, 2008; Hey & Orme, 1994). This analysis did not lead to significant changes in the results and can be found in Appendix C.

Table 6 presents the switching points for 451 respondents with consistent choices. We observed a peak in switching at the sixth choice in both choice sets. Those people selected Option A in the first five choices and switched to Option B in the sixth choice, meaning they are slightly risk-averse. We also observed a small peak at always selecting Option B and a large peak at always selecting Option A.

3.2. Results of the maximum likelihood estimation

3.2.1. Expected utility and rank dependant utility models

Table 7 provides the results of the maximum likelihood estimation for the basic EUT and RDU models. The EUT model (column 1) has a significant positive utility curvature coefficient, with $\beta \approx 0.887$. A positive β means that people are, on average, risk-averse (supporting Hypothesis 1).

Table 6
Switching points for respondents with consistent choices.

$N = 451$	Choice set 1 (varying P)		Choice set 2 (fixed P)	
Always B (risky)	16	3.5%	49	10.9%
2	4	0.9%	2	0.4%
3	3	0.7%	3	0.7%
4	13	2.9%	6	1.3%
5	56	12.4%	21	4.7%
6	124	27.5%	43	9.5%
7	41	9.1%	22	4.9%
8	19	4.2%	2	0.4%
9	3	0.7%	0	0.0%
Always A (safe)	172	38.1%	303	67.2%

In the RDU model (column 2), we obtained a similar but slightly higher utility curvature coefficient ($\beta = 0.950$), and the probability weighting coefficient is $\gamma \approx 1.166$. The Wald test reveals that γ is significantly different from 1; thus, people underweight low probabilities and overweight high probabilities (Fig. 5). As γ is significantly different from 1, we rejected the null hypothesis that $\gamma = 1$, and argued that the RDU model performs better than the EUT in explaining the risk attitudes in the sample (supporting Hypothesis 2). Furthermore, the RDU model has a lower Akaike information criterion (AIC) score, indicating that the RDU model better fits the data (Cavanaugh & Neath, 2019). Therefore, we focused on the RDU model in the remaining analysis.

We used two versions of the experiment, one with choices about livestock and one with choices about crops. Table 8 includes a dummy for the version to assess whether a difference exists between the results. The dummy has no significant effects, indicating that the risk attitudes in the livestock version are not significantly different from those in the crop version.

3.2.2. Explanatory variables

Table 9 provides the results of the maximum likelihood estimations with the utility curvature parameter as a function of the explanatory variables.[2] The first four models include the main psychological factors: locus of control, worry about future drought, and risk perception. We used four models to evaluate the effect of the three measures on risk perceptions. In the later models, we added several socioeconomic control variables.

All eight models reveal a significant positive effect of locus of control on the utility curvature, meaning that people with a high internal locus of control are more risk-averse on average (supporting Hypothesis 3). The effect of worry about future droughts is not significant in most of the models. We only observed a significant effect at the 10% level in Models 5, 6 and 8. The effect of worry about future droughts in these models is negative, which is the opposite of Hypothesis 4, but we did not discover much evidence for the effect of this variable given its low significance. For the risk appraisal variables, we discovered two opposite effects. The expected frequency of a drought significantly negatively affects the utility curvature (in Models 1, 4 and 5); thus, people who expect drought to occur more frequently are less risk-averse. In contrast, the risk appraisal variable has a significant positive effect (Models 2,4,5,6,7 and 8). This coefficient indicates that people who expect the severity and frequency of drought to increase are more risk-averse than others. The effect of the risk appraisal variable is more robust than the expected frequency variable because it stays significant in all models with control variables. Based on this variable, a higher risk perception is associated with higher levels of risk aversion (supporting Hypothesis 5).

In Model 5 we added control variables for access to financial resources (access to credit and access to village savings and loan schemes-VSAL) and in Model 6 we added access to forecast information and access to food aid. In Model 5, we see that people with access to village savings and loan schemes (VSAL) are less risk-averse, although this is no longer significant if we include access to forecast information and food aid in Model 6. People with access to forecast information are also significantly less risk-averse in Models 6 and 7, and those who receive food aid are significantly less risk-averse in Models 6, 7 and 8. These three variables suggest that people are willing to take more risks if they expect support or information from their social networks or the government to cope with drought.

In Model 7, we include several socio-economic and demographic variables. The only one that is significant is household head, which has a

[2] Some of the explanatory variables contain missing values (never more than 5%). To be able to compare the AIC scores we imputed the missing values with the median of these variables. In the online supplementary information, we provide the results when observations with missing values are excluded. Excluding the missing values does not significantly change the results.

Table 7
Maximum likelihood estimation for the EUT and RDU models with CRRA, p-values in parentheses. $+ p < 0.10$, $* p < 0.05$, $** p < 0.01$, $*** p < 0.001$.

	(1) EUT	(2) RDU
β	0.887***	0.950***
	(0.000)	(0.000)
γ		1.166***
		(0.000)
N	8118	8118
N clusters	451	451
AIC	7928.3	7915.7
Pseudo LL	−3963.1	−3955.8
Wald χ^2 (γ=1)		11.74 ($p = 0.0006$)

significant negative effect, meaning that household heads are less risk-averse on average than people who are not the heads of the household. In Model 8 we added dummies for location (Burat Ward), occupation, and ethnicity (Model 8), in which case we observed a slightly significant (at the 10% level) positive effect for the education level and household size. Furthermore, people from the Burat Ward are significantly less risk-averse than those from the Oldonyro Ward. Finally, livestock keepers are significantly less risk-averse than average, while crop farmers are significantly more risk-averse than average.

We also analysed the effect of all these independent variables on the probability weighting parameter. This did however not lead to conclusive results. The effects of locus of control and risk perception were ambiguous with positive effects in some models and negative effects in other models. For worry about future droughts, we found a small positive effect suggesting that people who are more worried are slightly more likely to overweight high-probability events, but this effect was only significant at the ten-percent level in only three out of the eight models. A more detailed reporting of the results for probability weighting can be found in Appendix B.

Table 8
Maximum likelihood estimation for the RDU model with a dummy for the experiment version, p-values in parentheses. $+ p < 0.10$, $* p < 0.05$, $** p < 0.01$, $*** p < 0.001$.

	(1)
β	
Livestock version (dummy)	−0.229
	(0.684)
_cons	1.084***
	(0.000)
γ	
Livestock version (dummy)	−0.182
	(0.882)
_cons	1.180***
	(0.000)
N	8118
N clusters	451
AIC	7910.9
Pseudo LL	−3951.5

4. Discussion

4.1. Discussion of main results

Only 4.85% of our respondents made inconsistent choices, which is much less than other field experiments in low- and middle-income countries which often find inconsistency rates of more than 50% (Charness & Viceisza, 2016; Jacobson & Petrie, 2009). De Brauw and Eozenou (2014), who use similar framing as in our experiment, also find low inconsistency levels, which indicates that a framed experiment can help participants to better understand the experiment which reduces the number of inconsistencies. Another factor that might have reduced the number of inconsistencies is the use of visual and contextual aids, which also helped the comprehension of the experiment by the participants (Estepa-Mohedano & Espinosa, 2023; Ihli, Chiputwa, & Musshoff, 2016). We only consider choices as inconsistent if participants switch more than once between options A and B, some studies also consider people who always select option A inconsistent (Charness & Viceisza,

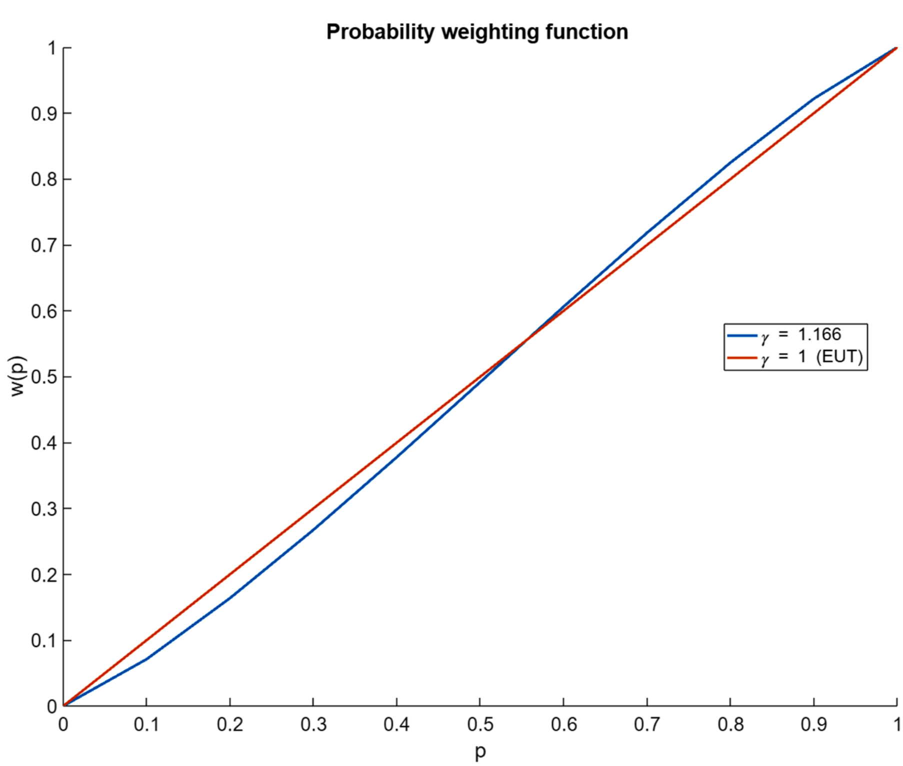

Fig. 5. Probability weighting function for $\gamma = 1.166$.

Table 9
Results of maximum likelihood estimation with utility curvature parameter β a function of variables of interest and socioeconomic control variables. p-values in parentheses. $+ p < 0.10$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
β								
Locus of control	0.0328***	0.0385***	0.0330***	0.0425***	0.0536***	0.0459***	0.0391**	0.0397**
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.005)	(0.005)
Worry future drought	−0.0267	−0.0976	−0.0142	−0.112	−0.127+	−0.127+	−0.0874	−0.0781+
	(0.777)	(0.288)	(0.905)	(0.189)	(0.077)	(0.051)	(0.111)	(0.085)
Expected frequency	−0.224**			−0.211***	−0.0775+	−0.0735	−0.0815	−0.0834
	(0.001)			(0.000)	(0.091)	(0.158)	(0.228)	(0.279)
Risk appraisal		0.222***		0.221***	0.198***	0.157***	0.154*	0.124**
		(0.000)		(0.000)	(0.000)	(0.000)	(0.018)	(0.004)
Relative impact			0.0542	0.0366	0.0288	−0.00150	0.0139	0.0199
			(0.378)	(0.459)	(0.528)	(0.976)	(0.832)	(0.690)
Access to credit					−0.0661	−0.0265	−0.00957	−0.0172
					(0.196)	(0.534)	(0.825)	(0.685)
Access VSAL					−0.166**	−0.105	−0.0941	−0.00115
					(0.002)	(0.145)	(0.177)	(0.976)
Access forecast info						−0.110**	−0.110**	0.00174
						(0.004)	(0.005)	(0.955)
Food aid						−0.229*	−0.256*	−0.250**
						(0.012)	(0.020)	(0.003)
Household head							−0.220**	−0.218*
							(0.003)	(0.014)
Education level							0.00710	0.0358+
							(0.664)	(0.055)
Age							−0.00313	−0.000400
							(0.242)	(0.868)
Gender (1=female)							−0.0425	0.0608
							(0.482)	(0.277)
Household size							0.0108	0.0316+
							(0.503)	(0.091)
Expenditures							−0.000127	0.0000490
							(0.827)	(0.896)
Burat Ward								−0.507***
								(0.001)
Livestock keeper								−0.360**
								(0.005)
Crop farmer								0.276***
								(0.000)
Ethnicity dummies	No	No	No	No	No	No	No	Yes
_cons	2.847***	0.0918	0.608	1.913*	1.288*	1.655**	1.715**	1.596*
	(0.001)	(0.841)	(0.360)	(0.012)	(0.018)	(0.001)	(0.008)	(0.047)
γ	1.166***	1.110***	1.188***	1.119***	1.025***	1.049***	1.032***	1.256***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
N	8118	8118	8118	8118	8118	8118	8118	8118
N clusters	451	451	451	451	451	451	451	451
AIC	7824.1	7812.1	7884.1	7728.6	7625.9	7489.9	7405.8	7210.4
Pseudo LL	−3907.1	−3901.1	−3937.1	−3857.3	−3804.0	−3734.0	−3685.9	−3581.2

2016). Most of these studies included a tenth choice in their MPL in which the good outcome happens with certainty. In which case option B has a higher payoff with certainty, selecting option A could therefore be considered as inconsistent. Including this tenth choice has the benefit that one can identify this other type of inconsistent choices. The disadvantages of using a tenth choice are that it might confuse people and that completing the experiment takes more time. We had to make a trade-off, and because we did not want to confuse people and the experiment was part of a relatively long household survey, we decided not to include the tenth choice. We do have a high number of people who always select option A and a limitation of our study is that we cannot identify if these choices are inconsistent. The majority of inconsistent choices in other field experiments is however switching back and forth multiple times (e.g. Charness & Viceisza, 2016; Hirschauer et al., 2014; Jacobson & Petrie, 2009), which happens significantly less in our results.

Our respondents are on average risk averse, which corresponds to results in previous literature. The probability weighting coefficient in the estimated models is significantly different from 1, which means that RDU performs better in explaining risk attitudes than EUT. People tend to underweight low probabilities and overweight high probabilities, leading to an s-shaped probability weighting function. This s-shaped function contradicts the inverse s-shaped probability weighting function that is generally found in lab experiments in Western countries (Fehr-Duda & Epper, 2012; Gonzalez & Wu, 1999; Verschoor & D'Exelle, 2022).

Field experiment studies in rural areas in low- and middle-income countries have found mixed results on the shape of the probability weighting function. Some studies have found evidence of the inverse s-shaped probability weighting function (e.g. Liu, 2013; Tanaka et al., 2010), but other studies also observed evidence of the s-shaped probability weighting function (De Brauw & Eozenou, 2014; Harrison et al., 2010; Humphrey & Verschoor, 2004). Verschoor and D'Exelle (2022) argued that a difference in the probability reference point could cause the difference between the inverse s-shaped and s-shaped probability weighting functions. An inverse s-shaped probability function assumes that the reference probabilities are at 0 and 1, indicating that people care more about a change in the probability from 5% to 10% than a change from 25% to 30% and that they care more about a change from 95% to 90% than a change from 65% to 60%. In contrast, with an s-shaped probability function, the reference probability is somewhere in the middle, indicating that a person cares more about a change from 50% to 55% than about a change from 90% to 95% or a change from 10% to 15%.

Studies on risk aversion in the context of natural hazards often examine low-probability extreme events (e.g. Li et al., 2011; Robinson & Botzen, 2020; Villacis et al., 2021), where it is plausible that people take 0 and 1 as the reference probability. However, people in rural communities in low-income countries frequently experience natural hazards, such as drought and flooding. Verschoor and D'Excelle (2022) argued that this frequent occurrence of natural hazards could inform people's reference probabilities. Events seldom occur with a probability of 0 or 1, making a reference probability somewhere in the middle more plausible. This hypothesis explains why only studies in low- and middle-income countries observe an s-shaped probability weighting function and provides an explanation for our results.

During the execution of the field experiment (May 2022), the Horn of Africa Drylands experienced its fourth failed rainy season in a row (WFP, 2023). A drought is thus not a low-probability event for our participants. Almost all our participants have high risk perceptions, 80% expect a drought once or twice every year, probably influenced by the failed rainy seasons they experienced. We can argue that we consider high-probability events, in which case an s-shaped probability weighting function indicates that people overweight the probability of this event. A further increase in the frequency of droughts due to climate change leads to more overweighting of the probability, leading to more risk-averse behaviour.

For the psychological variables, we find a positive effect of locus of control and risk appraisal on the utility curvature parameter, meaning that people with an internal locus of control and high risk perceptions are more risk-averse (supporting Hypotheses 3 and 5). This finding indicates that people who are aware of the drought risks and believe they can control the effects of these risks on their lives are more likely to take risk-reduction measures. Policies to stimulate risk-reduction measures should increase awareness about the potential drought effects and the effectiveness of risk-reduction measures that households can take themselves.

Finally, we analysed the effects of several socioeconomic variables on risk attitudes. People who received food aid during or after a drought were significantly less risk-averse. People are willing to take more risks if they trust they can receive support if they experience a drought. To some extent, it can be useful if policies support risk-taking behaviour because investments in new farming technologies involve some financial risk. Too much emergency aid can, however, create a charity hazard problem (Raschky & Weck-Hannemann, 2007). If people believe they will be fully compensated if they experience a drought, they might not take any risk-reduction measures.

Other notable exploratory findings from the control variables are the significant negative effects of household heads and the Burat Ward on utility curvature. Heads of households are willing to take more risks than those who are not. A likely explanation for these results is that heads of households are more familiar with these kinds of decisions, therefore, they can better assess acceptable risk levels. The negative effect of the Burat Ward (i.e. people in the Burat Ward are less risk-averse than those in the Oldonyiro Ward) can have multiple reasons. A study in Uganda found differences in risk aversion levels between regions with different climate zones (Tanaka & Munro, 2014). A possible explanation of the differences between the two wards could be that the Oldonyiro Ward receives less rainfall than the Burat Ward (MoALF, 2018). Another explanation could be the difference in distance to the main town and market access (Tanaka & Munro, 2014; Ullah et al., 2015). The Burat Ward is next to the capital of Isiolo County, which has better access to markets and other resources, whereas the Oldonyiro Ward is more remote. Future research could analyse the reason for this variation in more detail, but our results indicate that policymakers should consider regional differences in risk-taking behaviour when they develop climate change adaptation policies.

4.2. Advantages and disadvantages of using a framed experiment

We used an MPL experiment framed as livestock-keeping or crop-farming decisions in a drought to measure risk attitudes. As far as we know, we are the first to develop an MPL experiment related to livestock specifically aimed at pastoralists. Pastoralists and agro-pastoralists are amongst the most vulnerable groups to climate change-induced drought (Herrero et al., 2016). Understanding risk-taking behaviour is essential to inform how these groups can adapt to climate change effects (Freudenreich & Musshoff, 2022). An experiment framed as livestock-related decisions in the context of drought risk is more likely to capture actual decision-making in this context than an abstract experiment (Verschoor et al., 2016). Furthermore, framed experiments with contextual aids are less likely to lead to inconsistent choices (Alekseev et al., 2017; Estepa-Mohedano & Espinosa, 2023). We observed significantly fewer inconsistent choices than in abstract MPL experiments with smallholder farmers in low-income countries (e.g. Charness & Viceisza, 2016; Hirschauer et al., 2014), suggesting that the experiment is easier to comprehend for the participants.

A disadvantage of using framed experiments is that decisions may be influenced by values that the experimenter cannot control (Alekseev et al., 2017). It could be the case that the decisions of some of the respondents were influenced by the number of livestock they held instead of the hypothetical risks. However, we did not observe a significant difference between the risk attitudes of the participants in the crop and livestock versions of the experiment, indicating that risk attitudes were not influenced by the difference in framing. We had a large group of people who always selected the safe option, which is not an inconsistent choice, but we would have expected risk preferences to be more normally distributed. We are not the only study that finds a peak in the choices at always selecting the safe option (Angel et al., 2019; Brick et al., 2012; De Brauw & Eozenou, 2014; Jacobson & Petrie, 2009; Liu, 2013), but the percentage of people that always selected the safe choice is larger in our study. One possible explanation for this result could be that unknown personal values influence the choices. It might for example be the case that people have a certain preference for the number of cows they want to hold based on their experience, which can influence their decision. The high number of safe choices in our study is also partly influenced by the fact that we could only include a limited variation in payoffs to keep payoff values realistic in this context. There is a trade-off in field experiments between providing context to make it easier to comprehend and keeping it abstract to maximise experimental control. We believe that our method is more suitable for pastoralists and farmers in low- and middle-income countries because abstract experiments lead to many inconsistencies. Future studies could, however, compare our method with a neutrally framed experiment to assess the influence of framing on the decisions.

5. Conclusion

We conducted a framed field experiment to elicit risk attitudes in pastoral and agro-pastoral communities in Kenya. The experiment was framed as a farming decision in the context of drought. Creating a familiar context for respondents and combining that with visual aids makes the experiment easier to comprehend, leading to much fewer inconsistent choices than observed in studies with abstract experiments. Furthermore, the results are more likely to accurately represent risk attitudes in the specific context of agricultural drought risk. As far as we know, we are the first to develop such an experiment specifically for pastoralists. Pastoralists in the Horn of Africa Drylands are one of the world's most vulnerable groups to climate change-induced drought. Measuring their risk preferences enhances the understanding of climate change adaptation behaviour and can inform the development of adaptation policies.

The respondents are risk-averse overall, and they underweight small probabilities and overweight large probabilities. The communities in our case study area are frequently experiencing droughts and perceive droughts as high-probability events. Our probability weighting results thus indicate that people overweight the probability of a drought. An increase in the probability of a drought, caused by climate change leads to more overestimating of the drought probability in adaptation decisions that limit drought risk, causing more risk-averse behaviour and a higher demand for adaptation measures. We also found that an internal locus of control and drought risk perceptions positively correlate with risk-averse behaviour, whereas receiving emergency drought support negatively correlates with risk-averse behaviour. Policies that aim to stimulate anticipatory risk-reducing behaviour could demonstrate the effectiveness of individual actions, increase awareness of the problem, and minimise reliance on emergency assistance.

Data availability

The data that has been used is confidential.

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Supplementary materials

Supplementary material associated with this article can be found, in the online version, at doi:10.1016/j.socec.2023.102143.

Appendix A. Participant instruction

A.1. Participant instructions livestock version

Imagine that someone is giving you cows that you have to keep for at least one year. Afterwards you will be able to sell the cows that survived for 25 000 Kenyan Shilling per cow. This person gives you two options that you can choose from.

The first option is that this person will give you 10 cows. If the rains are good in the rainy season, all of the cows will survive, so you will still have 10 cows at the end of the year. If the rains are bad, then there will be less water and pasture available, which means that only 8 cows will survive to the end of the year.

The second option is that this person will give you 18 cows. If the rains are good, all 18 cows will survive, which means that you will have 8 cows more at the end of the year than in the first option. However, if the rains are bad, there will be insufficient pasture and water available for all 18 cows, which means that only 1 cow will survive.

Below we are going to ask you to make 9 choices for these two options under different rainfall scenarios. The choices are hypothetical and a simplification of reality, but your answers can help us to learn what you prefer, such that we can give advice on how policies can be improved.

In each scenario you have only 2 options to choose from. Option A would mean that you get the 10 cows. All 10 cows will survive if there is a good rainy season and 8 will survive in a bad rainy season. Option B would be that you get 18 cows, who will all survive in a good rainy season, but only 1 cow will survive in a bad rainy season.

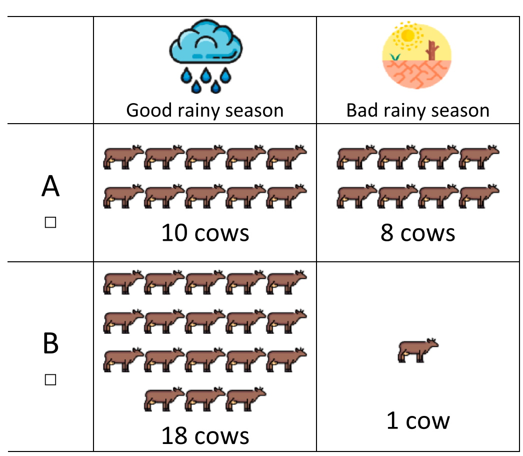


Fig. A1. Icons: Flaticon.com

A.2. Participant instructions crop version

Imagine that, because of climate change, you have to switch to a new crop type that is better adapted to drought than what you are used to at the present. Imagine that scientists are developing new varieties of maize crops that are better than what you are used to at present. The choices are hypothetical and a simplification of reality, but your answers can help us to learn what you prefer, such that we can give advice on how policies can be improved.

Assume that two different varieties of maize crops are being developed, with different yield potentials depending on how much it rains. Below we are asking you to make 10 choices between the two varieties under different rainfall scenarios. When making your choices, assume that you have access to one acre of land on which you can plant only one of the new varieties. The price on the market will be the same for both varieties, so they only differ in the possible yields they generate.

The table below gives an overview of the yield for both varieties in a good rainy season with normal rains and in a bad rainy season with little rainfall. Yields are measured in 50 kg bags. Variety A gives a relatively consistent yield: in a season with normal rainfall the yield will be around 20 bags and in a bad rainy season with little rainfall, the yield will be around 16 bags. Variety B performs much better in a good rainy season, with a yield of 36 bags, but performs much worse in a bad rainy season with only 2 bags.

Which maize variety would you choose?	Good rainy season	Bad rainy season
Variety A □	20 bags	16 bags
Variety B □	36 bags	2 bags

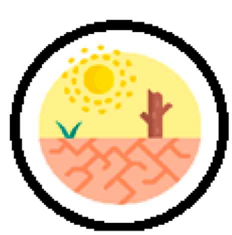
Fig. A2. Icons: Flaticon.com

A.3. Instructions for both the livestock and crop version

Part 1: Varying probabilities

We will ask you to make a choice between option A and option B in 9 different rainfall scenarios. The picture below Fig. A3 gives an example of such a rainfall scenario. The sack in this picture contains 10 balls, each ball represents one rainy season. A good rainy season is represented by a ball with a picture of a rain cloud:

And a bad rainy season is represented with a ball with a picture of dry land.



The picture below (Fig. A3) contains 1 ball representing a good rainy season and 9 balls representing a bad rainy season. This means that there is a small chance (1 out of 10) on a good rainy season and a high chance (9 out of 10) on a bad rainy season.

Fig. A3. Icons: Flaticon.com

Below we are going to ask to make a choice between option A or option B in 9 different rainfall scenarios. In the first scenario the chance of a good rainy season will be only 1 out of 10, in the second scenario it will be 2 out of 10 and this will increase until 9 out of 10 in the last scenario.

We are interested to know in which rainfall scenarios you will go for the safe option (option A) and in which scenarios you will go for the more risky option (option B). Some people might always go for the safe option and some other people always go for the risky option. Other people will be somewhere in between, meaning that they first go for the safe option when the chance on a good rainy season is small and switch to the risky option when the chance on a good rainy season becomes larger. None of these choices is wrong or right, we just want to know what you prefer.

Note for the interviewer: Take your time to carefully explain the probabilities. You should not steer people in their answer, however, in principle people should not switch back and forth between option A and option B multiple times. If they do switch multiple times, don't say that it is wrong, but ask why they make a choice, to make sure that they understand the choice that they are making.

Table A1 and A2 *give the payoffs and probabilities for the 9 choices that participants received in part 1 of respectively the livestock version and the crop version of the experiment. For the participant, all these choices were presented with pictures like the pictures in* Fig. A1*,* A2 *and* A3*. The last three columns give the expected values of options A and B and the difference in expected value. These expected values where not shown to the participants. Risk-neutral people would pick option A in the first four choices and switch to option B in choice 5. Risk-averse people switch later and risk-seeking people switch earlier.*

Table A1
Payoffs livestock version part 1 (varying probabilities).

P(A1)	A1	P(A2)	A2	P(B1)	B1	P(B2)	B2	E[A]	E[B]	E[A] - E[B]
0.1	10	0.9	8	0.1	18	0.9	1	8.2	2.7	5.5
0.2	10	0.8	8	0.2	18	0.8	1	8.4	4.4	4
0.3	10	0.7	8	0.3	18	0.7	1	8.6	6.1	2.5
0.4	10	0.6	8	0.4	18	0.6	1	8.8	7.8	1
0.5	10	0.5	8	0.5	18	0.5	1	9	9.5	−0.5
0.6	10	0.4	8	0.6	18	0.4	1	9.2	11.2	−2
0.7	10	0.3	8	0.7	18	0.3	1	9.4	12.9	−3.5
0.8	10	0.2	8	0.8	18	0.2	1	9.6	14.6	−5
0.9	10	0.1	8	0.9	18	0.1	1	9.8	16.3	−6.5

Table A2
Payoffs crop version part 1 (varying probabilities).

P(A1)	A1	P(A2)	A2	P(B1)	B1	P(B2)	B2	E[A]	E[B]	E[A] - E[B]
0.1	20	0.9	16	0.1	36	0.9	2	16.4	5.4	11
0.2	20	0.8	16	0.2	36	0.8	2	16.8	8.8	8
0.3	20	0.7	16	0.3	36	0.7	2	17.2	12.2	5
0.4	20	0.6	16	0.4	36	0.6	2	17.6	15.6	2
0.5	20	0.5	16	0.5	36	0.5	2	18	19	−1
0.6	20	0.4	16	0.6	36	0.4	2	18.4	22.4	−4
0.7	20	0.3	16	0.7	36	0.3	2	18.8	25.8	−7
0.8	20	0.2	16	0.8	36	0.2	2	19.2	29.2	−10
0.9	20	0.1	16	0.9	36	0.1	2	19.6	32.6	−13

Part 2: Fixed probabilities

For the following 9 choices, the chance of a good or a bad rainy season will be fixed. We want you to imagine that the chance of a good rainy season will be 5 out of 10, meaning that 5 out of the 10 coming rainy seasons are expected to have good rainfall and 5 out of 10 are expected to have no or little rainfall. This chance is represented by the balls in the sack below.

Fig. A4. Icons: Flaticon.com

Livestock version: To get more information about what you prefer, we are again asking you to make 9 choices. Instead of different rainfall scenarios, now imagine that the amount of cows that you will receive in the different options is different. The value of a cow is still the same. Cows that survive can be sold after one year for 25,000 Kenyan Shilling per cow.

Crop version: To get more information about your preferences for maize crop yields we are asking you to make a choice between various different types of maize crops, each crop has a different expected yield for a good rainy season and a bad rainy season. The price on the market is still the same for all different maize varieties, they only differ in the yields they generate.

Remember that for each of the choices below, the chance of a good rainy season is 5 out of 10.

Table A3 and Table A4 give the payoffs and probabilities for the 9 choices that participants received in part 2 of respectively the livestock version and the crop version of the experiment. For the participant, all these choices were presented with pictures like the pictures in Fig. A2, A3 and A4. The last three columns give the expected values of option A and B and the difference in expected value. These expected values where not shown to the participants. Risk-neutral people should pick option A in the first four choices and switch to option B in choice 5. Risk-averse people switch later and risk-seeking people switch earlier.

Table A3
Payoffs livestock version part 2 (fixed probabilities).

P(A1)	A1	P(A2)	A2	P(B1)	B1	P(B2)	B2	E(A)	E(B)	E(A)-E(B)
0.5	10	0.5	8	0.5	14	0.5	1	9	7.5	1.5
0.5	11	0.5	8	0.5	16	0.5	1	9.5	8.5	1
0.5	12	0.5	8	0.5	18	0.5	1	10	9.5	0.5
0.5	13	0.5	8	0.5	20	0.5	1	10.5	10.5	0
0.5	14	0.5	8	0.5	22	0.5	1	11	11.5	−0.5
0.5	15	0.5	8	0.5	24	0.5	1	11.5	12.5	−1
0.5	16	0.5	8	0.5	26	0.5	1	12	13.5	−1.5
0.5	17	0.5	8	0.5	28	0.5	1	12.5	14.5	−2
0.5	18	0.5	8	0.5	30	0.5	1	13	15.5	−2.5

Table A4
Payoffs crop version part 2 (fixed probabilities).

P(A1)	A1	P(A2)	A2	P(B1)	B1	P(B2)	B2	E(A)	E(B)	E(A)-E(B)
0.5	20	0.5	16	0.5	28	0.5	2	18	15	3
0.5	22	0.5	16	0.5	32	0.5	2	19	17	2
0.5	24	0.5	16	0.5	36	0.5	2	20	19	1
0.5	26	0.5	16	0.5	40	0.5	2	21	21	0
0.5	28	0.5	16	0.5	44	0.5	2	22	23	−1
0.5	30	0.5	16	0.5	48	0.5	2	23	25	−2
0.5	32	0.5	16	0.5	52	0.5	2	24	27	−3
0.5	34	0.5	16	0.5	56	0.5	2	25	29	−4
0.5	36	0.5	16	0.5	60	0.5	2	26	31	−5

Appendix B. Explanatory Variables and Probability Weighting

Table B1 presents the analysis of the relationship between the main psychological variables and the probability weighting score. We observed a significant effect of locus of control on probability weighting, but the direction of this effect is ambiguous. In the first four models, a significant positive effect of locus of control exists, but the effect becomes significantly negative with socioeconomic control variables. We performed a variance inflation factor (VIF) analysis to evaluate whether this reversed sign could be caused by multicollinearity, but the VIF score does not indicate a multicollinearity problem. The only control variable with a significant effect in Models 5 and 6 is the access to forecast information. Potentially, a relationship exists between access to forecast information and locus of control that changes the effect of locus of control on probability weighting.

For worry about future droughts, a small significant positive effect exists in Models 2, 4 and 5, suggesting that people who are more worried are slightly more likely to overweight high-probability events, but this evidence is not strong. For risk perception variables, a significant positive effect exists for the expected frequency of drought, indicating that the people who expect drought to occur more often in the future are more likely to overweight high probabilities. However, this effect disappeared when we added socioeconomic control variables in Model 6. In contrast, the risk appraisal variable has a significant negative effect in Models 5 and 6, suggesting that people with a higher risk appraisal are more likely to overweight low probabilities and underweight high probabilities. In Model 4, we selected the model with the highest AIC score[2] (Cavanaugh & Neath, 2019). This model is without the relative impact variable because including this variable did not have any significant effect and did not improve the AIC score.

Table B1

Results of maximum likelihood estimation with probability weighting parameter γ as a function of variables of interest p-values in parentheses + $p < 0.10$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

	(1)	(2)	(3)	(4)	(5)	(6)
β	0.927***	0.924***	0.936***	0.913***	0.841***	0.759***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
γ						
Locus of control	−0.0919***	−0.0897***	−0.0892***	−0.0908***	0.0452***	0.0329*
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.019)
Worry future drought	0.0582	0.0805+	0.0682	0.0756+	0.0984*	0.0439
	(0.198)	(0.074)	(0.127)	(0.090)	(0.043)	(0.444)
Expected frequency	0.0645+			0.0665+	0.0480*	−0.00731
	(0.058)			(0.059)	(0.045)	(0.771)
Risk appraisal		−0.0663		−0.0887	−0.372***	−0.303**
		(0.566)		(0.402)	(0.000)	(0.002)
Relative impact			−0.0000899			
			(0.998)			
Access to credit					0.130**	0.0679
					(0.003)	(0.158)
Access VSAL					−0.0699	−0.0705
					(0.109)	(0.106)
Access forecast info					0.145***	0.0880*
					(0.000)	(0.024)
Food aid					−0.0567	−0.0705
					(0.449)	(0.351)
Socioeconomic controls	No	No	No	No	No	Yes
_cons	0.999**	1.732***	1.526***	1.246**	1.046+	1.140+
	(0.372)	(0.448)	(0.300)	(0.457)	(0.542)	(0.600)
N	8118	8118	8118	8118	8118	8118
N clusters	451	451	451	451	451	451
AIC	7867.7	7872.3	7873.7	7866.8	7695.7	7597.4
Pseudo LL	−3928.9	−3931.2	−3931.8	−3927.4	−3837.9	−3776.7

Appendix C. Maximum likelihood estimation including inconsistencies with Fechner noise parameter

In this section, we repeat the maximum likelihood estimation of section 3.2, but now we included inconsistent choices and added a stochastic element to the model to capture noise in the decision of the participants. We use a Fechner error specification as has been done by, amongst others, Hey and Orme (1994) which is preferred over the Luce error specification, as used in Holt and Laury (2002), according to Wilcox (2008) and Harrison and Rutsröm (2008). According to this error specification, subjects make a choice between options A and B based on the difference between their expected utilities, plus a normally distributed error term μ (Crosetto & Filippin, 2016). We ran the same maximum likelihood estimation as before, but equation (5) in section 2.3 now changes into the following:

$$\Delta EU = \frac{EU_B - EU_A}{\mu} \tag{5'}$$

The probability of selecting option B thus depends on the difference in utility and the noise factor μ. If $\mu = 1$, then the model is the same as in section 2.3 and the choice only depends on the expected utility of the options. The choice becomes completely random if μ goes to infinity. Table C1 show the results of the maximum likelihood estimation for the EUT and RDU models. In both models, we find a significant noise factor, which indicates that there is some noise in the choices. Comparing these results with Table 7, shows that including the noise factor leads to a slightly lower utility curvature coefficients (β) and a slightly higher probability weighting coefficient (γ), but these differences are not very large. Table C2 duplicates the results of Table 9 to assess if the effects of the explanatory variables change if we include a noise factor. We do not observe any significant differences in the effects of the explanatory variables which indicates that our results in section 3.2 are robust.

Table C1
Maximum likelihood estimation for the EUT and RDU models with Fechner noise parameter, p-values in parentheses. + $p < 0.10$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

	(1) EUT	(2) RDU
β	0.777***	0.830***
	(0.000)	(0.000)
γ		1.295***
		(0.000)
μ	1.179***	1.241***
	(0.000)	(0.000)
N	8532	8532
N clusters	474	474
AIC	8439.3	8427.2
Pseudo LL	−4217.6	−4210.6
Wald χ^2 (γ=1)		54.37 ($p = 0.0000$)

p-values in parentheses
.* $p < 0.10$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table C2
Results of maximum likelihood estimation with utility curvature parameter β a function of variables of interest and socioeconomic control variables with a Fechner noise parameter. p-values in parentheses. + $p < 0.10$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
β								
Locus of control	0.0308***	0.0334***	0.0304***	0.0384***	0.0549***	0.0470***	0.0396*	0.0404*
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.018)	(0.027)
Worry future drought	0.0123	−0.0923	0.0247	−0.0950	−0.101	−0.100	−0.0727	−0.0837+
	(0.857)	(0.194)	(0.756)	(0.167)	(0.132)	(0.122)	(0.178)	(0.090)
Expected frequency	−0.163**			−0.166***	−0.0750+	−0.0672	−0.0591	−0.0612
	(0.002)			(0.000)	(0.079)	(0.201)	(0.339)	(0.493)
Risk appraisal		0.198***		0.202***	0.196***	0.154***	0.155*	0.121**
		(0.000)		(0.000)	(0.000)	(0.001)	(0.019)	(0.010)
Relative impact			0.0388	0.0338	0.0219	−0.0127	0.00524	0.0176
			(0.488)	(0.486)	(0.631)	(0.798)	(0.935)	(0.726)
Access to credit					−0.0730	−0.0336	−0.0228	−0.0204
					(0.150)	(0.452)	(0.586)	(0.696)
Access VSAL					−0.142*	−0.0839	−0.0734	−0.00634
					(0.017)	(0.267)	(0.300)	(0.888)
Access forecast info						−0.117**	−0.113**	−0.000779
						(0.004)	(0.006)	(0.984)
Food aid						−0.220*	−0.239*	−0.263**
						(0.011)	(0.012)	(0.006)
Household head							−0.213**	−0.214*
							(0.004)	(0.039)
Education level							0.0132	0.0361+
							(0.418)	(0.083)
Age							−0.00282	−0.000534
							(0.236)	(0.848)
Gender (1=female)							−0.0530	0.0457
							(0.351)	(0.510)
Household size							0.0117	0.0281
							(0.443)	(0.159)
Expenditures							−0.000349	−0.000105
							(0.465)	(0.809)
Burat Ward								−0.411*
								(0.017)
Livestock keeper								−0.305*
								(0.020)
Crop farmer								0.273***
								(0.000)
Ethnicity dummies	No	No	No	No	No	No	No	Yes
_cons	2.038**	0.137	0.389	1.489*	1.114*	1.484**	1.429*	1.375
	(0.002)	(0.635)	(0.419)	(0.016)	(0.034)	(0.003)	(0.012)	(0.167)
γ	1.278***	1.220***	1.315***	1.182***	1.033***	1.027***	1.009***	1.050***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Noise	1.188***	1.183***	1.219***	1.151***	1.058***	1.039***	1.040***	0.962***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
N	8118	8118	8118	8118	8118	8118	8118	8118
N clusters	451	451	451	451	451	451	451	451
AIC	7824.1	7812.1	7884.1	7728.6	7625.9	7489.9	7405.8	7210.4
Pseudo LL	−3907.1	−3901.1	−3937.1	−3857.3	−3804.0	−3734.0	−3685.9	−3581.2

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