Environmental and Resource Economics (2024) 87:967–1007
https://doi.org/10.1007/s10640-024-00850-5

Can Climate Shocks Make Vulnerable Subjects More Willing to Take Risks?

Stein T. Holden[1] · **Mesfin Tilahun**[1,2]

Accepted: 13 February 2024 / Published online: 18 March 2024

Abstract

While economists in the past tended to assume that individual preferences, including risk preferences, are stable over time, a recent literature has developed and indicates that risk preferences respond to shocks, with mixed evidence on the direction of the responses. This paper utilizes a natural experiment with covariate (drought) and idiosyncratic shocks in combination with an independent field risk experiment. The risk experiment uses a Certainty Equivalent-Multiple Choice List approach and is played 1–2 years after the subjects were (to a varying degree) exposed to a covariate drought shock or idiosyncratic shocks for a sample of resource-poor young adults living in a risky semi-arid rural environment in Sub-Saharan Africa. The experimental approach facilitates a comprehensive assessment of shock effects on experimental risk premiums for risky prospects with varying probabilities of good and bad outcomes. The experiment also facilitates the estimation of the utility curvature in an Expected Utility (EU) model and, alternatively, separate estimation of probability weighting and utility curvature in three different Rank Dependent Utility models with a two-parameter Prelec probability weighting function. Our study is the first to comprehensively test the theoretical predictions of Gollier and Pratt (Econom J Econom Soc 64:1109–1123, 1996) versus Quiggin (Econ Theor 22(3):607–611, 2003). Gollier and Pratt (1996) build on EU theory and state that an increase in background risk will make subjects more risk averse while Quiggin (2003) states that an increase in background risk can enhance risk-taking in certain types of non-EU models. We find strong evidence that such non-EU preferences dominate in our sample.

Keywords Covariate shocks · Idiosyncratic shocks · Stability of risk preference parameters · Field experiment · Ethiopia

JEL Classification C93 · D81

✉ Stein T. Holden
stein.holden@nmbu.no

Mesfin Tilahun
mesfintilahungelaye@gmail.com; mesfin.telahun.gelaye@nmbu.no

[1] School of Economics and Business, Norwegian University of Life Sciences, P. O. Box 5003, 1432 Ås, Norway

[2] Department of Economics, Mckcllc University, P. O. Box 451, Mekelle, Tigray, Ethiopia

1 Introduction

Climate change is associated with more frequent and/or more severe shocks in terms of severe droughts, floods, and storms. Whether, how much, and for how long risk preferences change as a result of shock exposure in the form of idiosyncratic and covariate shocks are still controversial and understudied, and therefore, more and better empirical studies are needed and of potential high policy importance given the threats from climate change.

Standard neoclassical economics assumed risk preferences to be stable and not subject to much change (Stigler and Becker 1977). However, does constant risk preferences mean constant absolute risk aversion (CARA) or constant relative risk aversion (CRRA)? As noted by Quiggin (2003), risk-neutral preferences are the only class of expected-utility preferences displaying constant risk aversion (CARA and CRRA). For risk averse individuals, more risk reduces welfare. A vulnerability perspective may point towards increasing marginal costs of increasing risk exposure, and it may be rational to become more risk averse for one's own protection. An increase in background risk (more serious shock exposure) may make people more vulnerable and risk averse (Gollier and Pratt 1996; Cameron and Shah 2015; Pratt and Zeckhauser 1987). On the other hand, Quiggin (2003) has shown that background risk can be a complement rather than a substitute for independent risks for certain non-expected utility theories. This implies that increased background risk can make subjects less averse to independent risks. This difference in predictions may give an important theoretical explanation for the contradictory findings in the literature on how shocks affect risk preferences. A near-linear utility function may thus be one explanation for shock exposure triggering more risk-taking in independent risk experiments after such a shock. Another explanation may be found in Prospect Theory (PT), which proposes that the curvature of the value function is different in the loss domain than in the gains domain, possibly causing people to take more risk after exposure to a negative shock (causing them to be in the loss domain) (Kahneman and Tversky 1979; Tversky and Kahneman 1992). This follows from a diminishing sensitivity perspective for deviations from a status quo (before a shock) position. Also, when people have little more to lose, they may become desperate risk-takers. Such switches could trigger sudden changes in survival strategies, such as desperate migration, criminal activity, and social unrest.

The empirical literature on the effects of shocks on risk preferences gives mixed findings. Some studies find that subjects have become more willing to take risks after shock exposure in line with Quiggin (2003) and possibly PT (Voors et al. 2012; Kahsay and Osberghaus 2018; Page et al. 2014; Cavatorta and Groom 2020; Hanaoka et al. 2018). Other studies find the opposite, that subjects have become less risk tolerant after exposure to shocks (Cassar et al. 2017; Liebenehm 2018; Guiso et al. 2018; Brown et al. 2019; Bourdeau-Brien and Kryzanowski 2020; Cameron and Shah 2015; Liebenehm et al. 2023). And yet other studies find that risk preferences are stable and unaffected by shocks (Sahm 2012; Brunnermeier and Nagel 2008; Drichoutis and Nayga 2021). There are also mixed findings regarding how covariate and idiosyncratic shocks affect risk preferences (Liebenehm 2018). Some studies show that risk preferences may be affected by fears even though individuals were not directly affected by the shocks, indicating that the change induced by shocks may be an emotional response and those directly exposed may be affected differently than those who only experience a shock from a distance (Bourdeau-Brien and Kryzanowski 2020; Said et al. 2015). Said et al. (2015) find that those who lived in a flood-exposed area in Pakistan but were not directly affected by the flood themselves became more risk averse, while those who were directly affected became less risk averse. Guiso et al. (2018) find that the 2008 financial crisis triggered a substantial increase in risk aversion of bank customers who were not directly affected by the crisis. Few studies investigate how persistent or long-lasting such shock effects on risk tolerance can be. Hanaoka et al. (2018) find that Japanese men became more risk tolerant after the Great East Japan Earthquake, and this effect persisted five years after the earthquake, while no such shift was observed for Japanese women. Few earlier studies have looked at how drought shocks may affect risk preferences. Voors et al. (2012) studied whether violent conflicts and droughts affected the risk preferences related to the civil war in Burundi and found that exposure to conflict made people more willing to take risks, while they found no significant effect from drought.

We assess whether the 2015–16 severe covariate drought and 2016–17 idiosyncratic shocks affected experimental risk-taking behavior in 2017 using an easy-to-understand incentivized tool to elicit risk preferences one and two years after shock exposures. We used a Certainty Equivalent (CE)-Multiple Choice List (MCL) experiment 1–2 years after the shocks that were treated as a natural experiment. With 12 Choice Lists (CLs), we elicited 12 risk premiums per subject and could assess whether the risk premiums were affected by the covariate and idiosyncratic shocks. Furthermore, this experiment allowed the estimation of disaggregated probability weighting using a two-parameter Prelec probability weighting function (Prelec 1998) and utility curvature based on a Constant Relative Risk Aversion (CRRA) utility function. Based on Rank Dependent Utility (RDU) theory (Quiggin 1982), the probability weighting and utility functions were jointly estimated while assessing their parameter sensitivity to past idiosyncratic and covariate shocks.

The general RDU and the special case dual (Yaari 1987) models predict that subjects become more willing to take risks (have lower risk premiums) after the severe covariate shock, which represents an increase in background risk. This result contradicts EU theory, which predicts that an increase in background risk should increase risk vulnerability and make subjects more risk averse (Gollier and Pratt 1996). So far, there has not been any rigorous empirical testing of these alternative theoretical explanations as possible explanations for the mixed effects of shocks on risk preferences.

There are reasons to believe that subjects' risk preferences are more sensitive to covariate than idiosyncratic shocks as insurance mechanisms do not work as well for covariate as for idiosyncratic shocks (Dercon et al. 2008). Günther and Harttgen (2009) showed that rural households were relatively more severely affected by covariate than by idiosyncratic shocks. There are, therefore, good reasons to judge the subjects as having become more vulnerable after exposure to a severe covariate shock.

Our paper makes four important contributions to the limited but expanding literature on how shocks affect risk preferences in field settings with poor and vulnerable subjects. The main types of shocks or disasters studied concerning risk preference stability include floods and earthquakes. To our knowledge, we present the first comprehensive study of how varying covariate drought shock exposure affects experimental risk premiums at different probability levels for good and bad (non-negative) outcomes. Most earlier studies have used simple tools that do not allow the separation of shock effects on utility and probability weighting. Second, to our knowledge, this is the first paper that disaggregates the shock effects on utility curvature and two probability weighting parameters. Third, we present the first paper that comprehensively tests the effect of an increase in background risk on risk-taking based on the EU risk vulnerability theory of Gollier and Pratt (1996) against the non-expected utility theory prediction of Quiggin (2003). Fourth, our study uniquely assesses the effects of recent idiosyncratic shock and a covariate climate (drought) shock on risk preference parameters in a rural poor and vulnerable population in a semi-arid environment in Sub-Saharan Africa. Such environments and vulnerable populations will likely face more severe climate shocks associated with future climate change. Our study indicates that subjects exposed to the covariate drought shock have become more willing to take risks, in line with non-expected utility theories. This may indicate a willingness to adapt to changing climatic conditions even though such shocks make people more vulnerable. This finding has potentially important policy implications as the frequency and severity of climate shocks are likely to increase as part of climate change, and climate adaptation needs to be carefully addressed by well-informed policy-makers who understand context-specific behavioral responses to such shocks.

Our paper proceeds as follows. Part 2 elaborates on the sample and survey data, assesses attrition, and tests whether we can regard the shock variables as natural experiments. Part 3 outlines the experimental design and inspects the experimental outcome distributions and data quality, including non-parametric assessment of stochastic dominance. Part 4 outlines the theoretical framework, the parametric estimation, and identification strategies. Part 5 presents the results discussed in Part 6 before we conclude in Part 7.

2 Survey, Experimental Design and Data

2.1 Sample and Survey Data

The study is based on a random sample of 120 youth business groups from a census of 742 such groups in five districts in the semiarid Tigray Region of Ethiopia. Up to 12 members were randomly sampled from each group. A baseline survey was implemented in July-August 2016. The second round of surveys and experiments were conducted in July-August 2017. The baseline survey covered 1104 subjects with complete information on all the variables. Attrition reduced the number of groups to 114 groups and 912 subjects in the second experiment in 2017 with complete data.

The business group program was established as a policy initiative to create a complementary natural resource-based livelihood opportunity for landless and near-landless youth and young adults in this risky environment. Eligibility criteria for joining the business groups were residence in the community and resource poverty in terms of limited land access. The main group production activities they could establish were animal rearing, beekeeping, forestry, and irrigation/horticulture. Self-selection into groups was most common (80% of the groups) by the youth in a group typically coming from the same neighborhood. It enabled them to continue living in their home community close to their parents. All the groups were formed before the severe 2015 drought took place.

The group members also have limited education, with a mean of 5.5 years of completed education. About one-third of the subjects were female, see Table 1.

All experiments and survey questions were translated and asked in the local language, *Tigrinya*. Trained experimental and survey enumerators introduced the experiments and asked survey questions in the local language. Tablets and CSPro were the digital tools used for the data collection. Careful training of enumerators was first conducted in classrooms at Mekelle University. They were then trained by doing experiments and interviews with each other before they were trained in the field with out-of-sample groups and subjects. To minimize within-group spillover effects, the twelve sampled members from each business group were interviewed simultaneously by 12 enumerators, using three classrooms in a local school (or Farm Training Centres). One enumerator was placed in the corner of each classroom, and the subjects faced them during the experiments and survey interviews. Supervisors were used to ensure order and no disturbance. The orthogonal placement of enumerators on groups minimizes the risk of enumerator bias in the analyses. In addition, the researchers monitored potential enumerator bias during data collection. They had follow-up meetings with the enumerators to identify reasons for observed enumerator bias in the data collected and find ways of minimizing such bias. Some poor-performing enumerators were replaced.[1]

2.1.1 Attrition and Test for Natural Experiment

To a varying degree, the study areas were affected by a severe drought shock in 2015[2] and recall data for the exposure and severity of this shock were collected in the 2016 baseline survey. The subjects were asked how severely their parent households were affected by the 2015 drought shock on a scale from 0 to 3, see Table 2.[3] As a measure of covariate risk, we constructed a variable that was the mean severity index within business groups. As groups have a joint land resource-based business, group members and their families are spatially concentrated in a neighborhood. We exploit the spatial variation in the severity of the drought shock across groups to generate a covariate shock variable. Its distribution in terms of average group severity (on the 0–3 scale) in the full sample and each district (*woreda*) are shown in Fig. 1a. We also show the distribution of the within-group deviation in drought shock severity (Fig. 1b), which to a large extent is a mixture of idiosyncratic noise in the perception responses and local variation in vulnerability and is therefore not included in the analyses.[4] We note the substantial within-district variation in the covariate shock severity in Fig. 1c. The severity of the 2015 drought is also illustrated by the fact that 43% of the families had to sell assets or livestock in response to the shock, and 55% received support from the government related to the drought.[5]

Descriptive statistics are provided for the included survey variables for individual group members, their main group production activities, and their parent household and farm characteristics. We used group members who were available and participated in the 2016 survey and the 2017 risk preference experiments. We obtained all variables of interest for 912 subjects from 114 business groups, see in Table 1. We have rich data and deep knowledge of the study area. We intend to use the group-level measure of drought shock severity as an explanatory variable based on the assumption that this group-level drought shock severity can be used as a natural experiment. By taking the group mean, we have removed within-group variation in vulnerability and noise to get a cleaner measure of the drought shock severity (El Nino effect) in a location. In order to critically examine whether the shock can be regarded as not only external but also exogenous in an econometric sense (Deaton 2010), we need to assess whether there can be spurious correlations between the

[1] This happened before the 2017 risk experiments for which we had a stable and well-trained group of enumerators.

[2] This drought is associated with the El Nino effect. Such droughts have previously been observed in Ethiopia in 1958/59, 1965, 1972/73, 1982/83, 1986, 1992/93, and 1997/98 (Mera 2018).

[3] The sample subjects mostly are youth or young adults from resident farm households in their community. We include the drought shock severity data for the final sample in Table 1 as well, and we test for potential attrition bias. We find no such bias. The test results are presented in Appendix 1, Table 11.

[4] Including it in the analyses does not change the results in any significant way.

[5] We avoid including these variables in our analyses due to their endogeneity and difficulty finding strong and valid instruments for their prediction.

Table 1 Descriptive statistics for shock variables and individual, group, and parent household characteristics

	Mean	sd
Shock variables		
Covariate shock severity 2015–16	1.730	0.420
Deviation in shock severity 2015–16	− 0.003	0.851
Idiosyncratic shock 2016–17, dummy	0.167	0.374
Subject characteristics(2016)		
Male, dummy	0.672	
Age, years	29.321	9.728
Education, years	5.411	3.956
Married, dummy	0.611	
Lives on parents' farm	0.524	
Group business activity		
Livestock	0.255	
Beekeeping	0.360	
Forestry	0.137	
Irrigation	0.248	
Parent household characteristics		
Parents have radio, dummy	0.491	
Parents oxen number	0.963	0.613
Parents own land, dummy	0.763	
Parents farm size, *tsimdi*	2.243	2.133
N	912	

1 *tsimdi* is approximately 0.25 ha

group-level drought shock severity variable and parent household and farm characteristics and business group characteristics. We also need to assess whether the drought may have caused migration and attrition that may have caused attrition bias. If we find no such correlations of significance, we go ahead with the natural experiment assumption and consider the relationship between the 2015 and 2016 shocks and the risk preferences elicited in independent risk experiments in 2017 for the same subjects to represent causal effects.

One possible threat to our assumption is that the natural experiment in the form of the severe drought shock in 2015 may have caused a selection (dropout) of group members with systematically different risk preferences in areas more severely affected by the drought. We assessed this by using dropout information from each group and group member. We regressed it on the 2015 drought severity variable and member and parent household characteristics. We found no significant correlation indicating that the drought caused such a selection that could bias our results.[6] Another potential selection problem could be related to whether group member selection and formation were significantly different across more severely drought-affected and other areas. About 80% of the groups were formed through the self-selection of eligible members within their community. We constructed a dummy variable for self-selected groups, ran a selection model with baseline group characteristics, and constructed an Inverse Mills Ratio (IMR) for possible selection

[6] The results are presented in Appendix 1, Table 11. This result is also supported by qualitative information about the reasons for dropout and migration. The drought was not given as the reason for dropout and migration by any informants.

Table 2 Severity of 2015 shock exposure

	Initial sample		Final sample	
	Frequency	Percent	Frequency	Percent
Not at all (0)	110	9.9	95	10.4
Somewhat affected (1)	338	30.6	284	31.2
Quite severely affected (2)	370	33.5	308	33.7
Very severely affected (3)	286	25.9	225	24.6
N	1104	100	912	100

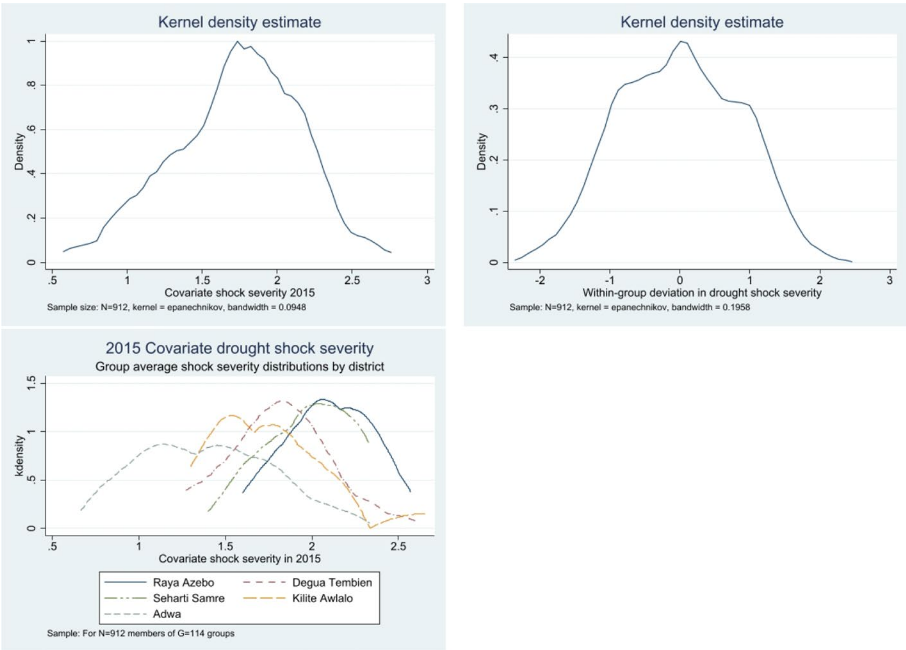

Fig. 1 The distribution of the covariate and within-group deviation in shock severity index variable and covariate shock severity by district in the N = 912 sample

bias associated with these groups. We included the predicted self-selection variable and the IMR in the attrition model (Appendix 1, Table 11) and used bootstrapping and re-sampling groups to correct the standard errors. These variables were not significantly correlated with member attrition.

Another potential source of bias is that we relied on the self-reported severity of the drought shock. Ideally, one would prefer objective measures, but such objective measures of drought, such as rainfall,[7] only exist from meteorological stations that are located far

[7] Even the transformation of rainfall to an indicator of the drought severity is a non-trivial task at a specific location as this depends on the inter-temporal distribution of rainfall, temperature distribution, soil type, slope, slope direction, position in the catena, vegetation, soil type, groundwater level and variation, and technologies used.

apart. They do not capture the large local micro-climatic variation, including rainfall variation over time and space, associated with the rugged topography in our study districts.[8]

To further inspect for potential endogeneity associated with the business group-level averaged perception-based covariate drought shock, we estimated models (Table 3), models (1) and (4)), using this covariate drought shock severity (model (1)) and the within-group deviation in the shock severity (model (4)) as dependent variables. We regressed these on the parent household and farm characteristics, including a dummy variable for whether the respondents lived on the farm of their parents, and the main business group production activity type,[9] and district dummies. In model (4) for the within-group deviation in perceived drought shock severity, we also included the predicted group level self-selection and IMR variables.[10]

Model (1) in Table 3 shows that none of these parent household characteristics or group production types were significantly correlated with the covariate shock variable. Only some of the district dummy variables were significant, as could be expected based on the patterns observed across districts in Fig. 1. However, the within-district variations in the covariate shock severity observed in Fig. 1 are substantial and demonstrate an important variation in drought severity that rainfall data from weather stations do not capture. The fact that none of the parent household and farm characteristics,[11] or group production activities were significant indicates that we cannot reject the natural experiment assumption for the covariate shock variable. However, we cannot rule out that other confounders can undermine our assumption. We follow up with further robustness checks (control function approach) in the analysis of how the 2015 group-level covariate and 2016 idiosyncratic shock variables affect or are correlated with the estimated risk preference variables with reduced-form and structural models based on the EU and RDU theories for our sample.

As a further inspection of the within-group deviation in drought shock severity perceptions, see model (4) in Table 3. We found no significant correlation between the predicted self-selection dummy and the Inverse Mills Ratio and the deviation in drought severity variable and, therefore, no sign of significant selection bias. We also included a dummy variable for the youth group members who live on their parents' farm.[12] We see in model (4) in Table 3 that the deviation in the drought severity index was significant (at 0.1% level) and negatively associated with the parents' farm size. This may be because more land-poor households are more vulnerable to droughts, and therefore, the subjects perceive the shock as more severe for their parents. This implies that we, by taking the group means, have removed a potentially important source of endogeneity in the covariate drought severity perception variable, as farm size is insignificant in model (1). Still, we keep in mind that

8 We observed that some of our study locations had very low rainfall but good access to groundwater, so rainfall was a poor predictor of drought problems there. There was also local variation in access to groundwater that is unobservable in the data from meteorological stations. This is local knowledge that our perception variable takes advantage of. For the protection of the anonymity of our sample, we are reluctant to provide detailed maps of their locations, especially as there has been a civil war in the area after we carried out this study, and many youths were victims of violence during the civil war.

9 See Appendix 2, Table 12.

10 These variables cannot be included in model (1) as they do not vary within groups.

11 Appendix 2 provides some further statistics on parent household heterogeneity.

12 Those who live on their parents' farm may have a closer connection to their parents, and this may have affected their drought perceptions. A closer inspection shows that the farm size of the parent households for those who live on the farm of their parents is 2.88 *tsimdi* on average against 1.54 *tsimdi* for the youth not living on the farm of their parents. This variable, therefore, also picks up some of the farm size effects. Farm size may be negatively correlated with vulnerability.

the farm size of parents may be an important additional variable to control for when we assess the relationship between the shock variables and risk preferences, as it may reflect local variation in vulnerability.

We also regressed the (idiosyncratic) 2016–17 shock dummy on the same variables as above; see models (2) and (3) in Table 3. We added model (3) with the two shock severity variables from the previous year to inspect the significance of their correlations. Table 3 shows that the dummy for the youth living on their parent's farm was negatively correlated (significant at 1% level) with the likelihood of being exposed to such a shock.[13] In model (3), where we tested for significant correlation between the 2015 and 2016 shock variables, we found the covariate shock variable to be significantly and positively correlated with the 2016 shock dummy.[14] The finding that the dummy for the youth group members living on the parents' farm is significant in the idiosyncratic shock models implies that we also will include this variable as an important control in the further analysis of how the idiosyncratic shock variable may have impacted or is correlated with the risk preference variables. As the irrigation group variable was weakly significant in the idiosyncratic shock models, we also included the main activity variables as a control in the following analyses. We need to be cautious in our causal interpretation of the effect of the idiosyncratic shock variable on risk preferences by taking these confounders into account.

3 Experimental Design

3.1 Certainty Equivalent Multiple Choice List (CE-MCL) Experiment

These experiments were implemented in July-August 2017 in combination with a follow-up survey of the same business groups and members, we used an MCL approach where the subjects answer multiple series of binary questions where they in each CL chose between a fixed risky prospect and alternative certain amounts. The advantage of this experiment is that it can separately identify the probability weighing function and the utility function, as we varied both probabilities and outcome levels (see Table 4 for an overview of the CL parameter variation). Table 5 provides an example of one of the CLs. The experimental protocol and relevant extracts of the survey instrument are included in the Appendix (Survey and Experimental Protocols).

The subjects are informed before the experiment is started that they will have to choose between a large number of risky prospects and certain amounts and that one of the prospects will be chosen randomly as a real game and for real payout immediately after the experiment has been completed. Each subject is allocated to an MCL with a randomized order of the CLs. For each CL, the subject is presented with the risky prospect, outlined on the desk in front of her/him, with real money for the good and bad outcomes and with the 20-sided die to illustrate the probability of winning and losing. It is only the certain

[13] A model without this dummy variable gave a significant negative correlation with farm size. This indicates that those who live on their parents' farms are less exposed to idiosyncratic risks, which may be because their parents are better endowed with land.

[14] The Pearson correlation coefficient between the 2015 covariate shock severity variable and the 2016 shock dummy is 0.0696, which is so low that it is not likely to have any strong mutual statistical influence, but we investigated this to be sure. Based on this, we inspected for the effect of alternatively removing one of these correlated shock variables. By including the parents' farm size variable as a control, we further investigated the robustness of our results. We cannot rule out that the 2015 covariate shock caused subjects to become more vulnerable to idiosyncratic shocks in the following year.

Table 3 Testing for shock correlations with other variables

Variables	(1) Covariate shock severity 2015–16	(2) Idiosyncratic shock 2016–17 dummy	(3) Idiosyncratic shock 2016–17 dummy	(4) Shock severity deviation 2015–16
Covariate shock severity			0.086**	
			(0.036)	
Shock severity deviation			0.019	
			(0.015)	
Parent household charact.				
Own radio	− 0.005	0.001	0.002	0.012
	(0.025)	(0.026)	(0.027)	(0.061)
Oxen number	0.008	0.000	0.001	− 0.049
	(0.028)	(0.021)	(0.022)	(0.046)
Own land, dummy	− 0.013	-0.001	-0.002	0.102
	(0.037)	(0.037)	(0.038)	(0.070)
Farm size, tsimdi	0.006	− 0.011	− 0.010	− 0.052***
	(0.006)	(0.007)	(0.007)	(0.017)
Live on parents' farm	− 0.032	− 0.074***	− 0.072***	− 0.012
	(0.032)	(0.026)	(0.028)	(0.056)
Main group prod. act., base = Animal rearing				
Beekeeping	0.025	− 0.052	− 0.052	− 0.002
	(0.079)	(0.038)	(0.037)	(0.037)
Forestry	0.021	− 0.064	− 0.067*	− 0.013
	(0.100)	(0.052)	(0.048)	(0.038)
Irrigation	0.047	− 0.069*	− 0.072*	− 0.051
	(0.087)	(0.041)	(0.041)	(0.037)
Self-selection group, pred.		− 1.420	− 2.493	0.156
		(4.481)	(4.400)	(3.330)
Self-selection, IMR		− 0.848	− 1.488	− 0.079
		(2.946)	(2.897)	(2.215)
District, base = Raya Azebo				
Degua Tembien	− 0.294***	− 0.150	− 0.147	0.051
	(0.081)	(0.093)	(0.096)	(0.096)
Seharti Samre	− 0.124	− 0.057	− 0.047	− 0.006
	(0.085)	(0.088)	(0.092)	(0.080)
Kilite Awlalo	− 0.349***	− 0.034	− 0.011	− 0.065
	(0.104)	(0.084)	(0.092)	(0.091)
Adwa	− 0.710***	− 0.054	0.011	−0.013
	(0.087)	(0.074)	(0.084)	(0.065)
Constant	2.079***	1.770	2.672	0.000
	(0.080)	(4.557)	(4.468)	(3.344)
Observations	912	912	912	912
R-squared	0.423			
Number of groups	114	114	114	114

Bootstrapped standard errors in models (2)–(4). Cluster-robust standard errors, Clustering on groups in model (2). Significance levels: $***p < 0.01$, $**p < 0.05$, $*p < 0.1$

Table 5 Example of choice list

CL no.	Start point	Task no.	Prob. low outcome	Low outcome	High outcome	Choice	Certain amount	Choice
8		1	2/10	20	100		100	
8		2	2/10	20	100		95	
8		3	2/10	20	100		90	
8		4	2/10	20	100		85	
8		5	2/10	20	100		80	
8		6	2/10	20	100		75	
8		7	2/10	20	100		70	
8		8	2/10	20	100		65	
8		9	2/10	20	100		60	
8		10	2/10	20	100		50	

amounts that have to be changed to narrow in on the switch point and the CE for the risky prospect before the next CL and the risky prospect are outlined.

By holding the risky prospect constant, including the good and bad outcomes and the probability of good (bad) outcomes, we limit the required numeracy skills to deciding on the preferred choice between the risky prospect and the certain amounts.[15] Another advantage of this approach is that it is easy to present the risky prospect with real money in front of the subjects and illustrate the probabilities with the 20-sided die. In each CL, a switch point is identified as the certain amounts are ordered in decreasing value from the top to the bottom of the CL. Table 4 shows the key characteristics of the 12 CLs used in the experiment. The order of the CLs was randomized across subjects to allow assessment of and control for eventual order bias.

To speed up the identification of the switch point in each CL, a quick narrowing-in approach was used. In each CL there is a randomized starting Task row number that identifies the certain amount that the risky prospect is to first be compared with. The quick elicitation approach means that the full CL is not presented to the subjects initially. The risky prospect is illustrated with real money in front of them, with the probabilities shown with the die. The enumerators ask the subject to indicate their preference for the risky prospect or the certain amount at the random starting row in the CL as the first binary choice. The decision at this point identified whether the switch point would be above or below the random starting point certain amount. The enumerators were instructed to go to the top or the bottom of the list depending on the first choice. If subjects preferred the risky prospect at the random starting point, the CE-value of the risky prospect must be higher than the certain amount at the starting row. The enumerator, therefore, goes to the top of the list and the opposite if the certain amount is preferred at the starting row. At the top of the list, we expect the respondents to prefer the certain amount.[16] Likewise, at the bottom of the list,

[15] The well-known Holt and Laury (2002) is more demanding as it asks respondents to compare two risky prospects and at the same time changes the probabilities from row to row within the same CL and thereby requiring substantial numeracy skills and frequent recalculations.

[16] This may not always be the case, and we then allow "corner solutions" with CLs without any switch point. We return to the inspection of such outcomes and the remedies.

we expect respondents to prefer the risky prospect. Still, if they preferred this low certain amount, we added rows with lower certain amounts till a switch point was detected, meaning that the CE is below the lowest certain amount in the standard CL.[17] With a switch in the choice from the starting row to the top or bottom rows, a mid-row is chosen between the random starting row and the second (top or bottom row) in the CL, as the third decision row in the CL. Again, the subject's choice in this third question is used to quickly narrow in towards the switch point as the two rows from where the subject switches from preferring the risky prospect to preferring the certain amount.

This bisection approach has several advantages: (a) it reduces the number of questions per CL needed to identify the switch point (this reduces boredom and fatigue related to having to respond to many similar questions) and is therefore time-saving; (b) the choices of random starting point reduces the likelihood of undetectable starting point bias such as if questions always start from one end of the CL; (c) the potential bias associated with the random starting point can be tested and controlled for in the analysis[18]; (d) a potential bias towards the middle of the CL is avoided as the whole list is not presented to the subjects[19]; (e) the approach identifies only one switch point per CL (unless there is no switch point).

A context-specific design element of the CLs is that the risky prospect has two outcomes, and the probability of a bad (but non-negative) outcome (instead of a good outcome) is stated to the subjects as a framing towards negative shocks. This framing is chosen as the experiment is intended to be used concerning behavior associated with low-probability shocks such as droughts. Droughts typically lead to low but non-negative yields.[20] Furthermore, 10 out of the 12 CLs have prob(bad outcome) ≤ 0.5, see Table 4. This also implies that we map most accurately the probability weighting function in the prob(bad outcome) range 0.05–0.5, the probability range within which most of the drought shocks may be found. The two last CLs include a low probability of winning high-return prospects to help us map the w(p) function in this probability region. It is quite rare to have access to such business opportunities in our field context. Therefore, cultural norms and experience may play less of a role in influencing their decisions in these CLs.

In the end, the random choice of CL and Task row for payout is identified using the 20-sided die and the underlying MCL. In the randomly identified CL for real payout, one task row is randomly identified, and the subject's choice in this row determines whether the respondent will get the preferred certain amount or the preferred risky prospect. If the risky prospect was preferred for this row, the die is used to play the lottery and determine whether the subject receives a good or a bad outcome. The subject then received the outcome in cash in an envelope.

[17] We dropped two subjects with extreme risk aversion where we failed to detect a switch point as extremely small certain amounts were preferred to the risky prospects.

[18] This bisection approach has earlier been used in risk and time preference field experiments by Holden and Quiggin (2017a, 2017b).

[19] Such bias has been an argument for placing the risk-neutral row at the center of the CL but would also lead to bias towards risk-neutrality for subjects that are risk averse.

[20] In Rank Dependent Utility (RDU), it is usual to sort outcomes from the best to the poorest (with their associated probabilities). We do this in our structural model and estimation. Still, we recognize that our framing gives higher salience to the negative shocks, which may have affected the responses in the intended way (focus on the non-negative bad outcomes and their probabilities).

Table 4 CE-multiple choice list treatment overview

Choice list	Prob (bad outcome)	Bad outcome (ETB)	Good outcome (ETB)	CE-range min, max (ETB)
1	1/20	0	100	50,100
2	1/10	0	100	50,100
3	2/10	0	100	50,100
4	3/10	0	100	30,80
5	5/10	0	100	10,60
6	1/20	20	100	50,100
7	1/10	20	100	50,100
8	2/10	20	100	50,100
9	3/10	20	100	30,80
10	5/10	20	100	40,100
11	15/20	20	300	20,90
12	19/20	20	1500	20,90

3.2 Experimental Outcome Distributions and Data Quality

To assess the data quality of our risk experiments, we carry out stochastic dominance analysis to assess the consistency of the responses at the aggregate level and the subject level. We present the outcome of these stochastic dominance assessments with graphs included in Appendix 3. These graphs also allow us to assess the placement of the risk-neutral row in each CL versus the distribution of the preferred switch points. The risk-neutral row in the CL is where the expected value of the risky prospect is equal to the certain amount.

The cumulative switch point distributions in the 2017 risk CE-MCL experiment are presented in Appendix 3 with detailed explanations. These graphs are used to assess stochastic dominance for comparable CLs. Such stochastic dominance is evident in the cumulative graphs and demonstrates rational behavior to changes in probabilities and bad outcome differences. We also include stochastic dominance tests at the individual level.[21]

To summarize our assessment of stochastic dominance violations at the subject level, we find that 58.7% of the subjects had no violations, 16.0% had one violation, 11.3% had two violations, 6.8% had three violations, 4.9% had four violations, and 2.3% had more than four violations. We may compare this with the study of Vieider et al. (2018), who found that 38% of their subjects in a rural sample of household heads from Ethiopia violated stochastic dominance at least once. This is very similar to our finding of 41% with at least one violation, using CLs that are of similar complexity but with larger probability differences between the CLs and subjects with a similar level of education and cultural background.[22]

[21] These graphs are also included in an Appendix in Holden and Tilahun (2022) but without the additional analysis made here of stochastic dominance violations at the subject level.

[22] For interested readers, we provide a further visual picture of the size distribution of the stochastic dominance violations by CL in Appendix 3, Fig. 9. Each figure presents the histogram distributions of the paired ΔCEs with the negative values representing the violations.

4 Theoretical Framework and Estimation Approach

We implemented the assessment of risk preferences and responsiveness to covariate and idiosyncratic stochastic shocks, treating these shocks as natural experiments after critically examining the statistical basis for this in Part 2. In this section, we outline the estimation approaches: first, the reduced form risk premium approach in Sect. 4.1 and then the structural EU and RDU models in Sect. 4.2. We investigate the potential effects of the lagged shocks on experimental outcomes in the 2017 CE-MCL experiment with 12 CLs. The key explanatory variables of interest are the covariate and idiosyncratic shock variables from 2015 and 2016 that may have influenced subject behavior in the risk experiments.

Based on the competing theories of Gollier and Pratt (1996) that shocks affecting vulnerable people make them more risk averse, and Quiggin (2003) who shows that background risk can be a complement to independent risk for subjects with constant risk preferences. Quiggin (2003) argues that an important special case of constant risk aversion is that of rank-dependent preferences with linear utility, first analyzed by Yaari (1987) as a dual theory. Such lower sensitivity to risks after shocks may also be associated with the diminishing sensitivity argument from Prospect Theory. The vulnerability theory of Gollier and Pratt (1996) implies that subjects affected by shocks should become more risk averse and, therefore, display higher risk premiums in independent risk experiments. If subjects possess (near) constant risk preferences, background risk should be a complement to independent risks such as the experimental risks we expose our subjects to. Subjects exposed to a background shock should then display smaller risk premiums than subjects not exposed to such shocks.

Based on this, we first develop the framework for analyzing reduced-form models with risk premiums. Then, we develop structural models that are used to frame the analysis of our comprehensive CE-MCL data such that it allows us to test the EU theory of Gollier and Pratt (1996) against the special-case RDU Yaari (1987) model and more general RDU models where we allow both the utility function CRRA parameter and two probability weighting parameters to be freely determined in the econometric estimation of shock effects.

4.1 Calibration of Risk Premiums and Estimation

We use the CE-MCL experiment first to assess whether and how the idiosyncratic and covariate shocks possibly affect the risk premiums in the CE-MCL experiments. With 12 CLs, we generate 12 risk premiums per subject, assuming w(p) = p.[23] We standardize the risk premiums across CLs. The risk premium (RP_{gim}) for each CL (m) for each subject (i) in each business group (g) is calculated as a fraction of the expected value of the risky prospect in each CL as follows:

$$RP_{gim} = -\frac{CE_{gim} - EV_m}{EV_m} \tag{1}$$

where CE_{gim} is the CL and subject-specific certainty equivalent associated with the switch point in the list. It is taken as the average value of the certain amounts for the rows just

[23] The risk premium is the difference between the average certain amount in the rows just below and just above the switch point in each CL and the risk-neutral (EV) value of the risky prospect, given w(p) = p.

above and below the switch point. EV_m is the expected value for the CL given objective probabilities.

We estimate how background risk in the form of lagged shocks may have affected the risk premium in the CE-MPL experiment without making any assumptions about how this effect may go through the utility or the probability weighting functions of the subjects. We use linear panel data models. We start from a parsimonious model with only the two shock variables as RHS variables (the lagged idiosyncratic and covariate shock variables (IS_{t-1}, CS_{t-2}), where $t-1$ represents 2016, and $t-2$ represents 2015. We assess the robustness of the shock effects by adding additional controls step-wise. The additional controls include the random order of the CL, the random starting row in each CL, the risk-neutral row number in each CL, the probability of a bad outcome in each CL, or CL fixed effects, represented by the vector CL_m, and subject-related variables ($z_{gi.t-1}$) such as sex, age, education, and parent characteristics, Z_g represents group characteristics in form of main production activity, E_d represents enumerator fixed effects, and i_i represents subject random effects. These different specifications are collapsed into the following general model specification to save space:

$$\begin{aligned} RP_{gim} = \pi_0 + \pi_1 IS_{gi,t-1} + \pi_2 CS_{g,t-2} \\ (+\pi_3 CL_m + \pi_4 z_{gi.t-1} + \pi_5 Z_g + \pi_6 E_d) + i_i + u_{gim} \end{aligned} \tag{2}$$

To further investigate systematically whether the shock effects on the risk premiums vary across CLs depending on the probabilities of bad and good outcomes in the CLs, we estimate separate models for each probability level. The likelihood of severe covariate climate shocks occurring is positive but likely less than 0.5. We have, therefore, concentrated most of the CLs in this probability range. We suspect subjects are more inclined to associate these CLs with their real-world shock experiences.

4.2 EU and RDU Model Estimation

To allow us to test the Gollier and Pratt (1996) versus the Quiggin (2003) theories and their relevance for the shock effects, we develop structural models for each of these theories to assess their econometric fit with the data.

Each choice of the subject is between a risky prospect and a certain amount. The risky prospect gives a good outcome (x) with probability p and a bad outcome (y) with probability $1-p$. We call the certain amount s. We place the choice between the risky and safe prospect into a Rank Dependent Utility (RDU) framework (Quiggin 1982). The net utility return for a specific risky and safe option can then be formulated as follows:

$$\Delta RDU = w(p)u(x) + [1 - w(p)]u(y) - u(s) \tag{3}$$

where $w(p)$ is the probability weighting function. The model nests the EU model where $w(p) = p$. In a specific CL x and y are fixed while s varies across the rows with falling values from the top. There will be a point where the ΔRDU switches from being negative (preference for larger certain amounts s), to becoming positive (preference for the risky prospect over smaller certain amounts s). The certainty equivalent (CE) is identified at the switch point.

The CE-MCL risk experiment included prospects with non-negative outcomes.[24] The probability weighting function is therefore modeled in the gains domain only with a Prelec (1998) 2-parameter weighting function:

$$w(p) = e^{-\beta(-\ln p)^{\alpha}}, \alpha > 0, \beta > 0 \quad (4)$$

where α captures the degree of (inverse) S-shape of the weighting function,[25] and the β captures the elevation of the function, with $\beta < 1$ giving more elevated (optimistic) and $\beta > 1$ giving less elevated (pessimistic) weighting of prospects. The function is strictly increasing and continuous within the interval [0, 1] with $w(0) = 0$ and $w(1) = 1$. Most studies of probability weighting have found that subjects exhibit diminishing sensitivity to small and large probabilities and probabilistic insensitivity at medium probabilities, implying an inverse S-shaped probability weighting function (Prelec 1998).

The local utility is captured with a Constant Relative Risk Aversion (CRRA) function[26]:

$$u(x) = (1 - r)^{-1}((bcons + x)^{1-r} - 1) \quad (5)$$

where r is the CRRA coefficient and *bcons* is the base consumption or asset integration level.[27]

Noise in the data is captured with a heteroscedastic Fechner (1860) type error (ξ), and the prospects are standardized with Wilcox (2008) type contextual utility. According to Wilcox the advantage of this approach is that the assessment of choices fits within the theoretical idea of capturing stochastically more risk-averse behavior without introducing extra parameters.[28] Binary choice models are better at measuring ratios of utility differences than utility differences. Utility differences need to be judged within their specific context. This is a fundamental problem in this kind of structural latent variable discrete choice model. Utilities have to be judged against a salient utility difference. Wilcox suggests using the utilities of the maximum and minimum possible outcomes in the riskiest prospect. This implies that choices are directly weighted by the subjective range of utility outcomes while holding marginal utility improvements constant near a maximum (Wilcox 2008).

Contextual heteroscedasticity can be due to error variance increasing with the subjective utility ranges. Wilcox (2008) argues that the contextual utility model uses the idea that the standard deviation of evaluation noise is proportional to the subjective range of stimuli, borrowing from the perception of stimuli literature, e.g. Gravetter and Lockhead (1973). This implies the assumption that each CL creates its own respondent-specific 'local context'.

The probability of the respondent choosing the risky lottery can then be formulated with a probit (standard normal) function:

[24] There are ethical reasons for not introducing incentivized experiments with negative outcomes to the type of poor and vulnerable subjects that are the focus of this study.

[25] $\alpha = 1$ implies $w(p) = p$, for $\alpha < 1$ the inverse S-shape becomes stronger as α declines.

[26] We assume incomplete (no or partial) asset integration based on the finding that prospect amounts have much stronger effects on decisions than the respondents' background wealth (Binswanger 1981).

[27] We set the base consumption equal to 0 ETB in most models (no asset integration). We ran robustness checks with $bcons = 30$ ETB, equivalent to a daily wage in the study areas at the time of the study, or the triple of this daily wage amount to assess how this potentially affected the shock effects and the estimated parameters.

[28] Wilcox (2008) shows that the contextual utility model performs better than the random parameter, strict and strong utility structural models in out-of-sample predictions of stochastic choice based on the Hey and Orme (1994) data.

$$Pr(Risky) = \phi(\frac{\Delta RDU_{gimk}}{\xi_{gim}[u(x_m) - u(y_m)]}) \tag{6}$$

Subscripts k represents row numbers in the CLs. The model flexibility allows respondent errors in identifying switch points within CLs. The latent Fechner error (ξ_{gim}) can be assessed at the within-subject CL level as a measure of subject response inconsistency across CLs as being related to a specified CL-characteristic at a higher structural model level and to assess model performance, see below for further details.

The log-likelihood function for the risk experiment is obtained by summing the natural logs over the cumulative density functions resulting from Eq. (6) and summing them over CLs (subscript m) and subjects:

$$\begin{aligned} &\ln L(\Omega_{gi}(IS_{gi,t-n}, CS_{g,t-2}, z_{gi}), \xi_{gim}(c_m, z_{gi}, E_d)) = \\ &\sum_{imk}(\ln \Theta(\Delta RDU) \mid_{Choice_{imk}=1}) + (\ln \Theta(1 - \Delta RDU) \mid_{Choice_{imk}=0}) \end{aligned} \tag{7}$$

Ω_{gi} is a vector of subject-specific risk preference parameters (r_i, α_i, β_i)[29] that are modeled as linear functions of the lagged idiosyncratic and covariate shock variables (IS_{t-n}, CS_{t-2}) and the observable respondent variables (z_i) such as sex, age, and education.

$$\Omega_{gi} = \eta_0 + \eta_1 IS_{gi,t-n} + \eta_2 CS_{g,t-2} + \eta_3 z_{gi} + \epsilon_{gi} \tag{8}$$

Equation (8) is used to test the two opposing theories of Gollier and Pratt (1996) and Quiggin (2003) to assess whether the lagged shock variables are associated with an increase or a reduction in the CRRA-r parameter and changes in the Prelec α and β parameters in RDU models. The Fechner error in Eq. (6) is also an important element of the estimation strategy as it is used to separate out noise and assess the extent to which the noise is associated with CL characteristics, enumerator, subject, and parent characteristics.

The Fechner error (ξ_{im}) is modeled linearly on the CL characteristics (CL_m).[30] Subject characteristics can also affect within-subject errors (inconsistencies across CLs), as we saw in the non-parametric assessment (Sect. 3.2). Noise is, therefore, also modeled on z_{gi}. A vector of enumerator dummy variables (E_d) is also included in the error model.[31]

$$\xi_{gim} = \rho_1 + \rho_2 CL_m + \rho_3 z_{gi} + \rho_4 E_d + u_{gim} \tag{9}$$

We estimated the likelihood function with the Broyden–Fletcher–Goldfarb–Shanno (BFGS) optimization algorithm[32] while clustering errors at the subject level. We use the

[29] Alternatively, they are the population-averaged parameters in the models without subject and parent characteristics.

[30] E.g. the order of CLs may affect learning and concentration of subjects, the random starting row in each CL may be associated with response errors that influence the identified CE, and the CL-specific range of certain amounts and the placement of the risk-neutral row in the CL may influence response errors. To relax the linearity assumption for CL characteristics, we included the squared terms for the random starting row in each CL and the position of the risk-neutral row in each CL.

[31] The ability of enumerators to minimize respondent errors may vary. 12 enumerators were randomly allocated to subjects within groups.

[32] This is a second-order optimization algorithm, utilizing the second-order derivatives of an objective function and has become one of the most widely used second-order algorithms. We also tested the Newton–Raphson algorithm for our base model, which was a bit faster, and they produced the same solution.

estimated parameters in Eq. (7) to predict individual risk preference parameters (Table 10) (Ω_{gi}) to inspect the distributional implications of the shock variables, *ceteris paribus*.

5 Results

We first present the results from the reduced-form risk premium models (Sect. 5.1). We then present the results for the structural models based on EU-theory (Gollier and Pratt 1996) (Sect. 5.2), the special-case RDU Yaari-model (Sect. 5.3), and finally, the population-averaged RDU model and the RDU model that includes subject characteristics as well (Sect. 5.4). This allows us to inspect whether and how the alternative models 'fit with the data' and to assess which theoretical logic is the most compelling.

5.1 Models with Risk Premiums

First, we impose minimal functional form assumptions for utility and probability weighting and assess the total effect of the shocks on risk-taking behavior by regressing the CL-level risk premiums on the shock variables (Eq. 2). We introduce additional controls in a step-wise way for robustness assessment. These models allow us to see whether the shocks (background risk) enhance or depress the standardized risk premiums.

Four different models are specified; see Table 6. The first parsimonious specification only includes the key shock variables. Controls for CL design characteristics are added in the second specification. The third and fourth specifications include CL fixed effects, implying that only the randomized CL-level variables can be retained. The last specification adds subject and parent characteristics as additional controls to further verify whether the natural experiment assumption is reliable.

Table 6 shows that the covariate shock severity variable is highly significant with a negative sign and a very stable parameter size in all four specifications. This is strong evidence in favor of the theory of Quiggin (2003) and is contrary to the theory of Gollier and Pratt (1996). The structural models in the next section will allow for a detailed investigation of the appropriateness of the alternative models. The standardized risk premiums are reduced by a 3.5–3.8 percentage point per unit increase in the covariate shock severity variable. It indicates that the subjects whose families were most severely affected by the covariate shock had become more willing to take risks in the CE-MCL experiment two years after the shock (significant at 0.1% level). Note, however, that the intercepts in the standardized risk premium models are all highly significant and with a positive sign. This indicates that respondents are risk averse overall, and the size of the intercept is much larger than the covariate shock effect. This implies that the subjects remain in the region with positive risk premiums also after the shock. The idiosyncratic shock dummy variable for 2016–17 is insignificant in all the models and with a positive sign. We, therefore, have no significant effect of or correlation between the idiosyncratic shock variable and the risk premiums. This may be because these idiosyncratic shocks were less severe than the previous convariate shock and because local insurance mechanisms work better for idiosyncratic risks than for covariate risks.

The first parsimonious model (1) in Table 6 included only the 2015 covariate shock severity variable and the 2016 idiosyncratic shock dummy variables.[33] Model (2) included the CL-related variables, i.e., the probability of a bad outcome, the order of the CL, the starting row in each CL, and the position of the risk-neutral row in each CL. Their inclusion resulted in slightly stronger shock effects. In model (3), we instead included CL fixed effects, which control for all subject-invariant CL characteristics, while we retained the randomized CL-level controls. This had no additional effect on the shock variables. In model (4), we added individual and parent controls. This caused a slight reduction in the idiosyncratic shock effect or correlation while the covariate shock severity effect was enhanced. This enhances our trust in the natural experiment assumption for the covariate shock severity variable and therefore our causal interpretation of the effect of the covariate shock on risk premiums and the underlying risk preferences.

As a further robustness check, we inspect the shock effects or correlations at different probability levels for good and bad outcomes in the different CLs. Note that we had constructed the CLs such that we have better coverage in the probability range where such shocks are likely to be found ($0.5 < p$ (good) < 1). The results from separate linear random effects models for the standardized risk premiums for each probability level are presented in Fig. 2 with 95% confidence intervals, including controls for the random order of the CLs and the random starting row in each CL. The figure shows that the covariate shock severity variable is significant and has a negative effect on the risk premium in all models in the probability range of 0.5–1. Only in the case of the low probability of good outcomes region, where such shocks are not likely to fall, is the covariate shock effect insignificant. We also see that the most recent 2016–17 idiosyncratic shock effect or correlation tends to go in the opposite direction (significant in two models), making people more risk-averse or indicating that more vulnerable people are more risk-averse. The intercepts indicate that, on average, subjects are risk averse at all p(good) levels.

5.2 Shock Effects in the EU Model

In an Expected Utility (EU) model, which is the foundation of the risk vulnerability hypothesis of Gollier and Pratt (1996), the risk preferences are captured by the curvature of the utility function. We handle the EU model as a special case of the RDU model, where $w(p) = p$.[34] In principle, it is similar to the risk premium model as the curvature of the utility function determines the risk premium. The risk premium is positive if the utility curve is concave. One benefit of the EU model is that we get a translation of the risk premiums into utility curvature parameters, given our CRRA functional form specification.[35] The shock effects or correlations can then also be captured as changes in the utility curvature parameter. Another advantage of the EU model is that it includes a Fechner error specification (noise) as an additional control for measurement error. The Fechner error is allowed to vary with the order of the CLs, the random starting point in each CL, the position (row number) of the risk-neutral row in the CL, the square of these variables (possible non-linear effects), and enumerator fixed effects. The population-averaged CRRA utility

[33] Based on the weak positive correlation between these two shock variables and the findings for the deviation in shock severity variable in Table 3, we did a robustness assessment for this parsimonious risk premium model by using alternative combinations of the three variables. These models are presented in Appendix 5. It shows that the results in Table 6, model (1), are robust.

[34] This implies that the Prelec probability weighting function parameters are Prelec $\alpha =$ Prelec $\beta = 1$.

[35] We assume no asset integration in the basic models.

function can vary only with the two shock variables, the covariate shock severity being continuous and the idiosyncratic shock variable being a dummy. The results are presented in Table 7. As a robustness check of the model, we have run it for *bcons* equal to 30 (daily wage rate) and 90 ETB as the CRRA-r parameter is sensitive to the degree of asset integration and asset integration is typically assumed under EU theory (Rabin 2000); see Table 15 in Appendix E.2.

Table 7 shows that the CRRA-r is significantly (at 0.1% level) reduced for those who experienced a more severe covariate shock. The idiosyncratic shock variable is insignificant. The constant term indicates that the utility function is quite concave with CRRA-r = 0.564 for those who did not experience a covariate shock in 2015. A covariate shock severity level of 2 (Fig. 1) reduces the CRRA-r by about 0.146 units, which gives a CRRA-r = 0.418. This still represents a quite concave utility function. Contrary to the prediction of Gollier and Pratt (1996), the respondents have become less sensitive to background risk (shock) according to this result. This gives reason to question the functional form assumptions in this model.

To further inspect the robustness of the EU model results, we assess the sensitivity to changes in the assumption about asset integration by varying the *bcons* parameter. Table 15 in Appendix E.2 shows that when we include a *bcons* = 30 ETB (a daily wage rate), the constant term for the CRRA-r = 1.225, while one unit of the covariate shock severity reduces the CRRA-r by 0.179 units. An increase to three daily wage rates base consumption increases the constant term to 1.98 and the covariate shock reduction per unit to 0.317. This reminds us about the Rabin paradox (Rabin 2000). Higher levels of asset integration lead to ridiculously high levels of risk aversion. In all specifications, we see that the covariate shock severity variable is highly significant, and the parameter size effect increases with the degree of assumed asset integration. But the covariate shock effect goes in the opposite direction of what Gollier and Pratt (1996) proposed.

5.3 RDU Model with Linear Utility Function

To test the relevance of the theory of Quiggin (2003), we first estimate a Yaari model, which is a special case RDU model with linear utility that displays constant risk aversion (Yaari 1987; Quiggin 2003). We can use the Yaari model to test Quiggin's (2003) claim that the premium for a given risk with this type of model is reduced by independent background risk or shocks. We estimate a population-averaged Yaari model with a 2-parameter Prelec probability weighting function to see how this dual version of the population-averaged EU model performs. This allows us to assess how the covariate and idiosyncratic shock variables have influenced or are correlated with the Prelec parameters. Noise is controlled in the same way as in the EU model. The model results are presented in Table 8.

The estimated Prelec $\alpha = 0.5$ and $\beta = 1.3$ parameters (constant terms in Table 8) imply a strong inverse S-shaped function with substantial "pessimism". The results indicate that the covariate shock two years earlier has significantly (at 1 and 5% levels) and increased the Prelec α and reduced the Prelec β parameters. Figure 3 shows the effect of a covariate shock severity = 2 versus no covariate shock and indicates a lower level of pessimism (elevated w(p) function) after such a shock. In this dual model of Yaari (1987), it is the convexity of the w(p) function that captures risk aversion, and the covariate shock has reduced this convexity. The covariate shock effect in this model is consistent with the theory of Quiggin (2003) that an increase in background risk or shock makes people more willing to take risk.

We note that the two-parameter Prelec function is more flexible than the one-parameter CRRA utility function. It can capture the variation in probabilistic sensitivity, which seems to be a dominant behavioral characteristic confounded with risk preferences. Next, we try to separate this variation in probabilistic sensitivity from the utility curvature by allowing joint estimation of the CRRA utility function curvature and the two-parameter Prelec w(p) in a more general RDU model. This model implicitly allows the population averaged parameters to be optimized in EU or RDU direction with the three parameters being allowed to vary with the covariate and idiosyncratic shocks.

5.4 Shock Effects in RDU Models Without and with Subject Characteristics

The results for dis-aggregated risk preference parameters in the parametric population-averaged RDU model are presented in Table 9. It is noteworthy that the changes in the w(p) Prelec α and β intercepts and covariate shock parameters are modest from Tables 8 and 9. However, the recent idiosyncratic shock variable becomes significant in the more flexible RDU model as the CRRA parameter in the utility function and Prelec α parameters are significantly (at 10 and 5 % levels) correlated with the idiosyncratic shock dummy variable. The utility function becomes significantly convex after such a recent idiosyncratic shock, while it is linear for those unaffected by the shocks. The effect of the recent idiosyncratic shock dummy variable on the w(p) function Prelec α parameter goes in the opposite direction of that of the covariate shock. However, this result is less robust, as seen in Table 10, where more control variables have been added. This gives reason to question whether this significant idiosyncratic shock result is causal in relation to the Prelec α parameter while it appears more robust to the addition of controls in the case of the CRRA-parameter.

Table 10 expands the RDU model by including subject, youth group, and parent household and farm characteristics in the CRRA utility, Prelec α, and β functions of the model. Compared to the previous models, no change is made in the Fechner error (noise) component. This allows us to inspect the predicted variation in the parameter estimates across our large rural sample.

Table 10 shows that the covariate shock effects on the w(p) parameters are robust and remain significant at 1 and 5% levels. The absolute values of the parameters even increase slightly after the inclusion of all controls. This gives no reason to reject the natural experiment assumption in the case of the covariate shock variable. The effect of the recent idiosyncratic shock only remains significant at the 10% level for the CRRA utility function parameter, while it is insignificant in the w(p) parameter estimates. Only one parent and subject characteristics variable is significant in the CRRA utility equation (parents with a radio are associated with a more convex function). Age, parents owning a radio, beekeeping, and irrigation groups are associated with significantly lower Prelec α, and the parent land-holding dummy is associated with a lower (more optimistic) Prelec β parameter.

From this Table 10 model, we predict the CRRA-r, Prelec α, and β parameters and graph the distributions to visualize better how the significant shock variables affected the parameter distributions. The graphs are presented in Fig. 4. Figure 4 demonstrates clear shifts in the distributions of the three parameters. The utility curvature (CRRA-r) shifts to the convex region for most of the subjects that experienced a recent idiosyncratic shock. The Prelec α distribution shifts to the right with a more severe covariate shock, and the Prelec β distribution shifts to the left, lifting the w(p) function, making it less pessimistic. The shift in the w(p) function goes in the same direction and is similar to that shown in Fig. 3.

Table 6 Shock effects on risk premiums at CL level

Variables	(1) rpst1	(2) rpst2	(3) rpst3	(4) rpst4
Covariate shock severity 2015–16	− 0.035*** (0.010)	− 0.036*** (0.011)	− 0.036*** (0.011)	− 0.038*** (0.011)
Idiosyncratic shock 2016–17, dummy	0.018 (0.013)	0.020 (0.013)	0.019 (0.013)	0.017 (0.013)
CL page no		0.001 (0.001)	0.002 (0.001)	0.002* (0.001)
CL start row		0.032*** (0.005)	0.030*** (0.005)	0.030*** (0.005)
Prob (bad outcome)		0.081*** (0.010)		
CL Risk neutral row		− 0.028*** (0.001)		
Subject characteristics				
Male, dummy				− 0.001 (0.010)
Education, years				− 0.001 (0.001)
Age, years				0.002*** (0.001)
Live on parents' farm				0.024** (0.011)
Main group activity				
Base: Livestock				
Beekeeping				0.016 (0.011)
Forestry				− 0.025 (0.016)
Irigation				0.012 (0.012)
Parent characteristics				
Radio				0.013 (0.009)
Number of oxen				0.002 (0.008)
Household owns land, dummy				− 0.046*** (0.012)
Farm size, *tsimdi*				− 0.008*** (0.002)
CL fixed effects	No	No	Yes	Yes
Constant	0.242*** (0.018)	0.283*** (0.019)	0.229*** (0.019)	0.242*** (0.038)
Observations	10,731	10,731	10,731	10,730
Number of subjects	912	912	912	912

Dependent variable: CL-level risk premium. Cluster-robust standard errors, clustered On business group members. Significance levels: ***$p < 0.01$, **$p < 0.05$, *$p < 0.1$

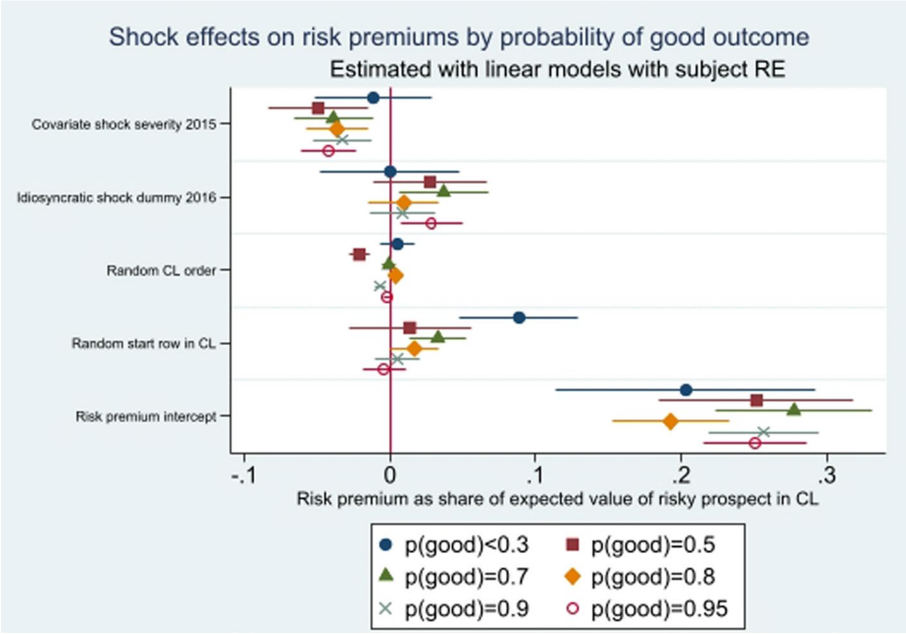

Fig. 2 Covariate shock severity and idiosyncratic shock effects or correlations with 95% confidence intervals by probability of good outcome in CLs

6 Discussion

Our study adds to the literature on how shock exposure influences people's risk preferences. In particular, our study shows how a severe covariate drought shock related to the 2015 El Nino affected poor and vulnerable people living in a semi-arid environment in Eastern Africa. Like most other studies of such shock effects, we rely on using a natural experiment approach. We tested for and found no evidence that selection can explain the results. The covariate shock variable was also not correlated with parent household and farm characteristics or the type of business group production activity. We, therefore, dare to make a causal interpretation of the covariate shock effect on the risk preferences of our study subjects. A recent study by Di Falco and Vieider (2022) found risk preferences correlated with average rainfall in the broader Ethiopian highlands. All our study locations are in the (semi-arid) lowest rainfall range covered in their study. Their study is a useful reference for our study as they found the lowest risk tolerance in this area with the lowest average rainfall. Our study shows that it is primarily the overweighting of the low probability bad outcomes (pessimistic expectations) that causes the low risk tolerance levels in this region.

Our main finding is that the covariate drought shock was associated with significantly lower risk premiums in aggregate and dis-aggregated reduced-form risk premium models.[36] These results are consistent with the theoretical predictions of Quiggin (2003) that a change in background risk (shock) is complementary to independent experimental risks

[36] disaggregated to different probability levels for good and bad outcomes in the risk experiment.

Table 7 EU-model: shocks and risk preferences ($w(p) = p, \alpha = \beta = 1$), $bcons = 0$

Variables	(1) CRRA-r	(2) Prelec α	(3) Prelec β	(4) Noise
Covariate shock severity 2015–16	− 0.075*** (0.020)			
Idiosyncratic shock 2016–17, dummy	0.025 (0.024)			
CL page no				0.003 (0.005)
CL page no, squared				− 0.001 (0.001)
Start point in CL, row				0.022*** (0.003)
Start point in CL, squared				− 0.002*** (0.000)
Risk neutral row no				− 0.079*** (0.005)
Risk neutral row no, squared				0.008*** (0.000)
Enumerator FE	No	No	No	Yes
Constant	0.564*** (0.034)	1.000 (0.000)	1.000 (0.000)	0.320*** (0.014)
Subjects	912			
Observations	107,616			

Cluster-robust standard errors in parentheses, clustered on subjects

Significance levels: ***$p < 0.01$, **$p < 0.05$, *$p < 0.1$

for certain types of non-expected utility preferences. Our data allowed us to comprehensively run EU versus the dual Yaari (1987) and the more general RDU models to test for the nature of risk preferences in our sample population. The results of the Yaari and the RDU models with fewer parameter restrictions (allowing the CRRA-r utility curvature parameter to be endogenously determined) reveal that the utility curvature is close to linear. This finding, and the fact that the covariate shock reduced risk premiums, indicate that the non-expected utility models best represent the subjects studied, and this finding resolves the puzzle that higher background risk leads to more risk-taking in the independent risk experiments played 2 years after the background covariate shock occurred. We, therefore, question the appropriateness of the EU model, which forces the shock effect to be captured as a substantial reduction in the concavity of the utility function, which is contrary to what is expected for such a concave utility function (Gollier and Pratt 1996). The general RDU model that nests the EU and the dual Yaari models as special cases provides robust estimates in favor of an inverse S-shaped w(p) function and a near-linear utility function. Our results demonstrate that the shock effect is more appropriately modeled as an upward shift in the w(p) function, which implies that the covariate shock has made subjects less pessimistic in the experimental games played two years later. In other words, a more severe covariate shock has made them less sensitive to the risks in these new games. This is equivalent to what Quiggin (2003) stated as independent risks being complements rather than substitutes.

These theoretical explanations for the contradictory findings on how shocks or disasters affect risk preferences have not been carefully tested before our study. Cameron and Shah (2015) discuss these alternative theoretical explanations. Still, they only use the Binswanger (1980) type of game, which does not vary probabilities and cannot separate the estimation of utility and w(p) functions. Another study that reflects on the relevance of these theories is Kahsay and Osberghaus (2018), who studied the effects of storms on risk preferences based on household panel data from Germany. However, they relied on a survey instrument where risk preferences were elicited on an 11-point Likert scale and could, therefore, also not rigorously test these theories.

Some other studies investigated the responses to low-probability lotteries after shocks. Li et al. (2011) used a natural experiment approach after large snow hit and an earthquake in 2008 in China to assess how severely affected subjects responded to hypothetical choices involving low probability (1 in 1000 chance) positive and negative outcomes and found that those affected by these low-probability disaster outcomes were more likely to choose the low-probability positive outcomes over sure outcomes in the gains domain after the snow hit and the earthquake, and more likely to choose a sure loss in the loss domain than a large low-probability loss after the snow hit. The study reveals that people have become more sensitive to low-probability events after such low-probability shocks. Page et al. (2014) found that a rare flood event along a river in Brisbane, Australia, made those directly affected by the flood more likely to prefer a low-probability lottery ticket than a safe amount as a reward for participating in a survey related to the flood effects.

Our CE-MCL approach, which exposes the subjects to 12 CLs with different probabilities of good and bad outcomes, allows us to comprehensively assess the possible shock effects in different probability regions, especially in the probability region where shocks usually occur (low probability risk of bad outcome). While we also included two CLs with a low probability of a good outcome (lottery-like), we found no significant shock effect for these CLs, unlike for the other CLs that resembled more the real risks that the subjects face in their real lives.

The earlier studies of shock effects on risk preferences have, to a limited extent, attempted to separate the shock effects into effects on the probability weighting and utility curvature representations of risk preferences. This is because most studies have used simple tools that do not allow for such a separation. Such a separation is the main contribution of our paper. After first demonstrating that most of the CLs for most of the subjects are associated with positive risk premiums, indicating that most people are risk averse in the probability region where the typical covariate and idiosyncratic shocks belong, we show that the covariate and idiosyncratic shock effects can be modeled as shifts in the utility as well as the probability weighting function at the population-averaged level as well as the individual subject level for the utility and w(p) function parameters. We are not aware of any other studies that have done this based on such shocks. Our findings from a general RDU model reveal that the utility curvature is close to linear and with a shift towards the convex region after a recent idiosyncratic shock. At the same time, the w(p) function makes an upward shift (subjects becoming less pessimistic) after the covariate shock. The latter indicates that an increase in background risk (covariate shock experience) has made subjects less sensitive to the independent experimental risk in the games.

Table 8 Yaari (1987) dual model (linear utility function) and 2-parameter Prelec w(p)

Variables	(1) CRRA-r	(2) Prelec α	(3) Prelec β	(4) noise
Covariate shock severity 2015–16		0.049***	− 0.061**	
		(0.015)	(0.027)	
Idiosyncratic shock 2016–17, dummy		− 0.027*	0.010	
		(0.016)	(0.032)	
CL page no				− 0.009**
				(0.003)
CL page no, squared				0.001**
				(0.002)
Start point in CL, row				0.019***
				(0.000)
Start point in CL, squared				− 0.002***
				(0.002)
Risk neutral row no				− 0.012***
				(0.003)
Risk neutral row no, squared				0.003***
				(0.000)
Enumerator FE	No	No	No	Yes
Constant	0.000	0.499***	1.302***	0.149***
	(0.000)	(0.025)	(0.047)	(0.010)
Subjects	912			
Observations	107,616			

Cluster-robust SEs in parentheses, clustered on subjects. Significance levels: ***p < 0.01, **p < 0.05, *p < 0.1

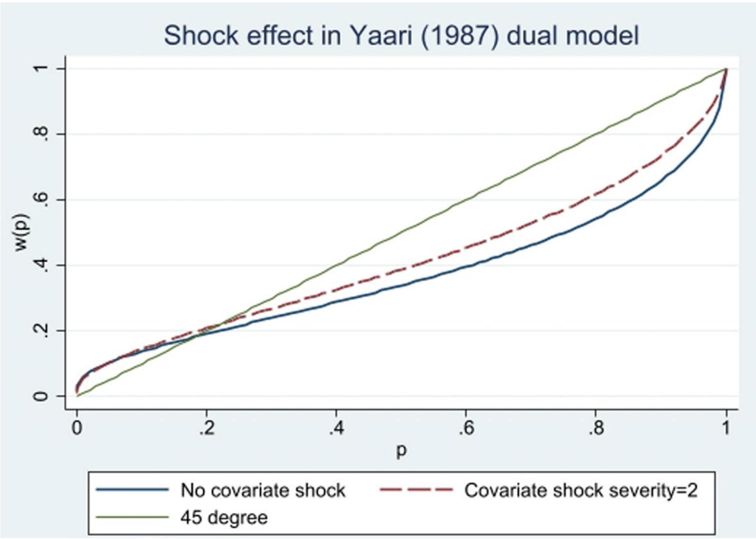

Fig. 3 Covariate shock effect on probability weighting function in Yaari (1987) dual model

Table 9 Population-averaged RDU model with shock variables

Variables	(1) CRRA-r	(2) Prelec α	(3) Prelec β	(4) Noise
Covariate shock severity 2015–16	0.028 (0.037)	0.052*** (0.015)	− 0.081** (0.040)	
Idiosyncratic shock 2016–17, dummy	− 0.085* (0.044)	− 0.036** (0.017)	0.067 (0.045)	
CL page no				− 0.009*** (0.003)
CL page no, squared				0.001** (0.001)
Start point in CL, row				0.019*** (0.002)
Start point in CL, squared				− 0.002*** (0.000)
Risk neutral row no				− 0.014*** (0.003)
Risk neutral row no, squared				0.003*** (0.000)
Enumerator dummies	No	No	No	Yes
Constant	− 0.001 (0.065)	0.505*** (0.027)	1.303*** (0.070)	0.154*** (0.010)
Subjects	912			
Observations	107,616			

Cluster-robust standard errors in parentheses

Significance levels: ***$p < 0.01$, **$p < 0.05$, *$p < 0.1$

7 Conclusions

We have studied the relationship between the severity of a covariate drought shock and idiosyncratic shocks and risk preferences elicited with a lab-in-the-field experiment 1–2 years after the shocks among poor rural residents belonging to youth business groups in northern (semi-arid) Ethiopia. we assess whether the shocks can be regarded as natural experiments and, therefore, used to elicit a causal relationship between the shocks and risk preferences. We find no evidence that the covariate shock effect is caused by spurious correlations and, therefore, conclude that its effect is causal. The weaker and more recent idiosyncratic shock is giving less robust and significant indications of a causal effect on risk preferences. We assume that the covariate shock has affected the perceived background risk of subjects and use the unaffected or less severely affected subjects as a counterfactual to assess whether the independent experimental risks are perceived as substitutes or complements to the background risk shock. We tested the theory of Gollier and Pratt (1996), which rests on EU-theory, which predicts that an increase in background risk should make risk-averse people more risk averse, against the theory of Quiggin (2003) that an increase in background risk or shock can make subjects with a certain type of non-expected utility more willing to take risk. Such subjects are represented by a dual (Yaari 1987) model with linear utility and a two-parameter probability weighting function and more general RDU models that allow the utility curvature and w(p) function parameters to be determined

Table 10 Shock effects: RDU model with subject and parent characteristics

Variables	(1) CRRA-r	(2) Prelec α	(3) Prelec β	(4) Noise
Covariate shock severity 2015–16	0.053 (0.042)	0.057*** (0.018)	− 0.100** (0.045)	
Idiosyncratic shock 2016–17, dummy	− 0.089* (0.049)	− 0.027 (0.018)	0.075 (0.046)	
Subject characteristics				
Male, dummy	− 0.013 (0.035)	0.001 (0.015)	0.020 (0.037)	
Education, years	− 0.003 (0.005)	− 0.003 (0.002)	− 0.004 (0.006)	
Age, years	− 0.002 (0.002)	− 0.003*** (0.001)	0.002 (0.002)	
Live on parents' farm, dummy	0.042 (0.037)	0.002 (0.016)	0.059 (0.042)	
Main group activity				
Base: Livestock				
Beekeeping	− 0.049 (0.042)	− 0.041** (0.018)	0.044 (0.044)	
Forestry	0.009 (0.053)	0.002 (0.024)	− 0.093* (0.053)	
Irrigation	0.005 (0.043)	− 0.048** (0.019)	− 0.012 (0.047)	
Parent characteristics				
Parents have radio	− 0.068** (0.035)	− 0.037*** (0.014)	0.060* (0.036)	
Parents oxen number	0.030 (0.026)	0.007 (0.011)	− 0.002 (0.026)	
Parents own land	0.063 (0.043)	0.021 (0.019)	− 0.161*** (0.046)	
Parents farm size, *tsimdi*	− 0.010 (0.009)	0.007* (0.004)	− 0.014 (0.008)	
CL page no				− 0.012*** (0.003)
CL page no, squared				0.002*** (0.000)
Start point in CL, row				0.019*** (0.002)
Start point in CL, square				− 0.002*** (0.000)
Risk neutral row no				− 0.015*** (0.003)
Risk neutral row no, squared				0.003*** (0.000)
Constant	− 0.030 (0.123)	0.606*** (0.053)	1.476*** (0.162)	0.161*** (0.011)
Subjects	912			
Observations	107,616			

Table 10 (continued)

Cluster-robust standard errors in parentheses, clustering on subjects

Significance levels: ***$p < 0.01$, **$p < 0.05$, *$p < 0.1$

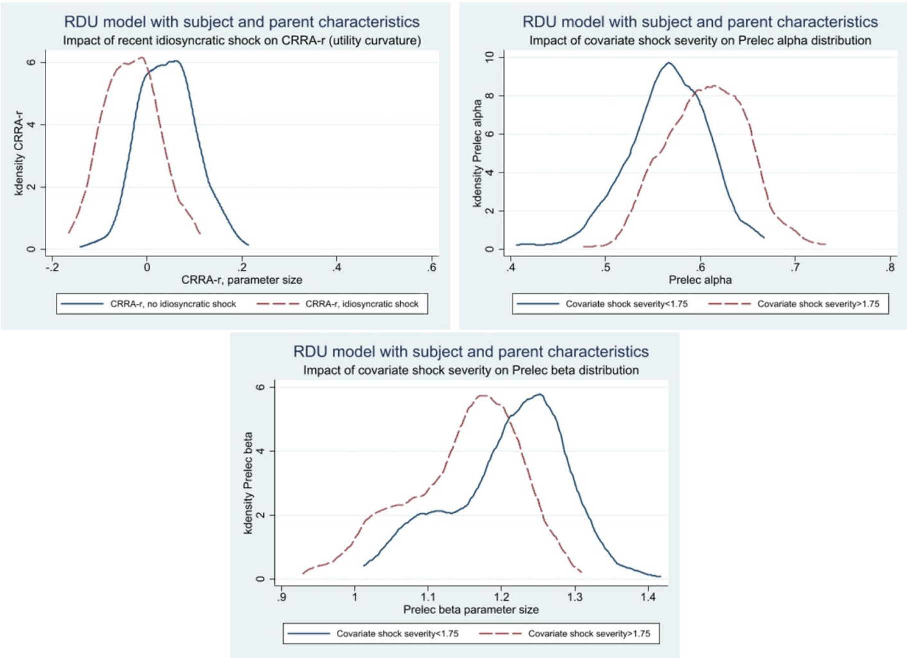

Fig. 4 Idiosyncratic and covariate shock effects on utility curvature and probability weighting function

endogenously. These alternatives claim that shocks make people less (Gollier and Pratt 1996) or more (Quiggin 2003) risk tolerant. We find strong evidence that the covariate drought shock made subjects more risk tolerant. The additional findings from the structural models provide additional evidence in favor of the theory of Quiggin (2003) and the RDU model over the EU model.

The general RDU model is estimated without and with subject and parent characteristics. The estimated CRRA utility function is found to be close to linear and unaffected by the covariate shock. Both in the dual Yaari model and the more general RDU models, the covariate shock resulted in a significant upward shift in the probability weighting function. This result was very robust to the inclusion of additional controls. The result in a reduced form model using a standardized risk premium as the dependent variable also demonstrated the robustness to additional controls and a more severe covariate shock associated with significantly lower risk premiums (Table 6). The effects of the more recent idiosyncratic shock were weaker and less robust across the model specifications.

Our study provides new insights on the importance of eliciting dis-aggregated measures of risk preferences that take probability weighting into account and may give a deeper insight into why shocks in some contexts make people more risk averse in independent experiments and other contexts make people more willing to take risks. Our study is the first to nail the theoretical predictions of Quiggin (2003) with empirical evidence. Earlier studies have treated these contradictory findings as a puzzle, and only a few have hinted at the possible theoretical reasons without being able to verify them.

Our study contributes to the literature on how recent idiosyncratic and covariate shocks affect risk preferences. Our robustness analyses revealed that the covariate drought shock had the most significant, robust, and lasting effect, showing up in independent risk experiments two years after the shock, and making subjects more willing to take risks. More research is needed to further investigate how long this type of effect can last.

Overall, our findings show that the covariate drought shock has reduced the revealed risk premiums of the subjects in the independent CE-MCL experiments. When we estimate an EU model versus the Yaari model, the Yaari model captures the shock effects through a change in the w(p) function parameters and the w(p) has an inverse S-shape and the two Prelec α and β parameters are significantly different from 1 (the assumption of EU-theory). This shape of the w(p) function is confirmed when we estimate the RDU models (population-averaged as well as a model with subject characteristics), which also display a near-linear CRRA utility function. The fact that the covariate shock reduced risk premiums and affected the w(p) function in an upward direction (less pessimistic expectations after a shock) indicates that the Yaari model and the RDU models are more appropriate representations of the preferences of our study subjects than the EU model. Several recent studies have revealed that the inverse S-shape of the w(p) function is a dominant characteristic of many populations (Vieider et al. 2018, 2019). This indicates that it is high time that empirical economists who study climate risks and shock effects go beyond EU theory when they choose their theoretical frameworks and data collection methods and aim to study the behavior of people exposed to such shocks. We suggest it should become standard to consider probability weighting in such studies.

The study of how shocks affect risk preferences is a relatively new area of research with apparent contradictory findings that are of high relevance not only from a theoretical perspective but also from a policy perspective. More research is needed to better understand how preferences adapt to environmental changes in the short and long run. Understanding behavior and adaptation to climate change and designing good policies to protect vulnerable people and enhance welfare are among the most important challenges of our time. There is a risk that climate shocks spill over into social unrest through preference change unless precautionary measures are taken. A civil war erupted in our study area after our field study. We cannot rule out that such a shock can have even larger effects on risk preferences with consequences for behavioral responses.

Appendix 1: Test for Attrition Bias

We tested for attrition bias related to attrition from the baseline survey in 2016 to the final experimental data obtained in 2017. No such attrition bias was found as can be seen in Table 11.[37]

[37] Two of the groups refused to participate in the risk experiments in 2017 for religious reasons as they did not want to participate in experiments with monetary rewards. The self-selection variables in Table 11 are for the groups that themselves decided on the member composition. The self-selection variables were predicted with a probit model for 742 youth groups based on a census of all existing youth groups in the districts at the time of the census (2016).

Table 11 Test for attrition bias

Variables	
2015 Drought severity	0.009
	(0.012)
Education, years	0.001
	(0.003)
Age, years	− 0.001
	(0.002)
Sex, dummy	0.032
	(0.025)
Married, dummy	− 0.017
	(0.028)
Parents have radio	0.003
	(0.023)
Parents' number of oxen	0.021
	(0.022)
Parents own land	− 0.038
	(0.032)
Parents' farmsize, tsimdi	− 0.002
	(0.008)
Self-selection into group, predicted	1.070
	(2.894)
Self-selection Inverse Mills Ratio	0.0381
	(1.900)
Constant	− 0.835
	(2.982)
Observations	1104
Number of youth groups	117
Wald chi2(8)	37.15
Prob > chi2	0.001

Bootstrapped standard errors in parentheses, Re-sampling groups. Significance levels: ***$p < 0.01$, **$p < 0.05$, *$p < 0.1$

Appendix 2: Exploring Parent Household and Farm Heterogeneity

Some additional statistics are provided for parent households in this section. Figure 5 shows the distribution of farm size and oxen in parent households. About 80% of the youth group members have parents that own land but almost all parent households can be classified as land-poor as only about 10% have more than 1 ha of land. Close to 20% own no oxen and just above 10% own more than one ox. Note that a pair of oxen is needed to plow the land. This implies that the majority with only one ox will need to team up and share the ox with another household that owns an ox to cultivate their land. This illustrates that the households are resource-poor but also dependent on agriculture. The same applies to the youth business groups in the sample which all have agricultural types of businesses, see Table 1.

Business group members typically have a close relationship with their parent households as long as they are alive. Table 12 shows where they live. 52.3% of the business group members live on their parents' farms. 61% of the members are married. Some of the

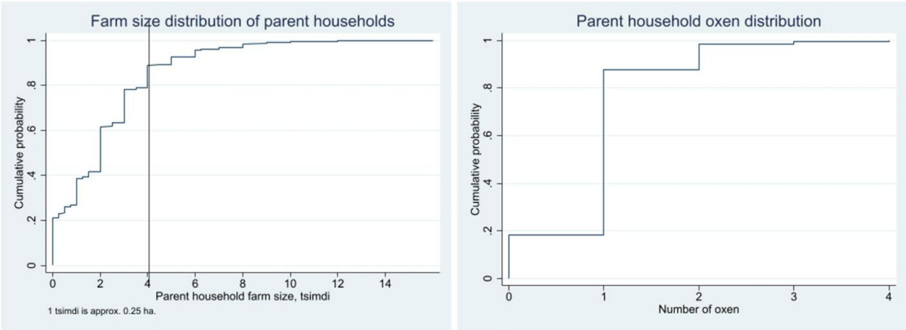

Fig. 5 Farm size and oxen endowment distributions for parent households in 2016

Table 12 Main production activities of the business groups

Main activity category	Freq	Percent	Cum
Animal rearing	233	25.52	25.52
Beekeeping	328	36.04	61.56
Forestry	125	13.69	75.25
Irrigation	226	24.75	100.00
Total	912	100.00	

Table 13 Where the group members live

Where do you live?	Freq	Percent	Cum
On farm of and in the house of parents	366	40.09	40.09
Own house on separate place	412	45.24	85.32
Own house on farm of parents	112	12.27	97.59
Live in house of in-laws	6	0.66	98.25
Rented house	16	1.75	100.00
Total	912	100.00	

group members have been provided a house plot by the community and have been able to build their own house there. It is youth coming from more land-scarce parent households that are less likely to live on the farm of their parents. The average farm size of parents with youth staying on their farm is 2.88 *tsimdi* compared to 1.54 *tsimdi* for youth staying outside their parents' farm (Table 13).

Appendix 3: Stochastic Dominance Analysis for the Risk Experiment

The cumulative switch point distributions in the 2017 risk CE-MCL experiment are presented in Figs. 6, 7, and 8, with CLs 1–3 and CLs 6–8 in Fig. 6.[38] The combined CLs in Fig. 7 only differ in the probability of a low outcome. The stochastic dominance is very

[38] These graphs are also included in an Appendix in Holden and Tilahun (2022) but without the additional analysis made here of stochastic dominance violations at the subject level.

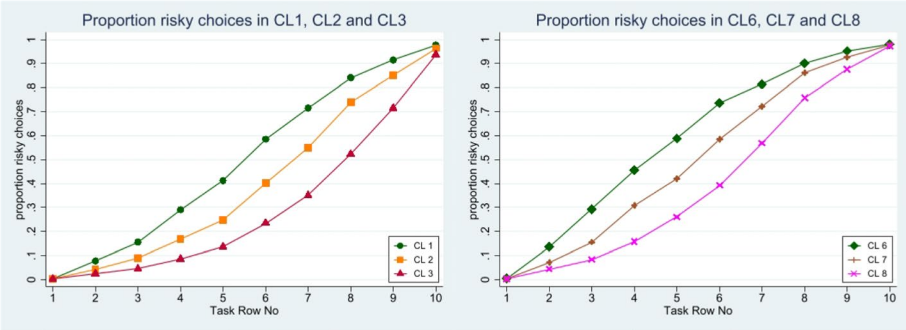

Fig. 6 The distribution of switch points in CL1–CL3 and CL6–CL8

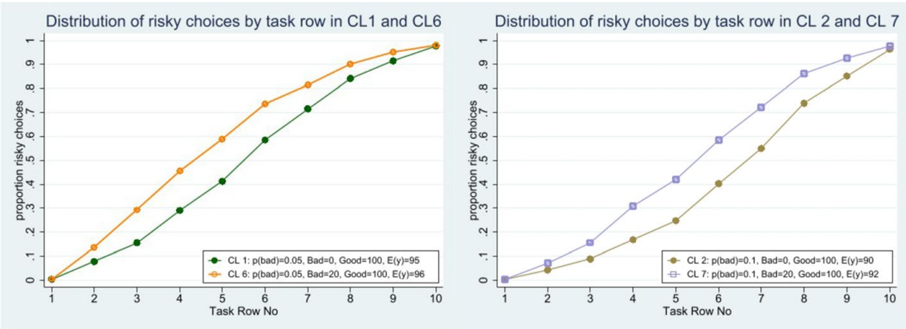

Fig. 7 The distribution of switch points in CL1 versus CL6 and CL2 versus CL7

clear from the graphs demonstrating that CE falls with an increasing probability of a bad outcome. Similarly, Figs. 7 and 8 demonstrate the effect of increasing the bad outcome in the risky prospect from 0 to 20 ETB, while all other characteristics are the same in the paired CLs. For CL1 versus CL6 (p(bad) = 0.05), CL2 versus CL7 (p(bad) = 0.1), and CL3 versus CL8 (p(bad) = 0.2), the stochastic dominance for the sorted responses is very clear.

It is noteworthy for CL1 and CL6 that the risk-neutral Task row is row 2 (or very close to row 2 for CL6).[39] For this low probability of a bad outcome (5%), close to 90% of the subjects are risk averse and prefer the certain amount. For CL2 and CL7 (p(bad) = 0.1), the risk-neutral row is row 3 or just below (for CL7), where about 90% of the subjects are risk averse and switch for $CE < E(y)$. For CL3 versus CL8 (p(bad) = 0.2), the risk-neutral rows are row 5 and (close to) row 4 (CL8), Fig. 8, the first graph, indicates that 85–90% are risk averse at this probability level.

Figure 8, the second graph, shows the cumulative distributions for CL11 and CL12 (low probability (0.15 and 0.05) high outcomes (ETB 300 and 1500)). The higher shares of corner solutions without switch points in CL11 and CL12 indicate a higher willingness to take the risk for such low probability high outcomes.[40] Only about 70% have $CE < E(y)$ for these CLs.

39 The certain amount offered is 95 in this row.

40 With hindsight, we realize that we should have included higher certain amounts at the top of these CLs.

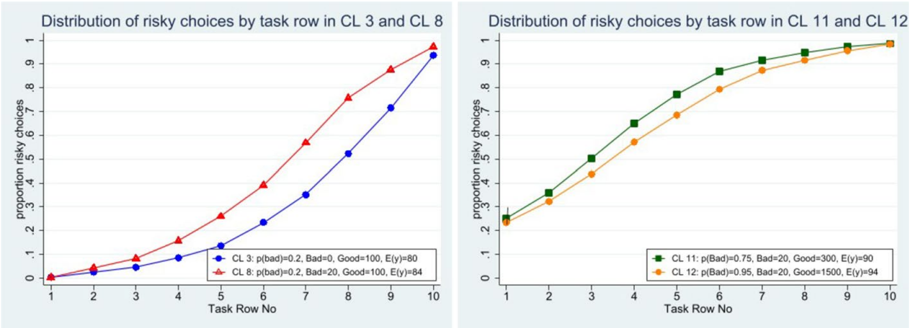

Fig. 8 The distribution of switch points in CL3 versus CL8 and CL11 versus CL12

To further inspect the data quality we inspect for stochastic dominance violations at the subject level. First, our choice lists CL1 versus CL6, CL2 versus CL7, and CL3 versus CL8 are particularly suitable for this as they only differ in the bad outcome amount. A clear violation of stochastic dominance would be for an individual to have a lower CE for the CL with 20 ETB as a bad outcome than the otherwise equivalent CL with 0 ETB as a bad outcome. We find that 9.0% of the subjects violate stochastic dominance for CL1 versus CL6, 7.0% violate for CL2 versus CL7 and 7.6% violate for CL3 versus CL8. Second, we can make within-subject comparisons for CL1 versus CL2 versus CL3 and CL6 versus CL7 versus CL8 which only differ in terms of the probabilities of a bad outcome, 0.05 versus 0.1 versus 0.2. We find 14.5% violations for CL1 versus CL2, 11.2% violations for CL2 versus CL3, and 8.3% violations for CL1 versus CL3, and 12.7% violations for CL6 versus CL7, 11.8% violations for CL7 versus CL8, and 8.8% violations for CL6 versus CL8. When we look at the aggregated distribution of stochastic dominance violations in our sample based on the assessment above (nine paired comparisons per subject), we find that 59.0% had no violations, 15.2% had one violation, 11.5% had two violations, 7.3% had three violations, 4.9% had four violations, and 2.2% had more than four violations. We may compare this with the study of Vieider et al. (2018), who found that 38% of their subjects in a rural sample of household heads from Ethiopia violated stochastic dominance at least once. This is very similar to our finding of 41% with at least one violation, using CLs that are of similar complexity and subjects with a similar level of education and cultural background.

We provide a further visual picture of the size distribution of the stochastic dominance violations by CL in Fig. 9. Each figure presents the histogram distributions of the paired ΔCEs with the negative values representing the violations. We see that the majority of the violations also are small in value. Very few are below − 10 ETB. We handle the inconsistent responses by introducing models with noise, allowing for response errors, rather than dropping subjects with such violations. This is explained in the next section on estimation.

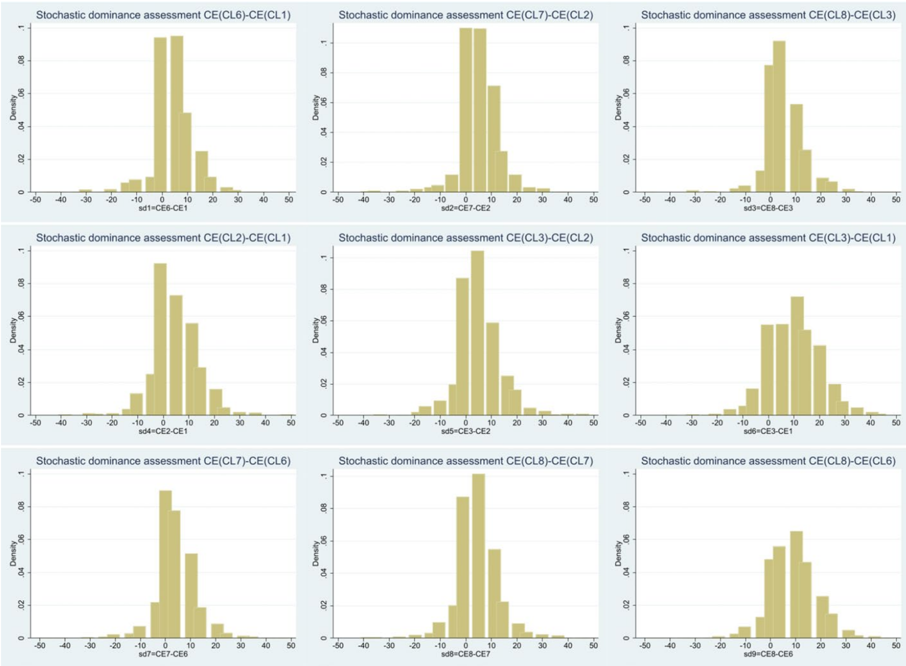

Fig. 9 Stochastic dominance assessment with value deviations

Appendix 4: Risk Premium Distributions

We calculated the risk premiums by CL for each subject in monetary terms; see Figs. 10 and 11 for their distributions by CL. We see some variation in the distribution across CLs that may indicate design weaknesses we should control for. We address this econometrically below.

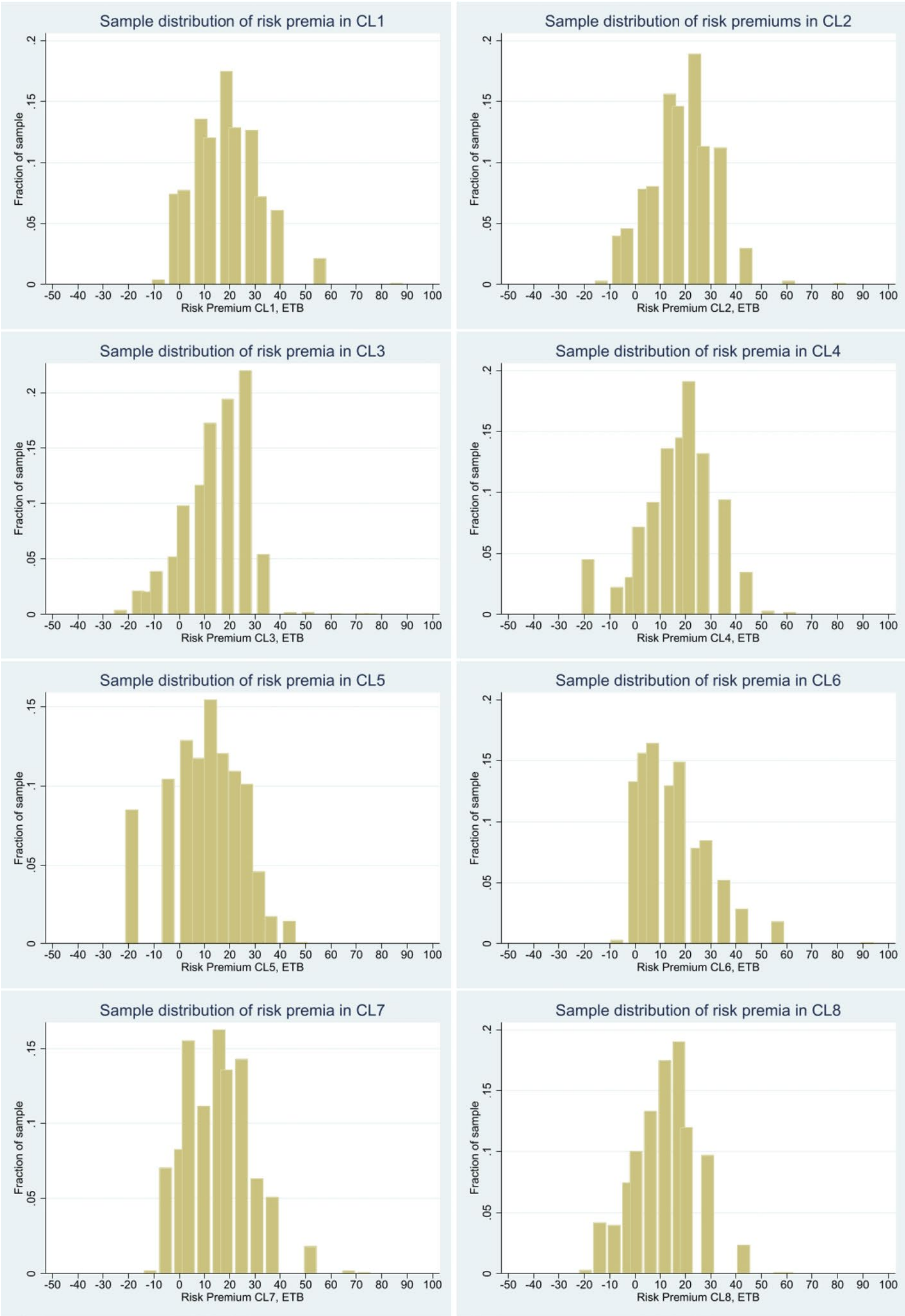

Fig. 10 Risk premium distributions by CL, CLs 1–8

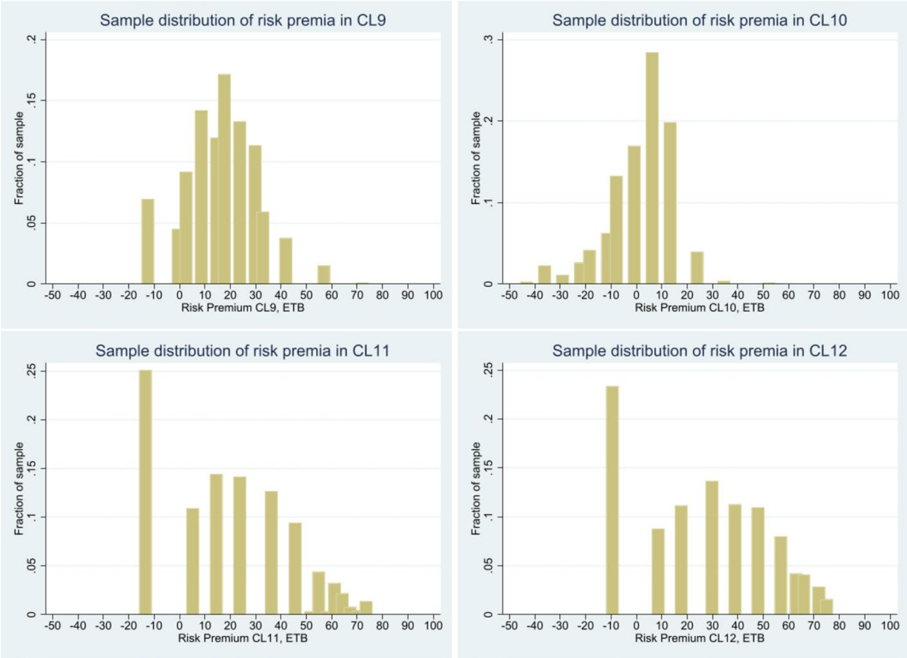

Fig. 11 Risk premium distributions by CL, CLs 9–12

Appendix 5: Robustness Analyses

E.1 Sensitivity to Dropping Shock Variables in Risk Premium Models

We have tested the robustness of the shock effects on risk premiums by alternatively removing one or more of the shock variables and inspecting the coefficients and significance of the retained shock variables. The results are presented in Table 14. The coefficient and significance for the covariate shock severity variable are very stable and highly significant in all specifications. In contrast, the 2016–17 idiosyncratic shock dummy variable remains insignificant in all models.

E.2 Sensitivity to Base Consumption in the EU Model

Table 15 presents population-average EU models with different base consumption (*bcons*) levels. A higher level of asset integration (higher *bcons*) is associated with a more concave utility function (the constant term for CRRA-r) and is associated with a larger reduction in the CRRA-r parameter due to the covariate shock. The shock effects are consistent in direction and significance under different assumptions about the degree of asset integration. However, the higher levels of asset integration involve very concave utility functions in line with Rabin (2000).

Table 14 Robustness checks for shock effects on risk premiums

Variables	(1) rpst	(2) rpst	(3) rpst	(4) rpst
Covariate shock severity	− 0.035***	− 0.035***	− 0.034***	
	(0.010)	(0.010)	(0.010)	
Idiosyncratic shock dummy	0.018	0.018		0.015
	(0.013)	(0.013)		(0.013)
Deviation in shock severity	0.001			
	(0.005)			
Constant	0.242***	0.242***	0.243***	0.181***
	(0.018)	(0.018)	(0.018)	(0.005)
Observations	10,616	10,616	10,616	10,616
Number of subjects	912	912	912	912

Cluster-robust standard errors in parentheses

Significance levels: ***$p < 0.01$, **$p < 0.05$, *$p < 0.1$

Table 15 EU model with limited but varying degree of asset integration

Equation	Variables	(1) bcons = 30	(2) bcons = 90
CRRA-r	Covariate shock severity 2015–16	− 0.182***	− 0.322***
		(0.052)	(0.094)
	Idiosyncratic shock 2016–17, dummy	0.070	0.127
		(0.063)	(0.114)
	Constant	1.227***	1.981***
		(0.090)	(0.166)
Prelec α	Constant	1.000	1.000
		(0.000)	(0.000)
Prelec β	Constant	1.000	1.000
		(0.000)	(0.000)
Noise	CL page no	0.012***	0.015***
		(0.004)	(0.005)
	CL page no, squared	− 0.002***	− 0.002***
		(0.001)	(0.001)
	Start point in CL, row	0.020***	0.024***
		(0.003)	(0.003)
	Start point in CL, squared	− 0.002***	− 0.002***
		(0.000)	(0.000)
	Risk neutral row no	− 0.094***	− 0.097***
		(0.005)	(0.006)
	Risk neutral row no, squared	0.010***	0.009***
		(0.000)	(0.001)
	Constant	0.334***	0.354***
		(0.014)	(0.016)
	Number of subjects	912	912
	Observations	107,616	107,616

Cluster-robust standard errors, clustering at subject level

Significance levels: ***$p < 0.01$, **$p < 0.05$, *$p < 0.1$

Appendix 6: Experimental Protocol

Attached in Supplementary information.

Supplementary Information The online version contains supplementary material available at https://doi.org/10.1007/s10640-024-00850-5.

Acknowledgements This research has been conducted as a collaboration between the Norwegian University of Life Sciences (NMBU) and Mekelle University. The authors acknowledge good support from local government authorities, local Youth Associations, and Mekelle University, and committed efforts by our team of enumerators and field supervisors. We acknowledge valuable comments to earlier versions of this paper presented at University of Adelaide, Australia, and School of Economics and Business, Norwegian University of Life Sciences. Valuable comments have been received from David Adamsson, John Quiggin, Kyrre Rickertsen, Dag Einar Sommervoll, Erlend Dancke Sandorf, three anonymous reviewers, and the editor of Environmental and Resource Economics, Astrid Dannenberg.

Funding Open access funding provided by Norwegian University of Life Sciences. This work received financial support from the Norwegian Agency for Development Cooperation (NORAD) NORHED I project "Climate Smart Natural Resource Management and Policy" and the Research Council of Norway (NORGLOBAL project "Youth Business Groups for Sustainable Development: Lessons from the Ethiopian Model". The funding sources had no involvement in the research process.

Data Availability All (anonymized) data (STATA files) used in the paper will be made available upon publication of the article as supplementary information.

Code Availability All codes (Stata do files) used for the analysis of the data will be made available upon publication as supplementary files.

Declarations

Conflict of interest The authors declare no conflicts of interest.

Consent to Participate All subjects participating in the project participated voluntarily and were always asked up-front about their willingness to participate after having received information about what participation implied and that the project adhered to strict confidentiality and anonymity of individual information (informed consent).

Consent for Publication The article will be published as an open-access article as required by the funding institution.

Ethics Approval Funding was approved based on an independent assessment and approval of ethical standards being met by the project by a scientific committee.

References

Binswanger HP (1980) Attitudes toward risk: experimental measurement in rural India. Am J Agr Econ 62(3):395–407

Binswanger HP (1981) Attitudes toward risk: theoretical implications of an experiment in rural India. Econ J 91(364):867–890

Bourdeau-Brien M, Kryzanowski L (2020) Natural disasters and risk aversion. J Econ Behav Organ 177:818–835

Brown R, Montalva V, Thomas D, Velásquez A (2019) Impact of violent crime on risk aversion: evidence from the Mexican drug war. Rev Econ Stat 101(5):892–904

Brunnermeier MK, Nagel S (2008) Do wealth fluctuations generate time-varying risk aversion? Micro-evidence on individuals. Am Econ Rev 98(3):713–36

Cameron L, Shah M (2015) Risk-taking behavior in the wake of natural disasters. J Hum Resour 50(2):484–515

Cassar A, Healy A, Von Kessler C (2017) Trust, risk, and time preferences after a natural disaster: experimental evidence from Thailand. World Dev 94:90–105

Cavatorta E, Groom B (2020) Does deterrence change preferences? Evidence from a natural experiment. Eur Econ Rev 127:103456

Deaton A (2010) Instruments, randomization, and learning about development. J Econ Lit 48(2):424–455

Dercon S, Bold T, Calvo C (2008) Insurance for the poor? Social protection for the poor and poorest. Springer, Cham, pp 47–63

Di Falco S, Vieider FM (2022) Environmental adaptation of risk preferences. Econ J 132(648):2737–2766

Drichoutis AC, Nayga RM (2021) On the stability of risk and time preferences amid the COVID-19 pandemic. Exp Econ 25(3):759–794

Fechner GT (1860) Elemente der psychophysik (2). Breitkopf u. Härtel, Wiesbaden

Gollier C, Pratt JW (1996) Risk vulnerability and the tempering effect of background risk. Econom J Econom Soc 64:1109–1123

Gravetter F, Lockhead G (1973) Criterial range as a frame of reference for stimulus judgment. Psychol Rev 80(3):203

Guiso L, Sapienza P, Zingales L (2018) Time varying risk aversion. J Financ Econ 128(3):403–421

Günther I, Harttgen K (2009) Estimating households vulnerability to idiosyncratic and covariate shocks: a novel method applied in Madagascar. World Dev 37(7):1222–1234

Hanaoka C, Shigeoka H, Watanabe Y (2018) Do risk preferences change? Evidence from the great east Japan earthquake. Am Econ J Appl Econ 10(2):298–330

Hey JD, Orme C (1994) Investigating generalizations of expected utility theory using experimental data. Econom J Econom Soc 62:1291–1326

Holden ST, Quiggin J (2017) Bounded awareness and anomalies in intertemporal choice: zooming in google earth as both metaphor and model. J Risk Uncertain 54(1):15–35

Holden ST, Quiggin J (2017) Climate risk and state-contingent technology adoption: shocks, drought tolerance and preferences. Eur Rev Agric Econ 44(2):285–308

Holden ST, Tilahun M (2022) Are risk preferences explaining gender differences in investment behavior? J Behav Exp Econmics 101:101949

Holt CA, Laury SK (2002) Risk aversion and incentive effects. Am Econ Rev 92(5):1644–1655

Kahneman D, Tversky A (1979) Prospect theory: an analysis of decision under risk. Econometrica 47(2):263–292

Kahsay GA, Osberghaus D (2018) Storm damage and risk preferences: panel evidence from Germany. Environ Resour Econ 71(1):301–318

Li J-Z, Li S, Wang W-Z, Rao L-L, Liu H (2011) Are people always more risk averse after disasters? Surveys after a heavy snow-hit and a major earthquake in China in 2008. Appl Cogn Psychol 25(1):104–111

Liebenehm S (2018) Temporal stability of risk attitudes and the impact of adverse shocks—a panel data analysis from Thailand and Vietnam. World Dev 102:262–274

Liebenehm S, Schumacher I, Strobl E (2023) Rainfall shocks and risk aversion: evidence from Southeast Asia. Am J Agric Econ 106(1):145–176

Mera GA (2018) Drought and its impacts in Ethiopia. Weather Clim Extrem 22(June):24–35

Page L, Savage DA, Torgler B (2014) Variation in risk seeking behaviour following large losses: a natural experiment. Eur Econ Rev 71:121–131

Pratt JW, Zeckhauser RJ (1987) Proper risk aversion. Econometrica 55:143–154

Prelec D et al (1998) The probability weighting function. Econometrica 66:497–528

Quiggin J (1982) A theory of anticipated utility. J Econ Behav Organ 3(4):323–343

Quiggin J (2003) Background risk in generalized expected utility theory. Econ Theor 22(3):607–611

Rabin M (2000) Risk-aversion for small stakes: a calibration theorem. Econometrica 68:1281–1292

Sahm CR (2012) How much does risk tolerance change? Q J Finance 2(04):1250020

Said F, Afzal U, Turner G (2015) Risk taking and risk learning after a rare event: evidence from a field experiment in Pakistan. J Econ Behav Organ 118:167–183

Stigler GJ, Becker GS (1977) De gustibus non est disputandum. Am Econ Rev 67(2):76–90

Tversky A, Kahneman D (1992) Advances in prospect theory: cumulative representation of uncertainty. J Risk Uncertain 5(4):297–323

Vieider FM, Beyene A, Bluffstone R, Dissanayake S, Gebreegziabher Z, Martinsson P, Mekonnen A (2018) Measuring risk preferences in rural Ethiopia. Econ Dev Cult Change 66(3):417–446

Vieider FM, Martinsson P, Nam PK, Truong N (2019) Risk preferences and development revisited. Theor Decis 86(1):1–21

Voors MJ, Nillesen EE, Verwimp P, Bulte EH, Lensink R, Van Soest DP (2012) Violent conflict and behavior: a field experiment in Burundi. Am Econ Rev 102(2):941–64

Wilcox NT (2008) Stochastic models for binary discrete choice under risk: a critical primer and econometric comparison. Risk Aversion Exp 12:197–292

Yaari ME (1987) The dual theory of choice under risk. Econometrica 55:95–115