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Can climate shocks make vulnerable subjects more willing to take risks?

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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. 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 (CE-MCL) approach and is played 1-2 years after the subjects were (to a varying degree) exposed to a covariate drought shock or idiosyncratic shocks. The experimental approach facilitated a comprehensive assessment of shock effects on experimental risk premiums 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 (RDU) models with a two-parameter Prelec probability weighting function. Our study is the first to comprehensively test the theoretical predictions of Gollin and Pratt (1996) versus Quiggin (2003). Gollin 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 and can explain the surprising result. In our sample of resource-poor young adults living in a risky semi-arid rural environment in Sub-Saharan Africa, we find that the covariate drought shock had negative effects on risk premiums and the utility curvature and caused an upward shift in the probability weighting function. To our knowledge, this is the first paper to carry out such a rigorous test of a shock effect on utility curvature and probability weighting.

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

JEL Classification: C93 , D81

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 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 & Becker, 1977). However, does constant risk preferences mean constant absolute risk aversion (CARA) or constant relative risk aversion (CRRA)? As noted by Quiggin (2003), the only class of expected-utility preferences displaying constant risk aversion (CARA and CRRA) are risk-neutral preferences. 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 own protection. An increase in background risk (more serious shock exposure) may therefore make people more vulnerable and more risk averse (Cameron & Shah, 2015; Gollier & Pratt, 1996; Pratt & Zeckhauser, 1987). On the other hand, Quiggin (2003) has shown that for certain non-expected utility theories, background risk can be a complement rather than a substitute for independent risks. This implies that an increase in 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. The presence of 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 & Tversky, 1979; Tversky & 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 (Cavatorta & Groom, 2020; Hanaoka, Shigeoka, & Watanabe, 2015; Kahsay & Osberghaus, 2018; Page, Savage, & Torgler, 2014; Voors et al., 2012). Other studies find the opposite, that subjects have become less risk tolerant after exposure to shocks (Bourdeau-Brien & Kryzanowski, 2020; Brown, Montalva, Thomas, & Velásquez, 2019; Cameron & Shah, 2015; Cassar, Healy, & Von Kessler, 2017; Guiso, Sapienza, & Zingales, 2018; Liebenehm, 2018). And yet other studies find that risk preferences are stable and unaffected by shocks (Brunnermeier & Nagel, 2008; Drichoutis & Nayga, 2021; Sahm, 2012). There are also mixed findings regarding how covariate and idiosyncratic shocks affect risk preferences (Liebenehm, 2018). Other 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 & Kryzanowski, 2020; Said, Afzal, & Turner, 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 that 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 that 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. (2015) found that Japanese men became more risk tolerant after the Great East Japan Earthquake and this effect remained there 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 past covariate and idiosyncratic shocks affect experimental risk-taking behavior using an easy-to-understand tool for the elicitation of risk preferences one and two years after shock exposures. We assess whether the covariate and idiosyncratic shocks influenced behavior in 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 et al., 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 that increases background risk. This result contradicts EU theory which predicts the opposite, that an increase in background risk should increase risk vulnerability and make subjects more risk averse (Gollier & 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, Bold, and Calvo (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 five 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 that have been 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, by alternatively separately mapping the mechanisms of the impacts on the utility curvature and probability weighting in the monetary games. 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 provide the first comprehensive empirical test of EU theory versus non-expected utility theories as a foundation to better understand the direction of the shock response in experimental risk-taking after such shocks. Fourth, 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). Finally, our study provides a unique assessment of the effects of recent idiosyncratic shocks 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 are likely to 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 and 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.

Our paper proceeds as follows. Part 2 elaborates on the sample and shock data, assessment of the natural experiment data, field experiment design, experimental outcome distributions, and data quality, including non-parametric assessment of stochastic dominance. Part 3 outlines the parametric estimation and identification strategies. Part 4 presents and discusses the results before we conclude in part 5.

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 combined with the incentivized risky investment game experiment was implemented in July-August 2016. The second experiment and survey questions were conducted in July-August 2017 and also included a hypothetical version of the risky investment game. The baseline survey covered 1133 subjects. Attrition resulted in a reduction in the number of groups to 116 groups and 935 subjects in the second experiment in 2017.[1]

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 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 2.

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.

[1] The number of subjects included in the models presented later in the paper can be slightly lower, depending on the completeness of some of the control variables that are included in each model.

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. 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 ensuring 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 and had follow-up meetings with the enumerators to identify reasons for observed enumerator bias in the data collected to find ways of minimizing such bias. Some poor-performing enumerators were replaced.

2.1.1 Natural experiment

The study areas were to a varying degree affected by a quite severe drought shock in 2015 and recall data for the exposure and severity of this shock were collected in the 2016 baseline survey. We use the shock data as a natural experiment to investigate how shocks affect the risk tolerance of subjects. The subjects were asked about how severely their parent households were affected by the 2015 drought shock, see Table 1.[2] The exact questions asked can be found in the Appendix with Survey and Experimental Protocols. 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 to generate an exogenous shock variable. Its distribution in terms of average group severity in the full sample and each district (*woreda*) are shown in Fig. 1. The severity of the 2015 drought is also illustrated by the facts 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.

Table 1 Severity of 2015 shock exposure

	Frequency	Percent
Not at all (0)	111	9.8
Somewhat affected (1)	346	30.5
Quite severely affected (2)	383	33.8
Very severely affected (3)	293	25.9
N	1133	100

Descriptive statistics are provided for the included survey variables for individuals that were available and participated in all the 2016 and 2017 risk preference experiments (958 subjects from 116 business groups) in Table 2.

[2] The sample subjects mostly are youth or young adults who come from resident farm households in their community.

Table 2 Descriptive statistics for shock variables and individual characteristics

	Mean	sd
Shock variables		
Covariate shock severity 2015-16	1.735	0.418
Idiosyncratic shock severity 2015-16	0.001	0.854
Idiosyncratic shock 2016-17, dummy	0.169	0.375
Subject characteristics		
Male, dummy	0.677	
Age, years (2016)	29.32	9.79
Education, years	5.388	3.939
Parent household characteristics		
Parents have radio, dummy	0.491	
Parents oxen number	0.962	0.614
Parents own land, dummy	0.765	
Parents farm size, *tsimdi*	2.273	2.155
N	958	

Note: 1 *tsimdi* is approximately 0.25 ha

One possible threat to our assumption is that the natural experiment in form of the severe drought shock in 2015 may have caused a selection (dropout) of group members that have systematically different risk preferences in the areas that were more severely affected by the drought. We assessed this by using dropout information from each group and regressed it on the drought severity variables but found no significant correlation indicating that the drought did not cause such a selection that could bias our results.[3] Another potential selection problem could be related to whether group member selection and formation were significantly different across 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 groups being self-selected and ran a selection model with baseline group characteristics and constructed an Inverse Mills Ratio (IMR) for possible selection bias associated with these groups. We included the self-selection dummy and the IMR in a model with the severity of the 2015 drought as the dependent variable. We found no significant correlation between the self-selection dummy and the drought severity variable and no sign of significant selection bias.

Another potential source of bias is the fact that we relied on the self-reported severity of the drought shock. Ideally one would prefer objective measures but such objective measures of rainfall only exist from meteorological stations that are located far apart and they do not capture the large local microclimatic variation, including rainfall variation, associated with the rugged topography.

The subjects were asked about the severity of the shock for their parent households. It is possible that their judgment also is influenced by parent household characteristics and their vulnerability to such shocks. We, therefore,

[3] The results are available from the authors upon request. 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 of the informants.

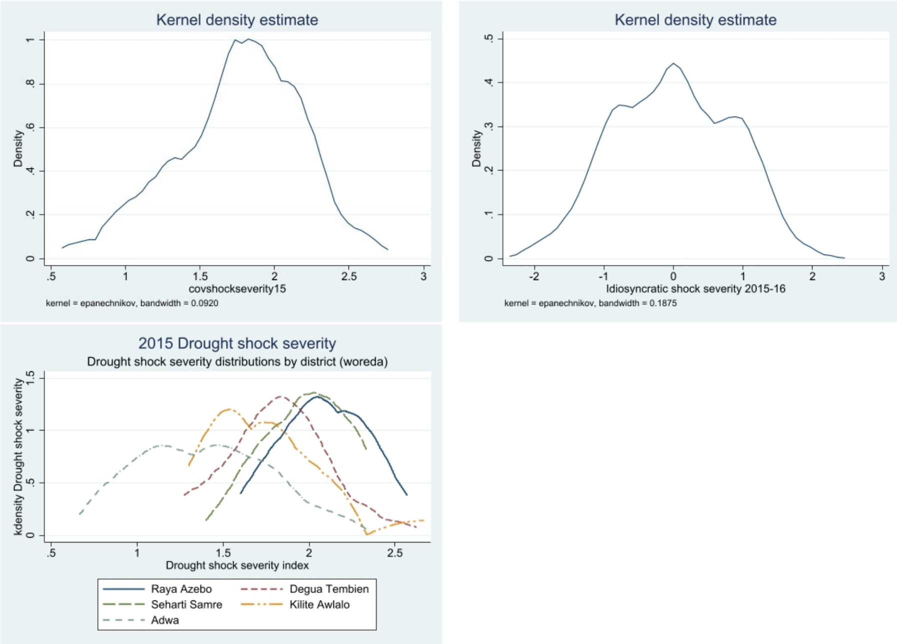

Fig. 1 The distribution of the covariate and idiosyncratic shock severity index variable in the full sample and covariate shock severity by district

regressed the idiosyncratic component (within-group deviation in the severity of the shock from the mean group severity measure) on the parent household characteristics, see model (1) in Table 3. We found that this idiosyncratic severity index was significantly and negatively associated with the farm size of their parents. 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.

However, when regressing the group mean (covariate) shock severity index on the parent household characteristics, see model (2) in Table 3, none of these parent household characteristics were significantly correlated with this measure. 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 are also substantial.

2.2 Experimental design

2.2.1 Certainty Equivalent Multiple Choice List (CE-MPL) 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

Table 3 2015 drought shock severity versus parent family and group characteristics

VARIABLES	(1) Idiosyncratic shock severity 2015-16	(2) Covariate shock severity 2015-16
Parent household characteristics		
Own radio	0.013	-0.011
	(0.062)	(0.024)
Oxen number	-0.046	0.007
	(0.050)	(0.026)
Own land, dummy	0.107	-0.015
	(0.072)	(0.036)
Total farmsize, tsimdi	-0.048***	0.002
	(0.016)	(0.006)
Business group characteristics		
Business Group, year start	-0.003	
	(0.010)	
Group business, base=Animal rearing		
Beekeeping (Apiclulture)	-0.002	0.009
	(0.038)	(0.076)
Forestry	-0.005	0.003
	(0.036)	(0.107)
Irrigation-horticulture	-0.039	0.049
	(0.036)	(0.084)
District, base=Raya Azebo		
Degua Tembien	0.051	-0.294***
	(0.107)	(0.079)
Seharti Samre	0.011	-0.114
	(0.085)	(0.080)
Kilite Awlalo	-0.046	-0.349***
	(0.104)	(0.103)
Adwa	-0.029	-0.715***
	(0.072)	(0.083)
Self-selection group, predicted	2.246	
	(3.716)	
Self-selection, Inverse Mills Ratio	1.292	
	(2.457)	
Constant	3.671	2.084***
	(20.133)	(0.075)
Observations	952	952
R-squared	0.013	0.426
Number of youth business groups	109	109

Bootstrapped standard errors in model (1). Cluster-robust standard errors, clustering on groups in model (2). Significance levels: *** p<0.01, ** p<0.05, * p<0.1

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 3 for an overview of the CL parameter variation). Table 4 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 which is 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 amounts then 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.[4] 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 3 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.[5] Likewise, at the bottom of the list we expect respondents to prefer the risky prospect but here 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

[4] 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 demanding substantial numeracy skills and frequent recalculations.

[5] 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.

standard CL.[6] 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;[7] d) a potential bias towards the middle of the CL is avoided as the whole list is not presented to the subjects;[8] 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 used concerning behavior associated with low-probability shocks such as droughts. Droughts typically lead to low but non-negative yields.[9] Furthermore, 10 out of the 12 CLs have prob(bad outcome)≤ 0.5, see Table 2. 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 also in this probability region. It is quite rare to have access to such business opportunities in our field context. Cultural norms and own experience may therefore 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 by the use of the 20-sided die using 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

[6] 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.

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

[8] 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.

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

the subject receives a good or a bad outcome. The subject then received the outcome in cash in an envelope.

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

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	

2.3 Experimental outcome distributions and data quality

The cumulative switch point distributions in the 2017 risk CE-MPL experiment are presented in Fig. 2-4, with CLs 1-3 and CLs 6-8 in Fig. 2.[10] The combined CLs in Fig. 3a and 3b only differ in the probability of a low outcome. The stochastic dominance is very clear from the graphs demonstrating that CE falls with an increasing probability of a bad outcome. Similarly, Fig. 3 and 4 demonstrate the effect of increasing the bad outcome in the risky prospect

[10]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.

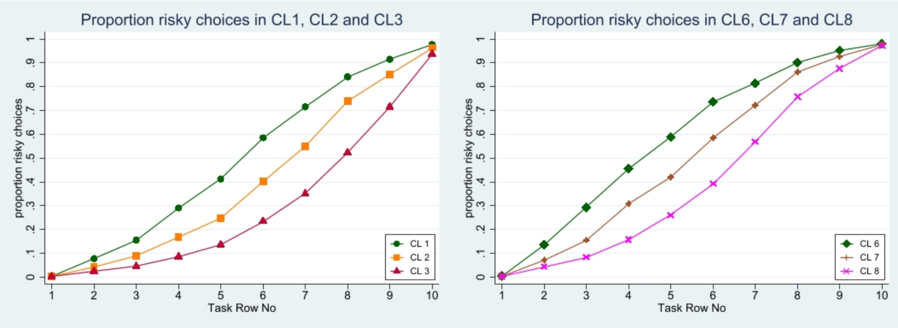

Fig. 2 The distribution of switch points in CL1-CL3 and CL6-CL8

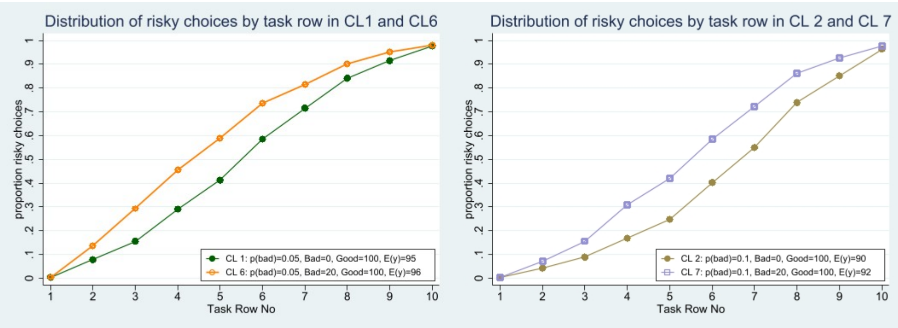

Fig. 3 The distribution of switch points in CL1 vs. CL6 and CL2 vs. CL7

from 0 to 20 ETB while all other characteristics are the same in the paired CLs. For CL1 vs. CL6 (p(bad)=0.05), for CL2 vs. CL7 (p(bad)=0.1), and for CL3 vs. CL8 (p(bad)=0.2), the stochastic dominance for the sorted responses is very clear. It is also noteworthy for CL1 and CL6 that the risk-neutral Task row is row 2 (or very close to row 2 for CL6).[11] For this low probability of a bad outcome, close to 90% of the subjects are risk averse and prefer the certain amount. For CL2 and CL7 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 vs. CL8, the risk-neutral rows are row 5 and (lose to) row 4 (CL8), Fig. 4, the first graph, indicates that 85-90% are risk averse at this probability level.

Fig.4, 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.[12] Only about 70% have $CE < E(y)$ for these CLs.

To further inspect the data quality we inspect for stochastic dominance violations at the subject level. First, our choice lists CL1 vs CL6, CL2 vs CL7,

[11]The certain amount offered is 95 in this row.

[12]With hindsight we see that we should have included higher certain amounts at the top of these CLs.

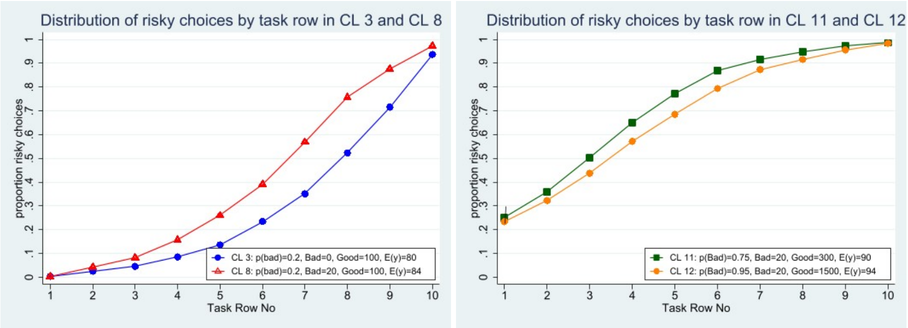

Fig. 4 The distribution of switch points in CL3 vs. CL8 and CL11 vs. CL12

and CL3 vs 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 vs CL6, 7.0% violate for CL2 vs CL7 and 7.6% violate for CL3 vs CL8. Second, we can make within-subject comparisons for CL1 vs CL2 vs CL3 and CL6 vs CL7 vs CL8 which only differ in terms of the probabilities of a bad outcome, 0.05 vs 0.1 vs 0.2. We find 14.5% violations for CL1 vs CL2, 11.2% violations for CL2 vs CL3 and 8.3% violations for CL1 vs CL3, and 12.7% violations for CL6 vs CL7, 11.8% violations for CL7 vs CL8, and 8.8% violations for CL6 vs 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. 5. Each figure presents the histogram distributions of the paired ΔCEs with the negative values representing the violations. We see that the large 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.

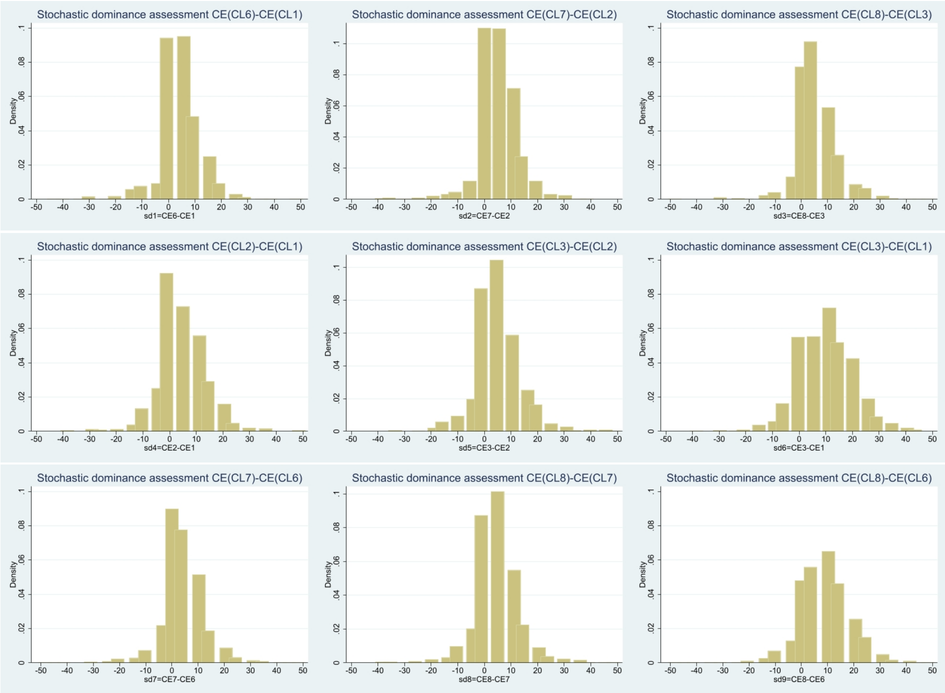

Fig. 5 Stochastic dominance assessment with value deviations

3 Shocks and Risk Preference Estimation

We implemented the assessment of risk preferences and responsiveness to idiosyncratic and covariate stochastic shocks treating these shocks as natural experiments. We investigated 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. Detailed specifications of the parametric models to assess the impacts on the experimental risk preference variables follow.

3.1 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-MPL experiments. With 12 CLs we generate 12 risk premiums per subject, assuming w(p)=p. The risk premium (RP_{gim}) for each CL for each subject is calculated as a fraction of the expected value for 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 above and below the switch point. EV_m is the expected value for the CL given objective probabilities.

We estimate how lagged shocks possibly 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. From a parsimonious model with only the three shock variables as RHS variables, 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, and subject and parent characteristics. These different specifications are collapsed into the following general model specification to save space:

$$RP_{gim} = \pi_0 + \pi_1 IS_{gi,t-n} + \pi_2 CS_{g,t-2} + (\pi_3 CL_m + \pi_4 z_{gi} + \pi_5 E_d + g_g +) u_{gim} \quad (2)$$

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 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 that subjects are more inclined to associate these CLs with their real-world shock experiences.

3.2 EU and RDU model estimation

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:

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

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-MPL risk experiment included prospects with non-negative outcomes.[13] The probability weighting function is therefore modeled in the gains

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

domain only with a Prelec et al. (1998) 2-parameter weighting function:

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

where α captures the degree of (inverse) S-shape of the weighting function,[14] 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 et al., 1998).

The utility is captured with a Constant Relative Risk Aversion (CRRA) function:[15]

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

where r is the CRRA coefficient and *bcons* is the base consumption or asset integration level.[16]

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.[17] 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 models. 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:

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

[15] 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).

[16] We set the base consumption equal to 0 ETB in most models (no asset integration). Alternatively, we run robustness checks with *bcons*=30 ETB which is 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.

[17] 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 i, m, and k represent subjects, CLs, and row numbers in the CLs. The model flexibility allows respondent errors in the identification of 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 or at a higher structural model level to assess model performance.

The log-likelihood function for the risk experiment is obtained by summing the natural logs over the cumulative density functions resulting from equation (5) 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) 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.

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

The Fechner error (ξ_{im}) is modeled linearly on the CL characteristics (CL_m) [18]. Subject characteristics can also affect within-subject errors (inconsistencies across CLs) as we saw in the non-parametric assessment (Fig. 9). Noise is therefore also modeled on z_{gi}. A vector of enumerator dummy variables (E_d) is also included in the error model[19].

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

We estimated the likelihood function with the Broyden-Fletcher-Goldfarb-Shanno (BFGS) optimization algorithm[20] while clustering errors at the subject level. We use the estimated parameters in equation (7) to predict individual risk preference parameters (Ω_{gi}) to inspect the distributional implications of the shock variables, *ceteris paribus*.

[18]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.

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

[20]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.

4 Results

We first present and discuss the results from the risky investment game based on the 2016 real game and the 2017 hypothetical game. After that, we go to the CE-MCL experiment and first use it to construct CL-level risk premiums and assess their sensitivity to the shocks before we dis-aggregate the responses in this experiment with parametric RDU models to further inspect the sensitivity of the dis-aggregated parameters to the drought shock variables.

4.1 Models with risk premiums

We use the CE-MCL experiment to assess whether this comprehensive tool is better at identifying risk preference effects from shocks than the simple risky investment game is. 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. We introduce additional controls step-wise way for robustness assessment. We constructed CL-level risk premiums assuming w(p)=p, for details we refer to the Appendix. This was done to see whether the shocks enhanced or depressed the risk premiums. The Appendix also shows histograms of the risk premium distributions for each CL, measured in ETB. The risk premiums are normalized by the Expected Value (EV) of the risky prospects in each CL before econometric models are run. Four different models are specified, see Table 7. 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.

Table 6 shows that the covariate shock severity variable is highly significant and with a negative sign and a very stable parameter size in all four specifications. 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). The idiosyncratic shock dummy variable for 2016-17 is significant at 10% level in three of four models and with a positive sign. This shock, therefore, appeared to pull in the opposite direction of the covariate shock and thereby enhancing the level of risk aversion.

The first parsimonious model (1) in Table 6 included only the shock variables. 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 should 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

Table 6 Shock effects on risk premiums at CL level

VARIABLES	(1) rpst1	(2) rpst2	(3) rpst3	(4) rpst4
Covariate shock severity 2015-16	-0.036***	-0.037***	-0.037***	-0.037***
	(0.010)	(0.011)	(0.011)	(0.011)
Idiosyncratic shock severity 2015-16	0.003	0.003	0.003	-0.000
	(0.005)	(0.006)	(0.006)	(0.006)
Idiosyncratic shock 2016-17, dummy	0.024*	0.026*	0.026*	0.019
	(0.014)	(0.014)	(0.014)	(0.014)
Prob(bad outcome)		0.082***		
		(0.010)		
CL page no		0.001	0.002*	0.002*
		(0.001)	(0.001)	(0.001)
CL start row		0.032***	0.031***	0.030***
		(0.005)	(0.005)	(0.005)
CL Risk neutral row		-0.028***		
		(0.001)		
Subject characteristics				
Male, dummy				-0.001
				(0.010)
Education, years				-0.000
				(0.001)
Age, years				0.002***
				(0.001)
Parent characteristics				
Radio				0.012
				(0.009)
Number of oxen				0.003
				(0.007)
Household owns land, dummy				0.045***
				(0.012)
Farm size, tsimdi				-0.006**
				(0.002)
CL fixed effects	No	No	Yes	Yes
Constant	0.244***	0.283***	0.229***	0.149***
	(0.018)	(0.019)	(0.019)	(0.034)
Observations	10,991	10,991	10,991	10,894
Number of subjects	934	934	934	926

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

a slight reduction in the idiosyncratic shock effects while the covariate shock effect did not change.

The risk premium has on average been reduced by the covariate shock severity variable. This indicates that the subjects exposed to a more severe covariate shock on average have become more willing to take risks in the CE-MCL experiment two years after this shock than those who were less severely exposed.

As a further robustness check, we inspect the shock effect at different probability levels for good and bad outcomes in the CLs. Note that we had

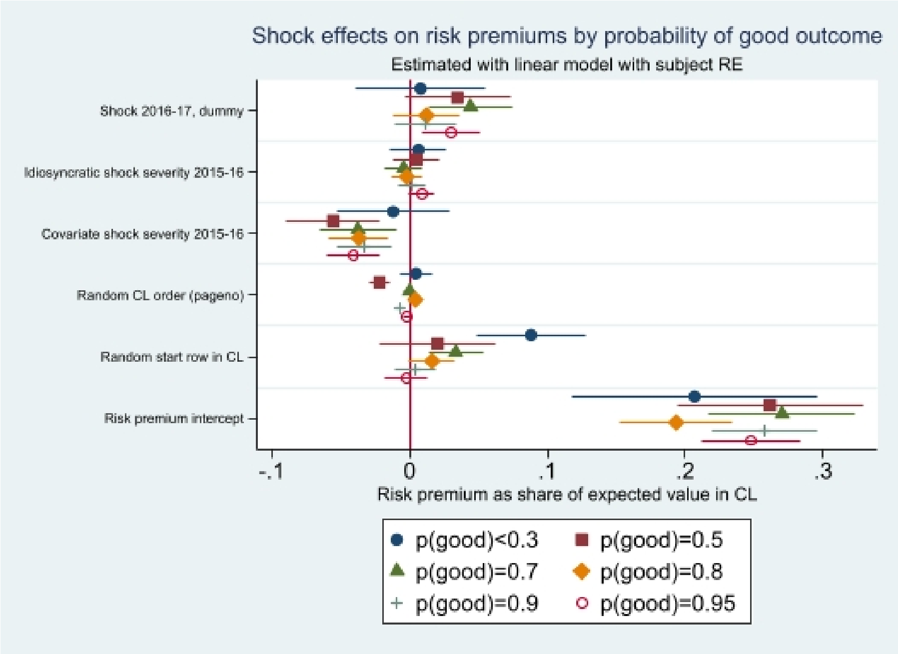

Fig. 6 Idiosyncratic and covariate shock effects by probability of good outcome in CL

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. 6, including also 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 with a negative effect on the risk premium in all models in the probability range of 0.5-1. Only in the case of a 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 tends to go in the opposite direction, making people more risk-averse. The intercepts indicate that on average subjects are risk averse at all p(good) levels.

4.2 Shock effects in the EU model

In an Expected Utility (EU) model 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. 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. The 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.[21] The shock effects

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

can then also be captured as changes in the utility curvature parameter. Both types of models assume $w(p) = p$ and thereby a linear probability weighting function such that Prelec α = Prelec $\beta = 1$. Another advantage of the EU model is that it includes a Fechner error specification (noise) as an additional control for measurement error. The Luce 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, and enumerator fixed effects. The population-averaged utility function is allowed to vary only with the three shock variables. 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, see Table B1 in Appendix B.1.

Table 7 shows that the CRRA-r is significantly reduced for those that experienced a more severe covariate shock. None of the idiosyncratic shock variables are significant. The constant term indicates that the utility function is quite concave with CRRA-r=0.564 for those that 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.

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 B1 in Appendix B.1 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. And an increase to three daily wage rates base consumption increase the constant term to 1.98 and 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.

4.3 RDU model with linear utility function

Yaari (1987) proposed a dual to EUT where the roles of payments and probabilities are reversed. Yaari proposed that the dual theory has intrinsic economic significance and that its predictions are superior to EU theory in some areas. Two distinct features of the dual theory are that its utility assigns the certainty equivalent to each random prospect and is linear in payments. Under EU a linear utility function implies CRRA and CARA but that is not the case under the dual theory although the utility function is linear. We estimate a population-averaged dual model with a 2-parameter Prelec probability weighting function to see how the dual version of the population-averaged EU model looks. This allows us also to assess how the covariate and idiosyncratic shock variables have influenced the two 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 show a strong inverse S-shaped function with substantial "pessimism". The results indicate that the

Table 7 EU-model ($w(p) = p$, $\alpha = \beta = 1$), $bcons = 0$

Shock effects on risk preference parameters

VARIABLES	(1) CRRA-r	(2) Prelec α	(3) Prelec β	(4) noise
Covariate shock severity 2015-16	-0.073***			
	(0.020)			
Idiosyncratic shock severity 2015-16	-0.010			
	(0.010)			
Idiosyncratic shock 2016-17, dummy	0.027			
	(0.023)			
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***	1.000	1.000	0.320***
	(0.034)	(0.000)	(0.000)	(0.014)
Subjects	935			
Observations	110,339			

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

covariate shock two years earlier has increased the Prelec α and reduced the Prelec β parameters. Fig. 7 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. We note that the two-parameter Prelec function is more flexible than the one-parameter CRRA utility function and that it, therefore, is better at capturing the variation in probabilistic sensitivity which seems to be a dominant behavioral characteristic that here is 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.

4.4 Shock effects in RDU models without and with subject characteristics

The results for disaggregated risk preference parameters in the parametric population-averaged RDU model are presented in Table 9. The changes in the

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		0.046***	-0.061**	
		(0.015)	(0.027)	
Idiosyncratic shock severity 2015-16		-0.001	-0.010	
		(0.008)	(0.014)	
Idiosyncratic shock 2016-17, dummy		-0.021	0.020	
		(0.016)	(0.033)	
CL page no				-0.010***
				(0.003)
CL page no, squared				0.001**
				(0.000)
Start point in CL, row				0.019***
				(0.002)
Start point in CL, squared				-0.002***
				(0.000)
Risk neutral row no				-0.012***
				(0.003)
Risk neutral row no, square				0.003***
				(0.000)
Enumerator FE	No	No	No	Yes
Constant	0.000	0.504***	1.302***	0.152***
	(0.000)	(0.025)	(0.047)	(0.010)
Subjects	935			
Observations	110,339			

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

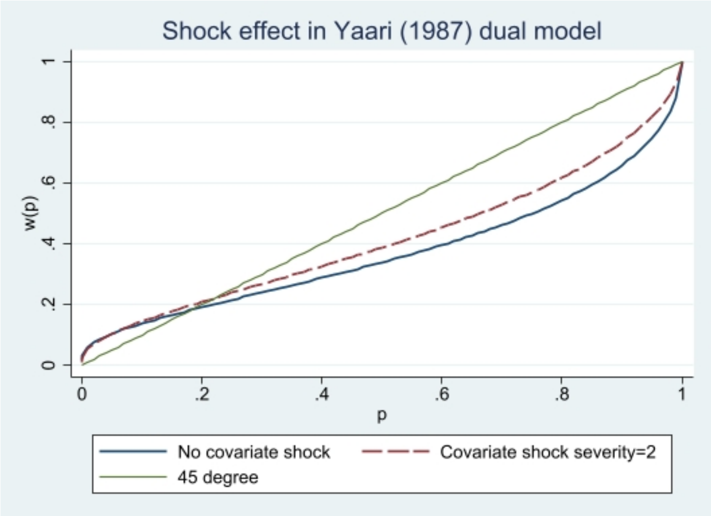

Fig. 7 Covariate shock effect on probability weighting function in Yaari (1987) dual model

w(p) Prelec α and β intercepts and covariate shock parameters are modest from Table 8 to Table 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 and β model parameters are significantly correlated with the recent idiosyncratic shock dummy variable (significant at 5, 10, and 10% levels). The utility function becomes significantly convex after such a recent idiosyncratic shock, while it is linear for those unaffected by the shocks. The effects of the recent idiosyncratic shock dummy variable on the w(p) function go in the opposite direction of that of the covariate shock.

Table 10 expands the RDU model by including subject and parent characteristics in the CRRA utility, Prelec α, and β functions of the model. No change is made in the Fechner error (noise) component compared to the previous models. This allows us to inspect the predicted variation in the parameter estimates across our large rural sample. Due to some gaps in the subject and parent characteristics data, our sample with complete data is reduced from 935 to 927 subjects.

Table 10 shows that the covariate shock effects on the w(p) parameters are robust and remain significant at 1 and 5% levels. The effect of the recent idiosyncratic shock only remains significant at the 10% level for the CRRA utility function while it is insignificant in the w(p) parameter estimates. Only one of the parent and subject characteristics variables is significant in the CRRA utility equation (parents with a radio are associated with a more convex function). The variables age, education, and parents owning a radio are associated with significantly lower Prelec α, and the parent land-holding dummy is associated with a lower (more optimistic) Prelec β parameter.

We predict the CRRA-r, Prelec α, and β parameters from this model and graph the distributions to get a better visual picture of how the significant shock variables affected the parameter distributions. The graphs are presented in Fig. 8. Fig. 8 demonstrates clear shifts in the distributions of the three parameters. The utility curvature (CRRA-r) shifts towards 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. 8.

5 Discussion

Our study adds to the literature on how shock exposure influences people's risk preferences. In particular, our study adds another study to those that find that shocks make people more willing to take risks. We add to the literature by having tested two different tools for assessing risk preferences and by assessing impacts of the covariate (drought) and idiosyncratic shocks that took place 1-2 years before the risk preferences were elicited. We rely, like other studies, on using a natural experiment approach. We rule out that selection can explain the results.

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	0.025	0.048***	-0.078**	
	(0.036)	(0.015)	(0.040)	
Idiosyncratic shock severity 2015-16	-0.000	-0.002	-0.010	
	(0.019)	(0.009)	(0.020)	
Idiosyncratic shock 2016-17, dummy	-0.089**	-0.031*	0.080*	
	(0.044)	(0.017)	(0.045)	
CL page no				-0.010***
				(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	0.505***	1.303***	0.154***
	(0.065)	(0.027)	(0.070)	(0.010)
Observations	110,339			

Cluster-robust standard errors in parentheses
Significance levels: *** p<0.01, ** p<0.05, * p<0.1

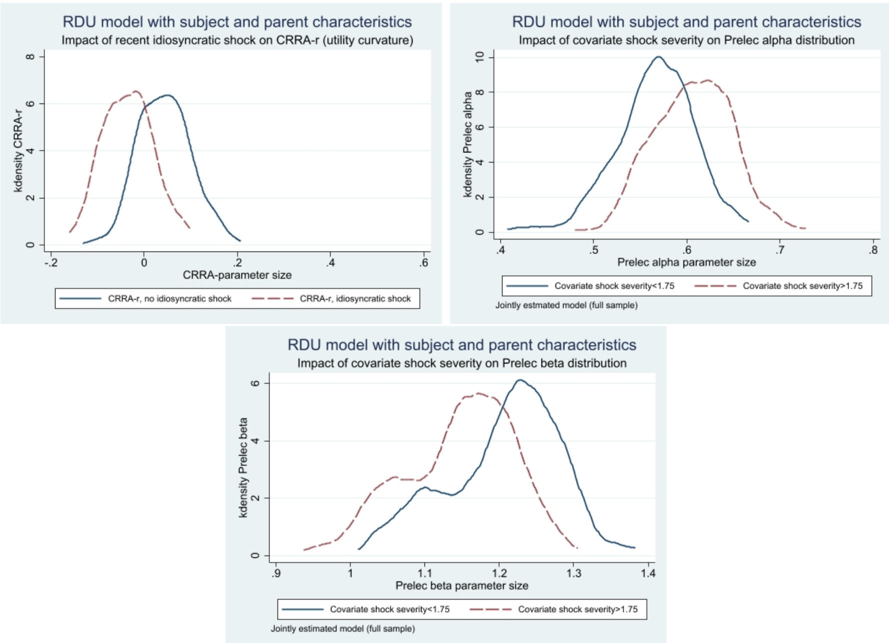

Fig. 8 Idiosyncratic and covariate shock effects on probability weighting function

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	0.036	0.047***	-0.089**	
	(0.040)	(0.018)	(0.041)	
Idiosyncratic shock severity 2015-16	0.006	0.004	-0.016	
	(0.019)	(0.009)	(0.020)	
Idiosyncratic shock 2016-17, dummy	-0.084*	-0.026	0.065	
	(0.047)	(0.017)	(0.044)	
Male, dummy	-0.004	-0.000	0.010	
	(0.033)	(0.016)	(0.035)	
Age, years	-0.002	-0.004***	0.001	
	(0.002)	(0.001)	(0.002)	
Education, years	-0.003	-0.004*	-0.005	
	(0.005)	(0.002)	(0.006)	
Parents have radio	-0.063*	-0.034**	0.057	
	(0.034)	(0.014)	(0.035)	
Parents oxen number	0.022	0.009	0.007	
	(0.024)	(0.011)	(0.026)	
Parents own land	0.057	0.022	-0.149***	
	(0.043)	(0.019)	(0.046)	
Parents farm size, tsimdi	-0.008	0.006	-0.009	
	(0.009)	(0.004)	(0.008)	
CL page no				-0.013***
				(0.003)
CL page no, squared				0.002***
				(0.000)
Start point in CL, row				0.019***
				(0.002)
Start point in CL, squared				-0.002***
				(0.000)
Risk neutral row no				-0.015***
				(0.003)
Risk neutral row no, squared				0.003***
				(0.000)
Constant	0.024	0.610***	1.487***	0.160***
	(0.114)	(0.051)	(0.135)	(0.010)
Enumerator dummies	No	No	No	Yes
Constant	1.126***	0.656***	0.996***	0.057***
	(0.378)	(0.048)	(0.191)	(0.014)
Subjects	927			
Observations	109,376			

Cluster-robust standard errors in parentheses, clustering on subjects.
Significance levels: *** p<0.01, ** p<0.05, * p<0.1

Our main finding was that covariate shocks reduced risk premiums significantly in aggregate and disaggregated models. These results are consistent with the theoretical predictions of Quiggin (2003) that background risk is complementary to independent experimental risks for certain types of non-expected utility preferences. Our data allowed us to comprehensively run EU, versus the dual Yaari and the more general RDU models. The results of the Yaari and the RDU model with fewer parameter restrictions (allowing the CRRA-r utility curvature parameter to be endogenously determined) and revealed that the utility curvature was close to linear. This finding and the fact that risk premiums were reduced by the covariate shock indicates that these 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 1-2 years after the background 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. The general RDU model that nests the EU and the dual Yaari models as special cases provided robust estimates in favor of an inverse S-shaped w(p) function and a near linear utility function. Our results, therefore, 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. Or, in other words, a more severe covariate shock has made them less sensitive to this new experimental risk. This is equivalent to what Quiggin (2003) stated as independent risks being complements rather than substitutes.

These theoretical explanations for the contradicting findings as to how shocks or disasters affect risk preferences have not been carefully tested before. These alternative theoretical explanations are discussed by Cameron and Shah (2015) but they only use the Binswanger (1980) type of game which does not vary probabilities and cannot therefore separately estimate utility and w(p) functions. Another study that reflects on the relevance of these theories is Kahsay and Osberghaus (2018) which 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, Li, Wang, Rao, and Liu (2011) used a natural experiment approach after large a 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 gain 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, therefore, reveals that people have become more sensitive to low-probability events after such low-probability shocks. Likewise, 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 study also speaks to the empirical experimental literature that aims to identify more appropriate tools for elicitation of risk preferences in the field.

There is a need for simple and reliable tools that are easy to comprehend by subjects with limited education and numeracy skills. We tested two tools that are simple to comprehend and implement. Our study shows that the simple risky investment game may not be well suited for investigating how shocks influence risk preferences. This tool did not pick up any effect from the strong covariate shock in the previous year. One reason for this limitation may be substantial measurement error in this game (Gillen, Snowberg, & Yariv, 2019). As an indicator of the measurement error we also found a fairly low correlation between the decisions in the game for subjects that were exposed to the game twice one year apart. Another limitation of the game is that probabilities are typically not allowed to vary. The game cannot, therefore, be used to assess how risk premiums or probability weighting changes with p.

The CE-MCL approach which exposes the subjects to 12 CLs with different probabilities of good and bad outcomes allows us to more 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. A reason for this is that 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-average 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 the covariate shock while the w(p) function makes an upward shift (becoming less pessimistic) after the covariate shock. The latter indicates an increase in background risk has made subjects less sensitive to the independent experimental risk in the games.

6 Conclusions

Relying on a natural experiment in form of a recent covariate drought shock and idiosyncratic shocks combined with two simple-to-understand tools used in field experiments among poor rural residents belonging to youth business groups in northern (semi-arid) Ethiopia, we assess how the shocks have influenced risk-taking behavior in independent experiments 1-2 years after the shocks. We assume that the shocks have 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. EU theory predicts that such risks are substitutes and that shock exposure makes subjects less willing to take a risk, that is they are risk vulnerable (Gollier & Pratt, 1996). However, certain non-expected utility theories predict that such shocks and experimental risks may be taken as complements and that therefore shocks that increase background risk can enhance risk-taking behavior (Quiggin, 2003). Our results for the effects of a covariate drought shock are in line with the latter finding. Our reduced-form econometric models as well as structural EU, dual Yaari, and RDU models provide results that give strong support for the dual Yaari and RDU models.

Our comprehensive, but easy to understand, Certainty Equivalent - Multiple Choice List (CE-MCL) experiment revealed a substantial covariate shock effect in terms of lower experimental risk premiums in reduced-form models. Our experimental tool allowed for the estimation of structural models that allowed us to provide new evidence on why the severity of the covariate shock enhanced the willingness to take risks in our independent experiments. We tested the EU model which predicts that an increase in background risk should make risk-averse people more risk-averse against the dual Yaari (1987) model with linear utility and a two-parameter probability weighting function, and a more general RDU model that allowed the utility curvature and w(p) function parameters to be determined endogenously. The results favor the Yaari and RDU models and this can explain why the subjects in our sample became more willing to take risks in our experiments after experiencing a more severe covariate shock.

The more general RDU model was estimated without and with subject and parent characteristics. The CRRA utility function moved from being closely linear to becoming weakly convex for subjects that were affected by a more severe covariate shock. Both in the dual Yaari model and the more general RDU model the covariate shock resulted in a significant upward shift in the w(p) function. The results for the more recent idiosyncratic shock were weaker and less robust across the model specifications.

Our study provides new insights on the importance of eliciting disaggregated 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 either 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 shock had the most significant and lasting effect and made subjects more willing to take risks in the CE-MCL experiment played two years after the shock.

The study of how shocks affect risk preferences is a relatively new area of research and 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 run as well as in the longer 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 A Risk premium distributions

We calculated the risk premia by CL for each subject in monetary terms, see Fig. A1 and A2 for their distributions by CL. We see some variation in the distribution across CLs that may indicate design weaknesses that we should control for. We address this econometrically below.

Appendix B Robustness analyses

B.1 Sensitivity to base consumption in the EU model

Table B1 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. However, 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). Retaining the moderate level of asset integration at one daily wage unit may therefore be considered appropriate.

Appendix C Experimental protocol

Attached in separate file.

Supplementary information. Experimental designs are attached in a separate pdf-file.

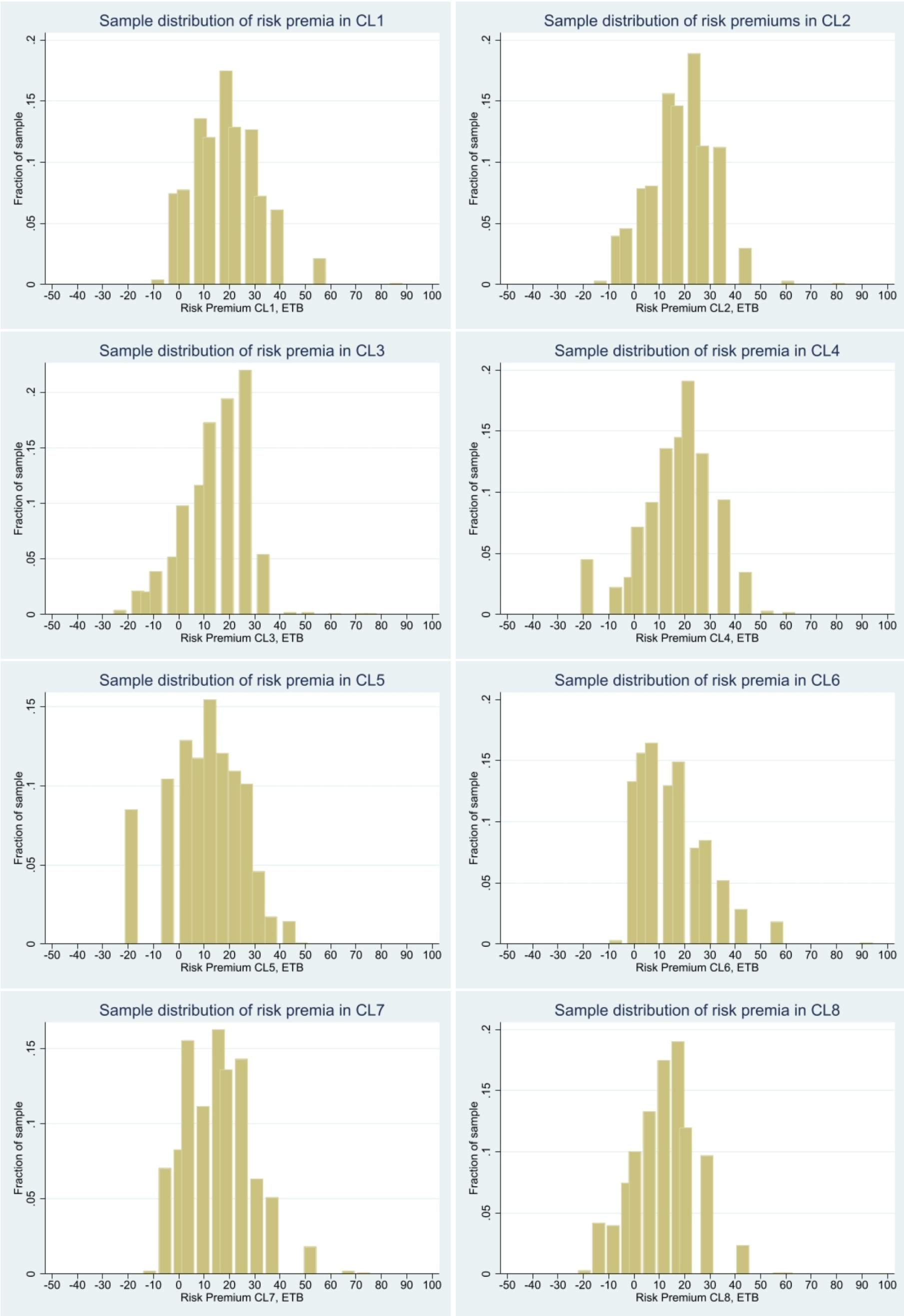

Fig. A1 Risk premium distributions by CL, CLs 1-8

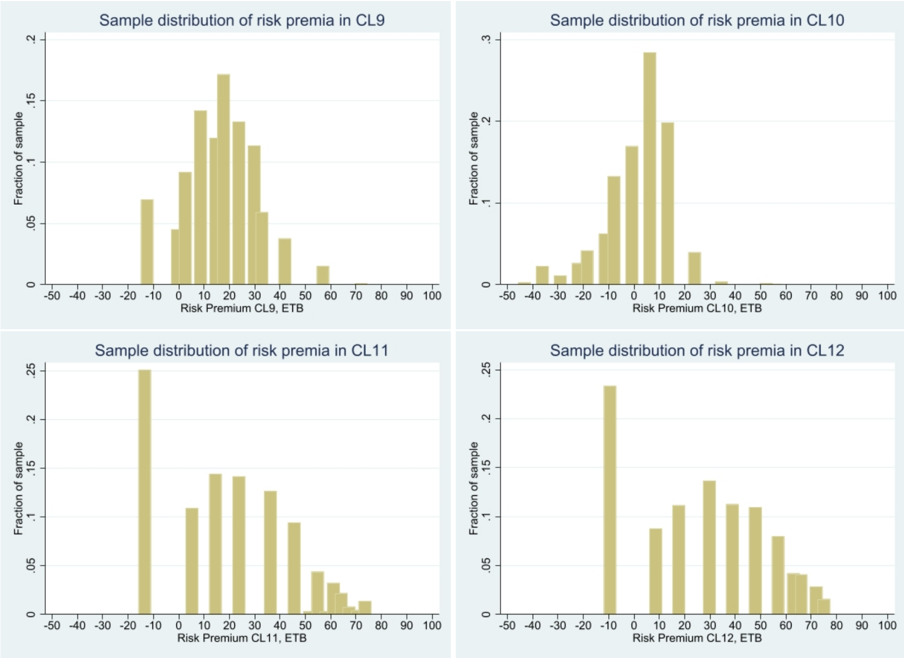

Fig. A2 Risk premium distributions by CL, CLs 9-12

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Declarations

- Funding
  Data collection: Stein T. Holden and Mesfin Tilahun, Grant Number ETH-13/0015 Norwegian Agency for Development Cooperation (NORAD), the NORHED I capacity building project "Climate Smart Natural Resources Management and Policy" (https://www.norad.no/en/front/funding/norhed/projects/capacity-building-for-climate-smart-natural-resource-management-and-policy–clisnarp–/) and own research fund of the first author. Data cleaning, organization and analyses: Stein T. Holden Grant Number: 288238 The Research Council of Norway https://www.forskningsradet.no/en/. The funding institutions had no role in study design, data collection and analysis, decision to publish, or preparation of the manuscript.
- Conflict of interest/Competing interests
  The authors declare no conflicts of interest.
- Ethics approval

Table B1 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	-0.179***	-0.317***
		(0.051)	(0.093)
	Idiosyncratic shock severity 2015-16	-0.017	-0.033
		(0.026)	(0.047)
	Idiosyncratic shock 2016-17, dummy	0.079	0.144
		(0.062)	(0.113)
	Constant	1.225***	1.980***
		(0.089)	(0.165)
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	0.011***	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***	0.023***
		(0.003)	(0.003)
	Start point in CL, squared	-0.002***	-0.002***
		(0.000)	(0.000)
	Risk neutral row no	-0.095***	-0.098***
		(0.005)	(0.006)
	Risk neutral row no, squared	0.010***	0.010***
		(0.000)	(0.001)
	Constant	0.335***	0.356***
		(0.014)	(0.016)
	Observations	110,339	110,339

Cluster-robust standard errors, clustering at subject level.
Significance levels: *** p<0.01, ** p<0.05, * p<0.1

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

- 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.
- Availability of data and materials
  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.
- Authors' contributions
  The first author made the initial experimental designs. Both authors collaborated on the field testing of the survey and experimental designs and the training of enumerators. The second author was in charge of all the data collection and organizing survey and experimental teams. The first author was in charge of data checking and both contributed to data cleaning and organization. The first author wrote up the paper and the second author commented on the drafts.

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