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Centre for Land Tenure Studies

Centre for Land Tenure Studies Working Paper 05/21
ISBN: 978-82-7490-296-1

Noname manuscript No.
(will be inserted by the editor)

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Draft: 14.10.2021

Abstract While economists in the past tended to assume that individual preferences, including risk preferences, are stable over time, a recent literature has developed that indicates that risk preferences respond to shocks. This paper combines survey data and field experiments with three different tools that facilitated elicitation of dis-aggregated measures of risk preferences, including utility curvature, probability weighting and loss aversion. By treating the recent shocks as natural experiments, the study assessed the sensitivity of each of these risk preference measures to the recent idiosyncratic and covariate (drought) shocks among a sample of resource-poor young adults living in a semi-arid rural environment in Sub-Saharan Africa. The results show that the dis-aggregated risk preference measures revealed substantial shock effects that were undetected when relying on a tool that elicited only one single measure of risk tolerance. Both the timing and covariate nature of the shocks affected the dis-aggregated measures of risk preferences differently, pointing towards the need for further studies of this kind in different contexts.

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

JEL codes C93; D81

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1 Introduction

Climate change is associated with more frequent and/or more severe adverse 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 is 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), 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. However, Prospect Theory (PT) proposed that the curvature of the value function is different in the loss domain and 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 PT (Hanaoka et al., 2015; Voors et al., 2012; Kahsay and Osberghaus, 2018; Page et al., 2014). 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). 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). 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 (Bourdeau-Brien and Kryzanowski, 2020). Guiso et al. (2018) find that the 2008 financial crisis triggered substantial increase in risk aversion of bank customers that were not directly affected by the crisis. There are few studies that 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.

In this study we assess stability of the risk preferences of poor and vulnerable people living in a risky semi-arid environment exposed to idiosyncratic shocks as well as a severe covariate drought shock one to two years before their risk preferences were revealed. We use the placement of the severity of the idiosyncratic and covariate shocks as a natural experiment to identify the shock effects on risk preferences.

We assess whether past covariate and idiosyncratic shocks affect behavior using three tools for the elicitation of risk preferences one and two years after shock exposure. First, we assess whether investment behavior in the (incentivized) risky investment game (Gneezy et al., 2009) is affected by covariate and idiosyncratic shocks of varying severity in the previous year. Second, we assess whether the same covariate and idiosyncratic shocks influenced behavior in a Certainty Equivalent (CE) – Multiple Choice List (MCL) experiment two years later. This experiment allowed elicitation of dis-aggregated probability weighting, using a two-parameter Prelec probability weighting function (Prelec et al., 1998) and utility curvature, based on a CRRA utility function. Third, we used a single Choice List (CL) incentivized loss aversion experiment two years after the covariate shock to elicit a rank measure of loss aversion. Based on Rank Dependent Utility (Quiggin, 1982) the probability weighting and utility functions were jointly estimated while assessing their sensitivity to past idiosyncratic and covariate shocks. Furthermore, we assessed whether the two-year lagged covariate shock and one- and two-year lagged idiosyncratic shocks affected loss aversion.

Our paper contributes the to the limited but expanding literature on how shocks affect risk preferences. In particular, our paper provides new evidence on the effects of idiosyncratic and covariate shocks on dis-aggregated measures of risk preferences by separating the effects on utility curvature, two probability weighting parameters and loss aversion. The experimental tools we used have the advantage that they are simple to introduce and explain to subjects with limited education and numeracy skills (Charness and Viceisza, 2016; Vieider et al., 2019; Holden and Tilahun, 2021). We assessed the ability of these tools to identify and measure shock effects and provide new insights about their suitability and possible design strengths and weaknesses. In particular, we show that the designs that elicit dis-aggregated measures of risk preferences reveal quite complex shock effects that were not detected by the simple risky investment game. Another strength of our paper is that we combine survey panel data and incentivized field experiments to elicit risk preferences from the same subjects one and two years after a severe covariate shock (2015-2017). Most other studies have used only survey data or only lab type of experiments. An exception is Guiso et al. (2018) who combine survey data and lab experiments but who were unable to directly combine the survey data and lab experiments, which we were able to. Finally, our study provides a unique assessment of the effects of recent idiosyncratic shocks and a covariate climate shock on risk preference parameters in a rural poor and vulnerable population in a semi-arid environment in Sub-Saharan Africa. Such environments and populations are likely to face more severe climate shocks associated with future climate change.

Our paper proceeds as follows. Part 2 elaborates on the survey design and shock data, experimental design and experimental 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 were implemented in July-August 2016. The second and third experiments and survey questions were conducted in July-August 2017. The baseline survey covered 1133 subjects. Attrition resulted in a reduction in the number of groups to 116 groups and 928 subjects in the second experiment in 2017 and to 111 groups and 830 subjects in the third experiment.

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 respondents 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 to 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 in Mekelle University. They then trained by doing experiments and interviews of 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. One enumerator was placed in the corner of each classroom and with the subjects facing 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 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.

Natural experiment. The study areas were 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[1]. 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 the sample is shown in Fig. 1. The severity of the 2015 drought is 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
Total	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 (830 subjects from 111 business groups) in Table 2.

2.2 Experimental design

Three incentivized experiments were used to measure individual risk tolerance. One was implemented during the baseline survey in 2016 and the two others were implemented sequentially in the follow-up round of the same groups and subjects one year later.

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

Table 2 Descriptive statistics for shock variables and individual characteristics

	Mean	sd
Idiosyncratic shock 2016-17, dummy	0.165	0.371
Idiosyncratic shock severity 2015-16	1.731	0.949
Covariate shock severity 2015-16	1.752	0.424
Male, dummy	0.680	0.467
Age, years (2016)	28.53	8.938
Education, years	5.492	3.971
N	830	

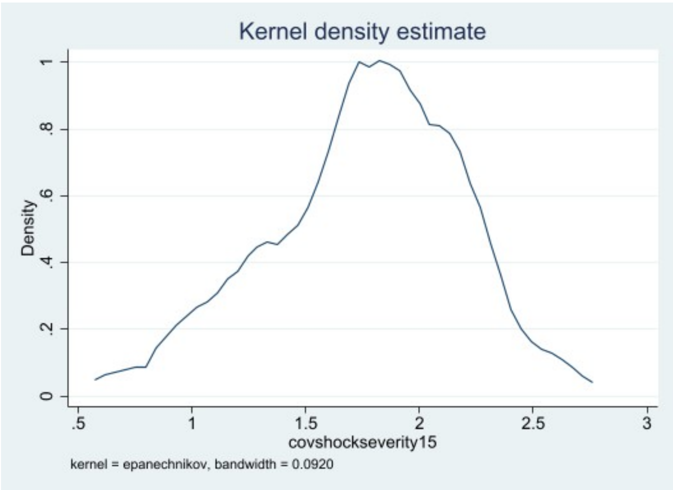

Fig. 1 The distribution of the covariate shock severity index variable.

1) Risky investment game. In the baseline survey in 2016 a one-shot version of the risky investment game was used (Gneezy et al., 2009). In this game the subjects are provided an initial endowment X that they may invest all, some or nothing of. The amount invested (x) is tripled $(3x)$ by the researcher and the subjects have a 50-50 chance of winning the tripled amount or nothing. The lucky winners then get $X+2x$ while the losers get $X-x$. Risk neutral subjects should invest the whole endowment they are initially given, X. The game has been proposed as a particularly suitable tool to investigate risk tolerance in the field in developing countries for its simplicity and cognitive requirements (Charness and Viceisza, 2016). However, a recent study revealed that the game invokes endowment effects that may be explained by loss aversion (Holden and Tilahun, 2021). The game also tends to identify stronger gender differences than some other tools used to elicit risk tolerance and the reasons for this are poorly understood. The game cannot be used to estimate separate parameters for utility curvature, probability weighting and loss aversion. We may, however, assess whether behavior in the game is sensitive to exposure to lagged shocks such as the covariate drought shock we study here. This is our first contribution in this paper.

2) Certainty Equivalent Multiple Choice List (CE-MPL) experiment. In the 2017 follow-up experiments and survey of the same business groups and members we used a 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 3 for an overview of the CL parameter variation). Table 4 provides an example of one of the CLs.

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 a 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 risky prospect is 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 preference choice between the risky prospect and the certain amounts[2]. 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

[2] 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.

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 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[3]. Likewise, at the bottom of the list we expect respondents to prefer the risky prospect but also here we allow corner solutions, meaning that the CE is below the lowest certain amount in the list. 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[4]; d) 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 bad outcome (instead of the good outcome) is stated to the subjects as a framing towards negative shocks. This framing is chosen as the experiment is intended used in relation to behavior associated with low-probability negative shocks such as droughts[5]. Furthermore, 10 out of the 12 CLs have prob(bad outcome)$\leq$ 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 shocks may be found. The two last CLs include low probability of winning high return prospects. It is quite rare to have access to such business opportunities in our field context. Cultural norms and own experience may therefore also play less of a role in influencing their decisions in these CLs.

At the end, the random choice of CL and Task row for payout is identified by 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

[3] 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.

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

[5] In Rank Dependent Utility (RDU) it is usual to sort outcomes from the best to the poorest and 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).

in this row determines whether the respondent will get the preferred certain amount or the preferred risky prospect[6]. If the risky prospect is preferred, the die is used to play the lottery and determine whether the subject receives the good or the bad outcome. The subject then received the outcome in cash in an envelope.

Table 3 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 4 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	

3) Loss Aversion experiment. After the completion of the CE-MPL experiment, including providing payouts for the randomly drawn real game, the respondents were introduced to a single CL loss aversion experiment with real

[6] The rapid elicitation approach identified a single switch point in each CL based on the assumption that the subjects made rational decisions and the decisions for the task rows that were not directly asked are therefore assumed to be known by the researcher (and have an equal chance of being drawn for real payout).

payments[7]. This game included losses which implied that the subjects could lose some of the money they won in the just completed CE-MPL experiment[8].

The CL for the loss aversion experiment is presented in Table 5. Like in the previous game, the respondents are presented with one binary choice at the time. In this case they have the choice between two risky prospects A or B, and with a 50-50 chance of winning or losing for both prospects. Like in the previous experiment, the starting task row was randomly drawn in advance and the rapid elicitation method was used to identify the switch point in the CL. The good and bad outcomes for the two prospects that are compared are illustrated with money on the desk in front of the subjects. We expect prospect A to be chosen in task row 1 and Prospect B to be chosen in task row 9 and the switch point to occur somewhere between.

After the switch point has been identified one task row is randomly chosen for real payout. The preferred risky prospect in that row is then used to play the real game and payout/payment requirement is made based on the random draw of win or loss in that game.

Table 5 Choice List in Loss aversion experiment

CL no.	Start point	Task no.	Prob. Win	Prospect Win	A (ETB) Loss	Choice	Prospect Win	B (ETB) Loss	Choice
13		1	0.5	50	-10		60	-40	
13		2	0.5	30	-10		60	-40	
13		3	0.5	20	-10		60	-40	
13		4	0.5	10	-10		60	-40	
13		5	0.5	5	-10		60	-40	
13		6	0.5	5	-10		60	-30	
13		7	0.5	5	-15		60	-30	
13		8	0.5	5	-15		60	-25	
13		9	0.5	5	-15		60	-20	

2.3 Experimental outcome distributions and data quality

The investment distribution for the 2016 risky investment game is presented in Fig. 2. About 18% invested the full 30 ETB endowment provided in the game, showing that the large majority invested less than the amount that gives the highest expected return, indicating risk aversion at this 50% probability level. The initial endowment of 30 ETB was approximately equivalent to a local

[7] This experimental design was inspired by Tanaka et al. (2010) who used such a choice list to elicit loss aversion in a Cumulative Prospect Theory framework. We have chosen to impose less strong parametric assumptions than what they did in their study. We therefore do not attempt to estimate a loss aversion parameter but use this experiment to get a ranked variable as an indicator of loss aversion.

[8] For ethical reasons we could not include any games with losses till after the subjects had received a positive cash amount that they could lose some of in the loss aversion experiment.

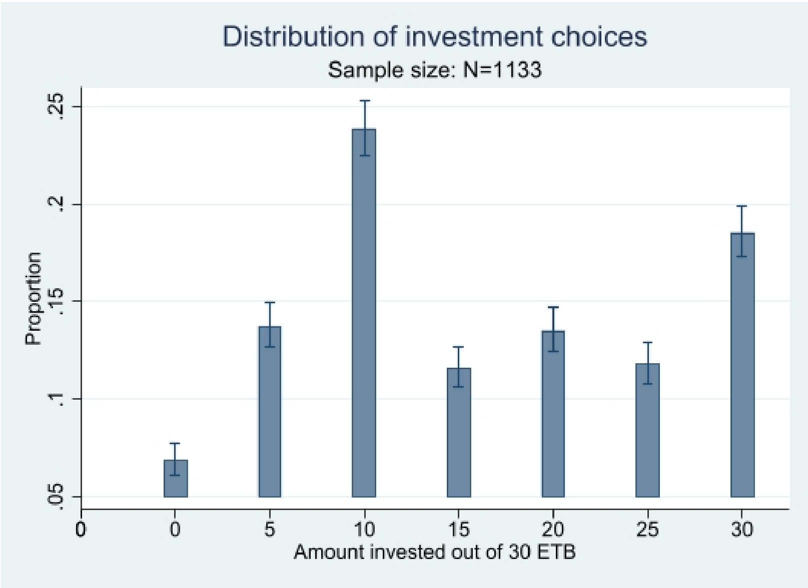

Fig. 2 The distribution of choices in the Risky Investment Game (2016).

daily rural wage rate at the time of the study and therefore was a significant amount of money for the subjects as they are considered relatively resource-poor even within their own communities. It is noteworthy that the dominance of interior solutions in the game points towards a non-linear value function as interior choices cannot be explained by loss aversion alone (Holden and Tilahun, 2021).

The cumulative switch point distributions in the 2017 risk CE-MPL experiment are presented in Fig.3-5, with CLs 1-3 and CLs 6-8 in Fig. 3. The combined CLs in Fig.3a and 3.b only differ in the probability of low outcome. The stochastic dominance is very clear from the graphs demonstrating that CE falls with increasing probability of bad outcome. Similary, Fig. 4 demonstrates 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 vs. CL6 (p(bad)=0.05) and for CL2 vs. CL7 (p(bad)=0.1) 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) (certain amount offered is 95 in this row). For this low probability of 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 $CE < E(y)$.

Fig.5 shows the cumulative distributions for CL11 and CL12 (low probability (0.15 and 0.05) high outcomes (ETB 300 and 1500)). The higher share of corner solutions without switch points in CL11 and CL12 indicate a higher

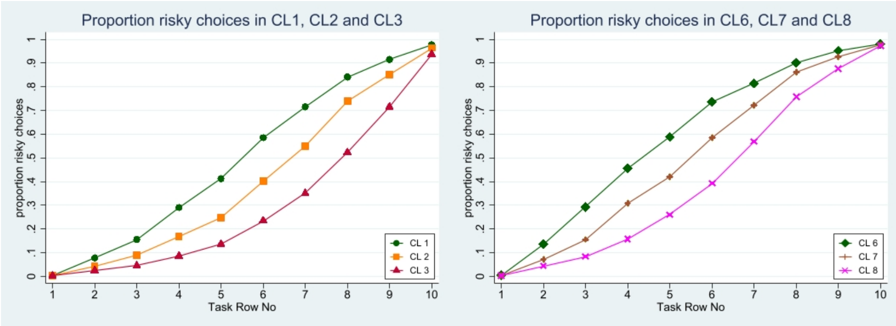

Fig. 3 The distribution of switch points in CL1-CL3 and CL6-CL8.

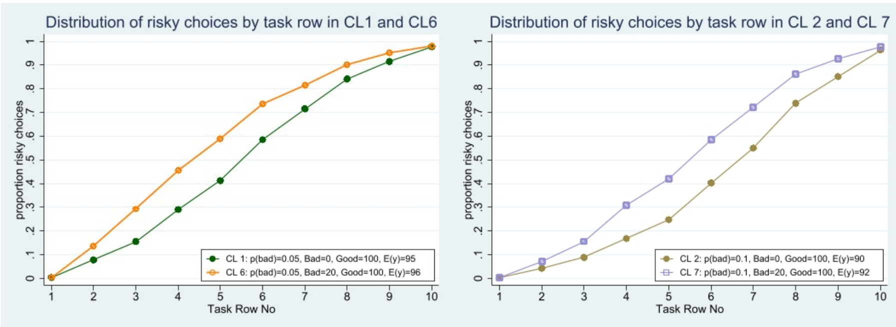

Fig. 4 The distribution of switch points in CL1 vs. CL6 and CL2 vs. CL7.

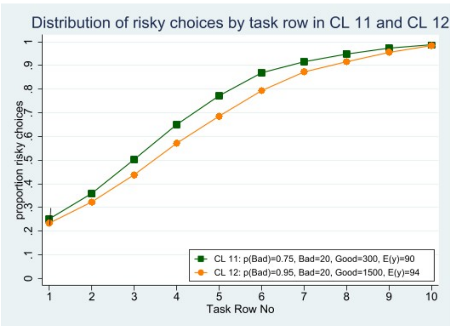

Fig. 5 The distribution of switch points in CL11 and CL12.

willingness to take risk for such low probability high outcomes[9]. Only about 70% have $CE < E(y)$ for these CLs.These findings are consistent with the findings in the risky investment game which also found the large majority of respondents to be risk averse at $p = 0.5$.

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

Fig. 6 The distribution of switch points in the loss aversion CL.

Fig. 6 presents the switch point distribution in the loss aversion CL. The risk neutral row in this CL is row 2 and we see that close to 90% preferred the risky prospect with lowest loss outcome in this row. This indicates that the large majority are averse to losses. However, we cannot rule out that this is due to the concavity of the value function or to pessimistic probability weighting at p=0.5. We return to investigating this issue in the parametric econometric analysis.

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 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 bad outcome than the otherwise equivalent CL with 0 ETB as 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 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 41% 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. 7. Each figure presents the histogram distributions of the paired ΔCEs with the negative values representing the

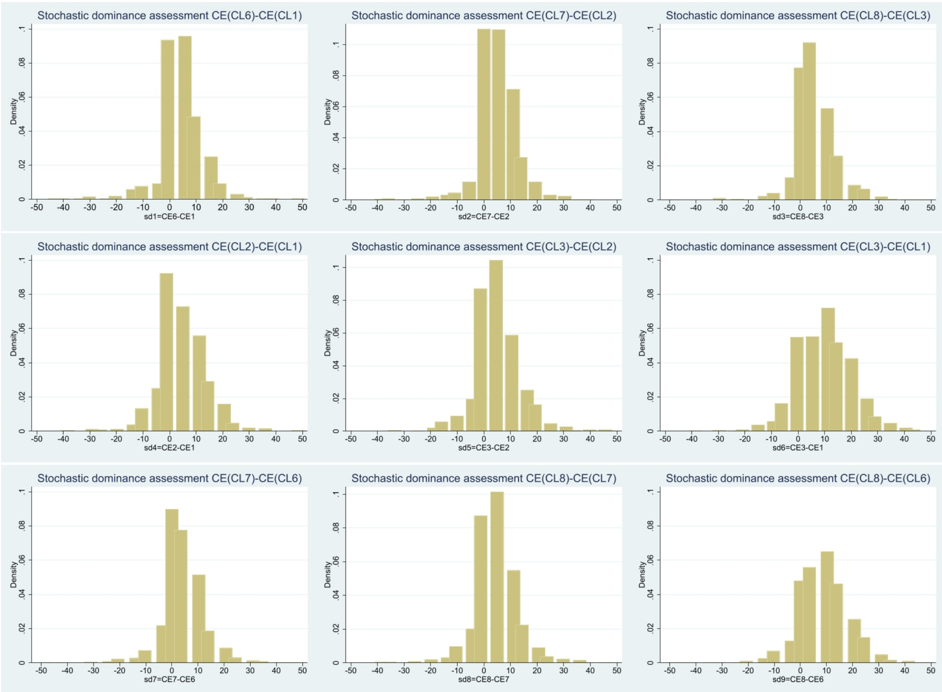

Fig. 7 Stochastic dominance assessment with value deviations.

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.

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 through separate estimation for the 2016 risky investment game, the 2017 CE-MCL experiment with 12 CLs, and the 2017 loss aversion CL. 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.

1) Risky investment game. We use the risky investment share from the maximum safe amount ($X = 30$ ETB) as the measure of risk tolerance in the risky investment game such that $r = \frac{x}{X}$ and $0 \leq r \leq 1$.

To assess the potential shock effects in the risky investment game we estimated a linear panel data model with the following specification:

$$r_{gi} = r_0 + r_1 IS_{gi,t-1} + r_2 CS_{g,t-1} + r_3 z_{gi} + r_4 E_d + g_g + \epsilon_{gi} \tag{1}$$

Subscript g represents group, subscript i represents individual subjects (group members), r_0 represents the estimated share invested by those that have not been affected by covariate or idiosyncratic shocks or any of the other included variables (constant term). r_1 captures the idiosyncratic (individual) shock exposure severity ($IS_{gi,t-1}$) effect on the investment share. r_2 captures the covariate shock severity ($CS_{g,t-1}$) effect on the investment share. These variables test whether the investment level in the game is sensitive to the severe shocks affecting the families of the subjects in the previous year. z_{gi} represents a set of individual characteristics (sex, age, and education), E_d represents a vector of enumerator dummy variables (orthogonal on groups), g_g represents group random effects, and ϵ_{gi} represents the error term.

2) Certainty Equivalent Multiple Choice List (CE-MCL) experiment. 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 a safe option can then be formulated as follows:

$$\Delta RDU = w(p)u(x) + [1 - w(p)]u(y) - u(s) \tag{2}$$

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. The probability weighting function is therefore modeled in the gains domain only with a Prelec et al. (1998) 2-parameter weighting function:

$$w(p) = e^{-\beta(-\ln p)^{\alpha}}, \alpha > 0, \beta > 0 \tag{3}$$

where α captures the degree of (inverse) S-shape of the weighting function[10], 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

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

$[0, 1]$ 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 inverted S-shaped probability weighting function(Prelec et al., 1998).

Utility is captured with a Constant Relative Risk Aversion (CRRA) function[11]:

$$u(x) = (1 - r)^{-1}((b + x)^{1-r} - 1) \tag{4}$$

where r is the CRRA coefficient and b is the base consumption or asset integration level[12].

Noise in the data are captured with a heteroscedastic Fechner (1860) type error (ξ) and the prospects are standardized with Wilcox (2008) type contextual utility. 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[13]. 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 suggested to use 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:

$$Pr(Risky) = \phi(\frac{\Delta RDU_{gimk}}{\xi_{gim}[u(x_m) - u(y_m)]}) \tag{5}$$

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

[11] We assume incomplete (partial) asset integration based on the finding that prospect amounts have much stronger effects on decisions than the respondents’ background wealth (Binswanger, 1981).

[12] We set the base consumption equal to 30 ETB which was equivalent to a daily wage. This is similar to what Andersen et al. (2008) did in their field experiment in Denmark for the elicitation of risk preferences.

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

the within-subject CL level as a measure of subject response inconsistency across CLs or at 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:

$$\ln L(\Omega_{gi}(IS_{gi,t-n}, CS_{g,t-2}, z_i), \xi_{gim}(c_m, z_i, E_d)) = \\ \sum_{imk}(\ln \Theta(\Delta RDU)|_{Choice_{imk}=1}) + (\ln \Theta(1-\Delta RDU)|_{Choice_{imk}=0}) \quad (6)$$

Ω_{gi} is a vector of subject-specific risk preference parameters (r_i, α_i, β_i) that are modeled linearly on 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.

$$\Omega_{gi} = \eta_0 + \eta_1 IS_{gi,t-n} + \eta_2 CS_{g,t-2} + \eta_3 z_{gi} + \epsilon_{gi} \quad (7)$$

Likewise, the Fechner error (ξ_{im}) is modeled on the CL characteristics (CL_m) [14]. 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_i. A vector of enumerator dummy variables (E_d) is also included in the error model[15].

$$\xi_{gim} = \rho_1 + \rho_2 CL_m + \rho_3 z_i + \rho_4 E_d + u_{gim} \quad (8)$$

We estimated the likelihood function with the Broyden-Fletcher-Goldfarb-Shanno optimization algorithm while clustering errors at the subject level.

3) Loss Aversion experiment: Identification strategy. We have a single CL for the assessment of loss aversion and this CL was implemented after payouts in the CE-MCL experiment. This implies that we are unable to measure noise in this game. We also did not elicit probability weighting or the curvature of the value function in the loss domain, both of which are likely to be different than in the gains domain. We therefore use only a loss aversion rank in form of the Task row number in the CL where the subjects switched from preferring Prospect A to preferring Prospect B (see Table 5). In addition to assessing whether the loss aversion rank was influenced by the lagged shock variables, we used an instrumental variable (IV) model to assess whether the risk tolerance expressed in the risky investment game played with the same subjects one year earlier was correlated with the loss aversion rank variable (see equation (9)). This is based on the finding by Holden and Tilahun (2021) that the

[14] 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.

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

risky investment game induces endowment effects that may be driven by loss aversion. As instruments to predict the share invested in the risky investment game ($rhat_{gi,t-1}$) we used enumerator dummy variables. Enumerators were randomly assigned to subjects within groups with one enumerator per group member, thereby ensuring orthogonality and that the instrument is uncorrelated with the outcome variable (loss aversion rank). Enumerator errors are assumed to be idiosyncratic on subjects but are likely to influence subject responses in the risky investment experiment which took place one year before the loss aversion experiment.

$$\begin{aligned} \lambda_{gi,t} &= \lambda_0 + \gamma_1 IS_{gi,t-n} + \gamma_2 CS_{g,t-2} + \gamma_3 z_i + \gamma_4 rhat_{i,t-1} + g_g + v_{gi} \\ r_{i,t-1} &= r_0 + r_1 IS_{gi,t-1} + r_2 CS_{g,t-1} + r_3 z_i + r_D E_d + g_g + \tau_{gi} \end{aligned} \tag{9}$$

This model was estimated as an IV random effects panel data model with business group random effects[16] with cluster robust standard errors (Table 7, model (3)).

4 Results and Discussion

We first present and discuss the results from the parametric RDU models based on the CE-MCL experiment. Then we combine the presentation of the parametric regression results for the risky investment game and the loss aversion experiment.

The parametric RDU model. The results for dis-aggregated risk preference parameters in the parametric RDU model are presented in Table 6. The table shows that the utility curvature (CRRA-r) and Prelec β parameters were sensitive to the most recent (last year) idiosyncratic shocks (significant at the 10 and 5% levels) but not to the two year lagged idiosyncratic and covariate shocks that were more severe. The shock reduced the concavity of the utility function (reduced "classical risk aversion") but at the same time resulted in more pessimistic probability weighting. On the contrary, the Prelec α parameter was sensitive to the two-year lagged covariate shock (significant at the 5% level). The covariate shock was associated with an increase in the α parameter, thereby reducing the degree of inverted S-shape. This illustrates that the risk preferences are sensitive to shocks but the effects on the dis-aggregated measures can vary by shock type, severity and timing or duration for the different risk preference measures.

Furthermore, Table 6 demonstrates that the subject characteristics have varying effects across the risk preference parametric models. Males have less concave utility functions but more pessimistic probability expectations, with the gender difference being similar to but about half the size of the recent

[16] g_g represents group random effects in equation (9).

idiosyncratic shock effect on these parameters. Age and education are significantly negatively associated with the Prelec α parameter and thereby enhancing the inverted S-shape. Finally, we also see that the Fechner error (noise) is sensitive to the socio-economic as well as CL characteristics.

To facilitate a visual inspection of the between subject variation in predicted risk preference parameters, the predicted distributions for all subjects are presented in Fig. 8a. Fig. 8a demonstrates a quite wide dispersion of the utility curvature parameter (CRRA-r) with the majority of subjects displaying significant risk aversion with r-values in the range 0.5-1. The figure also demonstrates a quite narrow range (0.5-0.7) for the Prelec α parameter, in line with the common finding of a quite strong inverted S-shape for the probability weighing function. The Prelec β parameter ranges from 0.7 to 1.3 but with the majority having parameter value below 1, indicating a degree of optimism on average.

In order to get a better sense of the significant shock effects on the between subject parameter distributions, the econometric model is used to predict these by predicting the *ceteris paribus* distributions without and with the 2016-17 idiosyncratic shock in the CRRA-r and Prelec β models. For the Prelec α between subject distributions we predicted the distribution for the below vs the above median severity of the 2015-16 covariate shock (the median value is 1.75, see Fig. 1). The parameter distribution outcomes without and with these (severe) shocks are presented in Fig. 8b for the CRRA-r (utility curvature), and in Fig. 9a and 9b for the Prelec α and β distributions. The increase in the Prelec β parameter is consistent subjects becoming less optimistic after experiencing negative shocks and with this being an emotional response that also affects the subjective judgement of objective probabilities in a framed field experiment. Real world shock effects therefore penetrate into the behavior in this type of field experiment that dis-aggregates risk preferences.

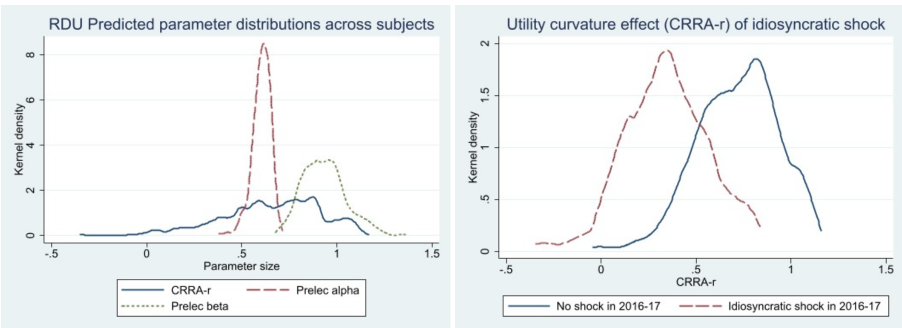

Fig. 8 a. Predicted RDU parameter distributions. b. Shock effect on utility curvature distribution.

Riky investment game and loss aversion models. The results for the parametric risky investment game and the loss aversion experiment are presented in Table

Table 6 Shock effects in jointly estimated RDU parametric models

VARIABLES	(1) CRRA r	(2) Prelec alpha	(3) Prelec beta	(4) Noise
Idiosyncratic shock 2016-17, dummy	-0.308*	-0.015	0.154**	
	(0.160)	(0.018)	(0.069)	
Idiosyncratic shock severity 2015-16	0.022	-0.002	-0.016	
	(0.052)	(0.008)	(0.025)	
Covariate shock severity 2015-16	0.007	0.051***	-0.055	
	(0.103)	(0.018)	(0.050)	
Male, dummy	-0.180**	0.007	0.074*	0.011**
	(0.083)	(0.015)	(0.039)	(0.004)
Age, years	-0.013*	-0.005***	0.004	0.001**
	(0.007)	(0.001)	(0.003)	(0.000)
Education, years	0.026	-0.004**	-0.015	-0.001
	(0.018)	(0.002)	(0.009)	(0.001)
CL page no				0.000
				(0.001)
Start point in CL, row				0.002***
				(0.000)
Risk neutral row no				0.008***
				(0.001)
Enumerator dummies	No	No	No	Yes
Constant	1.201***	0.680***	0.860***	0.057***
	(0.335)	(0.043)	(0.168)	(0.014)
Subjects	928	928	928	928
Observations	110,581	110,581	110,581	110,581

Cluster-robust SEs in parentheses, clustered on subjects
RDU (rank dependent utility) (CRRA) models with 2-parameter Prelec function
*** p<0.01, ** p<0.05, * p<0.1

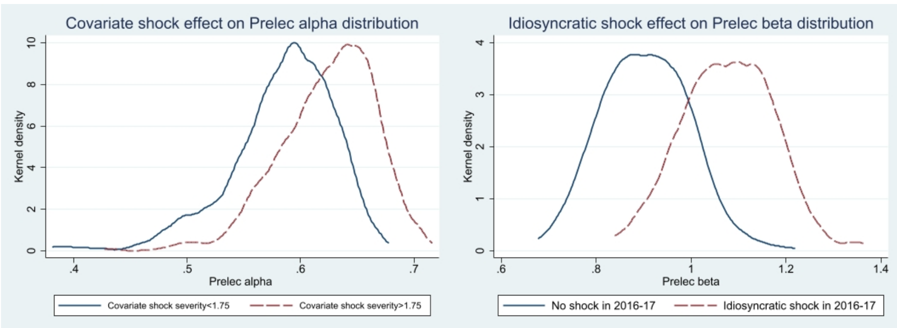

Fig. 9 a. Shock effect on Prelec α distribution. b. Shock effect on Prelec β distribution.

7. To facilitate comparison we include only subjects in the risky investment game regression that also participated in the loss aversion experiment one year later[17]. Perhaps surprisingly, the investment in the risky investment game was

[17] This includes 830 members of 111 business groups. We also estimated the model for the full sample in 2016 and the results showed minimal deviation from the results from the reduced sample, indicating minimal attrition bias.

not significantly affected by the severity of the one-year lagged covariate and idiosyncratic shocks. For reasons we can only speculate about, the behavior in this game was not influenced by the at the time this experiment was conducted, even more recent severe shock. One possible explanation we suggest is that the up-front allocation of 30 ETB may lead to a more myopic response that leads to a lower degree of integration with past shocks. The results in Table 7 also show, like has been found in earlier studies with this game, that males invested significantly more (significant at 1% level) than females (Charness and Gneezy, 2012; Gneezy et al., 2009).

The first loss aversion model (model (2) in Table 7) is estimated independently from the risky investment game. In this model the two-year lagged idiosyncratic shock is significant (at 1% level) and with a negative sign[18], while the more recent idiosyncratic and the two-year lagged covariate shocks were insignificant. The result may indicate that the loss aversion experiment is more sensitive to lagged shocks than the risky investment game. To further scrutinize this and the issue whether loss aversion and investment levels in the risky investment game are related, we estimated the two models recursively with a random effects instrumental variable (IV) model (model (3) in Table 7). The IV model demonstrates that the investment levels in the risky investment game are strongly negatively related to the loss aversion rank derived in the loss aversion experiment one year later, in support of the finding in other studies that the game picks up myopic loss aversion (Gneezy and Potters, 1997; Gneezy et al., 2009; Holden and Tilahun, 2021). The inclusion of the predicted risky investment variable only slightly changed the shock effect for the two-years lagged idiosyncratic shock severity variable, while the one-year lagged idiosyncratic shock variable became significant (at 1% level) and with a positive sign. The covariate shock variable remained insignificant. The result seems to indicate that the short-term (one year) effect of idiosyncratic shocks is enhanced loss aversion but this effect “bounces back” after some time (one to two years later). This may indicate that the shock effect on loss aversion is an emotional response (Bourdeau-Brien and Kryzanowski, 2020) that lasts for a limited time. It is, however, surprising that we did not detect any significant short-term shock effect in the risky investment game. A key distinction between this game and the two other experiments is that cash is allocated up-front in this game while payout only takes place after the completion of the other two experiments. We propose that this may have resulted in a stronger mental isolation (narrow bracketing) of the responses in the risky investment game. This may also imply that it is less suited for the prediction of real world behavior than the other experiments. We leave it to future studies to investigate this further. Real world prediction power is an important characteristic for these field experimental tools.

Overall, our results indicate that not only the shape of the utility function and the probability weighting function but also loss aversion can be affected by

[18] A higher loss aversion rank value is indicating higher loss aversion. The surprising finding is therefore that the lagged shock reduced the degree of loss aversion.

shocks and in dynamic quite complicated ways that affect the value function as well as the probability weighting function in a dynamic way may go beyond the standard assumptions in Prospect Theory and that may need to take shifting reference points into account. It is far from obvious how we otherwise can explain the contradictory shock responses in different studies.

Table 7 Shock effects, risky investment game and loss aversion

VARIABLES	(1) Riskshare	(2) Loss aversion rank	(3) IV-model Loss aversion rank
Idiosyncratic shock 2016-17, dummy		0.358	0.802***
		(0.220)	(0.290)
Idiosyncratic shock severity 2015-16	0.000	-0.351***	-0.290***
	(0.012)	(0.082)	(0.108)
Covariate shock severity 2015-16	-0.004	0.131	0.041
	(0.028)	(0.199)	(0.261)
Riskshare, predicted			-7.656***
			(1.591)
Male, dummy	0.083***	-0.433***	0.149
	(0.019)	(0.153)	(0.228)
Age, years	0.001	0.011	0.013
	(0.001)	(0.010)	(0.012)
Education, years	0.005*	-0.000	0.048
	(0.003)	(0.022)	(0.030)
Constant	0.281***	5.586***	8.243***
	(0.073)	(0.526)	(0.788)
Observations	830	830	830
Number of business groups	111	111	111

Model (3): Instruments: Enumerator dummies for enumerators used in the risky investment game.
All models: Cluster-robust SEs in parentheses, clustering at group level
*** p<0.01, ** p<0.05, * p<0.1

5 Conclusions

Our study has revealed that the dis-aggregated measures of risk preferences respond to shocks in subtle ways that cannot be revealed with a simple tool such as the risky investment game. Responses in the risky investment game were found to be unaffected by strong covariate and idiosyncratic shocks in the previous year. Contrary to this, the more sophisticated tools in form of a Certainty Equivalent Multiple Choice List experiment and a single Choice List loss aversion experiment revealed substantial shock effects on the dis-aggregated risk preference parameters. The utility curvature parameter from a CRRA utility function responded negatively to a recent idiosyncratic shock but remained in the concave region while at the same time the Prelec β parameter responded positively to a shock, implying more pessimistic probability weighting. The Prelec parameter responded positively to a strong lagged covariate shock and thereby reduced the degree of inverted S-shape of the probability weighting function. The loss aversion measure was found to respond both to recent (one year lagged) and two years lagged idiosyncratic shocks albeit in opposite directions. The most recent shock enhanced loss aversion while the more distant shock pulled in the opposite direction, possibly indicating that loss aversion is sensitive in the short run, but bounces back again over time. The loss aversion was also strongly negatively correlated with the investment level in the risky investment game that was played with the same subjects one year earlier. This is consistent with the idea that behavior in the risky investment game is driven by (myopic) loss aversion(Gneezy and Potters, 1997; Holden and Tilahun, 2021). We suggest that the fact that behavior in this game was unaffected by recent past severe shocks may imply that this game induces more narrow bracketing due to its up-front allocation of cash. Our study therefore speaks to the empirical experimental literature that aims to identify more appropriate tools for elicitation of risk preferences in the field. Our study provides new insights on the importance of eliciting dis-aggregated measures that take loss aversion and probability weighting into account. Our study also contributes to the literature on how idiosyncratic and covariate shocks affect risk preferences, especially dis-aggregated measures. Finally, our study provides additional insights into the stability and dynamics of the dis-aggregated risk preference measures by studying shock effects one and two years after the shocks occurred. These are areas where there still is a need for a lot more research.

More research is needed in different contexts before we can say more about the external validity of our findings. 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 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.

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