Framing Effects on Risk-Taking Behavior: Evidence from a Field Experiment

Supplementary Information

A Appendix A. Proofs

A.1 Proof of Lemma 1

Recall that $\bar{p}_i^{Mix}$ is the cut-off probability at which student i chooses to provide an answer, thus non-response is increasing in $\bar{p}_i^{Mix}$.

Rearranging (1), $\bar{p}_i^{Mix}$ is implicitly defined as the perceived probability satisfying:

$$\pi_i^c(\tilde{p}_i)\frac{u_i(1)}{u_i(\rho)} - \pi_i^w(\tilde{p}_i)\lambda_i = 0$$

Let $M_i \equiv \pi_i^c(\tilde{p}_i)\frac{u_i(1)}{u_i(\rho)} - \pi_i^w(\tilde{p}_i)\lambda_i$. Taking derivatives on M_i, it follows that $\frac{\partial}{\partial M_i}\lambda_i \leq 0$ and $\frac{\partial}{\partial M_i}\tilde{p}_i \geq 0$, where the latter inequalities follow from ${\pi_i^c}'(\tilde{p}_i) \geq 0$ and ${\pi_i^w}'(\tilde{p}_i) \leq 0$. Thus, by the implicit function theorem it follows that $\frac{\partial \bar{p}_i^{Mix}}{\partial \lambda_i} = -\frac{\frac{\partial}{\partial M_i}\lambda_i|_{\tilde{p}_i=\bar{p}_i^{Mix}}}{\frac{\partial}{\partial M_i}\tilde{p}_i|_{\tilde{p}_i=\bar{p}_i^{Mix}}} \geq 0$, which implies that non-response is increasing in loss-aversion in the mixed-framing.

We can also see that: i) given that $\rho < 1$, increasing concavity implies that the ratio $\frac{u_i(1)}{u_i(\rho)}$ is reduced and ii) $\frac{\partial}{\partial M_i}(\frac{u_i(1)}{u_i(\rho)}) \geq 0$ Thus, by combining i) and ii) and applying the implicit function theorem as above, it follows that the change in $\bar{p}_i^{Mix}$ when varying concavity is $-\left[\frac{\partial}{\partial M_i}\left(\frac{u_i(1)}{u_i(\rho)}\right)|_{\tilde{p}_i=\bar{p}_i^{Mix}} \times (-1)\right] \Big/ \frac{\partial}{\partial M_i}\tilde{p}_i|_{\tilde{p}_i=\bar{p}_i^{Mix}} \geq 0$, which implies that $\bar{p}_i^{Mix}$ is increasing in the concavity of $u_i(.)$ according to the Arrow-Pratt measure.

A.2 Proof of Lemma 2

Recall that $\bar{p}_i^{Loss}$ is the cut-off probability at which student i chooses to provide an answer, thus non-response is increasing in $\bar{p}_i^{Loss}$. That $\bar{p}_i^{Loss}$ is independent from the loss-attitude is immediately proved by noting that the parameter capturing loss-aversion (λ_i) cancels out in expression (2)

To see that $\bar{p}_i^{Loss}$ is decreasing in the concavity of $u_i(.)$, we can use (2) to implicitly define $\bar{p}_i^{Loss}$ as the perceived probability satisfying:

$$\frac{u_i(1)}{u_i(1+\rho)} - \pi_i^w(\tilde{p}_i) = 0$$

Let $M_i \equiv \frac{u_i(1)}{u_i(1+\rho)} - \pi_i^w(\tilde{p}_i)$. We can see that: i) given that $\rho>0$, increasing concavity implies that the ratio $\frac{u_i(1)}{u_i(1+\rho)}$ increases, ii) $\frac{\partial}{\partial M_i}\left(\frac{u_i(1)}{u_i(1+\rho)}\right) \geq 0$ and iii) $\frac{\partial}{\partial M_i}\tilde{p}_i \geq 0$ (since ${\pi_i^w}'(\tilde{p}_i) \leq 0$) . Thus, by combining i), ii), iii) and applying the implicit function theorem, it follows that the change in $\bar{p}_i^{Loss}$ when varying concavity is $-\frac{\partial}{\partial M_i}\left(\frac{u_i(1)}{u_i(1+\rho)}\right)|_{\tilde{p}_i=\bar{p}_i^{Mix}} \Big/ \frac{\partial}{\partial M_i}\tilde{p}_i|_{\tilde{p}_i=\bar{p}_i^{Mix}} \leq 0$, which implies that $\bar{p}_i^{Loss}$ is decreasing in the concavity of $u_i(.)$.

A.3 Proof of Proposition 1

Let us denote $\alpha_i(\tilde{p}_i) = \frac{\pi_i^c(\tilde{p}_i)}{\tilde{p}_i}$ and $\beta_i(\tilde{p}_i) = \frac{\pi_i^w(\tilde{p}_i)}{1-\pi_i^c(\tilde{p}_i)}$. Decision weights can be trivially rewritten in terms of $\alpha_i(\tilde{p}_i)$ and $\beta_i(\tilde{p}_i)$ as $\pi_i^c(\tilde{p}_i) = \alpha(\tilde{p}_i)\tilde{p}_i$ and $\pi_i^w(\tilde{p}_i) = \beta(\tilde{p}_i)[1-\pi_i^c(\tilde{p}_i)] = \beta(\tilde{p}_i)[1-\alpha(\tilde{p}_i)\tilde{p}_i]$. Prospect theory conditions on decision weights (conditions *i*-*v* on page 8 in the main text) imply that $\alpha_i(\tilde{p}_i) \in [0, \frac{1}{\tilde{p}_i}]$ and $\beta_i(\tilde{p}_i) \in [0, 1]$.[1]

Rewriting equation (1) in terms of $\alpha_i(\tilde{p}_i)$ and $\beta_i(\tilde{p}_i)$ student i would provide an answer under the Mixed-framing whenever:

$$\tilde{p}_i \geq \frac{\beta_i(\tilde{p}_i)\lambda_i u_i(\rho)}{\alpha_i(\tilde{p}_i)u_i(1) + \lambda_i\alpha_i(\tilde{p}_i)\beta_i(\tilde{p}_i)u_i(\rho)} \equiv p_i^{Mix}(\tilde{p}_i) \tag{3}$$

Proceeding similarly on equation (2), student i would provide an answer under the Loss-framing whenever:

$$\tilde{p}_i \geq \frac{\beta_i(\tilde{p}_i)u_i(1+\rho) - u_i(1)}{\alpha_i(\tilde{p}_i)\beta_i(\tilde{p}_i)u_i(1+\rho)} \equiv p_i^{Loss}(\tilde{p}_i) \tag{4}$$

Note that in contrast to $\bar{p}_i^{Mix}$ and $\bar{p}_i^{Loss}$, the expressions $p_i^{Mix}(\tilde{p}_i)$ and $p_i^{Loss}(\tilde{p}_i)$ do not denote a cut-off but a function used to determine the cut-off. The cut-offs $\bar{p}_i^{Mix}$ and $\bar{p}_i^{Loss}$ can be obtained by respectively solving $\tilde{p}_i = p_i^{Mix}(\tilde{p}_i)$ and $\tilde{p}_i = p_i^{Loss}(\tilde{p}_i)$.

Comparing the two expressions above we can see that $p_i^{Mix}(\tilde{p}_i) > p_i^{Loss}(\tilde{p}_i)$ for all $\tilde{p}_i \in [0, 1]$ if and only if

$$\lambda_i > \frac{\beta_i(\tilde{p}_i)u_i(1+\rho) - u_i(1)}{\beta_i(\tilde{p}_i)u_i(\rho)}$$

Since the conditions of Prospect theory on decision weights involve $\beta_i(\tilde{p}_i) \leq 1$ and the right hand side of the above expression is increasing in $\beta_i(\tilde{p}_i)$, then we can replace $\beta_i(\tilde{p}_i) = 1$ to obtain a sufficiency condition guaranteeing $p_i^{Mix}(\tilde{p}_i) > p_i^{Loss}(\tilde{p}_i)$ for all $\tilde{p}_i \in [0, 1]$:

$$\lambda_i > \frac{u_i(1+\rho) - u_i(1)}{u_i(\rho)}$$

If $p_i^{Mix}(\tilde{p}_i) > p_i^{Loss}(\tilde{p}_i)$ for all $\tilde{p}_i \in [0, 1]$, then $\bar{p}_i^{Mix} > \bar{p}_i^{Loss}$, which implies that the Loss-framing induces lower non-response than the Mixed-framing.

[1] We can write the different combinations of decision weights admitted by Prospect Theory in terms of $\alpha_i(\tilde{p}_i)$ and $\beta_i(\tilde{p}_i)$ as: *i)* both probabilities can be underweighted ($0 < \alpha_i(\tilde{p}_i) \leq 1$ and $0 < \beta_i(\tilde{p}_i) \leq \frac{1-\tilde{p}_i}{1-\alpha_i(\tilde{p}_i)\tilde{p}_i}$), *ii)* the probability of correct answer can be overweighted and of wrong answer underweighted ($1 \leq \alpha_i(\tilde{p}_i) \leq \frac{1}{\tilde{p}_i}$ and $0 < \beta_i(\tilde{p}_i) \leq 1$ and *iii)* the probability of correct answer underweighted and of wrong answer can be overweighted ($0 < \alpha_i(\tilde{p}_i) \leq 1$ and $\frac{1-\tilde{p}_i}{1-\alpha_i(\tilde{p}_i)\tilde{p}_i} \leq \beta_i(\tilde{p}_i) \leq 1$). Note that in all combinations $\beta_i(\tilde{p}_i) \leq 1$.

A.4 Proof of Corollary 1

Concavity of $u_i(.)$ implies that $u_i(1) \geq u_i(1+\rho) - u_i(\rho)$. Rearranging this inequality, we get that $1 \geq \frac{u_i(1+\rho)-u_i(1)}{u_i(\rho)}$. Since loss-aversion implies $\lambda > 1$, when test takers display, simultaneously, loss aversion and concavity on $u_i(.)$, the sufficiency condition in Proposition 1 necessarily holds, i.e. $\lambda_i > 1 \geq \frac{u_i(1+\rho)-u_i(1)}{u_i(\rho)}$.

B Appendix B. Additional Tables

Table B1: Balancing Tests (Session Level)

BAU	Mixed	Loss	Diff.	p-value	N^{Mix}	N^{Loss}
Session 1						
Female	0.120	0.077	0.043	0.614	25	26
Acad. Rec.	5.080	5.154	-0.074	0.857	25	26
Non-Int. %NR	0.115	0.071	0.045	0.407	24	22
Non-Int. %NR Before	0.161	0.108	0.053	0.679	14	13
Session 2						
Female	0.133	0.129	0.004	0.961	30	31
Acad. Rec.	5.600	5.516	0.084	0.844	30	31
Non-Int. %NR	0.082	0.050	0.032*	0.075	30	30
Non-Int. %NR Before	1	0.500	0.500	.	1	2
Session 3						
Female	0.136	0	0.136	0.109	22	18
Acad. Rec.	4.364	4.167	0.197	0.682	22	18
Non-Int. %NR	0.100	0.093	0.007	0.931	15	11
Non-Int. %NR Before	0.010	0	0.010	0.461	12	7
Session 4						
Female	0.556	0.737	-0.181	0.261	18	19
Acad. Rec.	6.111	6.263	-0.152	0.764	18	19
Non-Int. %NR	0.084	0.045	0.040	0.250	18	19
Non-Int. %NR Before	0.099	0.044	0.055	0.150	18	18
Session 5						
Female	0.364	0.429	-0.065	0.672	22	21
Acad. Rec.	5.045	5.333	-0.288	0.221	22	21
Non-Int. %NR	0.200	0.150	0.049	0.356	22	20
Non-Int. %NR Before	0.195	0.156	0.039	0.536	22	20
Session 6						
Female	0.889	0.813	0.076	0.544	18	16
Acad. Rec.	6.889	6.188	0.701**	0.037	18	16
Non-Int. %NR	0.069	0.092	-0.023	0.583	17	16
Non-Int. %NR Before	0.052	0.099	-0.047	0.400	17	16
Session 7						
Female	0.690	0.556	0.134	0.309	29	27
Acad. Rec.	6.103	5.741	0.363*	0.093	29	27
Non-Int. %NR	0.066	0.125	-0.059*	0.080	28	27
Non-Int. %NR Before	0.065	0.156	-0.092**	0.022	28	26
Session 8						
Female	0.556	0.455	0.101	0.673	9	11
Acad. Rec.	7.111	6.545	0.566	0.286	9	11
Non-Int. %NR	0.099	0.163	-0.064	0.367	9	11
Non-Int. %NR Before	0.071	0.133	-0.062	0.361	9	11
Session 9						
Female	0.650	0.467	0.183	0.292	20	15
Acad. Rec.	5.200	5.867	-0.667*	0.052	20	15
Non-Int. %NR	0.140	0.146	-0.006	0.850	20	15
Non-Int. %NR Before	0.140	0.150	-0.010	0.770	20	14
Session 10						
Female	0.588	0.630	-0.041	0.790	17	27
Acad. Rec.	6.059	5.556	0.503	0.232	17	27
Non-Int. %NR	0.094	0.167	-0.073**	0.025	17	27
Non-Int. %NR Before	0.094	0.167	-0.073**	0.025	17	27
Session 11						
Female	0.889	0.542	0.3472**	0.015	18	24
Acad. Rec.	6.333	6.458	-0.125	0.704	18	24
Non-Int. %NR	0.328	0.274	0.054	0.242	18	23
Non-Int. %NR Before	0.328	0.274	0.054	0.242	18	23
Session 12						
Female	0.643	0.615	0.027	0.888	14	13
Acad. Rec.	5.571	5.769	-0.198	0.617	14	13
Non-Int. %NR	0.214	0.162	0.053	0.221	14	13
Non-Int. %NR Before	0.214	0.162	0.053	0.221	14	13
Session 13						
Female	0.667	0.609	0.058	0.687	24	23
Acad. Rec.	6.875	6.870	0.005	0.986	24	23
Non-Int. %NR	0.115	0.124	-0.009	0.851	24	23
Non-Int. %NR Before	0.115	0.124	-0.009	0.851	24	23

Notes: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table B2: OLS estimation of the treatment effects on non-response: Total number (*NR*)

	(1)	(2)	(3)	(4)	(5)	(6)
Treatment	-0.586***	-0.576**	-0.494***	-0.537***	-0.561**	-0.626*
	(0.191)	(0.231)	(0.184)	(0.171)	(0.226)	(0.284)
Female		0.399*	0.335	0.393**	0.387*	0.287
		(0.197)	(0.214)	(0.136)	(0.192)	(0.265)
Acad. Rec.		-0.319***	-0.298***	-0.351***	-0.317***	-0.325**
		(0.0846)	(0.0767)	(0.0742)	(0.0838)	(0.115)
N	537	537	537	724	549	326
R^2	0.0173	0.0527	0.110	0.0638	0.0515	0.0645
Specific.	Main sample	Main sample	Main sample	Including pilot	Including Ses.14	Excluding non-balanced sessions
Clusters	–	13	–	15	14	8

Notes: All regressions include session fixed effects except column 1. Standard errors (in parentheses) clustered at session level, except for columns 1 (robust standard errors) and 3 (a robust to outliers estimation using rreg command in Stata). * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table B3: OLS estimation of treatment effects on non-response clustering at different levels: Total number (*NR*) and proportion (*% NR*)

	Total number (NR)			Proportion (% NR)		
	(1)	(2)	(3)	(4)	(5)	(6)
Treatment	-0.576*	-0.576**	-0.576	-0.0248*	-0.0248**	-0.0248
	(0.272)	(0.259)	(0.359)	(0.0113)	(0.0102)	(0.0139)
Female	0.399*	0.399**	0.399	0.0181*	0.0181**	0.0181*
	(0.182)	(0.158)	(0.145)	(0.00867)	(0.00720)	(0.00595)
Acad. Rec.	-0.319***	-0.319***	-0.319	-0.0149***	-0.0149***	-0.0149*
	(0.0875)	(0.0903)	(0.121)	(0.00386)	(0.00406)	(0.00414)
N	537	537	537	537	537	537
R^2	0.0527	0.0527	0.0527	0.0508	0.0508	0.0508
Cluster var.	Instruct.	Degree	Course	Instruct.	Degree	Course
Num. clusters	8	11	3	8	11	3

Notes: All regressions include session fixed effects. Standard errors clustered at session level, in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table B4: Treatment effects on non-response: Papke and Wooldridge (1996) method for fractional dependent variables

	(1)	(2)	(3)	(4)	(5)
Treatment	-0.0246***	-0.0240**	-0.0244***	-0.0232**	-0.0272**
	(0.00890)	(0.00961)	(0.00747)	(0.00928)	(0.0109)
Female		0.0180*	0.0199***	0.0172*	0.0123
		(0.00926)	(0.00726)	(0.00896)	(0.0122)
Acad. Rec.		-0.0151***	-0.0175***	-0.0147***	-0.0154***
		(0.00375)	(0.00462)	(0.00364)	(0.00503)
N	537	537	724	549	326
Specification	Main sample	Main sample	Including pilot	Including Ses.14	Excluding non-balanced sessions
Clusters	–	13	15	14	8

Notes: Replication of Table 4 using the method proposed by Papke and Wooldridge (1996) for fractional dependent variables. All regressions include session fixed effects except column 1. Standard errors (in parentheses) clustered at session level except for columns 1 (robust standard errors). * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table B5: Placebo test with group homogenous out-of-intervention non-response measures

	At least 5 students		At least 10 students		At least 15 students		At least 20 students		At least 25 students	
Treatment	-0.00592	-0.0125	-0.00445	-0.00995	-0.0120	-0.00623	-0.0111	-0.00489	-0.00983	-0.00481
	(0.0107)	(0.00801)	(0.00988)	(0.00738)	(0.0104)	(0.00661)	(0.0112)	(0.00664)	(0.0102)	(0.00673)
Female	0.0174	0.0103	0.0120	0.00555	0.00569	0.00109	0.00802	0.00115	0.0131	0.00294
	(0.0126)	(0.00930)	(0.00981)	(0.00851)	(0.00972)	(0.00762)	(0.0102)	(0.00767)	(0.00928)	(0.00761)
Acad. Rec.	-0.0253***	-0.0149***	-0.0252***	-0.0142***	-0.0266***	-0.0121***	-0.0284***	-0.0123***	-0.0261***	-0.0125***
	(0.00592)	(0.00339)	(0.00572)	(0.00311)	(0.00566)	(0.00278)	(0.00678)	(0.00280)	(0.00728)	(0.00284)
N	508	508	500	500	498	498	474	474	450	450
R^2	0.0563	0.398	0.0588	0.467	0.0716	0.554	0.0721	0.575	0.0683	0.596
Specific.	session. clustered s.e.	robust to outliers	session. clustered s.e.	robust to outliers	session. clustered s.e.	robust to outliers	session. clustered s.e.	robust to outliers	session. clustered s.e.	robust to outliers
Clusters	13	–	13	–	13	–	12	–	11	–

Notes: Homogeneous measures for out-of-intervention non-response constructed using only tests responded by at least 5, 10, 15, 20, 25 students in a session. This makes the nonanswer measure comparable across-subjects in a session. All regressions include session fixed effects. Standard errors (in parentheses) clustered at session level except for robust to outliers estimation (rreg command in Stata). * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table B6: OLS estimation of treatment effects on test scores

	(1)	(2)	(3)	(4)	(5)	(6)
Treatment	-0.177	-0.166	-0.204	-0.0106	-0.171	-0.112
	(0.158)	(0.115)	(0.137)	(0.156)	(0.112)	(0.135)
Female		-0.136	-0.0913	-0.0501	-0.132	-0.352
		(0.222)	(0.159)	(0.161)	(0.216)	(0.237)
Acad. Rec.		0.638***	0.634***	0.717***	0.640***	0.554***
		(0.0948)	(0.0570)	(0.107)	(0.0941)	(0.105)
N	537	537	537	724	549	326
R^2	0.00233	0.210	0.319	0.231	0.211	0.196
Specific.	Main sample	Main sample	Main sample	Including pilot	Including Ses.14	Excluding non-balanced sessions
Clusters	–	13	–	15	14	8

Notes: All regressions include session fixed effects except column 1. Standard errors (in parentheses) clustered at session level, except for column 3, a robust to outliers estimation (rreg command in Stata). * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

C Appendix C. Instructions Example

Instructions for Mixed-framing (Control):

Leave all your belongings out of sight. Keep only your pen or pencil and calculator.

You have two sheets in front of you. The one you are reading contains the instructions and the questions you need to answer. The other is where you need to answer the exam. Only this second sheet will be corrected.

The exam is a multiple-choice test with 20 question and 5 possible answers for each question. Only one of the 5 potential answers is correct. The maximum grade in the multiple-choice section is 100 points. Correct answers give you 5 points. Each incorrect answer subtracts 1.25 points and finally each unanswered question (omitted) (you do not mark any answer for that question in the answer sheet) does not subtract or add points. For instance, a student who answered 16 questions correctly, left 3 unanswered questions and answered 1 question incorrectly, would have a final score of 78.75 over 100 (16*5- 3*0 - 1*1.25 = 78.75).

You have 45 minutes to complete the exam.

Instructions for Loss-framing (Loss):

Leave all your belongings out of sight. Keep only your pen or pencil and calculator.

You have two sheets in front of you. The one you are reading contains the instructions and the questions you need to answer. The other is where you need to answer the exam. Only this second sheet will be corrected.

The exam is a multiple-choice test with 20 question and 5 possible answers for each question. Only one of the 5 potential answers is correct. The maximum grade in the multiple-choice section is 100 points. You start the exam with a grade equal to this maximum score. Correct answers do not subtract anything. Each incorrect answer will subtract 6.25 points and finally, each unanswered question (omitted) (you do not mark any answer for that question in the answer sheet) will subtract 5 points. For instance, a student who answered 16 questions correctly, left 3 unanswered questions and answered 1 question incorrectly, would have a final score of 78.75 over 100 (100-16*0- 3*5 – 1*6.25 = 78.75).

You have 45 minutes to complete the exam.

D Appendix D: Survey on Risk and Loss Attitude

We carried out an incentivized online survey in May 2019. Those who participated had to choose between different gambles that were designed to measure their attitudes towards risk and loss.

Incentives were introduced through a lottery, where the winner effectively participated in the gamble and was paid according to his/her choices. These tasks were in total 5, 3 measuring risk attitudes and 2 loss aversion.

Participation was voluntary and 166 of the subjects who participated in the main study took part in the online survey (30,91% of the total sample). This restriction imposes a challenge in terms of representativeness and power of this part of the study. However, randomness in the treatment allocation allows to obtain internally-valid conclusions about the interaction of the treatment and the measures of risk and loss. Finally, we recognise that the method used to disentangle risk and loss attitudes is not perfect. Still we are able to infer some information on subjects intrinsic preferences.

D.1 Measures of Risk Aversion

- **Ordered Lottery Selection Task**

  The task measures risk attitudes. This task is a modified version of the one introduced by Eckel and Grossman (2002). Subjects are presented with six gambles D1 and they have to select one. To indicate a decision, the subject marked the desired decision. As shown in D1, each gamble had two possible outcomes. Each of the two outcomes has a 50% change of being implemented if selected (e.g. if we select gamble 3 a coin will be thrown and if we obtain heads the earnings are 20 while if we obtain tails 40). Gamble 1 had a sure payoff of 28 Euros. The expected value increased by 1 Euro for each additional gamble, and the standard deviation (S.D.) also increased. Subjects who were extremely risk averse would sacrifice expected payoff to avoid variance, choosing the sure bet. Then in our analysis choosing higher gambles (e.g. choosing 5 instead of 1) indicates that the subject is less risk averse. All measures are codified to be increasing in risk/loss aversion.

Table D1: Ordered Lottery Selection Task

	Heads	Tails
Gamble 1	28	28
Gamble 2	24	34
Gamble 3	20	40
Gamble 4	16	46
Gamble 5	12	52
Gamble 6	2	60

- **SOEP**

Subjects filled a self-reported measure of attitude toward risk, SOEP (Dohmen et al., 2005). They were asked:

How do you see yourself: are you generally a person who is fully prepared to take risks or do you try to avoid taking risks? Please tick a box on the scale, where the value 0 means: 'not at all willing to take risks' and the value 10 means: 'very willing to take risks'.

The answer to this questions gives us a very accurate measure of subjects' risk attitude. Previous literature found that different measures of risk attitudes give different outcomes (Frey et al., 2017). These studies also find that a central measure for risk attitudes is the SOEP. We therefore decided to include this non-incentivized central measure.

- **Bomb risk elicitation task**

  This tasks is designed by Crosetto and Filippin (2013) to measure risk preferences. There are 100 boxes, 99 of which contain 1 Euro. The remaining box contains a bomb. The bomb is placed randomly between the other boxes. Subjects do not know where the bomb is but they are informed that they have to decide how many boxes to collect. They know that earnings increase linearly with the number of boxes collected but are equal to zero if one of them contains the bomb (e.g. if they collect 50 boxes and the bomb is in box 51 they earn 50 Euros but if it is in box 49 they earn 0). Subjects who collect less boxes are more risk averse.

- **Negative Ordered Lottery Selection Task**

  This task is a modified version of the Ordered Lottery Selection Task presented above (payoffs in Table D2). Subjects are presented with the questions of the Ordered Lottery Selection Task but now in a loss-domain. This provides a measure of risk-aversion in a loss-domain. According to Prospect Theory , we expect different choices in a loss-domain and in a gain-domain. Below, we exploit the change in the choice between the Ordered Lottery Selection Task (gain domain) and the Negative Ordered Lottery Selection Task (loss-domain) to capture reflection.

D.2 Other Measures

- **Change in Ordered Lottery Selection Task (Reflection)**

  Assign the value i if the subject chose gamble i in the Positive (Negative) Ordered Lottery Selection Task. Then we construct a measure of reflection by computing the difference between the gamble chosen in the Negative Ordered Lottery Selection Task and the gamble

Table D2: Negative Ordered Lottery Selection Task

	Heads	Tails
Gamble 1	-28	-28
Gamble 2	-24	-34
Gamble 3	-20	-40
Gamble 4	-16	-46
Gamble 5	-12	-52
Gamble 6	-2	-60

chosen in the Positive Ordered Lottery Selection Task. The greater is this value, the bigger the reflection effect.

- **Negative and Positive Ordered Lottery Selection Task (Loss-Aversion)**

  This tasks is designed to measure loss attitudes in different risky scenarios. The task was introduced by Gaechter et al. (2010) to measure loss attitudes when the level of risk varies. Subjects have to make 6 decisions. In each gamble they have to decide if they want to enter in a lottery or not. If they reject entering the lottery they do not win or earn anything. If, by contrast they accept the lottery they may earn or loose certain amounts of money (see Table D3 for more information on the lotteries).

Table D3: Negative and Positive Ordered Lottery Selection Task

	Heads	Tails
Gamble 1	-2	+6
Gamble 2	-3	+6
Gamble 3	-4	+6
Gamble 4	-5	+6
Gamble 5	-6	+6
Gamble 6	-7	+6