Supplementary material for

Monetary Incentives in Large-Scale Experiments: A Case Study of Risk Aversion

C. March, A. Ziegelmeyer, B. Greiner, and R. Cyranek

Appendix A presents the experimental instructions along with the demographic questionnaire of the incentive treatment *Scale50PrUnknown*. Appendix B offers additional illustrations on the inference of risk aversion from choices. Appendices C, D, and E complement the statistical analysis presented in the main text. Appendix F contains a short review of the literature on random incentive systems.

Appendix A. Demographic Questionnaire and Instructions

The following sections present the English version of the registration screen, the experimental instructions and the demographic questionnaire of the incentive treatment *Scale50PrUnknown*. Instructions and the demographic questionnaire of the two laboratory treatments were adapted accordingly.

A.1 Registration

To register for the TorLabor markets please fill in the form below. You will receive a confirmation e-mail upon receipt of your completed form. This e-mail contains a link which you must follow to complete the registration process.

First name: [ ]
Last name: [ ]
E-mail: [ ]
Repeat e-mail: [ ]
Language: [ ]
English
German

For each match of the World Cup 2006, a new market will open a few days before the start of the match. **Would you like to be informed via e-mail each time a new market opens?**

◉ Yes. ○ No.

(It is always possible to enable/disable the delivery of e-mails.)

Please choose a username and a password. Both are necessary to participate in the markets. For your username, use only letters, numbers, dot ('.') or underscore ('_'). Your password must be at least 6 characters long.

Username: [ ]
Password: [ ]
Repeat password: [ ]

Please read carefully the rules and the terms and conditions (T&Cs). If after reading the rules and the terms and conditions, you understand and accept them, check the following box:

☐ I have read the rules and the terms and conditions and I accept them.

Important: Multiple registrations of the same person are NOT permitted and will lead to exclusion from participation and payment.

[Register]

A.2 Instructions

The bottom of the screen shows ten decisions. Each decision is a paired choice between “Option A” and “Option B”. You are asked to make ten choices, and by completing this task you are offered a first possibility to earn some money at TorLabor soccer trading markets.

Later on, you will be offered more possibilities to earn money at TorLabor soccer trading markets. In particular, you may earn money by trading at TorLabor markets. Further details will be provided in due time. Please notice that if you are rewarded for completing the present task then you won’t be rewarded for trading and that this information will be provided to you only after the World Cup 2006.

How your choices affect your payoffs

At the end of the World Cup 2006, 5 participants will be randomly selected. Imagine that you are one of these 5 randomly selected participants. A ten-sided die will be used to determine your payoffs. The faces of the die are numbered from 1 to 10. The ten-sided die will be thrown twice. The first throw will determine which of the 10 decisions you made will affect your payoffs. For this decision we will look at the option you have chosen. Then, for the chosen option, the die will be thrown a second time. You will receive the payoffs attached to the number of the die throw’s result.

Thus, even though you will make ten decisions, only one of these will end up affecting your payoffs. You will not know in advance which decision will be used. Each decision has an equal chance of being used in the end.

Now, please look at Decision 1 at the top. Option A pays 100.00 euros if the throw of the ten-sided die yields 1, and it pays 80.00 euros if the throw yields 2, 3, 4, 5, 6, 7, 8, 9, or 10. Option B pays 192.50 euros if the throw of the die yields 1, and it pays 5.00 euros if the throw yields 2, 3, 4, 5, 6, 7, 8, 9, or 10. The other decisions are similar, except that as you move down the table, the chances of the higher payoff for each option increase. In fact, for Decision 10 in the bottom row, the die will not be needed since each option pays the highest payoff for sure, so your choice here is between 100 euros or 192.50 euros.

	Option A		I choose	**Option B**		I choose
Decision	Die throw yields	Option pays	option A	Die throw yields	Option pays	option B
1	1 2,3,4,5,6,7,8,9 or 10	100.00 euros 80.00 euros	○	1 2,3,4,5,6,7,8,9 or 10	192.50 euros 5.00 euros	○
2	1 or 2 3,4,5,6,7,8,9 or 10	100.00 euros 80.00 euros	○	1 or 2 3,4,5,6,7,8,9 or 10	192.50 euros 5.00 euros	○
3	1,2 or 3 4,5,6,7,8,9 or 10	100.00 euros 80.00 euros	○	1, 2 or 3 4,5,6,7,8,9 or 10	192.50 euros 5.00 euros	○
4	1,2,3 or 4 5,6,7,8,9 or 10	100.00 euros 80.00 euros	○	1,2,3 or 4 5,6,7,8,9 or 10	192.50 euros 5.00 euros	○
5	1,2,3,4 or 5 6,7,8,9 or 10	100.00 euros 80.00 euros	○	1,2,3,4 or 5 6,7,8,9 or 10	192.50 euros 5.00 euros	○
6	1,2,3,4,5 or 6 7,8,9 or 10	100.00 euros 80.00 euros	○	1,2,3,4,5 or 6 7,8,9 or 10	192.50 euros 5.00 euros	○
7	1,2,3,4,5,6 or 7 8,9 or 10	100.00 euros 80.00 euros	○	1,2,3,4,5,6 or 7 8,9 or 10	192.50 euros 5.00 euros	○
8	1,2,3,4,5,6,7 or 8 9 or 10	100.00 euros 80.00 euros	○	1,2,3,4,5,6,7 or 8 9 or 10	192.50 euros 5.00 euros	○
9	1,2,3,4,5,6,7,8 or 9 10	100.00 euros 80.00 euros	○	1,2,3,4,5,6,7,8 or 9 10	192.50 euros 5.00 euros	○
10	1,2,3,4,5,6,7,8,9 or 10 - - -	100.00 euros 80.00 euros	○	1,2,3,4,5,6,7,8,9 or 10 - - -	192.50 euros 5.00 euros	○

Continue

A.3 Demographic questionnaire

Please answer the questions below. Questions marked with a '*' are mandatory. In case you feel uncomfortable with answering some of the non-mandatory questions, you can skip them.

The Cologne Laboratory for Economic Research and the Max Planck Institute of Economics in Jena would be grateful if you would answer all questions truthfully. Your assistance is essential to the success of the research conducted by the Cologne Laboratory for Economic Research and the Max Planck Institute of Economics in Jena.

Our terms and conditions apply meaning that your data will be anonymized before the analysis.

Year of birth: [ ]

* Your home country: [ ]

* Your gender:
- ◯ female
- ◯ male

Your marital status:
- ◯ married
- ◯ single
- ◯ divorced
- ◯ widowed
- ◯ other

* Your degree of expertise in soccer is: low ◯ ◯ high

* Your degree of experience in trading markets is: low ◯ ◯ high

How have you heard about the TorLabor trading markets?:
- ◯ invitation email from an experimental lab
- ◯ friends
- ◯ newspaper
- ◯ coincidence
- ◯ another website
- ◯ other

Who in your household would you consider to be primarily in charge of expenses and budget decisions?:
- ◯ self
- ◯ spouse
- ◯ parent
- ◯ other
- ◯ don't know

How would you best describe your current employment situation?:
- ◯ full-time employed (not at university)
- ◯ part-time employed (not at university)
- ◯ self-employed (not at university)
- ◯ unemployed
- ◯ student only
- ◯ employed at university
- ◯ other

If you are a **student**, please answer these additional questions.

What describes your current situation best?:
- ◯ full-time student
- ◯ part-time student (less than 12 hours per week)

Your major field of studies: [ ]

Your current semester: [ ]

- ◯ undergraduate level
- ◯ graduate level

Who is primarily responsible for your tuition and living expenses while you are attending university?:
- ◯ self
- ◯ parent
- ◯ shared between parent and self
- ◯ scholarship / grant
- ◯ loans
- ◯ combination / other

Appendix B. Illustrations of Inferred Ratio Intervals for Inconsistent Sequences of Choices

In this appendix we illustrate our method of inferring bounds for the risk preference ratio r_i from choices. Recall that $d_{\text{last S}}$ denotes the largest decision $d \in \{1, \ldots, 10\}$ such that for all $d \leqslant d_{\text{last S}}$ the safe lottery is chosen, while $d_{\text{first R}}$ denotes the smallest decision such that for all $d \geqslant d_{\text{first R}}$ the risky lottery is chosen. If the risky (safe) lottery is chosen in decision 1 (10) we let $d_{\text{last S}} = 0$ ($d_{\text{first R}} = 0$). The inferred ratio interval is then given by

$$r_i \in (\underline{r}, \overline{r}) = \begin{cases} \left(\frac{d_{\text{last S}}}{10}, \frac{d_{\text{first R}}}{10}\right) & \text{if } d_{\text{last S}} \leqslant 9 \text{ and } d_{\text{first R}} \geqslant 1 \\ \left(\frac{d_{\text{last S}}}{10}, \infty\right) & \text{if } d_{\text{last S}} \leqslant 9 \text{ and } d_{\text{first R}} = 0 \\ \left(\frac{9}{10}, \infty\right) & \text{if } d_{\text{last S}} = 10 \end{cases} . \tag{1}$$

Notice that $d_{\text{last S}} = 10$ implies that $d_{\text{first R}} = 0$.

Decision	1	2	3	4	5	6	7	8	9	10		
$\Pr(h^\ell)$	0.1	0.2	0.3	0.4	0.5	0.6	0.7	0.8	0.9	1	$\underline{r}$	$\overline{r}$
(1)	S	S	S	S	R	R	R	R	R	R	0.4	0.5
(2)	S	S	S	S	S	S	S	R	R	R	0.7	0.8
(3)	R	R	R	R	R	R	R	R	R	R	0	0.1
(4)	S	S	S	S	R	S	S	R	R	R	0.4	0.8
(5)	S	R	S	S	S	S	S	R	R	R	0.1	0.8
(6)	R	R	R	R	S	R	S	R	R	R	0	0.8
(7)	S	S	S	S	S	S	S	S	S	S	0.9	∞
(8)	S	S	R	S	S	R	S	S	S	S	0.2	∞
(9)	R	S	S	S	S	S	S	R	R	S	0	∞

Table 1: Inferred bounds of the ratio r_i.

Table 1 provides nine exemplary decision sequences with the corresponding inferred intervals of the ratio r_i.

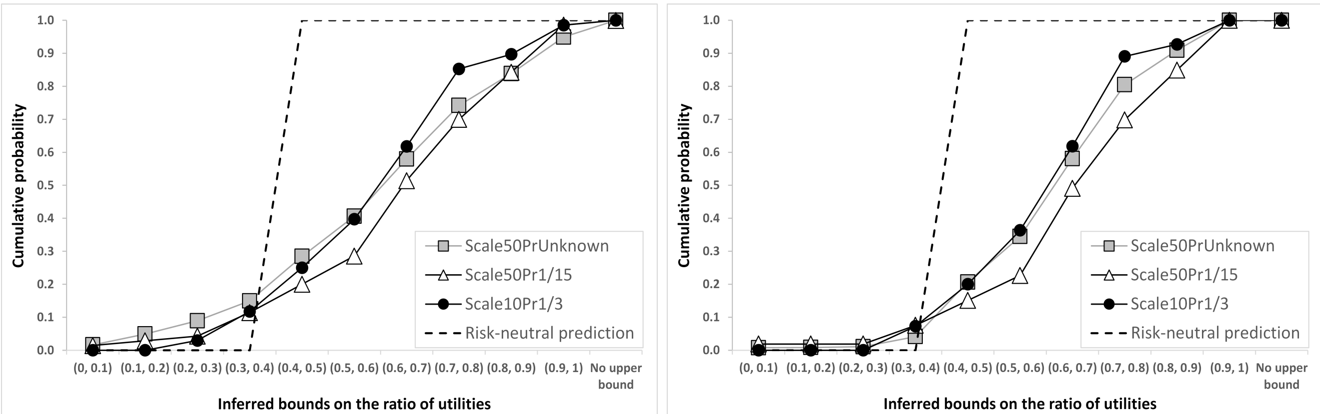
The first three decision sequences are consistent meaning that the risky lottery is chosen in decision 10, and there exists a unique switching point $d^* \in \{1, \ldots, 9\}$ such that the safe (risky) lottery is chosen for all decisions $d < d^*$ ($d \geqslant d^*$). In this case $d_{\text{first R}} = d_{\text{last S}} + 1$ and $r_i \in \left(\frac{d_{\text{first R}}-1}{10}, \frac{d_{\text{first R}}}{10}\right)$. Notice that the risky lottery may be chosen in decision $d = 1$.

Decision sequences (4), (5) and (6) are inconsistent because the subject switches between the safe and the risky lottery multiple times. In this case the inferred interval for r_i is wider, but the lower and upper bound are still well defined and satisfy $0 < \underline{r}, \overline{r} < 1$.

Finally, decision sequences (7), (8) and (9) are inconsistent since the safe lottery is chosen in the final decision $d = 10$. In this case no upper bound for the ratio interval may be inferred. Indeed, such a decision could stem from indifference, in which case $\overline{r} < 1$, or it could result from a non-increasing utility function in which case $u_i\left(h^S\right) \geqslant u_i\left(h^R\right)$, and $\underline{r} \geqslant 1$. Our data does not permit us to distinguish between these two cases, and we refrain from imposing any arbitrary upper bound.

Appendix C. Distributions of Inferred Bounds on the Ratio of Utilities in Subsamples

Figure 1 displays the cumulative distribution of inferred bounds on the ratio of utilities for students in the different treatments, separately for all sequences of choices (left panel) and for the subset of consistent sequences of choices (right panel). Comparing students' choices to the entire sample's choices (Figure 1 in the main text), we observe that distributions of inferred bounds on the ratio are very similar in the laboratory treatments where the proportion of non-students is at most 7% but distributions shift slightly to the right in the internet treatment when the sample is restricted to students (non-students constitute about 18% of the entire sample). The latter observation suggests that the degree of risk aversion is larger for students than for non-students in *Scale50PrUnknown*.

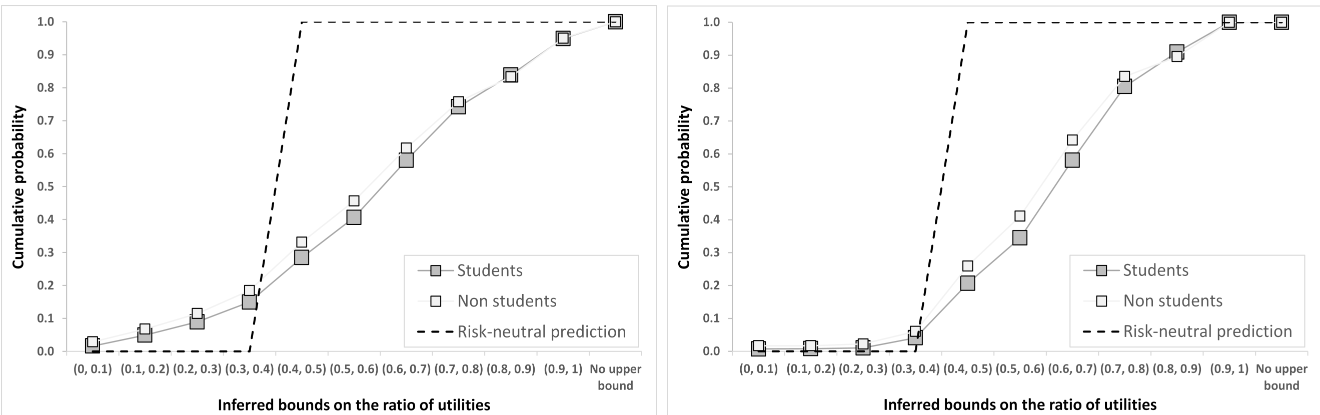


(a) All choice sequences

(b) Consistent choice sequences

Figure 1: Cumulative distributions of inferred bounds on the ratio of utilities for students

Figure 2 plots the students and the non-students cumulative distributions of inferred bounds on the ratio of utilities in *Scale50PrUnknown*, separately for all sequences of choices (left panel) and for the subset of consistent sequences of choices (right panel). It confirms that the degree of risk aversion seems larger for students than for non-students in *Scale50PrUnknown*.



(a) All choice sequences

(b) Consistent choice sequences

Figure 2: Cumulative distributions of inferred bounds on the ratio of utilities in *Scale50PrUnknown*

Appendix D. Complementary Descriptive Regression Results

In this appendix we report a series of interval regression results which complement the results reported in the main text. First, we compare the estimates of the ratio of utilities in the different incentive treatments. Second, we report the estimates of all the explanatory variables included in the regression models in Table 3 of the main text. Third, we show that the significant effect from age on risk attitudes is largely the consequence of less risk averse choices made by non-students older than most students. Finally, we compare the estimates of the CRRA index in our incentive treatments with those in the 10× and 1×10× treatments of Harrison, Johnson, McInnes, and Rutström (2005, HJMR hereafter).

D.1 Estimates of the ratio of utilities at the treatment level

Table 1 reports results from an interval regression model of ratios which only includes treatment dummies. Results for all (resp. consistent) choice sequences are shown in the left (resp. right) panel, and in each panel estimates for all subjects, non-students, part-time and full-time students are shown separately.

We observe that differences in estimated ratios between treatments vary with the education status of participants. For non-students, risk aversion in *Scale50PrUnknown* is lower than in the two laboratory treatments but there are no significant treatment effects (there are only 4 (resp. 2) non-students in the sample of *Scale50Pr1/15* (resp. *Scale10Pr1/3*)). For part-time students, risk aversion in *Scale50PrUnknown* is larger than in *Scale50Pr1/15* while it is lower than in *Scale10Pr1/3* but there are no significant treatment effects. For full-time students, risk aversion in *Scale50PrUnknown* is significantly lower than in *Scale50Pr1/15*—at the 10 (resp. 5) percent level for all (resp. consistent) choice sequences—while it is non-significantly larger than in *Scale10Pr1/3*, and risk aversion in *Scale50Pr1/15* is always significantly larger than in *Scale10Pr1/3*.

	All choice sequences				Consistent choice sequences			
	All subjects	Non-students	Part-time students	Full-time students	All subjects	Non-students	Part-time students	Full-time students
Constant	0.670***	0.654***	0.680***	0.673***	0.654***	0.634***	0.658***	0.659***
	(0.003)	(0.008)	(0.011)	(0.004)	(0.003)	(0.008)	(0.011)	(0.003)
Scale50Pr1/15	0.021	0.021	−0.076	0.047*	0.039*	0.041	−0.042	0.060**
	(0.024)	(0.099)	(0.056)	(0.028)	(0.023)	(0.091)	(0.053)	(0.026)
Scale10Pr1/3	−0.021	0.146	0.021	−0.042	−0.006	0.166	0.012	−0.022
	(0.024)	(0.139)	(0.060)	(0.026)	(0.023)	(0.129)	(0.058)	(0.025)
Log-likelihood	−6,737.82	−1,180.70	−665.67	−4,879.02	−6,234.54	−1,077.76	−608.62	−4,536.49
Observations	3,702	643	358	2,701	3,183	534	302	2,347
Left-censored obs.	0	0	0	0	0	0	0	0
Uncensored obs.	0	0	0	0	0	0	0	0
Right-censored obs.	309	59	35	215	0	0	0	0
Interval obs.	3,393	584	323	2,486	3,183	534	302	2,347

Note: * (10%); ** (5%); and *** (1%) significance level.

Table 1: Interval regression estimates for model of the utility ratio with treatment dummies only

We also note that, in line with the findings of Andersen, Harrison, Lau, and Rutström (2010), students exhibit higher risk aversion than non-students in *Scale50PrUnknown* whether all or only consistent choice sequences are considered (the comparison is less compelling in the laboratory treatments due to the small number of non-students).

D.2 Detailed interval regression results on the determinants of the ratio of utilities

Table 2 reports results from three interval regression models of ratio values for all choice sequences (left panel) and for the subset of consistent choice sequences (right panel) where coefficients are marginal effects. We rely on the full sample of participants in models 1 and 2 whereas model 3 relies on the restricted sample of students. Model 1 includes treatment dummies and controls for gender, age, employment and marital status, and whether the participant is in charge of budgeting or not. Model 2 enables us to distinguish between estimated ratios for participants with different education status (full-time students, part-time students and non-students). In addition to the explanatory variables included in model 1, model 3 controls for the duration (number of semesters) and level of education (undergraduate or graduate), the major field of study, and whether the student is primarily responsible for the payment of living expenses or not. For a given regression, participants with missing values for the included variables are omitted. An extensive discussion of the demographic and treatment effects is provided in the main text.

Table 2: Estimated ratios of utilities for interval regression models with full set of controls

	All choice sequences			Consistent choice sequences		
	All participants		Students	All participants		Students
	Model 1	Model 2	Model 3	Model 1	Model 2	Model 3
Constant	0.712***	0.671***	0.650***	0.706***	0.661***	0.647***
	(0.018)	(0.035)	(0.041)	(0.018)	(0.034)	(0.040)
Scale50Pr1/15	0.015	0.045	0.052*	0.033	0.057**	0.065**
	(0.024)	(0.028)	(0.028)	(0.023)	(0.027)	(0.026)
Scale10Pr1/3	−0.027	−0.044	−0.044	−0.012	−0.025	−0.024
	(0.024)	(0.027)	(0.027)	(0.023)	(0.026)	(0.026)
Female	0.015**	0.017**	0.016**	0.014**	0.013*	0.011
	(0.007)	(0.008)	(0.008)	(0.007)	(0.007)	(0.008)
Age	−0.002**	7E-05	−8E-05	−0.002***	−2E-04	−7E-04
	(0.001)	(0.001)	(0.002)	(0.001)	(0.001)	(0.002)
Married	0.001	−0.024	−0.017	0.002	−0.023	−0.009
	(0.017)	(0.027)	(0.030)	(0.016)	(0.026)	(0.030)
Not budgeting	0.009	0.006	0.010	0.010	0.009	0.011
	(0.008)	(0.010)	(0.010)	(0.008)	(0.009)	(0.010)
Full-time job	−0.024*	−0.054	−0.022	−0.024*	−0.038	−0.004
	(0.014)	(0.057)	(0.067)	(0.013)	(0.054)	(0.063)
Part-time job	−0.011	−0.015*	−0.015*	−0.010	−0.009	−0.009
	(0.008)	(0.009)	(0.009)	(0.007)	(0.008)	(0.009)
University job	−0.033**	−0.058**	−0.065**	−0.028*	−0.041	−0.049*
	(0.016)	(0.027)	(0.029)	(0.015)	(0.025)	(0.028)
Other job status	−0.005	−0.012	−0.013	−0.008	0.004	0.003
	(0.016)	(0.024)	(0.025)	(0.015)	(0.023)	(0.024)
Payment expenses: Self			0.009			0.002
			(0.012)			(0.012)
Payment expenses: Shared			−0.006			−0.010
			(0.009)			(0.009)

Continued on next page

Table 2 – Continued

	All choice sequences			Consistent choice sequences		
	All participants		Students	All participants		Students
	Model 1	Model 2	Model 3	Model 1	Model 2	Model 3
Payment expenses: Other			−0.008 (0.011)			−0.006 (0.011)
Semester			5E-04 (0.002)			8E-04 (0.001)
Graduate			0.005 (0.010)			0.012 (0.010)
Economics			0.023** (0.011)			0.020* (0.011)
MNE			0.037*** (0.011)			0.037*** (0.011)
SSH			0.029*** (0.010)			0.029*** (0.010)
Other field of study			0.011 (0.020)			0.014 (0.019)
Part-time student		0.051 (0.084)	0.032 (0.096)		−0.041 (0.086)	−0.012 (0.095)
PT student x *Scale50Pr1/15*		−0.132** (0.060)	−0.146** (0.063)		−0.106* (0.058)	−0.130** (0.061)
PT student x *Scale10Pr1/3*		0.057 (0.063)	0.028 (0.065)		0.032 (0.061)	0.028 (0.062)
PT student x *Female*		0.004 (0.024)	0.002 (0.025)		0.006 (0.023)	0.004 (0.025)
PT student x *Age*		−0.002 (0.003)	−1E-04 (0.004)		0.002 (0.003)	0.002 (0.004)
PT student x *Married*		0.171*** (0.065)	0.120* (0.073)		0.077 (0.077)	0.027 (0.084)
PT student x *Not budgeting*		0.033 (0.030)	0.034 (0.032)		0.023 (0.030)	0.020 (0.031)
PT student x *Full-time job*		−0.057 (0.077)	−0.083 (0.086)		−0.085 (0.075)	−0.116 (0.084)
PT student x *Part-time job*		0.002 (0.024)	0.005 (0.026)		−0.024 (0.024)	−0.014 (0.025)
PT student x *University job*		0.098 (0.073)	0.109 (0.074)		−0.004 (0.076)	0.013 (0.077)
PT student x *Other job status*		−0.047 (0.061)	−0.177** (0.075)		−0.076 (0.061)	−0.173** (0.075)
PT student x *Payment expenses: Self*			−0.012 (0.034)			−0.012 (0.033)
PT student x *Payment expenses: Shared*			3E-04 (0.032)			0.010 (0.032)
PT student x *Payment expenses: Other*			0.020 (0.042)			−0.015 (0.043)

Continued on next page

Table 2 – Continued

	All choice sequences			Consistent choice sequences		
	All participants		Students	All participants		Students
	Model 1	Model 2	Model 3	Model 1	Model 2	Model 3
PT student x *Semester*			2E-04 (0.003)			−5E-04 (0.003)
PT student x *Graduate*			−0.038 (0.030)			−0.033 (0.029)
PT student x *Economics*			−0.081** (0.034)			−0.082** (0.033)
PT student x *MNE*			0.005 (0.034)			0.002 (0.034)
PT student x *SSH*			0.033 (0.029)			0.008 (0.029)
PT student x *Other field of study*			−0.062 (0.063)			−0.098 (0.063)
Non-student		0.049 (0.093)			0.078 (0.088)	
Non-student x *Scale50Pr1/15*		−0.041 (0.098)			−0.013 (0.092)	
Non-student x *Scale10Pr1/3*		0.162 (0.133)			0.161 (0.124)	
Non-student x *Female*		−0.010 (0.019)			0.013 (0.019)	
Non-student x *Age*		−0.003* (0.002)			−0.004** (0.002)	
Non-student x *Married*		0.034 (0.036)			0.053 (0.035)	
Non-student x *Not budgeting*		−0.003 (0.024)			0.001 (0.023)	
Non-student x *Full-time job*		0.068 (0.101)			0.036 (0.095)	
Non-student x *Part-time job*		0.039 (0.084)			0.019 (0.079)	
Non-student x *University job*		0.060 (0.089)			0.035 (0.083)	
Non-student x *Other job status*		0.051 (0.088)			−0.009 (0.083)	
Log-likelihood	−6,315.83	−6,302.58	−4,953.32	−5,824.31	−5,814.31	−4,591.22
Observations	3,478	3,478	2,750	2,985	2,985	2,381
Left-censored obs.	0	0	0	0	0	0
Uncensored obs.	0	0	0	0	0	0
Right-censored obs.	294	294	223	0	0	0
Interval obs.	3,184	3,184	2,527	2,985	2,985	2,381

Continued on next page

Table 2 – Continued

	All choice sequences			Consistent choice sequences		
	All participants		Students	All participants		Students
	Model 1	Model 2	Model 3	Model 1	Model 2	Model 3

Notes: *PT student* x *MVI* refers to the interaction term between the dummy variable *Part-time student* and *MVI*, one of the main variables of interest. Similarly, *Non-student* x *MVI* refers to the interaction term between the dummy variable *Non-student* and a main variable of interest. * (10%); ** (5%); and *** (1%) significance level.

D.3 Age effect

Table 3 reports results from three interval regression models of ratios identical to those in the main text except that we control for age by partitioning subjects into three groups: (i) the 25% youngest subjects (dummy variable *Youngest*), the 25% oldest subjects (dummy variable *Oldest*), and (iii) the remaining middle-aged subjects who constitute the reference group. For the full sample of subjects, the 25% youngest are less than 22 years old whereas the 25% oldest are more than 27 years old. For the sample of full-time (resp. part-time) students, the 25% youngest are under the age of 22 (resp. 24) years whereas the 25% oldest are above the age of 26 (resp. 28) years. Finally, the 25% youngest non-students are less than 26 years old whereas the 25% oldest non-students are more than 36 years old.

We observe no significant age effect for part-time and full-time students (which in turn explains the absence of a significant age effect for all subjects). On the contrary, the youngest non-students, under the age of 26, are significantly more risk averse than those aged between 26 and 36, whereas the oldest non-students, above the age of 36, are strongly significantly less risk averse than those from the reference group. These observations are well in line with the findings reported in Andersen, Harrison, Lau, and Rutström (2010) who compare estimates of risk (and time) preferences elicited from a convenience sample of university students in Copenhagen with estimates from a sample of the adult population in Denmark.

D.4 Comparing Our CRRA Estimates with Those from Previous Studies

We compare the estimates of the CRRA index in our incentive treatments with those in the 10× and 1×10× treatments of HJMR. In treatment 1×10× participants complete HL's risk elicitation task with outcomes of the safe (resp. risky) lottery equal to US$2.00 and US$1.60 (resp. US$3.85 and US$0.10), and then they have the possibility to give up their earnings in return for the chance to complete the task with lottery outcomes scaled up by 10. In treatment 10× participants complete the task only once with lottery outcomes scaled up by 10. We exclude the choices made in treatment 1×10× with lottery outcomes scaled up by 10 from our statistical analysis.

Table 4 reports interval regression estimates of the CRRA index in the different treatments where *HJMR1x* takes value 1 if choices have been made in treatment 1×10× with low payment (1×) and *HJMR10x* takes value 1 if choices have been made in treatment 10×. Results for all (resp. consistent) choice sequences are shown in the left (resp. right) panel, and in each panel estimates for all participants and students are shown separately. In regressions with the entire sample of participants we control for age and gender and in regressions with students we additionally control for the level of education

	All choice sequences			Consistent choice sequences		
	All participants		Students	All participants		Students
	Model 1	Model 2	Model 3	Model 1	Model 2	Model 3
Constant	0.674*** (0.006)	0.675*** (0.007)	0.648*** (0.014)	0.658*** (0.006)	0.658*** (0.006)	0.627*** (0.013)
Scale50Pr1/15	0.015 (0.024)	0.046 (0.028)	0.053* (0.028)	0.034 (0.023)	0.057** (0.027)	0.066** (0.026)
Scale10Pr1/3	−0.026 (0.024)	−0.043 (0.027)	−0.044 (0.027)	−0.011 (0.023)	−0.025 (0.026)	−0.024 (0.026)
Female	0.016** (0.007)	0.016** (0.008)	0.015* (0.008)	0.015** (0.007)	0.013* (0.007)	0.011 (0.008)
Youngest	−0.002 (0.008)	−0.004 (0.008)	−0.002 (0.010)	−0.002 (0.007)	−0.002 (0.008)	0.004 (0.010)
Oldest	−0.015 (0.009)	−0.009 (0.011)	−0.009 (0.012)	−0.015* (0.009)	−0.008 (0.010)	−0.008 (0.011)
Part-time student		−0.006 (0.021)	0.038 (0.045)		0.006 (0.020)	0.049 (0.044)
PT student x *Scale50Pr1/15*		−0.136** (0.060)	−0.150** (0.063)		−0.110* (0.058)	−0.132** (0.061)
PT student x *Scale10Pr1/3*		0.053 (0.063)	0.024 (0.065)		0.032 (0.061)	0.028 (0.061)
PT student x *Female*		0.004 (0.024)	0.005 (0.025)		0.005 (0.024)	0.006 (0.026)
PT student x *Youngest*		0.015 (0.024)	−0.010 (0.028)		0.008 (0.023)	−0.008 (0.027)
PT student x *Oldest*		0.016 (0.030)	0.010 (0.032)		0.027 (0.029)	0.015 (0.032)
Non-student		−0.046 (0.083)			−0.034 (0.078)	
Non-student x *Scale50Pr1/15*		−0.030 (0.098)			−0.007 (0.092)	
Non-student x *Scale10Pr1/3*		0.165 (0.132)			0.167 (0.124)	
Non-student x *Female*		−0.013 (0.019)			0.011 (0.019)	
Non-student x *Youngest*		0.046** (0.020)			0.045** (0.020)	
Non-student x *Oldest*		−0.062*** (0.023)			−0.077*** (0.023)	
Controls for budgeting, marital status & employment status	Yes	Yes	Yes	Yes	Yes	Yes
Controls for duration and level of education, field of studies & payment of living expenses	No	No	Yes	No	No	Yes
Log-likelihood	−6,317.08	−6,298.09	−4,952.89	−5,826.90	−5,810.27	−4,590.85
Observations	3,478	3,478	2,750	2,985	2,985	2,381
Left-censored obs.	0	0	0	0	0	0
Uncensored obs.	0	0	0	0	0	0
Right-censored obs.	294	294	223	0	0	0
Interval obs.	3,184	3,184	2,527	2,985	2,985	2,381

Notes: *PT student* x *MVI* refers to the interaction term between the dummy variable *Part-time student* and *MVI*, one of the main variables of interest. Likewise, *Non-student* x *MVI* refers to the interaction term between the dummy variable *Non-student* and a main variable of interest. * (10%); ** (5%); and *** (1%) significance level.

Table 3: Interval regression estimates of the ratio of utilities for different groups of age

(undergraduate or graduate) and the major field of study. For a given regression, participants with missing values for the included variables are omitted.

	All choice sequences		Consistent choice sequences	
	All participants	Students	All participants	Students
Constant	0.771*** (0.048)	0.632*** (0.091)	0.745*** (0.046)	0.616*** (0.087)
Scale50Pr1/15	0.048 (0.076)	0.055 (0.077)	0.105 (0.070)	0.120* (0.072)
Scale10Pr1/3	−0.090 (0.075)	−0.120 (0.075)	−0.043 (0.070)	−0.049 (0.070)
HJMR1x	−0.305*** (0.055)	−0.291*** (0.054)	−0.232*** (0.052)	−0.211*** (0.052)
HJMR10x	−0.104 (0.079)	−0.078 (0.077)	−0.011 (0.076)	0.019 (0.075)
Controls for age and gender	Yes	Yes	Yes	Yes
Controls for level of education & major field of studies	No	Yes	No	Yes
Log-likelihood	−6,744.68	−5,447.31	−6,214.15	−5,041.58
Observations	3,771	3,067	3,238	2,653
Left-censored obs.	2	2	0	0
Uncensored obs.	0	0	0	0
Right-censored obs.	684	533	289	229
Interval obs.	3,085	2,532	2,949	2,424

Note: * (10%); ** (5%); and *** (1%) significance level.

Table 4: Interval regression estimates of CRRA in our treatments and in HJMR

At mean demographic values, the CRRA estimate in treatment $1\times10\times$ with low payment and in treatment $10\times$ equals 0.372 and 0.574 respectively. Compared to HJMR's treatments, we observe more risk aversion in *Scale50PrUnknown* and *Scale50Pr1/15* with CRRA estimates for all participants equal to 0.642 and 0.710 respectively (0.650 and 0.715 for students). Risk aversion in *Scale10Pr1/3* is of similar magnitude than in treatment $10\times$ with CRRA estimate for all participants equal to 0.573 (0.554 for students) and it is larger than in treatment $1\times10\times$ with low payment. We now evaluate the statistical significance of the observed differences.

HJMR recruited 178 students from the University of South Carolina to complete HL's task in their two treatments (55 participated in treatment $10\times$ and 123 in treatment $1\times10\times$). Therefore, the most appropriate comparison of CRRA estimates is between estimates in HJMR's treatments and estimates derived from the choices of our students. We find that risk aversion in treatment $1\times10\times$ with low payment is significantly lower than risk aversion in treatments *Scale50PrUnknown* and *Scale50Pr1/15* at the 1% level of significance but it is significantly lower than risk aversion in treatment *Scale10Pr1/3* only at the 10% level of significance. On the other hand, we cannot reject the null hypothesis that risk aversion in treatment $10\times$ equals the one estimated in any of our incentive treatments at any conventional significance level. These findings hold whether all or only consistent choice sequences are considered.

Appendix E. Complementary Structural Estimation Results

In this appendix we first discuss the econometric implementation of a general version of the structural model which allows for observed and unobserved heterogeneity in all three parameters. Second, we describe the estimation of this model. Third, we report on a simulation exercise to investigate the empirical identification of the model for different degrees of heterogeneity which justifies the use of the simplified model. Finally, we present additional results not reported in the paper.

E.1 A General Econometric Implementation

The econometric specification we employ in the paper assumes that all three parameters vary with observed characteristics, while only the ratio of utilities is characterized by a second, unobserved source of heterogeneity. The most general specification would allow for observed and unobserved heterogeneity in all modeling parameters. Concretely, taking into account the interval restrictions parameters are given by

$$z_i = g_z\left(\mathbf{x}_i\,\boldsymbol{\beta}^z + \tilde{\zeta}_i^z\right) \tag{1}$$

where $z \in \{r, k, w\}$, $g_k(x) = \exp(x)$ and $g_z(x) = \Lambda(x) = 1/\left(1 + \exp(-x)\right)$ for $z \in \{r, w\}$, $\mathbf{x}_i$ is a $1 \times K$ vector of regressors, $\boldsymbol{\beta}^z$ is a vector of coefficients of z, and $\tilde{\zeta}_i^z$ is the unobserved heterogeneity component of z. Assuming that $\tilde{\boldsymbol{\zeta}}_i = \left(\tilde{\zeta}_i^r, \tilde{\zeta}_i^k, \tilde{\zeta}_i^w\right)$ follows a joint normal distribution with mean $(0, 0, 0)$, covariance matrix $\Sigma'\,\Sigma$, and density $\phi_\Sigma(\cdot)$ implies that the likelihood contribution of subject i may be written as

$$\ell_i\left(\boldsymbol{\beta}^r, \boldsymbol{\beta}^k, \boldsymbol{\beta}^w, \Sigma\right) = \int_{\mathbb{R}^3} \left[\prod_{d=1}^{10} \ell_i^d\left(c_i^d \mid \Lambda\left(\mathbf{x}_i\,\boldsymbol{\beta}^r + \zeta^r\right), \exp\left(\mathbf{x}_i\,\boldsymbol{\beta}^k + \zeta^k\right), \Lambda\left(\mathbf{x}_i\,\boldsymbol{\beta}^w + \zeta^w\right)\right)\right] \phi_\Sigma\left(\boldsymbol{\zeta}\right) d\boldsymbol{\zeta}, \tag{2}$$

and the overall log-likelihood is given by

$$L\left(\boldsymbol{\beta}^r, \boldsymbol{\beta}^k, \boldsymbol{\beta}^w, \Sigma\right) = \sum_{i=1}^{I} \log\left(\ell_i\left(\boldsymbol{\beta}^r, \boldsymbol{\beta}^k, \boldsymbol{\beta}^w, \Sigma\right)\right). \tag{3}$$

While we are very much in favor of this specification with full heterogeneity, we acknowledge that practical considerations may force us to rely on a restricted version of it. In particular, it appears to be difficult to estimate heterogeneity in both k and w (von Gaudecker, van Soest, and Wengström, 2011). We therefore conducted a simulation analysis regarding the shape of the likelihood function to identify the appropriate model. Before presenting the simulation results in section , we first provide some details on the maximum likelihood estimation of (3) in the next section.

E.2 Estimation of the Econometric Model

Since the integral in (2) does not possess an analytical solution it has to be approximated. A standard simulation technique is to calculate a value of the functional at a series of randomly generated values of $\left(\tilde{\zeta}_i^r, \tilde{\zeta}_i^k, \tilde{\zeta}_i^w\right)$ and approximate the integral by the average across the function values (Train, 2003). We therefore construct a sequence of $J = 1,000$ shuffled Halton draws per parameter and individual. Letting H_i denote the $J \times 3$-matrix of Halton draws for subject i, and L the Choleski factor of Σ,[1] we then

[1] Thus, L is a lower-triangular matrix such that $L\,L' = \Sigma$.

generate J simulated values of $\tilde{\zeta}_i$ via

$$\begin{aligned}
\zeta^r_{i,j} &= L(1,1)\cdot\Phi^{-1}\left(H_i(j,1)\right),\\
\zeta^k_{i,j} &= L(2,1)\cdot\Phi^{-1}\left(H_i(j,1)\right) + L(2,2)\cdot\Phi^{-1}\left(H_i(j,2)\right),\\
\zeta^w_{i,j} &= L(3,1)\cdot\Phi^{-1}\left(H_i(j,1)\right) + L(3,2)\cdot\Phi^{-1}\left(H_i(j,2)\right) + L(3,3)\cdot\Phi^{-1}\left(H_i(j,3)\right),
\end{aligned}$$

where $\Phi^{-1}(\cdot)$ denotes the inverse cumulative distribution function of the standard normal distribution.

To maximize the (simulated) log-likelihood function (3) we employ the Broyden-Fletcher-Goldfarb-Shanno (BFGS) algorithm with numerical derivatives which we restart multiple times with random initial values to rule out local maxima. Finally, the variance-covariance matrix of the parameter estimates is based on the outer product of gradients, and standard errors for transformed parameters are calculated using the delta method.[2]

E.3 Identification of the Econometric Model

To see that the model presented above is identified in theory, consider first the model without heterogeneity. Let i denote a consistent subject who picks the safe (risky) lottery n $(10-n)$ times where $0 \leqslant n \leqslant 10$. Clearly, i's decision sequence is perfectly captured by individual parameters $r_i \in \left(\frac{n}{10}, \frac{n+1}{10}\right)$, $w_i = 0$, and $k_i \to \infty$.[3] Assume next that subject j differs from subject i by a single inconsistent decision $\hat{d}$ such that either $\hat{d} < n$ and $c_j^{\hat{d}} = -1$, or $\hat{d} > n+1$ and $c_j^{\hat{d}}$. Note that decreasing k increases the probability of choices not in line with the EU model more strongly for decisions close to the switch point $d = n+1$, while increasing w increases the probability of such deviations uniformly for all decisions. Accordingly, the decision sequence of the inconsistent subject j is best explained by $k_j \ll k_i$, $w_j = 0$ if and only if $\left|\hat{d} - (n+1)\right|$ is small, and by $k_j \to \infty$, $w_j > 0$ otherwise. Hence, k and w are both identified in theory since they capture different forms of deviation from the EU model. On the other hand r becomes identified once we consider a group of (consistent) subjects with differing frequencies of choosing the safe lottery. Allowing for observed heterogeneity does not change these results, as long as the number of explanatory variables considered is reasonably small, since it merely enables the model to distinguish between different subgroups of subjects. Unobserved heterogeneity enables the model to distinguish subjects *within* a given subgroup. Since a continuous distribution is assumed (as opposed to for instance a finite mixture model) identification is not affected by this assumption either.

While the model is identified in theory, it generates a likelihood function which is likely to be flat in k and w in a neighborhood of the likelihood-maximizing values. Concretely, since the true k (w) is likely to be large (small), changes in k and w in the neighborhood of the optimal values will lead to small changes in the likelihood function. This may pose a problem in terms of the *empirical identification* of the model. Indeed, von Gaudecker, van Soest, and Wengström (2011) argue that "in practice it appears to be difficult to estimate heterogeneity in k and w separately". We therefore conducted a simulation analysis to assess the empirical identification of different versions of the model. Concretely, for each of four different versions of the model (with and without unobserved heterogeneity in k and w), two different group sizes ($I = 10$ and $I = 20$), and various collections $(\mu_r, \sigma_r, \mu_k, (\sigma_k), \mu_w, (\sigma_w))$ of means and standard deviations of the parameters we constructed 15 simulated datasets as follows: For each subject

[2]The estimation was programmed in Stata; the code is available from the authors upon request.

[3]Incidentally, this implies that the model is not identified on the individual level.

$i = 1, \ldots, I$

(i) a vector of untransformed parameters $\left(\hat{r}_i, \hat{k}_i, \hat{w}_i\right)$ is determined by drawing for each parameter $z \in \{r, k, w\}$ a random value from the normal distribution with mean μ_z and standard deviation σ_z,

(ii) the transformed parameters are calculated via $r_i = \Lambda\left(\hat{r}_i\right)$, $k_i = \exp\left(\hat{k}_i\right)$, and $w_i = \Lambda\left(\hat{w}_i\right)$,

(iii) a decision sequence $\left(c_i^1, \ldots, c_i^{10}\right)$ is generated using 10 Bernoulli random draws with probabilities $\ell_i^d\left(c_i^d \mid r_i, k_i, w_i\right)$, $d = 1, \ldots, 10$.

For each simulated dataset and each parameter z we then performed a grid search for the likelihood-maximizing mean and standard deviation, holding fixed the mean and standard deviation of the other parameters at their true values in order to give best chances to identifying the true values. The likelihood values in the grid were simulated using the same fixed $1,000 \times 3$ shuffled Halton draws per individual.

The results of the simulation analysis are presented in Tables 1 to 4. Each table summarizes the results for a different version of the model. For a given number of subjects I, and a given vector of true means and standard deviations we report (i) the median likelihood-maximizing values of the means and standard deviations across the 15 datasets, and (ii) the differences between the true values and the median likelihood-maximizing values, normalized to lie between -1 (median at the lower bound of the grid) and +1 (median at the upper bound of the grid). There are three main findings: First, the mean and the standard deviation of the ratio of utilities r are usually well captured by the likelihood-maximizing values, regardless of the model. Second, the means of k and w are well captured, when no unobserved heterogeneity is present in either of these parameters. Third, when allowing for unobserved heterogeneity in either k or w, the standard deviations of the two parameters are badly captured, and this may affect estimation of the distribution means.

From the simulation analysis we conclude that allowing for unobserved heterogeneity in k or w might be asking too much from our data. Since unobserved heterogeneity in k or w is not essential to our research question, we will focus on the simplest of the four models, which allows for unobserved heterogeneity in r only.

10 subjects

	Simulation 1			Simulation 2			Simulation 3			Simulation 4		
	True	Median	Error	True	Median	Error	True	Median	Error	True	Median	Error
μ_r	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	-0.5	-0.2
σ_r	-1.0	-0.7	0.2	-1.0	-1.0	0.0	-1.0	-0.7	0.2	-1.0	-1.6	-0.4
μ_k	2.3	1.9	-0.2	2.3	2.3	0.0	1.4	1.4	0.0	1.4	1.4	0.0
μ_w	-1.5	-2.0	-0.2	-3.0	-4.5	-0.6	-3.0	-3.0	0.0	-1.5	-1.5	0.0

20 subjects

	Simulation 1			Simulation 2			Simulation 3			Simulation 4		
	True	Median	Error	True	Median	Error	True	Median	Error	True	Median	Error
μ_r	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
σ_r	-1.0	-1.0	0.0	-1.0	-1.3	-0.2	-1.0	-0.7	0.2	-1.0	-1.0	0.0
μ_k	2.3	2.3	0.0	2.3	2.3	0.0	1.4	1.4	0.0	1.4	1.4	0.0
μ_w	-3.0	-3.5	-0.2	-1.5	-2.0	-0.2	-3.0	-3.0	0.0	-1.5	-1.5	0.0

Table 1: Simulation Results: Model with (unobserved) heterogeneity in r only.

10 subjects

	Simulation 1			Simulation 2			Simulation 3			Simulation 4		
	True	Median	Error	True	Median	Error	True	Median	Error	True	Median	Error
μ_r	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
σ_r	-1.0	-1.0	0.0	**-1.0**	**-2.5**	**-1.0**	-1.0	-1.0	0.0	-1.0	-1.0	0.0
μ_k	2.3	2.3	0.0	2.3	2.3	0.0	1.4	1.4	0.0	2.3	2.3	0.0
μ_w	-3.0	-3.5	-0.2	-1.5	-2.5	-0.4	-3.0	-3.0	0.0	-3.0	-4.5	-0.6
σ_w	**-1.0**	**-2.5**	**-1.0**	**-1.0**	**0.5**	**1.0**	**-1.0**	**0.5**	**1.0**	**-2.5**	**-4.0**	**-1.0**

20 subjects

	Simulation 1			Simulation 2			Simulation 3			Simulation 4		
	True	Median	Error	True	Median	Error	True	Median	Error	True	Median	Error
μ_r	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
σ_r	-1.0	-1.0	0.0	-1.0	-1.3	-0.2	-1.0	-0.7	0.2	-1.0	-1.0	0.0
μ_k	2.3	2.3	0.0	2.3	3.0	0.4	1.4	1.4	0.0	2.3	2.3	0.0
μ_w	-3.0	-3.5	-0.2	-1.5	-2.0	-0.2	-3.0	-3.0	0.0	**-3.0**	**-5.5**	**-1.0**
σ_w	**-1.0**	**0.5**	**1.0**	**-1.0**	**0.5**	**1.0**	-1.0	-0.7	0.2	**-2.5**	**-4.0**	**-1.0**

Table 2: Simulation Results: Model with (unobserved) heterogeneity in r and w.

10 subjects

	Simulation 1			Simulation 2			Simulation 3			Simulation 4		
	True	Median	Error	True	Median	Error	True	Median	Error	True	Median	Error
μ_r	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
σ_r	-1.0	-1.0	0.0	-1.0	-1.3	-0.2	-1.0	-0.7	0.2	-1.0	-1.0	0.0
μ_k	2.3	2.3	0.0	2.3	2.3	0.0	1.4	1.4	0.0	2.3	2.3	0.0
σ_k	**-1.0**	**-2.2**	**-0.8**	**-1.0**	**-2.5**	**-1.0**	**-1.0**	**-2.5**	**-1.0**	-2.5	-2.8	-0.2
μ_w	-3.0	-3.5	-0.2	-1.5	-2.0	-0.2	-3.0	-2.5	0.2	-3.0	-4.0	-0.4

20 subjects

	Simulation 1			Simulation 2			Simulation 3			Simulation 4		
	True	Median	Error	True	Median	Error	True	Median	Error	True	Median	Error
μ_r	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
σ_r	-1.0	-1.0	0.0	-1.0	-1.0	0.0	-1.0	-1.0	0.0	-1.0	-1.0	0.0
μ_k	2.3	2.3	0.0	2.3	2.3	0.0	1.4	1.4	0.0	2.3	2.3	0.0
σ_k	-1.0	-1.3	-0.2	**-1.0**	**-2.5**	**-1.0**	**-1.0**	**-2.5**	**-1.0**	**-2.5**	**-4.0**	**-1.0**
μ_w	-3.0	-4.0	-0.4	-1.5	-2.0	-0.2	-3.0	-2.0	0.4	**-3.0**	**-5.5**	**-1.0**

Table 3: Simulation Results: Model with (unobserved) heterogeneity in r and k.

10 subjects

	Simulation 1			Simulation 2			Simulation 3			Simulation 4			Simulation 5		
	True	Median	Error	True	Median	Error	True	Median	Error	True	Median	Error	True	Median	Error
μ_r	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
σ_r	-1.0	-0.7	0.2	-1.0	-1.0	0.0	-1.0	-1.3	-0.2	-1.0	-1.3	-0.2	-1.0	-1.0	0.0
μ_k	2.3	2.3	0.0	1.4	1.4	0.0	2.3	3.4	0.6	2.3	2.7	0.2	2.3	2.3	0.0
σ_k	**-1.5**	**-2.5**	**-1.0**	**-1.0**	**-2.5**	**-1.0**	**-1.0**	**-2.5**	**-1.0**	-1.0	-1.3	-0.2	**-2.5**	**-4.0**	**-1.0**
μ_w	**-3.0**	**-5.0**	**-0.8**	-3.0	-2.5	0.2	-1.5	-2.5	-0.4	-3.0	-4.0	-0.4	-3.0	-3.5	-0.2
σ_w	**-1.0**	**0.2**	**0.8**	-1.0	-0.7	0.2	**-1.0**	**-2.5**	**-1.0**	-2.5	-2.8	-0.2	**-1.0**	**0.5**	**1.0**

20 subjects

	Simulation 1			Simulation 2			Simulation 3			Simulation 4			Simulation 5		
	True	Median	Error	True	Median	Error	True	Median	Error	True	Median	Error	True	Median	Error
μ_r	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
σ_r	-1.0	-1.0	0.0	-1.0	-0.7	0.2	**-1.0**	**-2.5**	**-1.0**	-1.0	-1.0	0.0	-1.0	-1.0	0.0
μ_k	2.3	2.3	0.0	1.4	1.4	0.0	2.3	1.9	-0.2	2.3	2.3	0.0	2.3	2.3	0.0
σ_k	-1.0	-0.7	0.2	-1.0	-0.7	0.2	**-1.0**	**-2.5**	**-1.0**	**-1.0**	**-2.5**	**-1.0**	-2.5	-2.2	0.2
μ_w	-3.0	-3.5	-0.2	-3.0	-2.0	0.4	-1.5	-2.0	-0.2	**-3.0**	**-5.0**	**-0.8**	-3.0	-4.5	-0.6
σ_w	**-1.0**	**0.2**	**0.8**	-1.0	-0.1	0.6	-1.0	-1.9	-0.6	**-2.5**	**-1.0**	**1.0**	**-1.0**	**0.5**	**1.0**

Table 4: Simulation Results: Model with (unobserved) heterogeneity in r, k and w.

E.4 Complete Results with a Homogeneous Sensitivity to Payoff Differences

Table 5 reports the estimation results from the structural econometric models with a homogeneous sensitivity to payoff differences k, and including all available covariates except home country. As in Table 4 in the main text the results are presented on the original parameter scale, i.e. the constant terms are given by $g_z\left(\beta^z_{\text{Constant}}\right)$, $z = r, k, w$, where $g_z(\cdot) = \Lambda(\cdot)$ for $z \in \{r, w\}$, and $g_k(\cdot) = \exp(\cdot)$, and the treatment effects are given by $g_z\left(\beta^z_{\text{Constant}} + \beta^z_{\text{Treatment}}\right) - g_z\left(\beta^z_{\text{Constant}}\right)$, $z = r, k, w$. Table 6 contains the corresponding median parameters, stratified by demographics variables.

Note that standard errors of the coefficients of the trembling probability cannot always be calculated for models 2 and 3. This is due to the fact that no inconsistent choice sequences are observed for several sub-samples of subjects. In such cases the trembling probability is zero for the sub-sample, and the maximization algorithm converges to a boundary solution. Since the likelihood function is very flat near the boundary, the algorithm is likely to encounter convergence problems. This usually results in maximum likelihood estimates with standard errors huge or lacking. To improve convergence we tried to estimate constrained versions of the models. Concretely, for model 2 we set the coefficients of *Non-student* and the interaction terms *Part-time Student* × *Scale10Pr1/3*, *Part-time Student* × *Unijob*, *Non-student* × *Scale50Pr1/15*, *Non-student* × *Scale10Pr1/3*, and *Non-student* × *Unijob* such that the transformed trembling probability equals zero for the corresponding sub-samples.[4] The constrained model 2 converged properly to the same value of the likelihood-function as the unconstrained version. Unfortunately, a similar technique could not be successfully implemented for model 3.

Table 5: All estimated parameters for model with full set of covariates.

	All Participants				Students	
	Model 1		Model 2		Model 3	
	r	w	r	w	r	w
Constant	0.749***	0.031***	0.714***	0.039***	0.697***	0.013***
	(0.017)	(0.003)	(0.040)	(0.008)	(0.048)	(0.004)
Scale10Pr1/15	0.017	-0.025***	0.056*	-0.032***	0.065**	-0.011***
	(0.027)	(0.004)	(0.033)	(0.008)	(0.032)	(0.004)
Scale10Pr1/3	-0.038	-0.026***	-0.058	-0.030***	-0.064	-0.009***
	(0.033)	(0.003)	(0.044)	(0.007)	(0.046)	(0.003)
Female	0.012	0.017***	0.015	0.022***	0.017*	0.004***
	(0.007)	(0.002)	(0.009)	(0.005)	(0.010)	(0.001)
Age	-0.002**	2.7E-04***	-1.7E-04	-1.1E-04	-0.001	0.001***
	(0.001)	(9.5E-5)	(0.002)	(3.4E-04)	(0.002)	(7.5E-05)
Married	0.003	0.005	-0.020	0.009	-0.026	0.001
	(0.017)	(0.003)	(0.035)	(0.008)	(0.042)	(0.003)
Not budgeting	0.013	0.010***	0.012	0.017***	0.014	0.005**
	(0.009)	(0.002)	(0.012)	(0.004)	(0.012)	(0.002)
Full-time job	-0.023	0.038***	-0.097	0.113***	-0.066	0.078**
	(0.016)	(0.006)	(0.145)	(0.038)	(0.160)	(0.034)

Continued on next page

[4]The concrete values we employed were -15 for the coefficient of *Non-student*, and -20 for the coefficients of the interaction terms.

Table 5: Continued

	All Participants				Students	
	Model 1		Model 2		Model 3	
	r	*w*	*r*	*w*	*r*	*w*
Part-time job	-0.017**	0.023***	-0.022**	0.027***	-0.026**	0.007***
	(0.009)	(0.003)	(0.011)	(0.006)	(0.012)	(0.003)
University job	-0.044**	-0.024***	-0.066	-0.011	-0.097*	-0.007**
	(0.021)	(0.003)	(0.043)	(0.007)	(0.052)	(0.003)
Other job status	-0.013	0.005	-0.047	-0.007	-0.054	-0.001
	(0.017)	(0.004)	(0.039)	(0.007)	(0.040)	(0.003)
Payment expenses: Self					0.021	0.003*
					(0.014)	(0.002)
Payment expenses: Shared					0.001	2.2E-04
					(0.012)	(0.001)
Payment expenses: Other					-0.008	-0.004**
					(0.014)	(0.002)
Semester					-0.001	-0.001***
					(0.002)	(3.4E-04)
Graduate					0.012	-0.002
					(0.013)	(0.001)
Economics					0.030**	-0.003*
					(0.014)	(0.002)
MNE					0.041***	0.007***
					(0.014)	(0.002)
SSH					0.032**	0.027***
					(0.013)	(0.007)
Other field of study					0.012	0.001
					(0.024)	(0.003)
Part-time student			0.093	0.069	0.068	0.231
			(0.074)	(0.065)	(0.104)	(0.192)
PT student × Scale50Pr1/15			-0.118	-0.053	-0.136	-0.181
			(0.073)	(0.054)	(0.085)	(0.167)
PT student × Scale10Pr1/3			0.070	-0.079	0.027	*-0.235*
			(0.075)	(0.065)	(0.116)	-
PT student × Female			-0.002	0.133**	0.004	0.211***
			(0.022)	(0.061)	(0.029)	(0.072)
PT student × Age			-0.003	-0.006	-0.001	-0.011
			(0.002)	(0.005)	(0.004)	(0.014)
PT student × Married			0.132***	0.230*	0.148**	0.287**
			(0.049)	(0.118)	(0.067)	(0.125)
PT student × Not budgeting			0.020	0.011	0.027	0.001
			(0.027)	(0.027)	(0.035)	(0.056)

Continued on next page

Table 5: Continued

	All Participants				Students	
	Model 1		Model 2		Model 3	
	r	w	r	w	r	w
PT student × Full-time job			-0.049	0.244**	-0.114	0.421***
			(0.166)	(0.124)	(0.195)	(0.081)
PT student × Part-time job			0.015	0.018	0.010	0.056
			(0.022)	(0.032)	(0.028)	(0.058)
PT student × University job			0.130**	-0.098	0.169**	*-0.238*
			(0.059)	(0.065)	(0.076)	-
PT student ×			-0.010	0.036	-0.181	0.208
Other job status			(0.065)	(0.063)	(0.111)	(0.170)
PT student ×					-0.023	0.021
Payment expenses: Self					(0.037)	(0.063)
PT student ×					-0.015	-0.119
Payment expenses: Shared					(0.036)	(0.093)
PT student ×					0.030	-0.126
Payment expenses: Other					(0.039)	(0.093)
PT student × Semester					3.7E-04	-0.010
					(0.004)	(0.007)
PT student × Graduate					-0.028	-0.049
					(0.035)	(0.044)
PT student × Economics					-0.095**	-0.079
					(0.048)	(0.077)
PT student × MNE					-0.006	-0.054
					(0.042)	(0.054)
PT student × SSH					0.024	0.051
					(0.037)	(0.074)
PT student ×					-0.029	-0.142
Other field of study					(0.065)	(0.206)
Non-student			0.026	-0.039***		
			(0.206)	(0.008)		
Non-student × Scale50Pr1/15			-0.096	0.032***		
			(0.197)	(0.008)		
Non-student × Scale10Pr1/3			0.176	0.030***		
			(0.130)	(0.007)		
Non-student × Female			-0.019	*-0.022*		
			(0.021)	-		
Non-student × Age			-0.003	*1.1E-04*		
			(0.002)	-		
Non-student × Married			0.023	*-0.009*		
			(0.043)	-		

Continued on next page

Table 5: Continued

	All Participants				Students	
	Model 1		Model 2		Model 3	
	r	w	r	w	r	w
Non-student × *Not budgeting*			-0.010	*-0.017*		
			(0.025)	-		
Non-student × *Full-time job*			0.139	-0.058		
			(0.248)	(0.040)		
Non-student × *Part-time job*			0.064	0.038***		
			(0.202)	(0.013)		
Non-student × *University job*			0.074	0.011		
			(0.206)	(0.007)		
Non-student ×			0.114	0.055***		
Other job status			(0.205)	(0.012)		
Standard deviation	1.019***		1.016***		0.984***	
	(0.016)		(0.016)		(0.019)	
k	17.937***		18.092***		18.857***	
	(1.103)		(1.143)		(1.411)	
Log-likelihood	-11,138.0		-11,087.7		-8,439.8	
Observations	3,478		3,478		2,750	

Regression coefficients are transformed back to the original scale, i.e. the constant is $g_z\left(\beta^z_{Constant}\right)$, coefficients of (standard) covariates are $g_z\left(\beta^z_{Constant} + \beta^z_{Covariate}\right) - g_z\left(\beta^z_{Constant}\right)$, the partial effect of setting the dummy variable to one or increasing age (or semester) by one, and coefficients of interaction terms are $g_z\left(\beta^z_{Constant} + \beta^z_{Cov.1} + \beta^z_{Cov.2} + \beta^z_{Cov.1\times Cov.2}\right) - g_z\left(\beta^z_{Constant} + \beta^z_{Cov.1}\right) - \left[g_z\left(\beta^z_{Constant} + \beta^z_{Cov.2}\right) - g_z\left(\beta^z_{Constant}\right)\right]$.

Significance level: 1% (***), 5% (**), 10% (*)

Table 6: Median elicited parameters stratified by major demographics.

		Scale50PrUnknown		*Scale50Pr1/15*		*Scale10Pr1/3*	
		r	w	r	w	r	w
All	Full-time students	0.710	0.058	0.766	0.011	0.652	0.015
	$N = (2,474 \mid 43 \mid 47)$	(0.686,0.737)	(0.037,0.097)	(0.739,0.789)	(0.007,0.027)	(0.618,0.670)	(0.009,0.035)
	Part-time students	0.708	0.041	0.639	0.016	0.724	0.000
	$N = (319 \mid 13 \mid 11)$	(0.600,0.790)	(0.020,0.169)	(0.504,0.822)	(0.004,0.083)	(0.649,0.846)	(0.000,0.000)
	Non-students	0.692	0.091	0.683	0.000	0.849	0.000
	$N = (565 \mid 4 \mid 2)$	(0.625,0.749)	(0.000,0.145)	(0.637,0.695)	(0.000,0.000)	(0.845,0.854)	(0.000,0.000)
Male	Full-time students	0.710	0.037	0.766	0.007	0.642	0.015
	$N = (1,491 \mid 18 \mid 19)$	(0.666,0.723)	(0.036,0.063)	(0.747,0.777)	(0.007,0.017)	(0.600,0.666)	(0.007,0.023)
	Part-time students	0.699	0.032	0.618	0.006	0.715	0.000
	$N = (204 \mid 4 \mid 3)$	(0.537,0.766)	(0.019,0.153)	(0.504,0.628)	(0.004,0.009)	(0.688,0.724)	(0.000,0.000)
	Non-students	0.692	0.093				
	$N = (391 \mid 0 \mid 0)$	(0.623,0.748)	(0.000,0.146)				
Female	Full-time students	0.726	0.059	0.761	0.016	0.658	0.021
	$N = (983 \mid 25 \mid 28)$	(0.703,0.738)	(0.057,0.101)	(0.739,0.790)	(0.009,0.027)	(0.618,0.682)	(0.012,0.035)
	Part-time students	0.726	0.100	0.644	0.018	0.731	0.000
	$N = (115 \mid 9 \mid 8)$	(0.651,0.869)	(0.062,0.340)	(0.582,0.822)	(0.012,0.083)	(0.649,0.846)	(0.000,0.000)
	Non-students	0.693	0.088	0.683	0.000	0.849	0.000
	$N = (174 \mid 4 \mid 2)$	(0.625,0.752)	(0.000,0.142)	(0.637,0.695)	(0.000,0.000)	(0.845,0.854)	(0.000,0.000)
Youngest 25%	Full-time students	0.711	0.058	0.767	0.011	0.646	0.015
	$N = (829 \mid 15 \mid 23)$	(0.688,0.738)	(0.037,0.098)	(0.747,0.790)	(0.007,0.027)	(0.618,0.670)	(0.009,0.025)
	Part-time students	0.726	0.077	0.649	0.017	0.750	0.000
	$N = (101 \mid 6 \mid 3)$	(0.639,0.778)	(0.028,0.169)	(0.623,0.715)	(0.008,0.025)	(0.737,0.777)	(0.000,0.000)
	Non-students	0.716	0.078	0.695	0.000	0.845	0.000
	$N = (159 \mid 1 \mid 1)$	(0.670,0.760)	(0.000,0.104)	(0.695,0.695)	(0.000,0.000)	(0.845,0.845)	(0.000,0.000)
Middle 50%	Full-time students	0.710	0.058	0.766	0.011	0.669	0.014
	$N = (1,229 \mid 19 \mid 14)$	(0.679,0.726)	(0.037,0.097)	(0.723,0.780)	(0.007,0.027)	(0.600,0.682)	(0.007,0.025)
	Part-time students	0.703	0.036	0.642	0.019	0.724	0.000
	$N = (167 \mid 4 \mid 6)$	(0.543,0.767)	(0.022,0.153)	(0.613,0.822)	(0.004,0.083)	(0.715,0.846)	(0.000,0.000)
	Non-students	0.694	0.092	0.683	0.000	0.854	0.000
	$N = (272 \mid 2 \mid 1)$	(0.654,0.729)	(0.000,0.119)	(0.676,0.689)	(0.000,0.000)	(0.854,0.854)	(0.000,0.000)
Oldest 25%	Full-time students	0.709	0.057	0.760	0.009	0.651	0.024
	$N = (416 \mid 9 \mid 10)$	(0.665,0.725)	(0.036,0.096)	(0.739,0.789)	(0.007,0.018)	(0.623,0.665)	(0.013,0.035)
	Part-time students	0.680	0.030	0.582	0.012	0.669	0.000
	$N = (51 \mid 3 \mid 2)$	(0.604,0.850)	(0.016,0.230)	(0.504,0.619)	(0.004,0.018)	(0.649,0.688)	(0.000,0.000)
	Non-students	0.643	0.124	0.637	0.000		
	$N = (134 \mid 1 \mid 0)$	(0.605,0.679)	(0.077,0.164)	(0.637,0.637)	(0.000,0.000)		
Only studying	Full-time students	0.711	0.052	0.772	0.008	0.669	0.014
	$N = (1,727 \mid 22 \mid 21)$	(0.710,0.737)	(0.037,0.083)	(0.766,0.790)	(0.007,0.016)	(0.652,0.682)	(0.009,0.021)
	Part-time students	0.712	0.028	0.654	0.016	0.737	0.000
	$N = (117 \mid 5 \mid 2)$	(0.685,0.778)	(0.019,0.093)	(0.613,0.715)	(0.004,0.025)	(0.724,0.750)	(0.000,0.000)
	Non-students	0.660	0.000				
	$N = (5 \mid 0 \mid 0)$	(0.629,0.694)	(0.000,0.000)				
Full-time job	Full-time students	0.613	0.144				
	$N = (12 \mid 0 \mid 0)$	(0.589,0.631)	(0.141,0.213)				
	Part-time students	0.531	0.161				
	$N = (18 \mid 0 \mid 0)$	(0.471,0.771)	(0.090,0.432)				
	Non-students	0.698	0.094			0.845	0.000
	$N = (244 \mid 0 \mid 1)$	(0.621,0.722)	(0.072,0.136)			(0.845, 0.845)	(0.000, 0.000)

Continued on next page

Table 6: Continued

		Scale50PrUnknown		*Scale50Pr1/15*		*Scale10Pr1/3*	
		r	w	r	w	r	w
Part-time job	Full-time students $N = (634 \mid 17 \mid 22)$	0.689 (0.687,0.716)	0.088 (0.062,0.136)	0.761 (0.747,0.772)	0.018 (0.011,0.027)	0.643 (0.627,0.658)	0.024 (0.015,0.035)
	Part-time students $N = (165 \mid 7 \mid 8)$	0.703 (0.675,0.774)	0.046 (0.029,0.164)	0.628 (0.582,0.822)	0.018 (0.008,0.083)	0.720 (0.649,0.777)	0.000 (0.000,0.000)
	Non-students $N = (145 \mid 0 \mid 0)$	0.692 (0.625,0.724)	0.110 (0.078,0.158)				
University job	Full-time students $N = (48 \mid 1 \mid 0)$	0.644 (0.621,0.662)	0.027 (0.027,0.043)	0.723 (0.723,0.723)	0.008 (0.008,0.008)		
	Part-time students $N = (8 \mid 0 \mid 0)$	0.794 (0.768,0.851)	0.000 (0.000,0.000)				
	Non-students $N = (87 \mid 0 \mid 0)$	0.660 (0.636,0.673)	0.000 (0.000,0.000)				
Other job	Full-time students $N = (53 \mid 3 \mid 4)$	0.676 (0.662,0.692)	0.044 (0.031,0.070)	0.739 (0.739,0.739)	0.009 (0.009,0.009)	0.618 (0.600,0.619)	0.012 (0.007,0.012)
	Part-time students $N = (11 \mid 1 \mid 1)$	0.654 (0.604,0.732)	0.075 (0.029,0.132)	0.504 (0.504,0.504)	0.004 (0.004,0.004)	0.846 (0.846,0.846)	0.000 (0.000,0.000)
	Non-students $N = (84 \mid 4 \mid 1)$	0.737 (0.626,0.762)	0.076 (0.052,0.146)	0.683 (0.637,0.695)	0.000 (0.000,0.000)	0.854 (0.854,0.854)	0.000 (0.000,0.000)
Not Married	Full-time students $N = (2,420 \mid 43 \mid 45)$	0.710 (0.687,0.737)	0.058 (0.037,0.097)	0.766 (0.739,0.789)	0.011 (0.007,0.027)	0.652 (0.618,0.670)	0.015 (0.009,0.035)
	Part-time students $N = (307 \mid 12 \mid 10)$	0.703 (0.600,0.770)	0.039 (0.020,0.153)	0.634 (0.504,0.715)	0.015 (0.004,0.025)	0.724 (0.649,0.777)	0.000 (0.000,0.000)
	Non-students $N = (426 \mid 4 \mid 2)$	0.700 (0.639,0.755)	0.090 (0.000,0.137)	0.683 (0.637,0.695)	0.000 (0.000,0.000)	0.849 (0.845,0.854)	0.000 (0.000,0.000)
Married	Full-time students $N = (54 \mid 0 \mid 2)$	0.689 (0.621,0.718)	0.072 (0.033,0.117)			0.641 (0.623 0.660)	0.028 (0.025 0.030)
	Part-time students $N = (12 \mid 1 \mid 1)$	0.868 (0.685,0.897)	0.291 (0.081,0.432)	0.822 (0.822,0.822)	0.083 (0.083,0.083)	0.846 (0.846,0.846)	0.000 (0.000,0.000)
	Non-students $N = (139 \mid 0 \mid 0)$	0.662 (0.608,0.708)	0.101 (0.000,0.152)				
Budgeting	Full-time students $N = (2,033 \mid 33 \mid 33)$	0.710 (0.679,0.726)	0.058 (0.036,0.097)	0.766 (0.739,0.780)	0.011 (0.007,0.018)	0.645 (0.618,0.670)	0.014 (0.009,0.025)
	Part-time students $N = (266 \mid 12 \mid 10)$	0.703 (0.543,0.743)	0.037 (0.020,0.153)	0.634 (0.504,0.822)	0.015 (0.004,0.083)	0.724 (0.649,0.846)	0.000 (0.000,0.000)
	Non-students $N = (447 \mid 4 \mid 2)$	0.692 (0.623,0.733)	0.095 (0.000,0.146)	0.683 (0.637,0.695)	0.000 (0.000,0.000)	0.849 (0.845,0.854)	0.000 (0.000,0.000)
Not Budgeting	Full-time students $N = (441 \mid 10 \mid 14)$	0.723 (0.700,0.738)	0.082 (0.053,0.136)	0.774 (0.758,0.790)	0.016 (0.010,0.027)	0.659 (0.641,0.682)	0.022 (0.013,0.036)
	Part-time students $N = (53 \mid 1 \mid 1)$	0.759 (0.707,0.868)	0.082 (0.027,0.373)	0.715 (0.715,0.715)	0.025 (0.025,0.025)	0.777 (0.777,0.777)	0.000 (0.000,0.000)
	Non-students $N = (118 \mid 0 \mid 0)$	0.700 (0.627,0.760)	0.076 (0.000,0.121)				
Expenses: Parents	Full-time students $N = (810 \mid 14 \mid 14)$	0.717 (0.677,0.744)	0.043 (0.016,0.139)	0.772 (0.739,0.804)	0.008 (0.003,0.040)	0.646 (0.587,0.684)	0.011 (0.005,0.028)
	Part-time students $N = (66 \mid 4 \mid 0)$	0.751 (0.607,0.818)	0.049 (0.015,0.241)	0.713 (0.576,0.736)	0.028 (0.002,0.044)		
Expenses: Self	Full-time students $N = (405 \mid 2 \mid 6)$	0.722 (0.674,0.756)	0.055 (0.019,0.198)	0.785 (0.784,0.785)	0.027 (0.019,0.034)	0.631 (0.626,0.672)	0.020 (0.012,0.038)
	Part-time students $N = (116 \mid 5 \mid 6)$	0.724 (0.533,0.841)	0.063 (0.013,0.298)	0.661 (0.406,0.702)	0.030 (0.013,0.045)	0.659 (0.551,0.721)	0.000 (0.000,0.000)

Continued on next page

Table 6: Continued

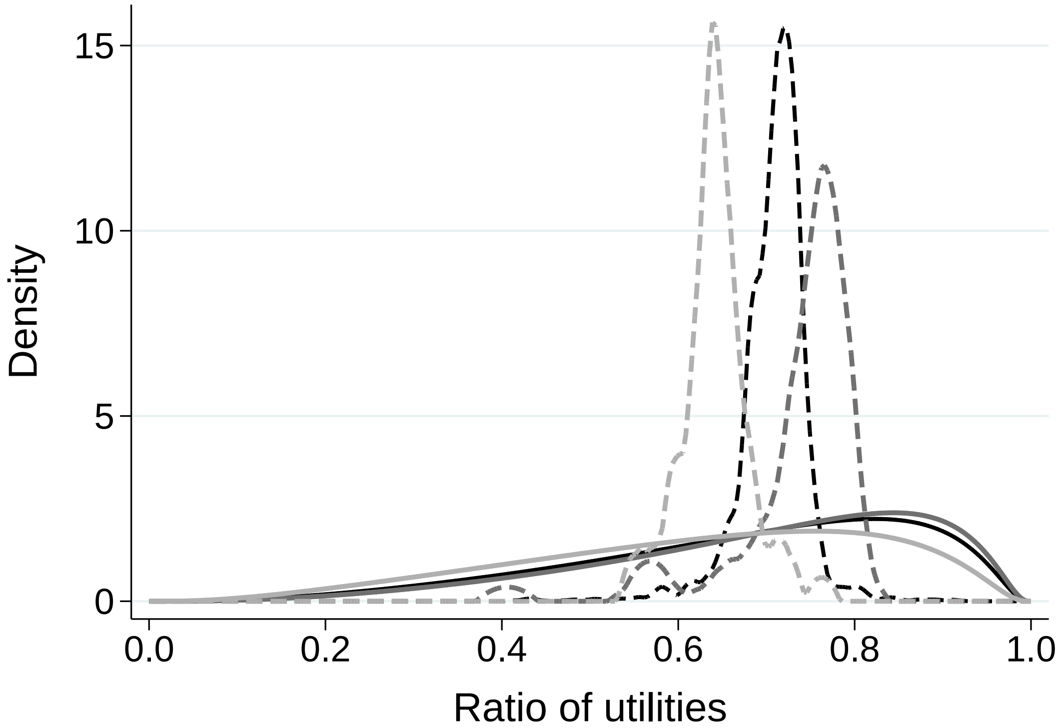
		Scale50PrUnknown r	*Scale50PrUnknown* w	*Scale50Pr1/15* r	*Scale50Pr1/15* w	*Scale10Pr1/3* r	*Scale10Pr1/3* w
Expenses: Joint	Full-time students $N = (757 \mid 21 \mid 20)$	0.709 (0.655,0.740)	0.041 (0.016,0.147)	0.765 (0.716,0.782)	0.012 (0.004,0.035)	0.640 (0.581,0.684)	0.019 (0.009,0.063)
	Part-time students $N = (89 \mid 2 \mid 3)$	0.697 (0.519,0.775)	0.023 (0.005,0.115)	0.564 (0.556,0.572)	0.005 (0.004,0.006)	0.725 (0.663,0.763)	0.000 (0.000,0.000)
Expenses: Other	Full-time students $N = (366 \mid 6 \mid 5)$	0.705 (0.653,0.733)	0.031 (0.013,0.101)	0.763 (0.735,0.784)	0.005 (0.003,0.016)	0.602 (0.554,0.643)	0.008 (0.004,0.064)
	Part-time students $N = (31 \mid 1 \mid 1)$	0.767 (0.510,0.837)	0.023 (0.007,0.121)	0.671 (0.671,0.671)	0.016 (0.016,0.016)	0.676 (0.676,0.676)	0.000 (0.000,0.000)
Field of studies: Business	Full-time students $N = (591 \mid 16 \mid 18)$	0.685 (0.649,0.712)	0.029 (0.016,0.062)	0.748 (0.716,0.776)	0.009 (0.003,0.018)	0.628 (0.554,0.653)	0.016 (0.004,0.028)
	Part-time students $N = (75 \mid 4 \mid 5)$	0.691 (0.503,0.772)	0.037 (0.009,0.264)	0.653 (0.572,0.722)	0.027 (0.004,0.041)	0.663 (0.624,0.677)	0.000 (0.000,0.000)
Field of studies: Economics	Full-time students $N = (435 \mid 8 \mid 8)$	0.715 (0.680,0.738)	0.023 (0.012,0.054)	0.774 (0.749,0.792)	0.004 (0.003,0.011)	0.636 (0.600,0.667)	0.010 (0.007,0.023)
	Part-time students $N = (57 \mid 1 \mid 1)$	0.608 (0.432,0.704)	0.021 (0.006,0.284)	0.556 (0.556,0.556)	0.006 (0.006,0.006)	0.551 (0.551,0.551)	0.000 (0.000,0.000)
Field of studies: MNE	Full-time students $N = (450 \mid 4 \mid 4)$	0.728 (0.687,0.752)	0.044 (0.019,0.084)	0.773 (0.715,0.804)	0.008 (0.005,0.012)	0.664 (0.636,0.684)	0.018 (0.012,0.024)
	Part-time students $N = (57 \mid 2 \mid 0)$	0.749 (0.546,0.839)	0.035 (0.000,0.225)	0.683 (0.661,0.704)	0.016 (0.015,0.017)		
Field of studies: SSH	Full-time students $N = (769 \mid 15 \mid 11)$	0.722 (0.687,0.748)	0.097 (0.049,0.185)	0.776 (0.754,0.803)	0.026 (0.013,0.041)	0.647 (0.626,0.693)	0.038 (0.012,0.071)
	Part-time students $N = (103 \mid 4 \mid 4)$	0.759 (0.557,0.837)	0.065 (0.014,0.241)	0.694 (0.406,0.736)	0.037 (0.013,0.045)	0.723 (0.705,0.763)	0.000 (0.000,0.000)
Field of studies: Other	Full-time students $N = (93 \mid 0 \mid 4)$	0.706 (0.664,0.727)	0.034 (0.017,0.069)			0.649 (0.643 0.655)	0.010 (0.008 0.016)
	Part-time students $N = (10 \mid 1 \mid 0)$	0.664 (0.444,0.706)	0.015 (0.004,0.077)	0.576 (0.576,0.576)	0.002 (0.002,0.002)		
Under-graduate	Full-time students $N = (1,015 \mid 28 \mid 28)$	0.712 (0.669,0.742)	0.059 (0.024,0.170)	0.770 (0.723,0.791)	0.014 (0.004,0.040)	0.640 (0.587,0.672)	0.019 (0.008,0.064)
	Part-time students $N = (88 \mid 9 \mid 4)$	0.748 (0.597,0.808)	0.065 (0.018,0.264)	0.686 (0.556,0.736)	0.030 (0.006,0.045)	0.691 (0.551,0.725)	0.000 (0.000,0.000)
Graduate	Full-time students $N = (1,323 \mid 15 \mid 17)$	0.715 (0.660,0.747)	0.033 (0.014,0.117)	0.767 (0.716,0.804)	0.007 (0.003,0.019)	0.636 (0.554,0.693)	0.009 (0.004,0.032)
	Part-time students $N = (214 \mid 3 \mid 6)$	0.707 (0.522,0.824)	0.033 (0.006,0.225)	0.572 (0.406,0.576)	0.004 (0.002,0.013)	0.669 (0.624,0.763)	0.000 (0.000,0.000)

The table shows predicted sub-sample medians and 90% confidence intervals of the utility ratio and the trembling probability along with the size of the respective sub-sample. The total number of observations is determined by the number of observations included in, respectively, model 2 (results for gender, age, employment status, marital status, and budgeting), and model 3 (results for tuition, field of studies, and graduate level for full-time students and part-time students).

E.5 Parameter Heterogeneity and Observed Characteristics

The results from the structural econometric models establish that there are important differences between sociodemographic groups. Still, the standard deviation of r is considerably and significantly larger than zero for each model, and it is reduced only slightly when taking into account more demographic covariates. This suggests that only a small part of the overall heterogeneity can be accounted for by observed characteristics. In order to assess the extent to which this is possible, Figure 1 plots for each treatment the density of the overall distribution of r against the density of the distribution implied by the observable characteristics only. The figure is based on model 3, but similar results are obtained for model 1 and

2. The figure clearly confirms that unobserved heterogeneity is an important part of individuals' risk preferences. 90% of the utility ratios predicted for treatment *Scale50PrUnknown* (*Scale50Pr1/15* and *Scale10Pr1/3*, respectively) by a model which relies on observed heterogeneity only lie in an interval that accounts for less than 20% (42% and 25%, respectively) of the distribution of r when unobserved heterogeneity is also considered. Moreover based on observed heterogeneity alone risk-loving behavior ($r < 0.4$) is predicted for less than 1% of the population in all three treatments.



Notes: Solid lines are the estimated parameter distributions taking observed and unobserved heterogeneity into account. Dashed lines are kernel density estimates over the predicted utility ratios when unobserved heterogeneity is neglected. The black, dark-gray, and light-gray lines picture, respectively, the distributions for treatment *Scale50PrUnknown*, *Scale50Pr1/15*, and *Scale10Pr1/3*.

Figure 1: Distribution of the utility ratio in the population with and without unobserved heterogeneity.

E.6 Robustness to Different Model Specifications

This section reports robustness checks which account for the influence of (heterogeneity in) the stochastic choice parameters k and w. For simplicity we focus (mainly) on the specification where the vector of covariates contains only treatment dummies.

We first consider the influence of including the two components of stochastic choice. Table 7 presents the results of the restricted model w/o trembles.

The simplified model is rejected by a likelihood ratio test (the value of the test statistic is 2,575.9 which is distributed chi-square with 3 degrees of freedom) which suggests that differences in decision errors are not captured well by differences in the sensitivity to expected utility differences. Still, the estimates confirm that there are no significant differences between treatments with respect to risk aversion. Moreover, with trembles excluded, differences in the sensitivity to expected utility differences between the internet and the laboratory become significant. We also estimated the model with stochastic decision-making

	r	k
Constant	0.691***	5.415***
	(0.003)	(0.023)
Scale50Pr1/15	0.024	4.444***
	(0.023)	(0.557)
Scale10Pr1/3	-0.030	4.147***
	(0.028)	(0.326)
Standard Deviation	0.804***	-
	(0.014)	

Number of observations is 3,702, and log-likelihood is -13,263.5. Regression coefficients are transformed back to the original scale.

Table 7: Estimated parameters for model with treatment dummies and w/o trembling.

captured solely by trembles. However, the resulting discontinuity in the likelihood function renders this model specification unsuitable for estimation with maximum simulated likelihood techniques. Indeed, from any (random) initial vector of coefficients, the model never converged and estimation steps were usually accompanied by warning messages regarding numerical derivatives and flatness of the likelihood function. Accordingly, allowing for errors in the *considered* choice probabilities is necessary to make the model amenable to maximum (simulated) likelihood techniques.

Second, we consider the influence of allowing for (observed) heterogeneity in the stochastic choice parameters. Tables 8 and 9 contain the results of the 4 models (w/o and with demographic covariates, respectively) when allowing for observed heterogeneity in the sensitivity to payoff differences.

	r	k	w
Constant	0.706***	17.537***	0.063***
	(0.004)	(1.020)	(0.002)
Scale50Pr1/15	-0.001	1.4E+06	-0.042***
	(0.004)	(1.3E+11)	(0.007)
Scale10Pr1/3	-0.033	5.416	-0.048***
	(0.035)	(8.238)	(0.005)
Standard Deviation	1.024***	-	-
	(0.015)		
Log-likelihood		-11,975.8	
Observations		3,702	
p-value (LR-test)		1.000	

Regression coefficients are transformed back to the original scale. Significance level: 1% (***), 5% (**), 10% (*)

Table 8: Estimated parameters for model with treatment dummies and observed heterogeneity in k.

Likelihood-ratio tests reveal that allowing for observed heterogeneity in k significantly improves the fit of models 2 and 3, but not for the other two models.[5] In addition, few of the coefficients of the covariates of k are significantly different from zero, and the coefficients of the estimated ratio of utilities hardly change. Furthermore treatment differences in the trembling probability are barely affected.

[5]Indeed, the log-likelihood is *lower* for the model w/o demographic covariates when allowing for observed heterogeneity in k. However, small differences in the likelihood-ratio need to be treated with care, since they may be caused by the finite number of Halton draws, or a failure of the algorithm to converge fully when the likelihood-function is very flat in the neighborhood of the optimum.

Table 9: Estimated parameters for models with observed heterogeneity in k.

	All Participants						Students		
	Model 1			Model 2			Model 3		
	r	k	w	r	k	w	r	k	w
Constant	0.749***	22.309***	0.033***	0.714***	20.465*	0.038***	0.682**	30.446	0.014**
	(0.019)	(5.579)	(0.005)	(0.040)	(10.597)	(0.010)	(0.040)	(19.425)	(0.005)
Scale50Pr1/15	0.018	7.973	-0.027***	0.055	3.832	-0.031*	0.065*	3.825	-0.012
	(0.026)	(16.744)	(0.007)	(0.035)	(25.654)	(0.018)	(0.034)	(49.901)	(0.009)
Scale10Pr1/3	-0.038	9.935	-0.027***	-0.069***	2.8E+05	-0.027***	-0.069**	3.7E+04	-0.009**
	(0.032)	(16.106)	(0.004)	(0.015)	(3.8E+08)	(0.007)	(0.010)	(5.3E+06)	(0.004)
Female	0.013*	-1.931	0.017***	0.014	-2.406	0.020***	0.020**	-3.287	0.004**
	(0.007)	(2.409)	(0.003)	(0.010)	(2.841)	(0.005)	(0.008)	(4.386)	(0.002)
Age	-0.002**	-0.147	2.0E-04	-1.3E-04	-0.060	-3.9E-05	2.3E-05	-0.508	0.001**
	(0.001)	(0.247)	(1.5E-4)	(0.002)	(0.460)	(4.1E-04)	(0.002)	(1.162)	(9.1E-05)
Married	0.002	0.028	0.006	-0.029*	4.7E+02	0.018*	-0.014	12.867	0.002
	(0.019)	(6.551)	(0.005)	(0.016)	(7.2E+03)	(0.011)	(0.023)	(33.448)	(0.003)
Not budgeting	0.013	0.335	0.010***	0.013	1.080	0.017***	0.012	-0.414	0.005**
	(0.009)	(3.297)	(0.003)	(0.012)	(3.975)	(0.006)	(0.009)	(5.216)	(0.002)
Full-time job	-0.022	-1.393	0.040***	-0.089	1.4E+02	0.110**	-0.056	6.9E+02	0.088**
	(0.017)	(5.033)	(0.009)	(0.118)	(7.4E+03)	(0.043)	(0.126)	(4.7E+04)	(0.044)
Part-time job	-0.017*	-3.029	0.022***	-0.023**	-1.344	0.025***	-0.023**	-0.342	0.008**
	(0.009)	(2.547)	(0.004)	(0.011)	(3.007)	(0.007)	(0.009)	(4.479)	(0.003)
University job	-0.043**	3.443	-0.025***	-0.052	2.922	-0.010	-0.114**	6.3E+04	-0.005
	(0.021)	(7.390)	(0.004)	(0.044)	(31.487)	(0.025)	(0.013)	(9.1E+06)	(0.003)
Other job status	-0.013	-1.684	0.004	-0.034	22.518	-0.006	-0.055*	24.838	-4.2E-04
	(0.018)	(4.922)	(0.005)	(0.025)	(2.2E+02)	(0.007)	(0.032)	(1.9E+02)	(0.004)
Payment expenses: Self							0.012	-8.423	0.001
							(0.011)	(6.068)	(0.002)

Continued on next page

Table 9: Continued

	All Participants						Students		
	Model 1			Model 2			Model 3		
	r	k	w	r	k	w	r	k	w
Payment expenses: Shared							-2.0E-04	-3.207	-7.2E-05
							(0.009)	(5.171)	(0.001)
Payment expenses: Other							-0.018	0.299	-0.004**
							(0.014)	(6.465)	(0.002)
Semester							-0.001	0.208	-0.001**
							(0.002)	(0.880)	(4.6E-04)
Graduate							0.014	5.617	-0.001
							(0.012)	(7.845)	(0.001)
Economics							0.032**	-1.211	-0.003
							(0.012)	(5.679)	(0.002)
MNE							0.044**	-2.994	0.007**
							(0.012)	(5.768)	(0.003)
SSH							0.035**	-5.400	0.027**
							(0.011)	(6.338)	(0.009)
Other field of study							0.016	-6.829	-0.001
							(0.017)	(8.825)	(0.004)
Part-time student				0.096	-18.158*	-0.032***	-0.063	49.174	0.204
				(0.081)	(10.751)	(0.012)	(0.133)	(92.944)	(0.476)
PT student × Scale50Pr1/15				-0.157**	2.9E+04	0.027	-0.191	6.2E+02	-0.103
				(0.075)	(7.0E+07)	(0.019)	(0.117)	(2.6E+03)	(0.244)
PT student × Scale10Pr1/3				0.040	-2.8E+05	0.021*	0.060	5.9E+06	-0.209
				(0.066)	(3.8E+08)	(0.011)	(0.043)	(2.9E+10)	(0.615)
PT student × Female				0.002	1.533	-0.013	0.012	-62.496	-0.100
				(0.024)	(2.957)	(0.009)	(0.038)	(77.633)	(0.199)

Continued on next page

Table 9: Continued

	All Participants						Students		
	Model 1			Model 2			Model 3		
	r	k	w	r	k	w	r	k	w
PT student × Age				-0.004	0.344	0.001	0.005	1.230	-0.007
				(0.002)	(0.488)	(4.7E-04)	(0.006)	(3.001)	(0.029)
PT student × Married				0.139***	-4.8E+02	-0.022**	0.234**	-64.970	-0.219
				(0.043)	(7.2E+03)	(0.011)	(0.080)	(67.888)	(0.921)
PT student × Not budgeting				0.018	-2.143	-0.022***	0.046	-10.287	-0.110
				(0.031)	(4.084)	(0.008)	(0.043)	(28.289)	(0.246)
PT student × Full-time job				-0.037	-1.4E+02	-0.088*	-0.132	-7.6E+02	0.023
				(0.151)	(7.4E+03)	(0.049)	(0.165)	(4.7E+04)	(0.198)
PT student × Part-time job				0.019	-0.074	-0.028***	-0.010	-44.427	-0.092
				(0.022)	(3.273)	(0.008)	(0.035)	(56.886)	(0.158)
PT student × University job				0.117*	-4.074	0.004	0.188**	-6.3E+04	-0.213
				(0.067)	(31.524)	(0.029)	(0.080)	(9.1E+06)	(0.707)
PT student × Other job status				-0.050	-24.160	-3.5E-04	-0.085	7.7E+02	0.407
				(0.073)	(2.2E+02)	(0.012)	(0.118)	(1.3E+05)	(0.307)
PT student ×							-0.017	8.692	0.152
Payment expenses: Self							(0.048)	(28.781)	(0.223)
PT student ×							-0.010	37.298	-0.069
Payment expenses: Shared							(0.044)	(55.035)	(0.155)
PT student ×							0.086	-8.873	-0.144
Payment expenses: Other							(0.055)	(32.768)	(0.371)
PT student × Semester							-0.002	13.222	0.005
							(0.005)	(16.764)	(0.011)
PT student × Graduate							-0.064	46.075	-0.012
							(0.043)	(93.963)	(0.093)

Continued on next page

Table 9: Continued

	All Participants						Students		
	Model 1			Model 2			Model 3		
	r	k	w	r	k	w	r	k	w
PT student × Economics							-0.079	-56.393	-0.185
							(0.049)	(72.354)	(0.394)
PT student × MNE							0.022	-55.492	-0.119
							(0.048)	(71.191)	(0.237)
PT student × SSH							0.052	-66.656	-0.179
							(0.042)	(84.395)	(0.291)
PT student × Other field of study							-0.039	1.1E+04	-0.040
							(0.062)	(2.5E+06)	(0.173)
Non-student				0.024	-17.488	-0.038			
				(0.232)	(2.4E+02)	(0.032)			
Non-student × Scale50Pr1/15				-0.060	7.1E+02	*0.031*			
				(0.061)	(2.3E+05)	-			
Non-student × Scale10Pr1/3				0.221	-2.1E+05	*0.027*			
				(0.157)	(2.8E+08)	-			
Non-student × Female				-0.018	5.932	-0.020*			
				(0.020)	(2.8E+02)	(0.011)			
Non-student × Age				-0.003	0.473	4.1E-05			
				(0.002)	(33.055)	(1.6E-03)			
Non-student × Married				0.036	-4.7E+02	-0.018			
				(0.027)	(7.2E+03)	(0.013)			
Non-student × Not budgeting				-0.006	11.413	-0.017*			
				(0.023)	(1.0E+03)	(0.010)			
Non-student × Full-time job				0.138	-1.4E+02	-0.088*			
				(0.257)	(7.4E+03)	(0.053)			

Continued on next page

Table 9: Continued

	All Participants						Students		
	Model 1			Model 2			Model 3		
	r	k	w	r	k	w	r	k	w
Non-student × *Part-time job*				0.071	-1.446	-0.009			
				(0.228)	(2.4E+02)	(0.031)			
Non-student × *University job*				0.073	-5.363	*0.010*			
				(0.233)	(2.4E+02)	-			
Non-student × *Other job status*				0.089	-25.212	0.019			
				(0.229)	(3.2E+02)	(0.031)			
Standard deviation	1.017***	-	-	1.026***	-	-	0.986**	-	-
	(0.016)			(0.016)			(0.016)		
Log-likelihood		-11,132.3			-11,061.9			-8,391.1	
Observations		3,478			3,478			2,750	
p-Value (H0: k=const.)		0.320			0.045			0.000	

Regression coefficients are transformed back to the original scale, i.e. the constants are given by $g_z\left(\beta^z_{\text{Constant}}\right)$, where $g_z(\cdot) = \Lambda(\cdot)$, $z = r, w$, and $g_k(\cdot) = \exp(\cdot)$, and represent the median parameters in treatment $Scale50PrUnknown$. Effects of standard covariates are $g_z\left(\beta^z_{\text{Constant}} + \beta^z_{\text{Covariate}}\right) - g_z\left(\beta^z_{\text{Constant}}\right)$. Interaction effects are $g_z\left(\beta^z_{Constant} + \beta^z_{Cov.1} + \beta^z_{Cov.2} + \beta^z_{Cov.1\times Cov.2}\right) - g_z\left(\beta^z_{Constant} + \beta^z_{Cov.1}\right) - \left[g_z\left(\beta^z_{Constant} + \beta^z_{Cov.2}\right) - g_z\left(\beta^z_{Constant}\right)\right]$.

Significance level: 1% (***), 5% (**), 10% (*)

	Homogeneous w		Homogeneous k and w
	r	k	r
Constant	0.706***	17.436***	0.706***
	(0.004)	(0.974)	(0.004)
Scale50Pr1/15	0.024	9.273	0.023
	(0.028)	(17.824)	(0.029)
Scale10Pr1/3	-0.073***	5.0E+05	-0.033
	(0.008)	(1.1E+09)	(0.036)
Standard Deviation	1.023***	-	1.021***
	(0.014)		(0.015)
Constant k	-		17.636***
			(1.008)
Constant w	0.061***		0.061***
	(0.002)		(0.002)
Log-likelihood	-11,986.2		-11,987.0
Observations	3,702		3,702
p-value (LR-test)	1.7E-4		3.0E-5

Regression coefficients are transformed back to the original scale.

Significance level: 1% (***), 5% (**), 10% (*)

Table 10: Estimated parameters for model with treatment dummies and w/o (observed) heterogeneity in w, or k and w.

Still, allowing k to vary with demographics refines some results for the trembling probability. Accordingly, decision errors of some sub-samples of subjects are better captured by a smaller trembling probability and a lower sensitivity to payoff differences (see e.g. the coefficient of *Part-time Student* in model 2), or vice versa (e.g. *Part-time Student* × *Scale50Pr1/15* in models 2 and 3).

Finally, table 10 presents the results of two model specifications which restrict, respectively, w, and k and w to be homogeneous across subjects. Only treatment dummies are included in the vector of covariates. Both specifications confirm the results regarding treatment effects on risk preferences. On the other hand when only w is restricted to be homogeneous there are no treatment differences with respect to the sensitivity to payoff differences, and the model is rejected by a likelihood ratio test (the value of the test statistic is 20.83 which is distributed chi-square with 2 degrees of freedom). When both k and w are assumed homogeneous, the estimated trembling probability is heavily distorted towards the estimated trembling probability for treatment *Scale50PrUnknown* and the model is rejected by a likelihood ratio test (the test statistic is 22.35 which is distributed chi-square with 4 degrees of freedom).

The results strongly confirm our claim that treatment differences between the laboratory and the internet are best captured by differences in the trembling probabilities. On the other hand randomness in the considered choice probabilities is important for estimation purposes, since it generates a reasonably smooth likelihood function. Our results therefore support the interpretation of Loomes, Moffatt, and Sugden (2002) that the tremble component of stochastic decision-making is a form of error which individuals can learn to avoid, while the component captured by the sensitivity to differences in expected utility results from the imprecision of people's preferences, and may be an inherent and stable property of preferences.[6]

[6]Notice however, that Loomes, Moffatt, and Sugden (2002) mainly argue about the random preference model.

Appendix F. Literature Review

Though our study seems to be the first to offer detailed evidence on the strength of monetary incentives depending on nominal payoffs and the selection probability, existing economic experiments provide some indicative evidence on the motivation effectiveness of BRIS.[7]

Herding behavior in financial markets under various BRISs is studied in Drehmann, Oechssler, and Roider (2005) who report the results of an Internet experiment with 4 phases (we exclude from our discussion their control group of 267 consultants from McKinsey & Company). In each phase subjects who make successful decisions earn tickets in a lottery to win one of the main prizes. In phase I, II and III, each lottery ticket has an equal chance of winning a prize of 1,000 Euros and the *average* selection probability is 5/1,409, 5/3,261 and 1/1,162 respectively, the first two selection probabilities being public knowledge and the third one being unknown. In phase IV each lottery ticket has an equal chance of winning a prize of 100 Euros and the publicly known *average* selection probability is 1/40. The authors conclude that the phase of the experiment has no significant effect on the patterns of observed responses.

Harrison, Lau, and Williams (2002) elicit individual discount rates for a nationally representative sample of the Danish population where nominal payoffs range from US$450 to US$1,840 (depending on the payment date) and one out of either 5, 10 or 15 participants receives actual payment (depending on the experimental session). The authors report that the level of the selection probability does not significantly impact predicted discount rates.

Two experimental studies compare the degree of risk aversion in HL's task when subjects are paid with a 1-in-10 probability and when subjects are paid for certain. Harrison, Lau, and Rutström (2007, footnote 16) report a small experiment where in the control condition 51 subjects complete HL's $10\times$ task and in the treatment condition 26 subjects complete the same task but with a 10% selection probability. They find that the estimated CRRA coefficient in the treatment condition is 0.11 lower than the control but with a standard error of 0.13. Accordingly, they cannot reject the null hypothesis that paying subjects with a 1-in-10 probability generates the same responses as paying them for certain in HL's task with $10\times$ nominal payoffs. In Laury, McInnes, and Swarthout (2012) subjects complete a modified HL's task with a menu of 20 paired lottery choices, lottery outcomes equal those in the $90\times$ payoff scale treatment, and only 10% of subjects on average receive payment. Their average number of safe choices indicates a lower CRRA coefficient than the one observed in the original Holt and Laury study for the same scale of nominal payoffs and a 100% selection probability. In HL's task with very large nominal payoffs only paying 10% of the subjects seems to dilute monetary incentives. However, one has to bear in mind that the two risk treatments differ with respect to other aspects than just the level of the selection probability (e.g. the menu of choices between the two lotteries and the presence of an order effect in the original Holt and Laury study).

Baltussen, Post, van den Assem, and Wakker (2012) investigate the capacity of BRIS to motivate subjects in a dynamic choice experiment. In the basic treatment subjects play the *Deal or No Deal* game once and for real payment. In the BRIS treatment subjects play the *Deal or No Deal* game once with identical nominal payoffs as in the basic treatment but with a 10% chance of real payment. Expected payoffs are ten times lower in the BRIS than in the basic treatment and, on average, subjects earned about 50 Euros in the basic treatment but only 5 Euros in the BRIS treatment. The authors find that

[7] There is also evidence in favor of the attractiveness of BRIS. In Abdellaoui, Baillon, Placido, and Wakker (2011) 31 subjects were asked which payoff scheme would motivate them better, paying each of them one randomly selected choice with moderate prizes or paying one of them one randomly selected choice with large prizes. Subjects expressed a clear preference for the latter payoff scheme.

between-subjects randomization significantly reduces risk aversion and generates an increase in subjects' error rates.

The existing evidence on simple choice tasks suggests that i) huge nominal payoffs (1,000 Euros) and a tiny selection probability (less than 0.25%) motivates subjects as well as large nominal payoffs (100 Euros) and a small selection probability (2.5%); ii) subjects' motivation is unaffected by whether the selection probability is known or not; and iii) for sufficiently large nominal payoffs, the dilution of monetary incentives following a reduction of the selection probability by a factor of up to ten reduces weakly subjects' motivation, if at all. In a more complex and dynamic task however a reduction of the selection probability by a factor of ten impacts significantly subjects' motivation. Finally, though the evidence suggests that the use of BRIS does not alter significantly ultimatum game behavior (see Armantier, 2006, and references therein), dictator game behavior is more egalitarian under BRIS possibly due to warm-glow effects (Sefton, 1992; Stahl and Haruvy, 2006).

Evidence From Within-Subjects Selection

Most large-scale economic experiments, including ours, combine BRIS with the *within-subjects random incentive system* (WRIS) where each subject performs a series of individual tasks knowing that only one of these tasks will be randomly selected for real payment. Evidence on the capacity of WRIS to motivate subjects is potentially informative about the motivation effectiveness of BRIS though the two incentive systems are likely to impact subjects' motivation differently. In Wilcox (1993) subjects decide between pairs of lotteries and only one decision is randomly selected for payment. In the simple treatment subjects face one-stage lotteries whereas in the complex treatment they face equivalent two-stage versions of the former lotteries. The probability that a given decision is selected for payment differs between decisions. The author finds that increasing the selection probability improves decisions in the complex treatment but makes no difference in the simple treatment suggesting that the dilution of monetary incentives has no impact on subjects' motivation for choosing between one-stage lotteries. In Laury (2012) subjects complete HL's task with baseline payoffs in treatment "1× Pay One" and with baseline payoffs scaled up by a factor of 10 in treatment "10× Pay One". In treatment "1× Pay All" nominal payoffs equal those in treatment "1× Pay One" but all ten decision are paid. The author observes no significant difference between risk aversion in treatments "1× Pay One" and "1× Pay All" but scaling up nominal payoffs by a factor of 10 causes a statistically significant increase in risk aversion. These observations suggest that there is little impact on subjects' motivation from paying only one of the many simple choice tasks they performed. Baltussen, Post, van den Assem, and Wakker (2012) also consider a WRIS treatment where subjects play the *Deal or No Deal* game ten times, one of which is then randomly selected for real payment. The authors find that risk aversion in the WRIS treatment is not different from that in the basic treatment though subjects' error rates are larger.

Evidence on the motivation effectiveness of WRIS suggests that the selection probability has little impact on subjects' motivation in simple choice tasks. The evidence is however mixed in more complex tasks.

References

Abdellaoui, M., A. Baillon, L. Placido, and P. Wakker (2011): “The Rich Domain of Uncertainty: Source Functions and Their Experimental Implementation,” *American Economic Review*, 101, 695–723.

Andersen, S., G. Harrison, M. Lau, and E. Rutström (2010): “Preference Heterogeneity in Experiments: Comparing the Field and Laboratory,” *Journal of Economic Behavior and Organization*, 73, 209–224.

Armantier, O. (2006): “Do Wealth Differences Affect Fairness Considerations?,” *International Economic Review*, 47, 391–429.

Baltussen, G., T. Post, M. J. van den Assem, and P. P. Wakker (2012): “Random Incentive Systems in a Dynamic Choice Experiment,” *Experimental Economics*, 15, 418–443.

Drehmann, M., J. Oechssler, and A. Roider (2005): “Herding and Contrarian Behavior in Financial Markets: An Internet Experiment,” *American Economic Review*, 95, 1403–1426.

Harrison, G., E. Johnson, M. McInnes, and E. Rutström (2005): “Risk Aversion and Incentive Effects: Comment,” *American Economic Review*, 95, 897–901.

Harrison, G., M. Lau, and E. Rutström (2007): “Estimating Risk Attitudes in Denmark: A Field Experiment,” *Scandinavian Journal of Economics*, 109, 341–368.

Harrison, G., M. Lau, and M. Williams (2002): “Estimating Individual Discount Rates in Denmark: A Field Experiment,” *American Economic Review*, 92, 1606–17.

Laury, S. (2012): “Pay One or Pay All: Random Selection of One Choice for Payment,” Discussion Paper, Andrew Young School, Georgia State University.

Laury, S., M. McInnes, and J. Swarthout (2012): “Avoiding the Curves: Direct Elicitation of Time Preferences,” *Journal of Risk and Uncertainty*, 44, 181–217.

Loomes, G., P. G. Moffatt, and R. Sugden (2002): “A Microeconometric Test of Alternative Stochastic Theories of Risky Choice,” *Journal of Risk and Uncertainty*, 24(2), 103–130.

Sefton, M. (1992): “Incentives in Simple Bargaining Games,” *Journal of Economic Psychology*, 13, 263–267.

Stahl, D. O., and E. Haruvy (2006): “Other-Regarding Preferences: Egalitarian Warm Glow, Empathy, and Group Size,” *Journal of Economic Behavior and Organization*, 61, 20–41.

Train, K. (2003): *Discrete Choice Methods with Simulation.* Cambridge University Press, New York.

von Gaudecker, H., A. van Soest, and E. Wengström (2011): “Heterogeneity in Risky Choice Behavior in a Broad Population,” *American Economic Review*, 101, 664–694.

Wilcox, N. (1993): “Lottery Choice: Incentives, Complexity and Decision Time,” *Economic Journal*, 103, 1397–1417.