Estimating Risk Attitudes in Conventional and Artefactual Lab Experiments: The importance of the underlying assumptions

Andreas C. Drichoutis[1] and Phoebe Koundouri[2]

[1]Dept. of Economics, University of Ioannina, University campus, Ioannina, Greece, email: adrihout@cc.uoi.gr, tel: +30-26510-05954, corresponding author

[2] Dept. of International and European Economic Studies, Athens University of Economics and Business, 76 Patision st., 10434, Greece, email: pkoundouri@aueb.gr

Abstract

In this paper we assess the importance of sample type in the estimation of risk preferences. We elicit and compare risk preferences from student subjects and subjects drawn from the general population, using the multiple price list method devised by Holt and Laury (2002). We find evidence suggesting that under Rank Dependent Utility, students exhibit approximately risk neutral preferences while subjects drawn from the general population exhibit risk loving preferences. However, when we assume an incorrect characterization of risk preferences, in particular we adopt the framework of Expected Utility theory, our estimation results lead to erroneous inferences. In this case, students are on average risk averse, while subjects drawn from the general population exhibit risk neutrality. Our results have implications for economic policy making under uncertainty.

Keywords: Risk aversion, CRRA, expo-power, rank dependent utility, multiple price list

JEL codes: C91, D01, D81

1. Introduction

Economic lab experiments have been mainly performed in academic environments and students have therefore posed as the natural standard subject pool. Whether student samples provide a reliable sample for extrapolating results to the general population is an issue that is heavily criticized. Concerns on the use of students as research surrogates for consumers or adults in general, is rather old (Enis *et al.*, 1972; McNemar, 1946). Reasons are attributed to the fact that students exhibit psychological, social and demographical differences from other segments of the population but also to the fact that students are not yet complete personalities.

In addition, most decisions in life and in the lab are made under conditions of uncertainty, rendering risk behavior as a fundamental concept in the economic decision making process. Risk preferences are important to decisions varying from career choice to stock picking (Barsky *et al.*, 1997), as well as production decisions (Koundouri *et al.*, 2009; 2006) and agri-environmental policy making (see for example, Isik, 2002; Karagiannis, 1999; Xavier et al., 2011). If risk-neutrality is not a general characterization of the sample under investigation, it is important to know the subject's pool preferences over risk. Several studies in the literature have examined a plethora of issues on risk preference elicitation e.g., the stability of risk preferences across elicitation methods (Anderson & Mellor, 2009), risk preferences and physical prowess (Ball *et al.*, 2010) as well as the complexity of the elicitation method (Dave *et al.*, 2010). However, only a few studies have examined risk preferences with respect to the nature of the subject pool and results have not been uniform (2010; Andersen *et al.*, 2011). This study sheds more light to risk preference elicitation in a conventional lab experiment (i.e., using a student subject pool) and an artefactual lab experiment (i.e., using a general population subject pool) in the Harrison and List (2004) terminology.

2. Experimental data

We compiled data from two previous experiments that involved risk preference elicitations tasks. These two experiments were part of a larger project on choice under risk, which also involved some standard experimental auction tasks. Experimental instructions for the experiments are available at https://sites.google.com/site/riskprefs/. The first experiment used a student subject pool, while the second experiment used a subject pool drawn from the general population. General population subjects were recruited by a professional company. The same proctor was used in both experiments, i.e., one of the authors.

In the student subject pool experiment, the purpose was to explore whether risk preferences can be manipulated by some treatment variables, so we only used data from the control treatment sessions. In the consumer subject pool experiment, risk preferences were not part of the experimental manipulation. In all, we used elicited risk preferences from 34 general population subjects and 23 student subjects. Given that data were compiled from previous experiments, we had no control on sample size. Although in small sample sizes results may be more sensitive to outliers, Grubb's (1969) test for outliers showed this is not a problem with our data. In the student subject pool experiment, in one session the auction task was placed after risk elicitation. For all other subjects, risk elicitation followed the auction. We use a dummy variable in our econometric estimation to control for this session-specific characteristic.

To elicit risk preferences we used the multiple price list (MPL) design devised by Holt and Laury (2002). In this design each subject is presented with a choice between two lotteries, A or B as illustrated in Table 1. In the first row the subject is asked to make a choice between lottery A, which offers a 10% chance of receiving €2 and a 90% chance of receiving €1.6, and lottery B, which offers a 10% chance of receiving €3.85 and a 90% chance of receiving €0.1. The expected value of lottery A is €1.64 while for lottery B it is €0.475, which results in a difference of €1.17 between the expected values of the lotteries. Proceeding down the table to the last row, the expected values of the lotteries increase but increases much faster for lottery B.

For each row, a subject chooses A or B and one row is then randomly selected as binding for the payout. The last row is a simple test of whether subjects understood the instructions correctly. In our experiments subjects undertook three risk aversion tasks: they made choices from Table 1 (the 1x table), a table where payoffs were scaled up by 10 (the 10x table) and a table similar to Table 1 but without the last three rows (the framed table). The order of appearance of the tables for each subject was completely randomized to avoid order effects (Harrison *et al.*, 2005). One of these tables was chosen at the end as binding for the payout. Thus, to infer risk preferences, subjects were asked to provide 27 binary choices from the risk preference task. Table 1 also shows implied Relative Risk Aversion coefficients under the assumption of Expected Utility Theory (EUT).

3. Estimation and Results

To estimate risk attitudes and assess the importance of the sample type as well as the demographics on risk preferences, we follow similar procedures to Holt and Laury (2002) and Harrison, et al. (2007).

Let the utility function be the constant relative risk aversion (CRRA) specification:

$$U(M)=\frac{M^{1-r}}{1-r} \qquad (1)$$

for $r\neq 1$, where r is the CRRA coefficient. In (1), r=0 denotes risk neutral behavior, r>0 denotes risk aversion behavior and r<0 denotes risk loving behavior.

The binary choices of the subjects in the risk preference tasks can be explained by different CRRA coefficients (as reported in Table 1).

If we assume that Expected Utility Theory holds for the choices over risky alternatives, the likelihood function for the choices that subjects make can be written for each lottery i as:

$$EU_i=\sum_{j=1,2}\left(p\left(M_j\right)\cdot U\left(M_j\right)\right) \qquad (2)$$

where $p\left(M_j\right)$ are the probabilities for each outcome M_j that are induced by the experimenter. To specify the likelihoods conditional on the model, the Luce stochastic specification is used. The expected utility (EU) for each lottery pair is calculated for candidate estimate of r, and the ratio:

$$\nabla EU = \frac{\exp\left(EU_B/c/\mu\right)}{\exp\left(EU_A/c/\mu\right)+\exp\left(EU_B/c/\mu\right)} \tag{3}$$

is then calculated where EU_A and EU_B refer to options A and B respectively, and μ is a structural noise parameter used to allow some errors. The index in (3) is linked to observed choices by specifying that the option B is chosen when $\nabla EU > 1/2$. In (3), c is a normalizing term for each lottery pair A and B. The normalizing term is defined as the maximum utility over all prizes in this lottery pair minus the minimum utility over all prizes in this lottery pair. Since the value of c varies between lottery choices, it is said to be "contextual." This contextual utility specification proposed by Wilcox (2011), basically accounts for lottery specific heteroskedasticity. Drichoutis and Lusk (2012) have shown that different error specifications, with and without accounting for contextual utility, produce strikingly different results in models of individual decision making under risk. They also show that certain model fit criteria can be used to identify the model that best fits the data. In our case, the contextual utility specification provides the best model fit with our data.

The conditional log-likelihood can then be written as:

$$\ln L^{RA}\left(r,\mu;y,\mathbf{X}\right)=\sum_i\left(\left(\ln\left(\nabla EU\right)\mid y_i=1\right)+\left(\ln\left(1-\nabla EU\right)\mid y_i=-1\right)\right) \tag{4}$$

where $y_i = 1(-1)$ denotes the choice of the option B (A) lottery in the risk preference task i. Each parameter in equation (4) is allowed to be a linear function of demographic and treatment variables as exhibited in Table 2. A portion of subject's fees was stochastic since this have been demonstrated to be very important for recruitment (Harrison *et al.*, 2009). Student subjects received a fixed fee of 15€ and subjects from the general population received a fixed fee of 20€. Recruitment practices necessitated a higher show-up fee for consumer subjects. Thus, a total fee endowment variable is included in the econometric model. Equation (4) can be maximized using standard numerical methods. The statistical specification also takes into account the multiple responses given by the same subject and allows for correlation between responses. Standard errors were computed using the delta method.

We can extend the analysis by accounting for probability weighting. Rank Dependent Utility (Quiggin, 1982) extends the EUT model by allowing for decision weights on lottery outcomes. To calculate decision weights under RDU one replaces expected utility defined by (2) with:

$$EU_i = \sum_{j=1,2}\left(w\left(p\left(M_j\right)\right)\cdot U\left(M_j\right)\right)=\sum_{j=1,2}\left(w_j\cdot U\left(M_j\right)\right) \tag{5}$$

where $w_2 = w\left(p_2+p_1\right)-w\left(p_1\right)=1-w\left(p_1\right)$ and $w_1 = w\left(p_1\right)$, with outcomes ranked from worst (outcome 2) to best (outcome 1) and $w(\cdot)$ is the weighting function proposed by Tversky and Kahneman (1992) and assumes weights of the form:

$$w\left(p\right)=p^{\gamma}\Big/\left[p^{\gamma}+\left(1-p\right)^{\gamma}\right]^{1/\gamma} \tag{6}$$

In (6), when γ=1, it implies that $w(p)$=p and this serves as a formal test of the hypothesis of no probability weighting.

The assumption of a CRRA function, implicitly assumes that risk aversion is constant across different prize domains. We can relax this assumption by adapting a more flexible form, the hybrid expo-power function of Saha (1993). The expo-power function can be defined as $u(M)=\left(1-\exp\left(-aM^{1-r}\right)\right)/a$, where M is income and α and r are parameters to be estimated. Relative risk aversion (RRA) is then $r+a(1-r)M^{1-r}$, so RRA varies with income if $a\neq 0$. The expo-power function nests CRRA (as $a\rightarrow 0$).

4. Results

Figure 1 illustrates the proportion of subjects choosing option A over B across the three risk preference tasks. Results are consistent across tasks; students appear to be more risk averse than consumers. A t-test of the number of times option A was chosen across each risk aversion task, shows that the differences between students and consumers are statistically significant at the 10% level for the x1 and the x10 HL tasks (p-value=0.062 and 0.078 respectively) but not for the framed task (p-value=0.236). This implies that the gap between the lines in figures 1a and 1b is statistically significant but not for figure 1c. An ANOVA test of whether the three HL tasks (x1, x10, framed) elicit different switch-points (i.e., different number of times the A choice was selected) fails to reject the null (p-value=0.206).

Table 3 shows estimates when assuming a CRRA function and EUT. We use the *Age* variable as the variable that differentiates the groups of students and subjects from the general population. Another option would be to include a dummy variable for subjects but the age variable contains more information than a dummy. Entering both variables at the model would lead to possible multicollinearity problems since the variables are highly correlated. Table 3 shows that results with and without demographics for gender, income and education are fairly robust. Results shows that age has a negative and statistically significant effect on risk aversion implying that general population subjects (which are older than students) have a lower coefficient of relative risk aversion. Table 4 exhibits predictions of RRA coefficients (r) averaged across subjects, by subject pools. Predicted RRA for consumer subjects is very close to zero which points to approximately risk neutral preferences, on average, while the coefficient for student subjects is positive which suggests that risk preferences are characterized by risk aversion. Note, that confidence intervals for consumer subjects span around zero. Overall, it appears as if student subjects are significantly more risk averse than consumer subjects, confirming insights gained from Figure 1.

To check the robustness of our findings we opted for estimating a RDU specification with an expo-power utility function (which nest EUT and CRRA respectively). However, Wald tests showed that we can’t reject the null that α=0 coefficient. Thus, the expo-power specification is not favored by our data. Table 5 shows parameter estimates when assuming RDU instead of EUT and a CRRA function. Wald test of $\gamma = 1$ highly reject the null. Thus there is support that RDU is a better characterization of our samples risk attitudes. Table 5 presents results with and without demographics for gender, income and education. It is evident that results are robust to the inclusion/exclusion of demographic control variables.

In Table 5, it is evident that the age variable has a statistically significant effect on risk aversion. To better grasp what this effect implies for the characterization of risk attitudes of our consumer and student sample, Table 6 displays predictions of RRA coefficients (r) and probability weighting (γ) averaged across subjects, by subject pools. Both models (with and without demographics) imply risk neutrality for students since confidence intervals span around zero. On the contrary, for the consumer subject pool, both models imply risk loving preferences.

Overall, our results imply that observed differences in risk attitudes in conventional and artefactual lab experiments can be sensitive on the assumptions. Although both competing models (EUT and RDU) imply that subjects from the general population are less risk averse than students, the models imply different characterizations of risk attitudes. For example assuming CRRA/EUT we would have incorrectly characterized students as risk averse while the CRRA/RDU model implies risk neutrality. Similarly, subjects from the general population would have incorrectly been characterized as risk neutral while the RDU model shows they exhibit risk loving preferences.

4. Concluding Remarks

In this article we tested whether risk preferences of subjects drawn from the general population differ with respect to a standard student subject pool. In summary, we found evidence suggesting that under a proper characterization of risk attitudes (i.e., RDU) subjects drawn from the general population exhibit risk loving preferences while students exhibit risk neutrality. However, when the characterization of risk attitudes is incorrect (i.e., EUT), students appear as risk averse and subjects from the general population as risk neutral.

Our findings have significant implications for conventional laboratory experiments practice given the importance of risk preferences in everyday economic decision and policy making. In particular, our results have implications on decision making at the household, firm and policy levels. To give an example from the agri-environmental literature, various environmental policies have been proposed to control agricultural runoff of nutrients and pesticides. The impact of these policies on input use depends on farmers' risk attitudes, as well as the form of production uncertainty, risk-input relationships and degrees of output price and production uncertainty (see for example Antle, 1987; Koundouri, et al., 2009; Karagiannis, 1999; Xavier et al., 2011). Our work highlights the importance of adopting a proper characterization of risk attitudes, when using experimental techniques to estimate the relevant risk preferences, as the assumptions employed for the estimation of risk, will affect the estimated preferences differently under varying sample choices. Given that risk-preferences are an integral part of the construction of the optimal agri-environmental policies our results contribute to the correct development of such policies.

Finally, our findings complement the empirical literature that has found either no difference in risk aversion between students and the general adult population (Andersen, et al., 2010a) or that students are more risk averse (Andersen, et al., 2010b). More studies examining differences in risk preferences between students and the general population are indeed warranted.

5. References

Andersen, S., G.W. Harrison, M.I. Lau, & E.E. Rutström. (2010). Preference heterogeneity in experiments: Comparing the field and laboratory. *Journal of Economic Behavior and Organization 73*:209-224.

Andersen, S., G.W. Harrison, M.I. Lau, & E.E. Rutström. (2011). Discounting behavior: A reconsideration. *Center for the Economic Analysis of Risk, Working Paper 2011-03*.

Anderson, L., & J. Mellor. (2009). Are risk preferences stable? Comparing an experimental measure with a validated survey-based measure. *Journal of Risk and Uncertainty 39*:137-160.

Ball, S., C. Eckel, & M. Heracleous. (2010). Risk aversion and physical prowess: Prediction, choice and bias. *Journal of Risk and Uncertainty 41*:167-193.

Barsky, R.B., F.T. Juster, M.S. Kimball, & M.D. Shapiro. (1997). Preference parameters and behavioral heterogeneity: An experimental approach in the health and retirement study. *Quarterly Journal of Economics 112*:537-579.

Dave, C., C. Eckel, C. Johnson, & C. Rojas. (2010). Eliciting risk preferences: When is simple better? *Journal of Risk and Uncertainty 41*:219-243.

Enis, B.M., K.K. Cox, & J.E. Stafford. (1972). Students as subjects in consumer behavior experiments. *Journal of Marketing Research 9*:72-74.

Grubbs, F. (1969). Procedures for Detecting Outlying Observations in Samples. *Technometrics 11*:1-21.

Harrison, G.W., E. Johnson, M.M. McInnes, & E.E. Rutström. (2005). Risk aversion and incentive effects: Comment. *The American Economic Review 95*:897-901.

Harrison, G.W., M.I. Lau, & E.E. Rutstrom. (2007). Estimating risk attitudes in Denmark: A field experiment. *Scandinavian Journal of Economics 109*:341–368.

Harrison, G.W., M.I. Lau, & E.E. Rutström. (2009). Risk attitudes, randomization to treatment, and self-selection into experiments. *Journal of Economic Behavior & Organization 70*:498-507.

Harrison, G.W., & J.A. List. (2004). Field experiments. *Journal of Economic Literature 42*:1009-1055.

Holt, C.A., & S.K. Laury. (2002). Risk aversion and incentive effects. *The American Economic Review 92*:1644-1655.

Koundouri, P., M. Laukkanen, S. Myyrä, & C. Nauges. (2009). The effects of EU agricultural policy changes on farmers' risk attitudes *European Review of Agricultural Economics 36*:53-77.

Koundouri, P., C. Nauges, & V. Tzouvelekas. (2006). Technology Adoption under Production Uncertainty: Theory and Application to Irrigation Technology. *American Journal of Agricultural Economics 88*:657-670.

McNemar, Q. (1946). Opinion-attitude methodology. *Psychological Bulletin 43*:289-374.

Quiggin, J. (1982). A theory of anticipated utility. *Journal of Economic Behavior & Organization 3*:323-343.

Saha, A. (1993). Expo-power utility: A flexible form for absolute and relative risk aversion. *American Journal of Agricultural Economics 75*:905-913.

Tversky, A., & D. Kahneman. (1992). Advances in prospect theory: Cumulative representation of uncertainty. *Journal of Risk and Uncertainty 5*.

Table 1. Sample payoff matrix for the risk preferences tasks

Lottery A				Lottery B				Open CRRA interval if subject switches to Lottery B (EUT is assumed)	
p	€	*p*	€	*p*	€	*p*	€		
0.1	2	0.9	1.6	0.1	3.85	0.9	0.1	-∞	-1.71
0.2	2	0.8	1.6	0.2	3.85	0.8	0.1	-1.71	-0.95
0.3	2	0.7	1.6	0.3	3.85	0.7	0.1	-0.95	-0.49
0.4	2	0.6	1.6	0.4	3.85	0.6	0.1	-0.49	-0.15
0.5	2	0.5	1.6	0.5	3.85	0.5	0.1	-0.15	0.14
0.6	2	0.4	1.6	0.6	3.85	0.4	0.1	0.14	0.41
0.7	2	0.3	1.6	0.7	3.85	0.3	0.1	0.41	0.68
0.8	2	0.2	1.6	0.8	3.85	0.2	0.1	0.68	0.97
0.9	2	0.1	1.6	0.9	3.85	0.1	0.1	0.97	1.37
1	2	0	1.6	1	3.85	0	0.1	1.37	+∞

Note: Last two columns showing implied CRRA intervals were not shown to subjects.

Table 2. Variable description

Variable	**Description**	**General population subject pool**		**Student subject pool**	
		Mean	*Std.dev.*	*Mean*	*Std.dev.*
Age	Subject's age	41.176	10.376	20.739	1.322
Gender	Dummy, 1=males, 0=females	0.324	0.475	0.391	0.499
Income	Dummy, household's economic position is above average=1, else=0	0.471	0.507	0.435	0.507
Education	Dummy, university graduate or higher=1, else=0	0.676	0.475	0	0
TotFee	Total fee endowment	22.662	1.613	16.717	1.146
ExpCharact	Dummy, risk preference task was conducted after an auction, else=0	1	0	0.522	0.511

Table 3. Estimates of risk preferences (CRRA function-EUT)

	r coefficient			
	Estimate	Std.Error	Estimate	Std.Error
Age	-0.041**	0.016	-0.040**	0.014
Gender	-0.275	0.209	-	-
Income	-0.009	0.164	-	-
Education	-0.220	0.244	-	-
ExpCharact	-0.194	0.221	-0.229	0.245
TotFee	0.094*	0.052	0.076*	0.044
Constant	0.036	0.666	0.228	0.583
μ	0.145**	0.015	0.147**	0.015
Log-Likelihood	-682.339		-695.767	

Note: ** (*) Statistically significant at the 5% (10%) level

Table 4. Average predicted RRA under EUT

		RRA	**95% Confidence Intervals**	
With demographics	Consumers	0.033	-0.536	0.602
	Students	0.539	0.134	0.945
Without demographics	Consumers	0.066	-0.340	0.472
	Students	0.544	0.196	0.893

Table 5. Estimates of risk preferences (expo-power function-RDU)

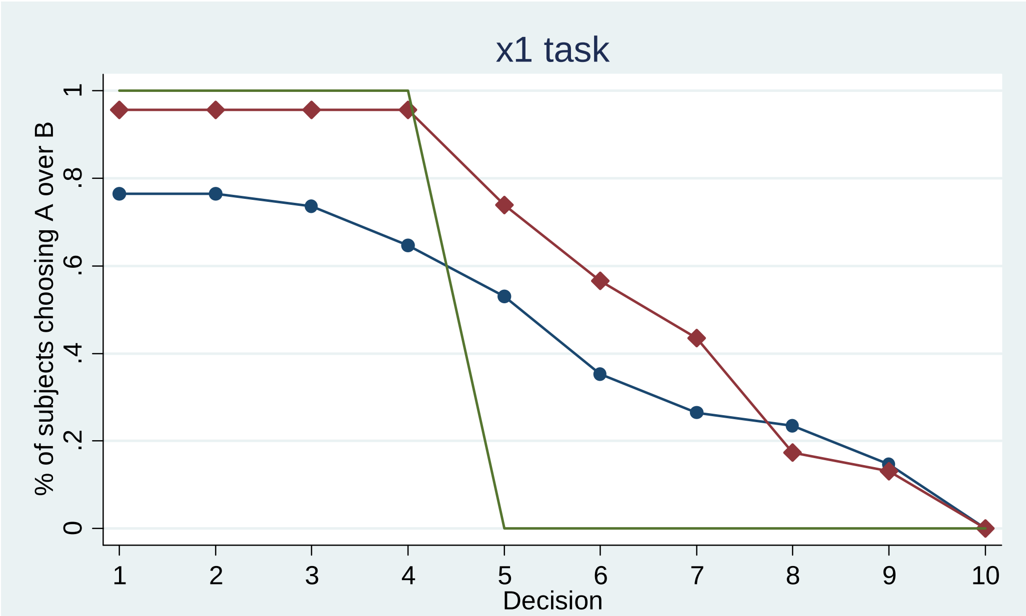
	r coefficient		*γ coefficient*	
	Estimate	Std.Error	Estimate	Std.Error

A. With demographics (Log-Likelihood= -628.034)				
Age	-0.107**	0.015	0.150**	0.066
Gender	-0.786	0.483	0.276	0.889
Income	-0.170	0.298	0.902	0.806
Education	0.076	0.360	-3.165**	0.969
ExpCharact	-0.584	0.385	0.795	1.075
TotFee	0.161*	0.053	0.145	0.115
Constant	0.142	0.776	-3.743*	2.266
μ	0.115**	0.012		
B. Without demographics (Log-Likelihood= -677.363)				
Age	-0.099**	0.019	0.118	0.090
ExpCharact	-0.374	0.547	0.113	0.907
TotFee	0.197*	0.078	-0.268**	0.131
Constant	-0.901	1.270	4.268**	2.063
μ	0.145**	0.020		

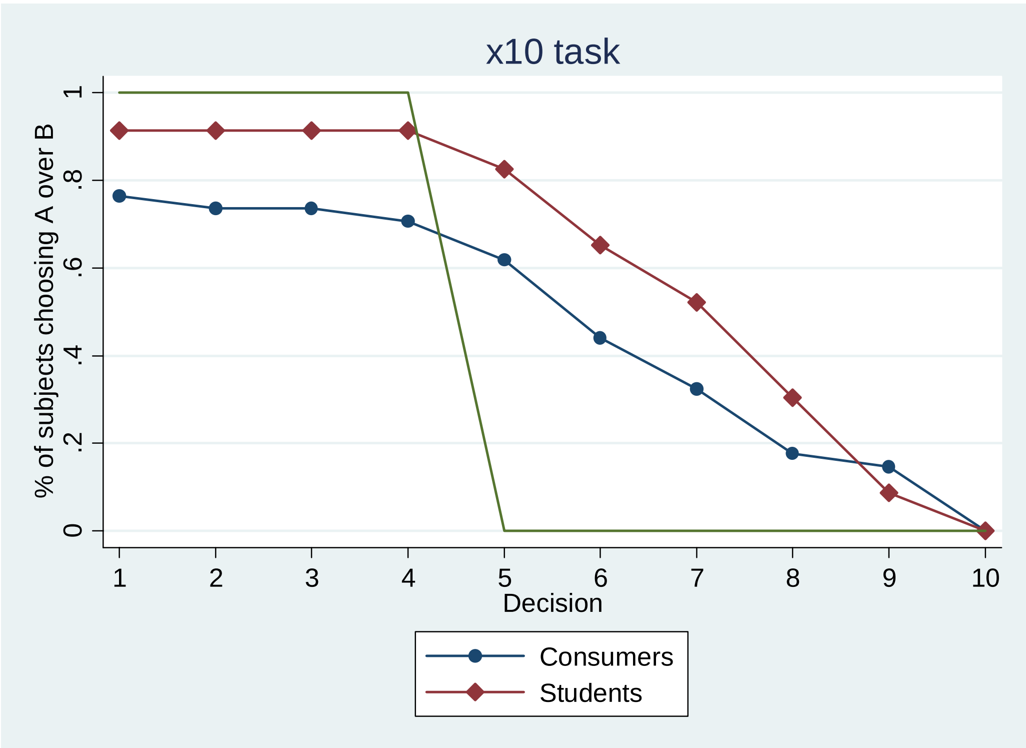
Note: ** (*) Statistically significant at the 5% (10%) level

Table 6. Average predicted RRA and γ under RDU

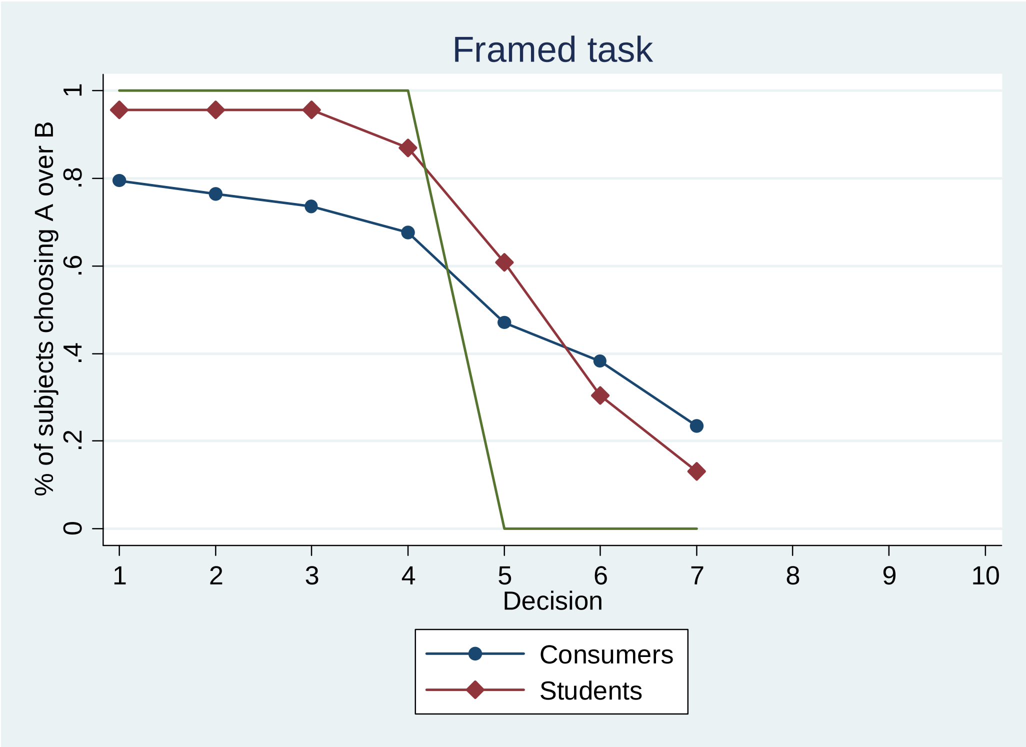
		RRA	**95% Confidence Intervals**		γ	**95% Confidence Intervals**	
With demographics	Consumers	-1.470	-2.398	-0.542	4.883	2.296	7.470
	Students	-0.066	-0.770	0.637	2.705	1.106	4.303
Without demographics	Consumers	-0.885	-1.681	-0.089	3.167	0.723	5.610
	Students	0.144	-0.607	0.895	2.293	1.072	3.513


x1 task
% of subjects choosing A over B
0
.2
.4
.6
.8
1
1
2
3
4
5
6
7
8
9
10
Decision

(a)


x10 task
% of subjects choosing A over B
0
.2
.4
.6
.8
1
1
2
3
4
5
6
7
8
9
10
Decision
Consumers
Students

(b)



(c)

Figure 1. Proportion of choices in each decision for (a) the x1 task (b) the x10 task and (c) the framed task (solid line without markers represents risk neutrality under EUT)