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Raising "lab rats"

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Abstract Experimental subjects usually self-select to the laboratory and this may introduce a bias to the derived conclusions. We analyze data stored by a subject-pool management software at an experimental laboratory and speculate about the effect of individual decisions on returning. In particular, we test whether experience and earnings in previous sessions together with demographic variables explain the decision to return to the laboratory. We find that males and (in monetary terms) well-performing subjects are more likely to participate again in experiments.

Keywords demographic characteristics · experiments · subject pool
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1 Introduction

The purpose of laboratory experiments is to test hypotheses in a controlled environment. However, the composition of the subject pool stays often out of the experimenter's control and its characteristics rarely enter the statistical analysis of experimental data.

Subject pools used in economic experiments typically consist of college students who are usually recruited online or on campus on a voluntary basis to participate. In other words, they self-select to the laboratory and this may introduce a bias to the conclusions. In this note, we study the evolution of the subject pool at a specific experimental laboratory and speculate about its consequences.

In a related study, Andersen et al. (2009) argue that the subject pool in the laboratory may not constitute a representative sample of the broader population and call for complementary field experiments.[1] Harrison et al. (2009) analyze the problem of self-selection into experiments using both laboratory and field experiments. They observe that by changing the reward scheme, the constitution of the subject pool also changes (e.g., the proportion of risk-averse subjects). Rutström (1998) makes a similar conclusion using data from laboratory experiments on the Vickrey and the English auctions. These studies open an important line of research concerned with the basic rules of running laboratory experiments.

We consider administrative data from the recruitment system of an experimental laboratory located at a university in the Northeastern United States. The database contains individual participation and earnings histories along with some demographic information. We use simple statistical and econometric tools to analyze subjects' decision to return to the laboratory by treating it as a function of variables like gender, age, experience and previous earnings.

We find a significant positive effect of previous earnings and age in explaining the probability of coming back to the laboratory. On the other hand, experience seems to have a significant negative effect. Although significant, these effects tend to be small. Interestingly being a male student at Boston University or Harvard and majoring in social sciences increase the odds of returning to the laboratory where our data have been recorded. The effect of these characteristics cannot be considered negligible as each increases the odds of returning to the laboratory by a factor between 14 and 26 percentual points.

The effect of studying at Boston University and at Harvard can be traced back to their proximity to the experimental laboratory. The effect of social sciences might be explained by the fact that the word "economics" is often used in the recruitment material and this may bias the sample towards students with an interest in the field. Interestingly, even if we control for the other characteristics, it turns out that males are more prone to return.

[1] They consider experiments to elicit preference heterogeneity and claim that "the lab might not be the best place to search for demographic effects".

The abundance of male experimental subjects might introduce a serious bias. A recent study by Croson and Gneezy (2008) surveys research on gender differences in risk aversion, social preferences and preference towards competition. They claim that women tend to be more risk averse, act according to social cues rather than principles when facing social dilemmas and dislike competition.

2 Descriptives

Our data set consists of 8,755 observations. Each of them represents a subject's participation in an experimental session. Our analysis covers a total of 2,408 subjects who participated in 597 experimental sessions corresponding to 74 different studies. All the data come from the same laboratory located at a university in the Northeastern United States. We use entries recorded after April, 2003, because that is the month when the laboratory started gathering participants' personal data on a regular basis. The latest observations included in this analysis were gathered in January, 2006. The available data include various self-reported personal characteristics of the subjects, including their gender, age, and the university (if any) they are affiliated with, along with their earnings in the experiment.

In some experiments, subjects' payment does not depend, or depends very little, on the subjects' behavior. Since our objective is to study economic experiments where monetary incentives are the norm, we have deleted observations from sessions with fixed payments or in which payments do not vary much. We excluded all the sessions in which 80 percent or more of the participants received the same amount of money.[2] We have not discovered important qualitative changes in the results when performing the same analysis using cutoffs of 50 percent, 90 percent and 100 percent, instead of 80 percent.[3] We have also deleted records with zero registered payment, and repeated entries, keeping the one with the highest payment.[4] These two categories are a result of faulty data entries: no subject actually received zero payment, and no subject was paid more than once for the same participation. We found a total of 176 zero entries and 277 repeated entries. This leaves 8,755 observations in the data set.[5]

[2] This selection is in line with the philosophy of regression analysis we perform on the data, since ignoring fixed and quasi-fixed payments guarantees larger variance in the dependent variable. As a result, we effectively exclude most tournament experiments, and also those sessions with fixed payments in which a few of the subjects earned more money, due to the "early show-up fee" that rewards people who arrive at experiments early with an extra payment.

[3] The excluded observations belong to participants who on average earned almost $4 less than the included ones. They also tend to be older (by 0.78 years) and are more likely to be college students (by 2.3% points).

[4] We enquired and found that lower payments usually correspond to show-up fees.

[5] The laboratory has recently started collecting information on subjects' ethnic group. As there are only 4,559 (52.97%) entries that contain a value for this variable, in order to not reduce the number of observations in the analysis we decided not to include this variable

Apart from the recorded personal data such as age, gender, racial group, educational level (with intended major and the name of the college), and the basic characteristics of the experimental session (final payment, experiment id), we also created several variables for the empirical analysis. Of the 2,408 subjects in the data, 70 percent came more than once to the laboratory over the course of the period we investigate. In order to control for experience, i.e. training in experiments, we have constructed three variables. EXP_T counts the total number of occasions the subject appears in the database prior to the experimental session in question. EXP_I counts only experiments that make the 80 percent cutoff described earlier. The third experience variable, EXP_A, is dichotomous and takes the value 1 if the subject appears in the database prior to the given record, and 0 otherwise. It turns out that subjects who participate in experiments have a long experience record: At the time of our analysis they have participated in more than 6 sessions on average (in almost 5 if we solely consider incentives based experiments). This number is in line with the usual concern on the validity of experimental results as explained by List and Levitt (2006) who discuss the problem of subjects' self-selection into experiments.

As for the return decisions themselves, the variables RET_30/60/90/365 take value 1 if the subject returns to participate in an experiment in the subsequent 30, 60, 90 and 365 days, respectively. In order to eliminate the survivorship bias from our analysis we excluded the observations from the last 30, 60, 90 and 365 days in the analysis, respectively, given that we can not know whether those observation belong to a subject who wishes to (and actually does) return to the laboratory in the future or not.

Table 1 displays descriptive statistics on all the variables included in our analysis for the whole sample and also for two subsamples. We call "newcomers" all those participants who has no experience with incentive-based experiments, while we refer to those who have participated in more than 27 sessions as "experts". The latter set of observations constitutes 1% of the entries with the most experience. The picture that this table reflects is typical for laboratory experiments in economics. The vast majority of the subjects are college students (74 percent), and almost 82 percent have experience in experiments by the time of participation. The largest share comes from the area of social sciences, though other specialities such as humanities or natural sciences are also well represented. Participants earn roughly $24 on average. The distribution of payments is positively skewed as income distributions tend to be. Its variance is large, with a standard deviation is approximately $9. The subject pool of the experimental laboratory that we study seems to be well-trained, as subjects have experience from more than six experiments on average (almost five if we consider only incentive-based sessions).

in the final data set. If we compare the mean payoffs across the nine ethnic groups using analysis of variance (ANOVA) tables we cannot reject the null hypothesis of them being equal. The p-value in this case is of 0.14.

Table 1 Subject descriptives. Newcomers: subjects with no experience in incentive-based experiments. Experts: subjects with experience of more than 27 incentive-based experiments.

characteristics		variable	newcomers	all	experts
age		AGE	23.03	23.56	35.86
gender		MALE			
	female		48.59	44.81	19.05
	male		41.69	46.61	64.29
	n/a		9.72	8.58	16.67
education					
	some high school	E1	0.26	0.27	0.00
	high school diploma	E2	8.93	7.86	0.00
	some college	E3	53.13	52.27	9.52
	associate level degree	E4	0.73	0.51	0.00
	bachelor level degree	E5	16.51	18.52	17.86
	other masters	E6	6.37	6.72	20.24
	MBA	E7	0.31	1.11	0.00
	doctoral level degree	E8	0.94	1.28	19.05
	n/a		12.80	11.47	33.33
college					
	other	U1	4.60	3.86	0.00
	Univ. of Massachusetts	U2	0.47	0.95	27.38
	Tufts University	U3	2.04	2.44	8.33
	Northeastern University	U4	1.52	2.22	0.00
	Boston College	U5	0.73	0.62	0.00
	Boston University	U6	11.13	12.26	20.24
	Harvard University	U7	46.92	47.64	0.00
	MIT	U8	4.70	4.05	0.00
	n/a		27.90	25.96	55.95
major					
	natural sciences	M1	13.27	12.51	0.00
	social sciences	M2	30.25	32.24	0.00
	engineering	M3	4.65	5.15	20.24
	humanities	M4	12.33	11.98	9.52
	other	M5	3.97	4.20	17.86
	n/a		31.71	30.47	52.38
earnings		EARN	23.21	23.80	22.79
experience					
	any	EXP_A	0.20	0.82	1.00
	incentives	EXP_I	0.00	4.80	32.99
	total	EXP_T	0.20	6.47	42.10
return					
	in 30 days	RET_30	0.47	0.57	0.56
	in 60 days	RET_60	0.53	0.64	0.80
	in 90 days	RET_90	0.55	0.67	0.84
	in 365 days	RET_365	0.68	0.82	1.00

Table 2 Logit regression analysis of return decisions (part 1).

	RET_30	RET_60	RET_90	RET_365
EARN	0.02***	0.02***	0.01***	0.01*
AGE	2.22***	2.76***	2.23***	2.72
AGE^2	−0.01***	−0.01***	−0.01	−0.03
EXP_I	−0.43***	−0.58***	−0.72***	−2.12***
EXP_I^2	0.01***	0.01***	0.01***	0.02**
control	subject	subject	subject	subject
$pseudo - R^2$	0.10	0.14	0.17	0.61

3 Return decisions

One would expect a high correlation between the fact of being a student and the decision of returning to the laboratory on a voluntary basis. Pearson's χ^2 confirms such a positive relationship at any usual significance level, however the values of Cramer's V statistics around 10% indicate that the association is very low.[6] It is equal to 10.63%, 10.52%, 10.02%, and 12.94% for the variables RET_30/60/90 and 365 respectively.

We ran logit regressions with subject-specific fixed effects in order to explain the decision of returning to the experimental laboratory in the next 30, 60, 90 and 365 days with personal characteristics.[7] Table 2 shows the estimation and the related test results. Experience and earnings from previous experiments along with the subject's age have a significant effect on the return decisions. Experience affects the odds of returning to the laboratory negatively, while age and earnings affect it positively.[8]

Previous earnings unsurprisingly incentivize subjects to return to the laboratory (the odds of returning are 1-2% higher for every dollar earned previously in the lab).[9] However, it seems that participating in experiments is not addictive, since the odds of repeating decreases with experience. The relatively large positive effect of age may be funded on two pillars. On one hand, while college students often instinctively decide to enter the laboratory encouraged by randomly posted adds on campus, older participants tend to look for experiments and therefore be "more frequent guests". As List and Levitt (2006) argue, subjects self-select into experiments, and therefore people who are more interested in the announced research topic are more likely to participate. On

[6] With usual, we refer to significance levels between 1% and 10%.

[7] We estimate logit models, because we wish to study subject-related fixed effects both in the return decisions and in individual earnings from experiments. As Wooldridge (2002) points out, the unobserved-effect logit model has an important advantage over the probit, because a consistent estimator can be obtained without any assumption about how the unobserved effects are related to the observed ones.

[8] The sign of the above-mentioned effects is unambiguous on the domain of our database in which age ranges from 18 to 73, while experience in incentive-based experiments from 0 to 43.

[9] In the interpretation of the logit coefficients we use that a small change in the logarithm of a variable (now the odds ratio) is approximately its percentage change.

Table 3 Logit regression analysis of return decisions (part 2).

RET_30					
EARN	0.01***	EARN	0.01***	EARN	0.01***
AGE	−0.06***	AGE	−0.08***	AGE	−0.05***
AGE^2	0.00**	AGE^2	0.00***	AGE^2	0.00**
EXP_I	0.06***	EXP_I	0.06***	EXP_I	0.06***
EXP_I^2	−0.00***	EXP_I^2	−0.00***	EXP_I^2	−0.00***
MALE	0.14***	MALE	0.13***	MALE	0.13**
U1	0.14	−	−0.66	M1	0.11
U2	−0.34	E2	−0.70	M2	0.20**
U3	0.02	E3	−0.62	M3	−0.01
U4	0.07	E4	−0.71	M4	0.11
U5	0.22	E5	−0.60	M5	−0.06
U6	0.26***	E6	−0.36	−	−
U7	0.18**	E7	−0.48	−	−
U8	−0.03	E8	−	−	−
const.	0.67**	const.	1.95***	const.	0.65*
control	−	*control*	−	*control*	−
$pseudo-R^2$	0.01	$pseudo-R^2$	0.01	$pseudo-R^2$	0.01

the other hand, also causality in the opposite direction may hide behind this significant effect, given that those who return in the future are necessarily older.

It is interesting that the significant effect of earning and age tend to fade away the longer we look into the future for return decisions. The increasing goodness-of-fit of the model suggests that short-term decisions are more random than long-term ones. The rather small values also indicate that decisions are largely influenced by factors that lie out of the scope of our analysis.

The regression models with subject-specific fixed effects have a large number of dummy variables and do not allow for studying whether gender, college, education level or intended major have any significant effect on the return decisions. This is why, table 3 reports estimation results for “simple” logit models that include these as regressors to explain RET_30.[10] Although our database is relatively large, it does not allow for including all these dummy variables in the same model.

Males tend to return to the laboratory more frequently than females (the odds of returning are 13-14% higher for males than females). The location of the experimental laboratory relative to BU and Harvard seem to have a significant effect too. Education level does not seem to be an important determinant. Nevertheless students of social sciences return more likely than others (their odds of returning are 20% higher). In the logit estimates in table 3 the variables related to age and previous experience have the opposite sign when compared to the results in table 2. While the latter can be interpreted on an individual level (“as subjects grow older and gain more experience...”), the

[10] The regressors have similar explanatory power in explaining the other return decisions, therefore those estimation results are omitted.

Table 4 OLS regression analysis of earnings (part 1).

	EARN			
EARN_MIN	0.66***	0.59***	–	0.35***
EARN_MAX	0.22***	0.29***	–	0.22***
AGE	−0.10**	−0.48	−0.11	−0.12*
AGE^2	0.00*	0.01	0.00	0.00
EXP_I	0.07***	−0.09	0.05	0.05*
EXP_I^2	−0.00	0.00	−0.00	−0.00
const.	5.90***	7.87	25.65***	12.19***
control	–	subject	session	experiment
$adj - R^2$	0.19	0.37	0.42	0.41

former capture population effects ("older subjects and subjects with experience..."). That is, older subjects are less likely to return and those who has participated in experiments before tend to do return.

4 Earnings

Personal earnings in experiments have a significant positive effect on the decision of returning to the lab. This section examines whether personal characteristics have any explanatory power in the determination of these experimental earnings. We use regression analysis to separate the effects that these variables might have.

On top of these demographic variables we include the minimum (EARN_MIN) and the maximum (EARN_MAX) payment in the session. These two variables control for subjects' motivation induced by the payments themselves. For example, when payments are too low, subjects may not take as much care in their decision making.

Table 4 shows the estimation results for linear regression models with robust variance estimates that explain the observed variation in real money earnings. We use the standard ordinary least squares method (OLS) to estimate the coefficients. In order to account for unobservable subject, session or experiment-related effects we studied several specifications of our regression model including the so-called fixed effects.

It seems that personal earnings are mainly determined by the rules set by the experimenter, i.e. the minimum and the maximum payment in the session, and by variables other than the here included demographic ones. This is in line with the philosophy of incentives-based economic experimental studies that usually assume that earning do not differ across demographic groups, but do vary with individual behavior and decisions that escape from the scope of our analysis. Probably this explains why the goodness-of-fit of these models is below 50%.

When significant, age effects the earnings negatively, while experience does so positively. As for the qualitative variables, males tend to earn more than

Table 5 OLS regression analysis earnings (part 2).

EARN					
AGE	−0.10	AGE	−0.14	AGE	−0.05
AGE^2	0.00	AGE^2	0.00	AGE^2	0.00
EXP_I	0.04	EXP_I	0.03	EXP_I	0.05
EXP_I^2	−0.00	EXP_I^2	−0.00	EXP_I^2	−0.00
MALE	0.22	MALE	0.27	MALE	0.35**
U1	0.34	–	–	M1	0.36
U2	0.20	$E2$	0.12	M2	0.35
U3	0.44	$E3$	0.38	M3	0.22
U4	0.19	$E4$	0.18	M4	−0.13
U5	0.77	$E5$	0.33	M5	0.52
U6	0.07	$E6$	0.58	–	–
U7	0.38	$E7$	0.50	–	–
U8	1.03**	$E8$	−0.13	–	–
const.	25.04***	const.	25.78***	const.	24.46***
control	session	*control*	session	*control*	session
$adj - R^2$	0.41	$adj - R^2$	0.41	$adj - R^2$	0.42

females, and so do MIT students than their colleagues from other universities.[11] The model specifications (that include information on college, educational level or major) behind the results in table 5 assume session-specific fixed effect, therefore the session minimum and maximum are excluded from the regressor list. Remarkably, only two of the analyzed factors appear to have a significant (positive) effect on earnings: gender and studying at MIT.

5 Conclusion

Our analysis on return decisions to the experimental laboratory discovers that although demographic variables have little effect on individual decisions, males and (in monetary terms) well-performing subjects are more likely to return. That is, we have found some evidence of “lab rats” being raised. Research on gender differences has already put the distinct attitudes towards risk, social preferences and competition into spotlight (e.g. Croson and Gneezy, 2008). Hence the fact male subjects return more often to the lab may introduce some behavioral bias. Likewise, it is possible that subjects who are more familiar with the laboratory environment and have been performing well in the past may behave in a different way when compared to unexperienced subjects. However our data does not contain precise information about behavior in a particular experiments. We observe only earnings, therefore we cannot be more assertive. In order to overcome this caveat, demographic information should be routinely and systematically collected in experimental laboratories across the world. Even more, precise information about the type of experiments should be

[11] Although the regressor for gender is not significant in the first two specification the p-values are not far from the usual 10% by being equal to 18% and 11%.

stored and made widely available.[12] By doing that, the effect of subject pools on experimental results could be studied more precisely than it is done in our exercise, and future analysis could compare different subjects pools, males with females, students with non-students in numerous experimental settings.

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[12] At least gender, age, student status, experience and college status should be routinely recorded. The experimental community should reach an agreement in order to give access of the collected data, since replicas of well known experimental designs can be very useful for comparative studies similar to ours.