

Opting-in: Participation Bias in Economic Experiments*

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Abstract

Assuming individuals rationally decide whether to participate or not to participate in lab experiments, we hypothesize several non-representative biases in the characteristics of lab participants. We test the hypotheses by first collecting survey and experimental data from a typical recruitment population and then inviting them to participate in a lab experiment. The results indicate that lab participants are not representative of the target population on almost all the hypothesized characteristics, including having lower income, working fewer hours, volunteering more often, and exhibiting behaviors correlated with interest in experiments and economics. The results reinforce the commonly understood limits of laboratory research to make quantitative inferences. We also discuss several methods for addressing non-representative biases to advance laboratory methods for improving quantitative inferences and consequently increasing confidence in qualitative conclusions.

Key words: Participation Bias, Laboratory Experiments

*Acknowledgements: We have greatly benefitted from numerous seminar participant comments at the University of Sydney, the Winter School on Experimental Economics at the University of Sydney, the University of Technology, Sydney, the University of New South Wales and the 6th annual Australia-New Zealand Workshop in Experimental Economics. We also appreciate comments and suggestions from Paul Frijters, Simon Gaechter, Ben Greiner, Nickolas Feltovich, Nikos Nikiforakis, Andreas Ortmann, the editor and two anonymous reviewers at the *Journal of Economic Behavior and Organization*. We also thank Roxana C. Dawidoski, Michael Major and Elina Gilbourd for invaluable research assistance. This project was generously supported by funds from the School of Economics in the Faculty of Arts and Social Sciences at the University of Sydney and the Australian Research Council Discovery Grant 1095222.

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1. Introduction

Economic laboratory experiments have been responsible for some of the most profound advances in the understanding economic behavior and theory in recent decades.¹ With the lab's growing importance, interest has grown in whether inferences drawn from the lab context and lab participants extend to contexts outside the lab and to non-participants. Studies have explored this question in various directions, most commonly by comparing results from lab participants recruited from different populations.² However, few studies have assessed whether the characteristics of the lab participants are the same as the characteristics of the population the subjects were recruited from. Moreover, the few studies that have directly compared the characteristics of the people who chose to participate with those who chose not to participate have focused on just one or two preferences (Cleave, et al 2013; Falk, et al 2013).

In this paper, we study the selection bias in who chooses to participate in a lab experiment. We assume that people rationally choose to participate; people choose to participate if and only if the expected utility of participation exceeds the expected utility of not participating. Central to the participation decision is the common information people receive about the experiment: monetary earnings, time commitment and (sometimes) task information. Based on this common information and using a standard model of expected utility, we derive four core hypotheses regarding how the characteristics of participants might systematically differ from non-participants.

Specifically, we hypothesize that rational decision-making with the common recruitment information will result in participants being less wealthy, having more leisure time, having interests related to the tasks in economic experiments, and being more pro-social in the dimension of volunteering time. Levitt and List (2007a, b) also conjectured greater pro-social preferences among participants. However, studies have yet to find support for this conjecture either by directly comparing pro-social measures of participants with those who chose not to participate (Cleave et al. 2013; Falk et al. 2013) or by indirectly comparing whether pro-social behavior differs across subject populations (Bowles and Polonia-Reyes 2011). One reason for lack of support for this conjecture could be that these studies have focused on pro-social *monetary* decisions; however, monetary decisions may not be the dimension on which subjects are more pro-social since (1) experimenters invite participants to

¹ E.g., by 1998 over 200 experimental economics papers were being published annually (Holt, 2006).

² Cleave, Nikiforakis and Slonim (2013) review this literature. Many studies compare results across populations (across occupation: Cooper et al. 1999; Hannah et al. 2002; Fehr and List 2004; Carpenter et al. 2004; Güth et al. 2007; Carpenter et al. 2008; Andersen et al. 2009; Anderson et al. 2010; Hoffman and Morgan 2011; across age: Harbaugh et al. 2003, across nationality/culture: Roth et al. 1991; Henrich et al., 2001; Herrmann et al. 2008; Cameron et al. 2009; Henrich et al. 2010, and between students and a representative sample of the population: Bellemare and Kröger 2007; Alatas et al. 2009; Anderson et al. 2010; Belot et al. 2010; Remoundou et al. 2010; Brañas-Garza et al. 2011; and Falk et al. 2013). Other studies compare behavior across context (e.g., laboratory and field) using the same population (see Eckel and Grossman 2000; Güth et al. 2007; Benz and Meier 2008; Baran et al. 2010; and Glaeser et al. 2000). Other approaches explore whether participants select *out* of experiments after some experience (Casari et al. 2007) and whether recruitment procedures affect selection into experiments (which also follows from our hypotheses): Harrison et al. (2009) find that participants take greater risks when the advertised earnings have greater variation, and Krawczyk (2011) finds that an invitation stressing monetary benefits attracted more students to register on ORSEE (Greiner 2004) than the invitation stressing non-pecuniary benefits.

sacrifice time in exchange for receiving money (Smith's (1976) induced value premise) and (2) monetary donations may be positively correlated with wealth (which we hypothesize will have a negative effect on participation). On the other hand, since experiments invite people to sacrifice time and subjects may also believe they are assisting researchers, testing whether participants are more pro-social should examine the pro-social dimension regarding volunteering time. We also present additional hypotheses regarding risk attitudes and patience that could be important depending on the idiosyncratic features of the recruitment process (e.g., experiments that offer a large show up fee may minimize participation bias with respect to financial risk attitudes).

To examine the hypotheses, we collected individual level data from a large classroom population ($n=892$) that completed a 20-item survey and three incentivized experimental tasks.³ The classroom population was subsequently invited to attend a lab experiment. The invited population was informed that the experiment would take 60 to 90 minutes and they would receive at least \$30 (roughly twice the minimum wage).⁴ Our core analyses compare the characteristics of the invited population who chose to attend the experiment with those who chose not to.

Our results unambiguously document that the characteristics of participants attending the experiment differ from those who chose not to attend on all of our core hypotheses. In particular, the participants have significantly less income, more leisure time, are more interested in the economic lab tasks (e.g., more likely to major in economics) and are more pro-social on the dimension of volunteering. We also find that the characteristics of lab participants differ on other hypothesized characteristics that may be more idiosyncratic (e.g., patience).

The magnitudes of the estimated effects suggest substantial non-representative participant biases. Note that even small differences in the participation decision across characteristics can lead to large non-representative biases because of low participation rates in lab experiments.⁵ To see this, suppose the population is *divided equally* between people with characteristics A and B who are respectively 4 and 8 percent likely to participate in an experiment. In this case, the *four percent absolute difference* (8%-4%) in the decision to participate results in a **2 to 1** (8%/4%) ratio of B to A types in the lab relative to the equal division in the population. Most of our results show even greater over-representative ratios than in this example for our core hypotheses. Thus, the contribution of this paper goes beyond being the first empirical evidence showing a broad range of non-representative biases; we provide clear evidence that the magnitudes of the non-representative biases are dramatic.

The results of this paper also emphasize how the *experimental recruitment* procedures interact with the rational participation decision leads to non-representative subjects. Moreover, our conclusions do not require recruitment from a general/representative (or any other specific) population. Rather, because we compare *participants* with non-participants in a *target population*

³ Our classroom procedures closely follow Cleave et al. 2013, but we use entirely different measures.

⁴ The time and payment offered was consistent with other economics experiments at the university and across the country.

⁵ Few studies report participation rates. The few examples we found include Cleave et al. (2013) and Falk et al. (2013) indicating approximately 12% participation rate and Krawczyk (2011) reports less than 2%.

directly, the target population *per se* is not critical. Nonetheless, we chose a target population that is commonly used for lab experiments (university students) in order to demonstrate results with a standard population. Further, because a student population is more homogenous on many characteristics than possible alternative populations (e.g., students likely have less variability in age, income, education, and possibly moral and cultural values), there is *a priori* less opportunity for participation bias. To this extent, the substantial participation biases we present here very likely under-estimate participation bias that would occur with a more diverse or representative population.⁶

The paper is organized as follows. **Sections 2, 3 and 4** present the hypotheses, design and results, respectively, on the non-representative characteristics of the population attending the lab. Beyond identifying and quantifying the magnitudes of participation biases, we discuss several approaches to reduce participation bias in **Section 5**. Section 5 first presents several recruitment methods to address the specific biases that we hypothesized and substantiated in our study. These approaches, based on our model of the participation decision, include increasing the payoffs, reducing the laboratory time, increasing the convenience to participate and reducing the information on the task nature.

Experimenters can also vary the recruitment procedures (e.g., the payoffs and duration of the experiment) and track whether participants volunteer after a first or later invitation to partially estimate the potential extent of participation bias. Section 5 also discusses several econometric approaches to address bias including collecting data on the population being invited to participate and using common IV techniques. Most of these approaches are very practical to implement, have been used in other contexts (e.g., to conduct surveys) and are already used occasionally by experimenters. We also strongly encourage experimenters to make recruitment procedures available and report the number of people who were invited and participated to help readers understand potential participation biases. **Section 6** concludes. Before turning to the details, we discuss why participation biases can limit inferences from experiments. While most contributions from experiments focus on qualitative conclusions drawn from treatment effects, we point out in the following sub-section that qualitative inferences derived from treatment effects are not in themselves immune from participation bias.

1.1 Why participation bias can limit inferences from experiments: Signal to bias

Economists have recognized since Heckman (1979) that influences on the participation decision can limit inference from a study. For instance, in evaluating an education program (e.g., Head Start), if more educationally motivated families with higher resources choose to participate in the program, then ignoring the participation decision can lead to biased estimates *over-estimating* the program's

⁶ Distinct to our objective to study *participation bias*, researchers should also recognize that even with no participation bias (e.g., 100% participation), a student population (or many other target populations) can be non-representative of a broader population. However, this paper hypothesizes and demonstrates that *additional* non-representative biases can result from common experimental *recruitment* practices. Consistent with our theoretical model, our results on the existence and nature of participation bias due to recruitment processes generalize to recruitment from broader populations other than students; in other words, participation bias can occur even when recruiting from more general target populations.

success. Since laboratory and (many) field experiments have a participation decision,⁷ participation bias is likely; indeed, a central reason to offer monetary incentives in the recruitment process is to attract subjects who are motivated by the payoffs.

While random assignment of participants to treatments in experiments reduces bias concerns in inferences from treatment effects, it does not eliminate them. Al-Ubaydli and List (2012) demonstrate that randomly assigning subjects to treatment has no *a priori* reason to alleviate bias entirely. They note that within experiment treatment comparisons provide an estimate on the effect of behavior b between treatments t_0 and t_1 , $E[b(t_1 | p=1)] - E[b(t_0 | p=1)]$, where $p=1$ indicates the observed people in the population who chose to participate. Internal validity on estimated effect b is provided by appropriate statistical analyses of the standard error on b . However, the critical question for extending the inference beyond internal validity (i.e., on the participating subject population) is whether this behavior holds for people who chose not to participate, $p=0$, as well as for anyone else not invited whom we wish to generalize to, i.e., whether $E[b(t_1 | p=0)] - E[b(t_0 | p=0)] = E[b(t_1 | p=1)] - E[b(t_0 | p=1)]$. It follows that inference from an estimated treatment effect in an experiment to non-participants could under-estimate, over-estimate or even change the sign of the effect (see Al-Ubaydli and List (2012) for a formal analysis). The potential sources for an inference being biased to an environment outside of the lab include different contexts (i.e., anything not identical between the experiment and the contexts the inference is intended to extend to), different population characteristics (e.g., age, gender, ethnicity religion, and social and behavioral norms) and biases that emerge from the participation decision.

Participation bias has implicitly been part of the recent discussion concerning the generalizability (external validity) of lab results to broader contexts and populations. Presenting common ground in this discussion, Kessler and Vesterlund (2012) emphasize that experimental researchers generally focus on making qualitative inferences (that rely on the direction of results) rather than quantitative inferences. They note, “Few experimental economists would argue that the precise magnitude of the difference between two laboratory treatments is indicative of the precise magnitude one would expect to see in the field or even in other laboratory studies in which important characteristics of the environment have changed.” Thus, few experimental economists would defend the position that the magnitude of quantitative estimates will hold for contexts outside the lab. However, the qualitative inference does not necessarily circumvent the concern with bias since the *magnitude of the quantitative effect* is itself critical for confidence in the qualitative conclusion.

To see why the magnitude of an estimated experimental treatment effect is critical for confidence in a qualitative inference, consider an experiment that finds an $S_E = E[b(t_1 | p=1)] - E[b(t_0 | p=1)] > 0$ percentage point difference in behavior in Experimental subjects between treatments t_0 and t_1 . Further, assume there is unobserved bias $B > 0$ that affects the difference between S_E and the “true” effect S_{PC}

⁷ One exception is the natural field experiment in which there is no participation decision (Harrison and List 2004)

in the Population and Context of interest, so $S_{PC} = S_E - B$.⁸ If $B < S_E$, then the bias would only result in S_E being a quantitative over-estimate of behavior outside the lab but would not affect the qualitative conclusion. However, if $B > S_E$, then participation bias would result in the sign of S_E incorrectly reflecting the directional (qualitative) inference for behavior outside the lab. Thus, the qualitative inference depends on the size of the bias B ; the confidence in the qualitative inference is a “signal S_E to bias B ” issue. While a larger number of subjects in the lab reduce the signal S_E to noise concern to improve internal validity, this neither reduces the bias B nor addresses the signal to bias issue. Kessler and Vesterlund implicitly acknowledge that the qualitative concern does not go away completely using List and Levitt’s (2007) framework and extended by Falk and Heckman (2009) when they conclude, “the requirements for securing external validity of the qualitative effects *are weaker*,” (italics added). How weak the requirements are, though, depends on the magnitude of the estimated quantitative effect (the signal) to the potential Bias.

Interestingly, despite the recent literature (Kessler and Vesterlund 2012 and references therein) emphasizing the centrality of qualitative inference, virtually all experimental economics papers report quantitative estimates. For instance, essentially all experimental paper published in a major economics journal in 2012 present quantitative results. Perhaps the most important reason to report quantitative results rather than *only* qualitative results is to provide a sense of the likely external validity of inference from S_E to S_{PC} . For instance, a result showing significance at the 1% level with an estimated $S_E = 50$ percentage point difference in behavior between treatments is more likely to be qualitatively robust to bias than an estimated $S_E = 5$ percentage point difference. This greater confidence is because bias B is more likely to be less than 50 than less than 5 percent. In sum, the magnitudes of quantitative results from experiments are critical for the confidence in the robustness of the qualitative inferences.

Finally, several recent studies have taken an alternative approach to address generalizability of inferences by examining whether experimental results are similar across different populations.⁹ This approach assumes no bias in the participation decision; with no participation bias subjects would be representative of the population they were recruited from, and thus to the extent that ‘representative’ samples of subjects behave similarly in the experiment, the populations they were recruited from would also behave similarly. However, as we show in this paper, these samples are not representative of the populations from which they were recruited. Moreover, we hypothesize that the same participation decision biases exist in recruitment across populations (for instance, towards lower income individuals who volunteer more often), which implies that experimental participants will be

⁸ Bias B is the result of many factors including participation bias on making an inference from an experimental result to the behavior that would occur in a population and context of interest outside of the lab. Thus, B is more than the participation bias that we measure in this paper because it can reflect many additional factors for making inference outside the lab.

⁹ See footnote 2

more similar to each other than the populations they were recruited from, *ceteris paribus*.¹⁰ This homogenizing effect can potentially explain similar results across populations.

2. Hypotheses

Voluntary participation is a core feature of almost all economic lab experiments. To advertise a lab experiment, researchers typically provide information on potential rewards (usually cash payments), participation time, and sometimes on the activities.¹¹ In this context, we assume individual i decides to attend ($a = 1$) or not attend ($a = 0$) a lab experiment k in order to maximize his expected utility,

(1) Individual i attends experiment k iff $E[U_i(a=1 | X_i, E_k)] \geq E[U_i(a=0 | X_i, E_k)]$.

X_i is a vector of heterogeneous individual characteristics and E_k is a vector of information on experiment k shared by all potential subjects. X_i includes income I_i , leisure time T_i , intellectual curiosity c_i and social preferences s_i . E_k includes potential earnings $r(a)$ and time $t(a)$ and the potential experimental tasks.¹² The information E_k , serving several practical purposes, may also attract a non-representative sample. Specifically, we assume individual i 's expected marginal utility of participation is a function of the common information and heterogeneous characteristics:

(2) $U_i = U_i[W(I_i+r(a)), V(T_i-t(a)), M(c_i(a), s_i(a)) | E_k]$,

where W captures utility of wealth, a function of existing wealth I_i plus the expected lab earnings $r(a)$ if i participates; V captures the subjective utility of leisure time, a function of uncommitted time outside the lab T_i minus the lab time $t(a)$ if i participates; M captures the non-pecuniary benefits of participation that we separate into intellectual curiosity $c_i(a)$ and social preferences $s_i(a)$. If i does not participate in the experiment ($a = 0$), we assume $r(a) = 0$, $t(a) = 0$ and we normalize $M(c_i(0), s_i(0)) = 0$.

2.1 Main hypotheses

Using this model of utility and the common information given for a lab experiment, we first present our main hypotheses (H1-H4) that should be robust across most economic labs. We then consider

¹⁰ For instance, consider two populations H and L with mean incomes of \$60,000 and \$40,000, respectively, and identical variance in income σ^2 . If people in both populations with income less than \$30,000 choose to participate and everyone else chooses not to participate, the distribution of income among participants from both populations will be identical (and a higher percentage of the population in L than H will choose to participate).

¹¹ Offering monetary compensation serves several practical purposes. First, it allows subjects to make decisions with real financial incentives rather than hypothetical ones. Second, it encourages participation among people who are motivated by the incentives manipulated in an experiment. Third, it increases the benefit to participate, thus also increases the participation rate. Providing the participation time ensures that participants do not have other obligations that could result in them leaving before completing the experiment, and with information on money, allows participants to calculate per hour compensation. In environments where other researchers conduct experiments with the same population, indicating that the lab task is an economics experiment can signal a reputation that includes, among other features, no deception.

¹² We assume utility over time is only affected here by leisure time. We believe this is reasonable since most experiments give very short notice between the time of the invitation and the experiment, often one week or less, thus non-leisure time is more likely to be committed and not flexible (e.g., class and work scheduling). For experiments with longer planning time, the model can be made more flexible by allowing greater substitution of time in the lab with other activities, nonetheless, the hypotheses derived with respect to time would still hold, but we would expect the magnitude of the effect to be smaller the greater the flexibility a participant has with time commitments.

three additional hypotheses (H5-H7) that rely on recruitment procedures that vary more widely across experiments.

2.1.1 Wealth

We assume concave utility over wealth, $W' > 0$ and $W'' < 0$, thus higher wealth I_i will result in lower expected marginal utility from the identical belief in the lab payment $r(a)$. This implies, *ceteris paribus*, that the identical anticipated payment $r(a)$ will generate less expected marginal utility the greater an individual's wealth. Therefore, we anticipate non-random participation:

H1 (Wealth): Individuals with lower wealth, *ceteris paribus*, will be more likely to participate.

2.1.2 Leisure time

We also assume concave utility over leisure time, $V' > 0$ and $V'' < 0$, thus having more uncommitted (leisure) time T_i will result in a lower expected loss in marginal utility from the identical belief in the lab participation time $t(a)$. This implies, *ceteris paribus*, that the identical anticipated lab time $t(a)$ will generate a smaller loss in expected marginal utility the greater an individual's initial leisure time. Therefore, we anticipate non-random participation:

H2 (Time): Individuals with more leisure time, *ceteris paribus*, will be more likely to participate.

2.1.3 Intrinsic motivations

In addition to monetary benefits, lab experiments involve participating in tasks which individuals may anticipate deriving utility based on intrinsic interests $M(c_i(a), s_i(a))$. Thus, heterogeneous intrinsic interests may also lead to non-representative biases. Two intrinsic motivations that economists and psychologists have conjectured might affect participation are intellectual interests and pro-social preferences.

Intellectual curiosity - $c_i(a)$

A few older papers that examined participation in unpaid psychology and economics lab experiments noted that students who volunteered were more interested in the study. For instance, Rosenthal and Rosnow (1969, 1973) mentioned volunteers in social psychology experiments are 'scientific do-gooders that are interested in the research' (also discussed in Levitt and List, 2007b).¹³ Running an unpaid economics experiment, Kagel et al. (1979) found volunteers were more interested in the experiment than non-volunteers. People may thus attend experiments in part for the utility gained from the task, which could include interests in academic studies, intellectual activities or the specific lab tasks. Therefore, we anticipate non-random participation:

H3 (Intellectual Curiosity): Individuals with intellectual interests in the lab tasks, *ceteris paribus*, will be more likely to participate.

¹³ See also Dixon 1978, Jackson et al. 1989 and Jung 1969 on psychology experiment volunteers.

Additionally, in some economic labs participants are either explicitly informed or are implicitly aware that they are being invited to an *economics lab* experiment.¹⁴ Thus, we anticipate that people who are more interested in economics or closely related areas of study, such as business, will have higher expected marginal utility from the lab activities. Therefore, we anticipate non-random participation:

H3a (Economics Interests): Individuals with interests in economic topics, *ceteris paribus*, will be more likely to participate in ‘economics’ experiments.

Pro-social preferences - $s_i(a)$

Levitt and List (2007a, b) conjecture that experimental subjects are more cooperative and pro-social based on evidence from previous psychology and economics experiments. In two early studies, Rosenthal and Rosnow (1969, 1973) noted that students who volunteered for social psychology experiments ‘more readily cooperate with the experimenter and seek social approval’ (see also Orne 1962; Rosen 1951). Pro-social preferences among participants may not be surprising for unpaid experiments (e.g., in psychology or health research) where participation often is framed around helping either the researchers or the greater community. These preferences could nonetheless also affect the participation decisions in incentivized economic lab experiments.¹⁵ For instance, in a gift exchange experiment List (2006) observed that those who declined to participate in the lab experiment were less pro-social (less reciprocal) in a later field experiment than the lab participants.¹⁶ Thus, participants who respond to researcher requests may obtain utility from participating in the same way as when they respond to other pro-social requests, e.g., a call for volunteers. In other words, students may be participating in an experiment to help out the researcher or general community. Therefore, we anticipate non-random participation:

H4 (Pro-social Preferences): Individuals with higher pro-social preferences, *ceteris paribus*, will be more likely to participate.

Two recent papers provide some initial evidence regarding this hypothesis. Falk et al. (2013) test whether students who donate money (when given the option while paying term fees) are more likely to participate in a later lab experiment, and Cleave et al. (2013) test whether students who reciprocate more (in a classroom trust game) are more likely to participate in a subsequent lab experiment. Neither study finds any relationship between the observed pro-social behavior and participating in the later lab experiment, suggesting no pro-social bias in participation. However, measuring pro-social behavior using monetary decisions may not be the most appropriate measure to understand whether

¹⁴ Even if the advertisement does not explicitly indicate an economics experiment, potential subjects may infer an economics experiments either by the location of the experiment (e.g., in the economics building or where other economics experiments have been run) or if the population were initially signed up in a data base to be contacted for an economics experiment.

¹⁵ Extensive research examines the effects of monetary incentives on the supply of pro-social behavior. The results suggest that offering money can in some situations undermine (crowd out) intrinsic motivations, thus reducing the pro-social supply (e.g., see Bowles and Polini-Reyes, 2011, for a review). To the extent that the monetary rewards crowd out the pro-social intrinsic benefits to participations, participation bias based on pro-social preferences will thus be less prevalent.

¹⁶ List (2006) recruited by personally approaching potential subjects, which may contribute to screening more socially cooperative individuals into the lab. Selection effect was also not the main purpose of the study and the sample size for those who declined was small.

pro-social preferences affect the participation decision. Wealthier people may be more likely to be donate money to charities given their larger budget, but less likely to participate as hypothesized in H1 above. Thus the correlation between participation and monetary donations may capture other countervailing factors than purely pro-social preferences.¹⁷ More fundamentally, to participate in a lab experiment, participants sacrifice time in exchange for money, thus *they are deciding whether to give up time, not money*.¹⁸ Camerer (2011) makes a similar point, “A likely reason why there are not systematic volunteering effects” (with respect to pro-social preferences) “is that subjects volunteer to earn money ...” Thus, the decision to participate in a lab study in which substantial monetary rewards are offered should motivate people to participate who are interested in earning money rather than donating money. On the other hand, to the extent that people perceive participation to assist university researchers, participation is similar to a decision to volunteer time. Our study adds to the literature on pro-social preferences and participation bias by recognizing that participation based on social preferences should reflect volunteering time:

H4a (Volunteering Time): Individuals with higher pro-social preferences for volunteering time, *ceteris paribus*, will be more likely to participate.

2.2 Additional Hypotheses

The proceeding hypotheses (H1-H4) address features that are largely universal across lab studies, we now discuss three additional potential non-representative biases (H5-H7) arising from recruitment procedures which may vary substantially across experiments.

2.2.1 Risk Attitudes

Assuming concave utility over wealth ($W' > 0$ and $W'' < 0$) and leisure time ($V' > 0$ and $V'' < 0$), higher uncertainty with respect to either the lab payment $r(a)$ or session time $t(a)$ will result in less participation among more risk averse individuals, *ceteris paribus*. Consistent with this hypothesis, Andersen et al. (2009) found that a decrease in the variance in the advertised lab payments led to greater risk aversion among lab participants.¹⁹ Similar to the payment uncertainty, greater uncertainty regarding any other dimension of the experiment could bias the participation decision toward less risk-averse individuals on these dimensions.²⁰ For instance, there could be uncertainty with respect to

¹⁷ In these studies, wealth was not directly controlled for. As we will show in the current work, controlling for wealth is critical for understanding the relationship between monetary donations and the participation decision.

¹⁸ If volunteering time and donating money are perfectly correlated indicators of pro-social behavior, then there is no difference in measuring monetary donations or volunteering time. However, we are unaware of any study that has examined this correlation, and see no reason to assume *a priori* that they are perfectly correlated.

¹⁹ On the other hand, Cleave et al. (2013) find no overall evidence of differences in risk-aversion between individuals who participate and do not participate in a lab study. However, their disaggregated analysis finds that women who participated were less risk-averse than women who did not, which is consistent with the hypothesis. They also find that men who participated were more risk-averse than men who did not, which is inconsistent with our hypothesis. Thus, the existing evidence is in general consistent with our hypothesis with the exception of disaggregated behavior of men in Cleave et al. (2013).

²⁰ Roe et al. (2009) provides an example of risk attitudes affecting participation in research studies that involve greater risks. They find that more risk-averse subjects are less likely to participate in an fMRI study and a genetics study requiring a blood sample than the population they were recruited from.

whether someone will actually get to participate if he shows up, uncertainty regarding how long he might have to wait for a session to begin and uncertainty as to how much he will enjoy the tasks.

Therefore, we anticipate non-random participation:

H5 (Risk Aversion): Individuals who are less risk averse with respect to either wealth, time or task activities, *ceteris paribus*, will be more likely to participate.

2.2.2 Patience

Because of the delay between individuals' decision to participate and the lab session time, the net benefit of the experiment will be discounted whereas additional costs will occur prior to the experiment, such as signing up (e.g., going online and filling out forms) and scheduling.²¹ Therefore, we anticipate non-random participation:

H6 (Patience): Individuals who are more patient, *ceteris paribus*, will be more likely to participate.

2.2.3 Recruitment conditions

In addition to individual characteristics, we also examine whether different recruitment procedures can increase participation rates (and consequently reduce participation bias). Economic lab experiments conventionally require students to make an appointment with a fixed starting time. The fixed starting time solves the logistical need for having a fixed number of participants (e.g., for games and markets). However, compulsory appointments may affect participation because making an appointment incurs higher transaction costs than just showing up; for instance, subjects need to register in advance, thus adding a step to the recruitment process. Mandatory appointments can also reduce the likelihood of participation among people who receive negative utility from commitments.

An alternative recruitment method is to allow participants to show up (drop-in) at any time without making an appointment.²² The ability to drop-in at any time should increase the likelihood of participation by offering greater flexibility and eliminating the costs associated with having to sign up in advance.

H7 (Recruitment conditions): A higher percentage of individuals will participate if they can drop-in rather than if they have to make an appointment.

One countervailing force when allowing potential participants to drop-in may occur among people who procrastinate since having to make an appointment can solve a time inconsistency problem (Strotz 1955). Further, if participants do not have an appointment they may have greater uncertainty regarding session availability and wait time, for instance whether the experimenters will be prepared and whether they will have to wait for others to show up. Thus, whether participation will increase

²¹ An alternative possibility is that individuals who are more patient will be less likely to participate if they have an alternative activity with greater long-term benefits (e.g., studying) than lab participation. While this seems plausible, the timing of the current experiment was several weeks prior to any exams and thus likely mitigates this effect. However, this effect could be stronger for experiments run closer to, or during, exam periods.

²² Allowing drop-ins may not be feasible for many kinds of experiments that need a fixed number of participants, such as market experiments and games.

depends on whether the added flexibility and lower transaction costs are greater than procrastination and uncertainty effects. While we anticipate that the hypothesized core participation biases (H1-H4) will be robust across recruitment conditions, other biases may differ. For instance, more risk-averse individuals may be more likely to participate when they have to make an appointment than when they must drop-in to the extent that fewer perceived uncertainties are associated with appointments.

To further explore these potential effects, we also examine a third recruitment condition in which individuals have the option to either make an appointment or drop-in. We include this condition to test the effect of greater flexibility and importantly to examine the characteristics of participants who choose to make an appointment rather than to drop-in. We anticipate that more risk-averse participants will be more likely to make an appointment to reduce uncertainties associated with dropping in. Therefore, we anticipate non-random participation:

H7a (Recruitment conditions): More risk averse individuals will be more likely to participate when they have to make a mandatory appointment than when they have to drop-in, and will be more likely to make an appointment when given an option.

3. Study Design

We first discuss the population (S3.1), then the measures we collected for each hypothesis (S3.2) using survey questions and experimental data. We conclude this section by discussing the precise procedures and time flow (S3.3) and recruitment conditions (S3.4).

3.1 Population

The classroom data collection was conducted in the first year undergraduate Introductory Microeconomics class at the University of Sydney. This class provides a large heterogeneous population similar to typical target populations for economic lab experiments. The course is required for an economics or business degree, but many other students take this course as an elective. The course is predominantly taken during students' first term at the university and our intervention occurred during the fourth week of the term when the course material would not have involved any topic related to our data collection.²³

Our population data collection occurred during students' normal tutorials (typically small classes of at most 18 students). At the beginning of each tutorial, students were asked to participate in a 20-minute survey and experiment. Our target population (hereafter 'the population') consists of the 892 students who participated in the *classroom tasks*. Participation in the classroom task itself is unlikely to suffer from any *voluntary* participation bias for two reasons. First, attendance in the tutorials is uncorrelated with our classroom tasks because the tasks were not announced in advance; thus students would not have chosen to attend the tutorial in order to participate in the classroom tasks. Second participation in the classroom tasks is extremely high; over 96 percent of the students who attended a

²³ Topics covered: introduction, scarcity, choice; supply and demand; elasticity; consumer and firm behavior.

tutorial participated in our tasks. After the classroom data collection, the population was invited to participate in a lab experiment (see Procedures **S3.3** below). We are interested in how well the characteristics of the students who subsequently attended the lab experiment represent the characteristics of the class population.

3.2 Classroom tasks

The classroom tasks contain two parts: three incentivized experiments and a 20 item survey. To address our hypotheses, the survey contained questions to measure income, leisure time, intellectual and academic interests, pro-social preferences (time and money based pro-social activities), patience and risk attitudes, and controls for demographics. To complement the survey, we measured individual's pro-social, risk and inter-temporal preferences using standard lab tasks over monetary outcomes. The experimental tasks were conducted first and were followed by the survey. All tasks were conducted with multiple choice responses using paper and pencil. Students worked alone at their own pace throughout these tasks. A copy of the instructions, experimental decisions and survey questions are included in supplemental materials (available from the authors). We discuss our measures in depth given the key role they play for examining non-representative characteristics.

3.2.1 Measuring wealth (H1)

We measure both household and disposable income with the questions “What is your family’s annual household income approximately?” and “How much money do you spend in a typical week?”²⁴ While the household income measure is common in surveys and reflects overall resources available to the family, it may not correlate well with the resources available to the individual. In contrast, measuring spending per week, used by Andreoni and Sprenger (2010) as a proxy for weekly consumption, may better identify the resources immediately available to the individual and thus be a better proxy for disposable income. The two measures thus capture different aspects of wealth. Household income is a more direct measure of wealth for a student who does not yet have her own stable income and is not affected by students’ spending habits. However, weekly spending more accurately reflects the disposable income currently accessible to students, either from household income or their own earnings. Students may focus more on disposable income, if they do not fully follow lifetime consumption smoothing models.

3.2.2 Measuring leisure time (H2)

We measure available leisure time as the inverse of weekly working hours, “How many hours per week do you currently work for pay?” We chose work hours because it reflects fixed commitments students would have difficulty altering in the short time between the invitation and participation and since most students have identical class commitment time given the rigid undergraduate structure.

²⁴ We stressed that weekly spending only includes short term consumption items with examples for both short and long term items: “(This should be your daily expenses e.g. food, travel, mobile charges, excluding e.g. rent, tuition).”

One potential drawback with work hours is that it may be correlated with higher income which we hypothesized will reduce the likelihood of participation. However, in our analyses we control for this potential correlation with our income measures.

3.2.3 Measuring intellectual curiosity (H3, H3a)

We measure two broad aspects of intellectual curiosity, interest in economics and interests related to general experimental economics lab tasks, using survey questions and consistency of behavior in one of the experimental tasks. The survey question “What is your major area of study?” reflects individual’s interest in economics. Among the five responses (Economics; Business; Arts or Social Sciences; Science or Engineering; Other), majoring in economics or business suggests either innate interest, enjoyment or ability with the subject matter which could carry over to an economics lab experiment.²⁵

We also used three additional measures to capture general interests in experimental lab activities. The first measure is students’ academic performance based on their university admission ranking, “Please indicate your ATAR²⁶ (Australian Tertiary Admission Rank),” and, “If you don’t have an ATAR, what was your equivalent ATAR (reflecting class standing) when applying to university?” Higher academic performance suggests, all else equal, greater academic curiosity, and thus may predict more interest in lab experiments to the extent that the experiments may involve academic subject matter.

The last two measures to capture general interest in experimental economic lab activities examine how much attention individuals give to tasks that require reflection. We assume that an individual who is more interested in a task, *ceteris paribus*, will put more effort and reflection into the task. The first of these measures is the three item Cognitive Reflection Test (CRT; Frederick 2005). The CRT attempts to assess how reflective people are on thinking about simple logical problems. Each CRT question has a quick/impulsive but incorrect response and a correct solution that requires a little reflection (Frederick 2005).²⁷ We anticipate that higher scores on the CRT, *ceteris paribus*, reflect individuals’ interest in thinking about intellectual activities common in experimental economics lab activities. The second measure examines “consistent” choices over two sets of three inter-temporal

²⁵ Had we instead advertised a “psychology experiment,” we would have hypothesized that psychology rather than economics students would have been more likely to participate in the experiment.

²⁶ Australian Tertiary Admission Rank (ATAR) is a rank that allows the comparison of students who have completed different combinations of HSC (High School Certificate) courses. See Australian Universities Admissions centre website for details: <http://www.uac.edu.au/undergraduate/atar/>

²⁷ The three questions are: (1) “In a lake, there is a patch of lily pads. Every day, the patch doubles in size. If it takes 48 days for the patch to cover the entire lake, how long would it take for the patch to cover half of the lake? ____ days” The potentially impulsive answer ‘24 days’ is incorrect. People who reflect on the fact that if the lily patch cover the entire lake on day 48, on day 47 it must be half the size, will give the correct answer 47 days. (2) ‘A bat and a ball cost \$1.10 in total. The bat costs \$1.00 more than the ball. How much does the ball cost? ____ cents’ (impulsive answer is often reported to be 10 cents, correct answer is 5 cents), and (3) ‘If it takes 5 machines 5 minutes to make 5 widgets, how long would it take 100 machines to make 100 widgets? ____ minutes’ (impulsive answer is 100 minutes, the correct answer is 5 minutes). In the survey, we provided four options in a multiple choice format and always included the impulsive response as one of the options. For control, we also asked “Have you seen any of the last three questions (Decision 9-11) before?” Anyone who had seen any of the three questions were treated as a missing observation in the data analysis for this question.

saving decisions (discussed below in Measuring time preferences section **S3.2.6**) in which we asked subjects to allocate money between an early and later period. Within each set we only varied the interest rate. We define a set of decisions as *consistent* if an individual saves the same amount or more when facing higher interest rates.²⁸ Similar to the CRT measure, but with monetary incentives, we assume that people who make more consistent decisions are likely to have given more effort to the decisions, *ceteris paribus*, and hence enjoy thinking about the types of decisions in economic lab experiments.

3.2.4 Measuring pro-social preferences (H4, H4a)

Given the large body of experimental research on pro-social preferences, we included four survey questions and one experimental decision to measure the population's pro-social behavior. The survey questions measured the frequency and absolute amount of money (donation) and time (volunteering) related to charitable behavior over the past year. To measure monetary donation frequency, we asked: "Excluding today, how many times have you donated money to a charitable organization, such as an international aid organization, child agency, church and so forth, in the past year?" and for the total dollar amount: "Approximately how much money have you donated to charitable organizations in the past year?" To measure time-based volunteering frequency, we asked: "How many times have you volunteered some of your time to a charitable organization, such as a non-profit, university charity effort, church and so forth, in the past year?" and for the total hours of volunteering: "Approximately how many hours have you donated to charitable organizations in the past year?" The frequency measures capture the number of distinct times individuals did pro-social activities whereas the total dollar amount captures the overall financial contribution, *ceteris paribus*. Measuring time volunteering is central to our analyses since (1) participating in an experiment involves sacrificing time rather than income, (2) money donations are likely positively correlated with income, and (3) the Levitt and List (2007a,b) conjecture is based on past evidence of volunteering time (e.g., to help researchers) rather than sacrificing money to attend the lab.

The experimental donation decision is a modified dictator game initially used in the lab by Eckel and Grossman (1996) that pairs subjects with a well-known charity. In our classroom experiment, students received \$100 to allocate between themselves and the Australian Red Cross (ARC). For each dollar donated, the ARC received two dollars, thus the opportunity cost, including tax considerations, to donate money through the experiment is lower than if the subject kept the money and donated outside of the experiment. We paid the classroom students for their experimental decisions after the lab experiment was completed (discussed in 3.3 Procedures below). To ensure that all classroom students would incur the identical transaction cost on the later date no matter how much they gave to the ARC, including giving everything to the ARC and keeping nothing for themselves, we included an

²⁸ Although the wealth effect could cause individuals to save less when interest rates increase, we consider it to be negligible in this case, due to the small overall earnings (\$100), and relatively large (\$20) increments in saving amount choices.

additional \$10 payment for the students to receive on the later date. Students were given the following six options:

Table 3.1: The donation decision

| Donation Choice | To keep for myself | To donate to the Australian Red Cross |
|-----------------|--------------------|---------------------------------------|
| 1 | \$10 + \$100 | \$0 |
| 2 | \$10 + \$80 | \$40 |
| 3 | \$10 + \$60 | \$80 |
| 4 | \$10 + \$40 | \$120 |
| 5 | \$10 + \$20 | \$160 |
| 6 | \$10 + \$0 | \$200 |

3.2.5 Measuring risk preferences (H5)

We included two measures of risk preferences, one to capture a broad risk assessment and the other to capture financial risk since, as discussed in the hypotheses, the risks to participate may be partially financial (uncertainty over money earnings) and partially other risks such as time involved and the enjoyment of the lab tasks. The survey question, “In general, how much of a risk taker are you compared to other students?” was used to measure self-perception of risk attitude broadly. The financially based risk measure is a modified version of the ordered lottery sequence (OLS) used in the lab by Eckel and Grossman (2008) and earlier by Binswanger (1980, 1981) in a field experiment. We use the same OLS values used in Garbarino et al. (2011). In this task, students chose one of the six lotteries shown in Table 3.2. Each lottery has two outcomes with a 50 percent chance of occurring. Lottery 1 has a sure payoff of \$22, Lotteries 2-5 offer increasingly higher expected value with increasingly greater risk (measured by either variance or CRRA preferences), and Lottery 6 has the same expected value to, but higher risk than Lottery 5. Less risk averse individuals will choose higher numbered lotteries and a risk seeking individual will prefer Lottery 6. We chose a single OLS task over other common measures due to its simplicity to explain and administer given our limited time.

Table 3.2: The Lottery decision

| Lottery Choice | Information for Subjects | | | | Additional Information | | |
|----------------|--------------------------|------|---------------------|------|------------------------|-----------------------|-------------------|
| | Outcome 1 Payoff | Prob | Outcome 2 Payoff | Prob | EV | Standard Deviation | CRRA* Range |
| 1 | \$22 | 50% | \$22 | 50% | 22.00 | 0.00 | $r > 2.74$ |
| 2 | \$30 | 50% | \$18 | 50% | 24.00 | 6.00 | $0.91 < r < 2.74$ |
| 3 | \$38 | 50% | \$14 | 50% | 26.00 | 12.00 | $0.55 < r < 0.91$ |
| 4 | \$46 | 50% | \$10 | 50% | 28.00 | 18.00 | $0.37 < r < 0.55$ |
| 5 | \$54 | 50% | \$6 | 50% | 30.00 | 24.00 | $0 < r < 0.37$ |
| 6 | \$60 | 50% | \$0 | 50% | 30.00 | 30.00 | Risk Seeking |

*CRRA: $U(x) = [x^{(1-r)}]/(1-r)$ for $r > 0$ & $r \neq 1$; $U(x) = \ln(x)$ for $r = 1$.

3.2.6 Measuring time preferences (H6)

We included two measures of patience, one to capture a broad patience assessment and the other to capture financial patience since future participation may be partially discounted based on the future money and partially on other aspects of the future benefits and costs. The survey question, “In general, how patient are you compared to other students?” was used to measure self-perception of patience broadly.

Table 3.3: The saving decision

| Dec | Choice | Information for Subjects | | | | Saving | 4 wk Rate (simple) |
|-----|--------|--------------------------|----------|-----------------|----------------|--------|-----------------------|
| | | Front End Delay | Duration | Early Payoff | Late Payoff | | |
| 1 | 1 | 2 weeks | 4 weeks | \$10 + \$100 | \$10 + \$0 | \$0 | 5% |
| | 2 | 2 weeks | 4 weeks | \$10 + \$80 | \$10 + \$21 | \$20 | |
| | 3 | 2 weeks | 4 weeks | \$10 + \$60 | \$10 + \$42 | \$40 | |
| | 4 | 2 weeks | 4 weeks | \$10 + \$40 | \$10 + \$63 | \$60 | |
| | 5 | 2 weeks | 4 weeks | \$10 + \$20 | \$10 + \$84 | \$80 | |
| | 6 | 2 weeks | 4 weeks | \$10 + \$0 | \$10 + \$105 | \$100 | |
| 2 | 1 | 2 weeks | 4 weeks | \$10 + \$100 | \$10 + \$0 | \$0 | 10% |
| | 2 | 2 weeks | 4 weeks | \$10 + \$80 | \$10 + \$22 | \$20 | |
| | 3 | 2 weeks | 4 weeks | \$10 + \$60 | \$10 + \$44 | \$40 | |
| | 4 | 2 weeks | 4 weeks | \$10 + \$40 | \$10 + \$66 | \$60 | |
| | 5 | 2 weeks | 4 weeks | \$10 + \$20 | \$10 + \$88 | \$80 | |
| | 6 | 2 weeks | 4 weeks | \$10 + \$0 | \$10 + \$110 | \$100 | |
| 3 | 1 | 2 weeks | 4 weeks | \$10 + \$100 | \$10 + \$0 | \$0 | 20% |
| | 2 | 2 weeks | 4 weeks | \$10 + \$80 | \$10 + \$24 | \$20 | |
| | 3 | 2 weeks | 4 weeks | \$10 + \$60 | \$10 + \$48 | \$40 | |
| | 4 | 2 weeks | 4 weeks | \$10 + \$40 | \$10 + \$72 | \$60 | |
| | 5 | 2 weeks | 4 weeks | \$10 + \$20 | \$10 + \$96 | \$80 | |
| | 6 | 2 weeks | 4 weeks | \$10 + \$0 | \$10 + \$120 | \$100 | |
| 4 | 1 | 6 weeks | 4 weeks | \$10 + \$100 | \$10 + \$0 | \$0 | 5% |
| | 2 | 6 weeks | 4 weeks | \$10 + \$80 | \$10 + \$21 | \$20 | |
| | 3 | 6 weeks | 4 weeks | \$10 + \$60 | \$10 + \$42 | \$40 | |
| | 4 | 6 weeks | 4 weeks | \$10 + \$40 | \$10 + \$63 | \$60 | |
| | 5 | 6 weeks | 4 weeks | \$10 + \$20 | \$10 + \$84 | \$80 | |
| | 6 | 6 weeks | 4 weeks | \$10 + \$0 | \$10 + \$105 | \$100 | |
| 5 | 1 | 6 weeks | 4 weeks | \$10 + \$100 | \$10 + \$0 | \$0 | 10% |
| | 2 | 6 weeks | 4 weeks | \$10 + \$80 | \$10 + \$22 | \$20 | |
| | 3 | 6 weeks | 4 weeks | \$10 + \$60 | \$10 + \$44 | \$40 | |
| | 4 | 6 weeks | 4 weeks | \$10 + \$40 | \$10 + \$66 | \$60 | |
| | 5 | 6 weeks | 4 weeks | \$10 + \$20 | \$10 + \$88 | \$80 | |
| | 6 | 6 weeks | 4 weeks | \$10 + \$0 | \$10 + \$110 | \$100 | |
| 6 | 1 | 6 weeks | 4 weeks | \$10 + \$100 | \$10 + \$0 | \$0 | 20% |
| | 2 | 6 weeks | 4 weeks | \$10 + \$80 | \$10 + \$24 | \$20 | |
| | 3 | 6 weeks | 4 weeks | \$10 + \$60 | \$10 + \$48 | \$40 | |
| | 4 | 6 weeks | 4 weeks | \$10 + \$40 | \$10 + \$72 | \$60 | |
| | 5 | 6 weeks | 4 weeks | \$10 + \$20 | \$10 + \$96 | \$80 | |
| | 6 | 6 weeks | 4 weeks | \$10 + \$0 | \$10 + \$120 | \$100 | |

The financially based measure is a modified version of the ‘convex time budget’ inter-temporal task developed by Andreoni and Sprenger (2010).²⁹ We gave each student the six multiple-choice questions shown in Table 3.3. For each question, students allocated \$100 between an early and later payoff date. The early payoff date was either two weeks (decisions 1-3) or six weeks (decisions 4-6) from the date of the experiment while the later payoff date was always four weeks after the early payoff date. Each decision offered one of three levels of simple interest for the later payment for each dollar saved: 5, 10 or 20 percent. Following Andreoni and Sprenger (2010), in all decisions we included an additional \$10 payment to both the early and later payoff date to ensure participants would incur the identical transactions costs on the early and later payment dates. We also had the

²⁹ The novel feature of this method is that subjects are free to choose interior points under a convex time budget constraint rather than having to allocate all payments on a single date. This method allows jointly estimating a discount rate and the curvature of the utility function within a set of inter-temporal choices without needing to estimate risk preferences separately (Andreoni and Sprenger 2010). However, due to classroom time constraints, we only asked a few of these inter-temporal choices, thus we will only use a simple ‘average saving’ amount (and control for risk using our risk task) to measure possible representative biases based on time preferences.

identical procedures for receiving future payments regardless of the payment date in order to have the same transaction cost on each date. A student who allocates more to the later payoff date thus saves more and, controlling for risk, is more patient. We used the six decisions to let us test whether the relationship between savings and participation varies with (1) different frontend delays (decisions 1-3 vs. 4-6) or (2) different interest rates. However, we find that once we control for an individual's average saving rate across the six decisions, variation in either frontend delay or interest rates offers no further explanatory power on the participation decision and is not discussed further.

3.2.7 Demographics

We also collected each individual's gender and ethnicity on the survey. For ethnicity, we asked, "How would you describe your ethnicity (please pick the most applicable)?" to identify four main ethnic groups in Australia: Caucasian, East Asian, South Asian and Middle Eastern.

3.3 Procedures

We collected the population data during tutorials. Tutorials have 18 or fewer students, most with less than 15 (mean 11.6), so tutors could easily ensure no communication between students. We prepared detailed tutor instructions (Appendix 1) explaining the precise procedures to follow and scripts to read. All tutors attended a training session and received a take home packet for practice. Tutors were explicitly instructed not to encourage or discourage students to attend the subsequent lab experiment.³⁰ The classroom exercise was not announced prior to the tutorial to avoid biasing tutorial attendance based on our intervention.

On the day of the classroom intervention, each tutor announced the tasks at the beginning of class and handed out the material to each student. Each student was asked to read the cover page and then decide whether to complete the tasks. If a student decided *not* to participate, he could go over tutorial material or do anything else but was asked to remain quiet while other students completed the tasks. If a student decided to participate, the student would immediately begin working through the tasks at his own pace. After completing the tasks, the tutor collected all the material from the students. The tutor then made an announcement about an upcoming lab experiment and distributed the randomly assigned flyer invitation (Appendix 1) to the class.³¹

In total, 96% of the students attending the tutorial agreed to participate in the tasks. However, tutors were instructed to begin tutorial topics after a maximum of 20 minutes, and since some students came late or worked slowly, not everyone completed all the tasks. For our analyses, we include everyone who began the tasks, and treat any incomplete responses as missing observations in the

³⁰ To compensate tutors for the time involved in preparing our classroom tasks, we held a lottery after we completed the laboratory experiment; we drew 5 of the 22 tutors to receive \$100 gift certificates to a local major shopping mall.

³¹ The lab study measured charitable donations, risk and inter-temporal preference to address different questions from the current study.

analyses. Nonetheless, virtually all students (97%) completed the experimental (first) part, and almost 2/3 provided a response to every survey question.

The classroom tasks and subsequent lab experiment spanned two weeks (see Time Flow below). The classroom tasks were run during the entire Week 4 to cover all tutorials in the class. The opportunity to participate in the lab experiment began exactly one week after the classroom intervention and remained open for exactly five weekdays. To have the identical time between the initial invitation and the time students could participate we staggered the invitations based on the day of the tutorials; for example, students in the *Tuesday* tutorials received invitations stating the lab sessions would be available from the following *Tuesday* to the Monday a week later. Exactly one week after the classroom tasks (and thus on the first day that a student was eligible to attend a lab session) tutors reminded students of the lab experiment by distributing the identical flyer invitation in the tutorials. Finally, in the last two days of the second week of the lab experiment we emailed a third round of the identical flyer invitations.

Time Flow: Classroom Tasks, Invitation to Participate and Lab Experiment

| | |
|-------------|--|
| Day 0: | In class: intervention then lab experiment flyer invitation |
| Day 7: | In class: reminder lab experiment flyer invitation |
| Day 7 – 13: | Lab experiment open for participation |
| Day 11: | E-mail reminder sent with lab experiment flyer invitation |
| Day 13: | Last day for lab experiment |
| Day 14: | Students receive e-mail indicating whether chosen for pay for the class experiment |

To pay classroom participants for the experimental tasks, we randomly chose 40 students who participated in the classroom tasks and paid each one for one of their decisions, also randomly chosen. We informed students that they would learn whether they got paid two weeks after their classroom participation (coinciding with the first possible payment date for the saving decision). Importantly, since the classroom task only compensated a random sample of the classroom participants, we explained in the invitation flyer to the lab experiment that unlike the classroom exercise, everyone who participates in economics lab experiments gets paid.

3.4 Recruitment conditions

We varied the flyer invitation (Appendix 1) to examine three recruitment conditions: ‘Appointment,’ ‘Drop-in’ and ‘Option.’ The appointment condition required students to make an appointment using an online scheduling option on the course webpage.³² The drop-in condition asked students to walk in anytime during lab hours and no appointment was mentioned. Students in the option condition were given the choice of making an appointment or walking in. The invitation provided a reason for the option by explaining, ‘appointments are helpful since spaces may be limited.’ Since the drop-in condition gave students the most flexibility, starting any time between 10:00 AM and 4:00 PM each

³² Signing up for an appointment took about two minutes. To avoid any differences in the information participants had to provide across the conditions, we did not collect any information beyond their name when they made an appointment.

day, in the appointment condition we allowed students to choose times to arrive in 20 minute intervals, thus on each day a student could sign up for an appointment for 19 different times, or 95 different times over the course of the week. Besides these differences, the three flyers were identical.

The recruitment conditions were balanced across both the tutorial day of the week and tutors. The class had 77 one-hour tutorials each week run by 22 tutors. Within each tutorial, the same flyer was handed out to all students in the tutorial to reduce the chance that students would have been aware of the different flyer conditions. Across tutorials, and since all tutors taught either three or six tutorials (except one who taught two tutorials), each tutor was assigned to hand out a different flyer in each tutorial if they taught three tutorials, or each flyer in two tutorials if they taught six tutorials. The tutors were given separate sealed envelopes with the flyers in them for each of their tutorials and were instructed to not open the envelopes until handing out the flyers. Thus, the tutors would not have been aware of the invitation condition until after the class tasks had been completed. The tutors were never told the purpose of our study or that there were different recruitment conditions, thus the study was conducted double blind.

4. Results

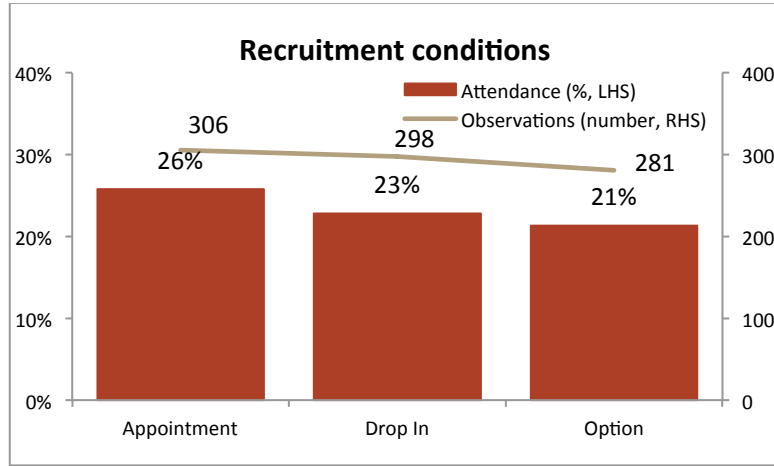
4.1 Non-representative biases

We examine whether the characteristics of lab participants are representative of the characteristics of the population from which they were recruited. We first examine the effect of the recruitment conditions on participation, followed by individual tests for the core hypothesized non-representative biases over income, leisure time, intellectual curiosity and social preferences, and then the more specialized hypotheses over risk and time preferences. We then test the robustness of the individual results estimating all biases simultaneously, and conclude by testing whether the biases differ across recruitment conditions.

4.1.1 Recruitment conditions

Figure 4.1 shows lab attendance by the three recruitment conditions: appointment, drop-in and option. The bars and left-hand y-axis indicate the participation rate for each condition; the line and the right-hand y-axis indicate the number of respondents for each condition (subsequent figures have the same format). Figure 4.1 shows that of the 306 students in the appointment condition, 26 percent participated in the lab experiment, while 23 percent of the 298 students in the drop-in condition participated and 21 percent of the 281 in the option condition participated. On average, 23 percent of the population attended the lab experiment.

Figure 4.1: Participation by recruitment condition



We estimate the following probit model to test whether the differences in attendance across conditions are statistically significant:

$$(3) \quad y_i = f(a + \beta_1 \text{drop-in}_i + \beta_2 \text{option}_i + \sum \delta_j X_{ji} + \varepsilon_{it})$$

where y_i equals 1 if student i in the population participated in the lab experiment, and 0 otherwise; f is the normal Probit function, drop-in_i and option_i are dummy variables indicating student i 's recruitment condition. X_{ji} is a vector of dummy variables for the day of the week students attended their tutorials³³ and the 22 tutors who ran the classroom tasks. Although tutors were given identical training and instructed to follow the identical procedures, they may have inadvertently influenced students' participation decisions differently across their tutorials. Thus, in addition to controlling for tutor effects, we also estimate and report standard errors clustered at tutorial level to address possible differences across the 77 tutorials.

Table 4.1 presents the results. Column 1 shows the estimates without the controls for weekday and tutor (X_{ji}) and without clustering for the 77 tutorials, Column 2 includes the controls for weekday and tutor (X_{ji}) as well as clustering the errors at the tutorial level, and Column 3 reports the marginal effect based on the Column 2 estimates. In both regressions, the difference among recruitment conditions did not reach a conventional level of significance ($p > 0.10$), although directionally subjects in the drop-in and option conditions were 3.2 and 4.2 percentage points less likely to participate in the lab experiment, respectively, compared to those in the appointment condition.³⁴

³³ Students from Friday tutorials were more likely to attend the lab experiment ($p < 0.01$) relative to every other day of the week, otherwise we found no differences across the days of the week. One concern with this Friday effect is that it might indicate that students on Friday, the last day of the classroom tasks, may have been more likely to have heard about the in class tasks, and thus Friday classroom attendees might reflect participation bias. However, we find no statistical difference in the percent of students attending Friday tutorials than any other day, thus attending Friday tutorials is unlikely to reflect participation bias in response to the classroom tasks. A more likely explanation for the Friday effect is that students have fewer classes on Friday, thus the students who attend Friday classes have more spare time to participate in the lab experiment on the day they attend their tutorial.

³⁴ We further find that the combined Drop-in plus Option conditions was also not jointly significantly different than the Appointment condition ($p < 0.10$).

Result 0: In contrast to hypothesis, H7, lab participation was not significantly different across the three recruitment conditions.

Table 4.1: Participation by recruitment condition

| | (1) | (2) † | Marginal Effect† |
|--|-----------------------|-------------------|---------------------|
| Drop-in | -0.0958 (0.112) | -0.109 (0.127) | -0.0322 (0.0371) |
| Option | -0.145 (0.114) | -0.144 (0.124) | -0.0422 (0.0355) |
| Constant | -0.649*** (0.0774) | -0.942 (0.579) | |
| Tutorial Effect | N | Y | Y |
| Observations | 885 ³⁵ | 885 | 885 |
| Log Likelihood | -480.5 | -463.9 | -463.9 |
| Probit regressions with robust standard errors in parentheses | | | |
| †Regressions include dummy variables for tutors and tutorial days; | | | |
| *** p<0.01, ** p<0.05, * p<0.1 | | | |

Discussion: While we anticipated that the greater flexibility would lead to greater participation when the population could drop-in or could choose to drop-in or make an appointment, we find no evidence in this direction. Instead, the highest participation rate occurred directionally when an appointment was required. Thus, we find no evidence that the two alternative recruitment methods examined here can improve the participation rate over the standard appointment system commonly used in experimental economics labs.

We now turn to our main hypotheses. In the subsequent analyses, we always control for recruitment conditions, fixed weekday and tutor effects (X_{ji}) and cluster standard errors at the tutorial level. For each subsection, we estimate variations of the following model:

$$(4) \quad y_i = f(a + \sum \theta_j Z_{ji} + \beta_1 \text{drop-in}_i + \beta_2 \text{option}_i + \sum \delta_j X_{ji} + \varepsilon_i),$$

where Z_{ji} is a vector of the core characteristics j of interest (e.g., income and time) for individual i .

4.1.2 Wealth (H1)

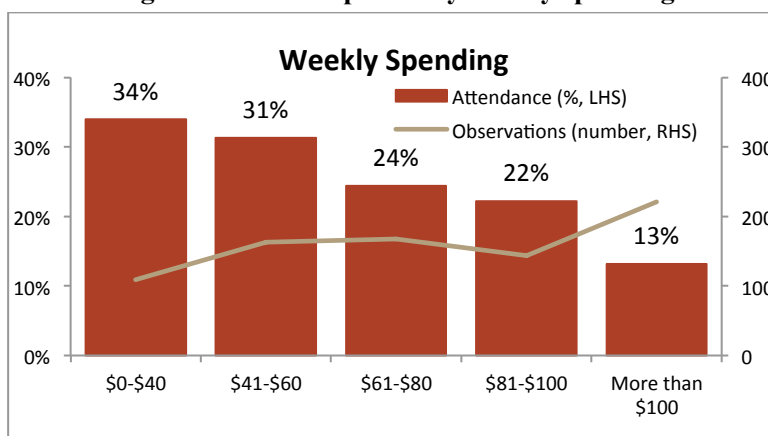
Spending per week: Figure 4.2 and Table 4.2 Columns 1 and 4 examine lab participation based on students' weekly spending. Figure 4.2 shows a clear negative correlation of about a 10 percentage point decrease in participation for every \$40 increase in weekly spending. The regressions in Table 4.2 Columns 1 and 4 show that students who spend more per week were less likely to attend the lab. The variable 'weekly spending' is highly significant ($p < 0.001$) either on its own (Column 1) or with the household income and work hours variables in the regressions (Column 4).

It is worth discussing immediately the relationship between the magnitude of the participation bias and its (disproportionately large) effect on the representativeness of the lab participants relative to the population. To see this, suppose for simplicity there are an identical number of people in the

³⁵ We excluded seven classroom task participants in all our analyses because we were unable to match their student IDs from the self-reported classroom data with either university or course administrative records, and we had two lab participants who did not provide us with valid IDs, thus we could not determine the participation status of these seven students in the subsequent lab experiment.

population within each weekly spending category. The raw participation rates shown in Figure 4.2 suggest that lab participants, rather than being equally divided as assumed for the population, would instead include a ratio of 34 to 13 participants in the lowest and highest income categories, thus around 72% (34/47) of the lab participants would be members of the population from the lowest income group relative to the highest income group despite the population consisting of an equal number of people in these groups. We discuss the magnitudes of all the estimates after presenting the remainder of the results, but note here that even small differences in participation rates (e.g., 10 percentage points per \$40 spending levels) can lead to large differences in the non-representativeness (e.g., about **2.6 to 1**) in the lab.

Figure 4.2: Participation by weekly spending

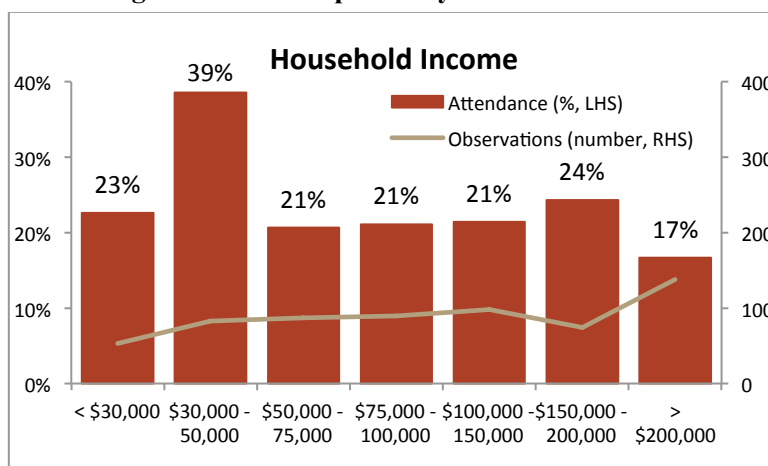


Household income: Figure 4.3 and Table 4.2 Columns 2 and 4 examine lab participation based on students' household income. Figure 4.3 places the population into seven categories from the lowest income (less than \$30,000 per year) to the highest (over \$200,000 per year). We observe similar participation rates of around 20-24 percent across the middle-income range (from \$50,000 to \$200,000), with higher attendance, around 32 percent, averaging across the two lowest income groups (< \$50,000) and lower participation, around 17 percent, for the top income group (> \$200,000). The regression with household income alone, not controlling for spending per week, indicates that students with a higher household income were significantly less likely to attend the lab experiment (Column 2, $p < .05$). However, Column 4 shows that the effect of household income is insignificant when controlling for weekly spending and work hours.³⁶

Result 1: *Students with less weekly spending or lower family income were more likely to attend the lab experiment compared to the population from which they were recruited.*

³⁶ The correlation between household income and weekly spending is only 0.126.

Figure 4.3: Participation by household income

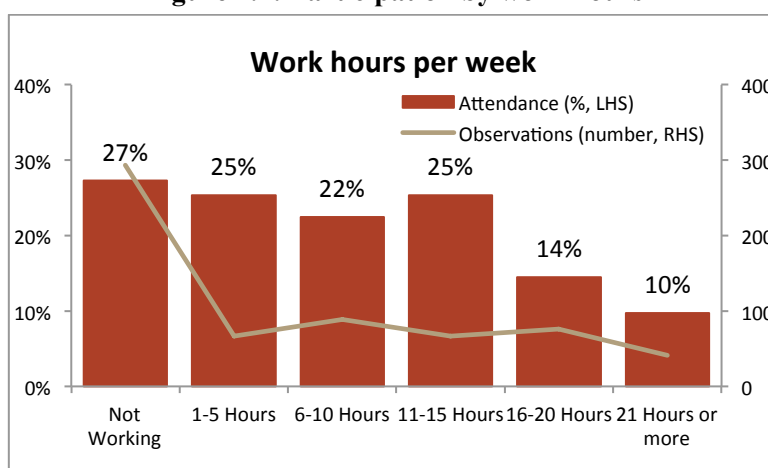


4.1.3 Leisure time (H2)

Work hours: Figure 4.4 and Table 4.2 Columns 3 and 4 examine lab participation based on hours worked per week. The work hours range from 0 (not working) to working 21 hours or more per week in 5-hour increments.³⁷ Figure 4.4 shows a downward trend in participation rates as hours worked increases. We observe higher participation rates for students who work 0-15 hours per week (22-27 percent) than for students who work more than 15 hours per week (10-14 percent). Regressions confirm that students who work more hours were less likely to come to the lab experiment. The variable work hours is significant both alone (Column 3, $p < .01$) and when controlling for the income variables (Column 4, $p < .05$).

Result 2: *Students who work fewer hours were more likely to attend the lab experiment compared to the population from which they were recruited.*

Figure 4.4: Participation by work hours



³⁷ The top three categories are 21-25, 26-30, and 31 hours or more are collapsed into the category 21 hours or more in Figure 4.4, due to small number of observations (less than 15 per cell). The regressions include all categories.

Table 4.2: Participation by income and work hours

| | (1) | (2) | (3) | (4) | Marginal Effect |
|------------------|-----------------------|-----------------------|------------------------|-----------------------|------------------------|
| Weekly Spending | -0.171*** (0.0340) | | | -0.157*** (0.0352) | -0.0460*** (0.0102) |
| Household Income | | -0.0645** (0.0312) | | -0.0448 (0.0315) | -0.0131 (0.00922) |
| Working Hours | | | -0.0991*** (0.0344) | -0.0799** (0.0348) | -0.0234** (0.0102) |
| Constant | -0.407 (0.561) | -0.646 (0.596) | -0.632 (0.585) | 0.0165 (0.586) | |
| Observations | 885 | 885 | 885 | 885 | 885 |
| Log Likelihood | -452.4 | -461.5 | -459.1 | -447.0 | -447.0 |

Probit regressions with robust standard errors at tutorial level in parentheses

*** p<0.01, ** p<0.05, * p<0.1;

Regressions include dummy variables for tutors, tutorial days and recruitment conditions

Discussion: Results 1 and 2 indicate that the participation decision is consistent with a rational response to monetary recruitment incentives and time requirements given individual's existing income and time commitments. We interpret the negative correlation between income and participation as the result of lower marginal utility for the experimental payments among individuals with greater wealth (H1). When both weekly spending and household income are included in the model, the estimates suggest students are influenced more by disposable income than family wealth when deciding whether to participate. We included the variable 'work hours' to proxy for the opportunity cost of the time to participate (controlling for possible correlation with income); thus the negative correlation between work hours and participation confirms significantly lower participation among students with higher value for their leisure time (H2).

4.1.4 Intellectual curiosity (H3, H3a)

University majors: Figure 4.5 and Table 4.3 Columns 1 and 5 investigate the effect of students' major areas of study on participation. Figure 4.5 shows participation based on five areas of study:

Economics, Business, Arts and social sciences, Science and engineering and Other majors.

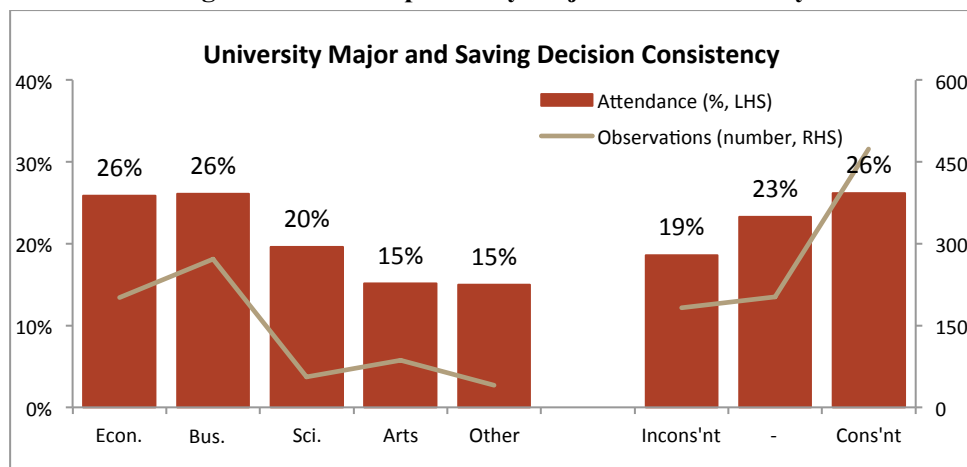
Approximately 26 percent of economics and business majors participated in the lab experiment compared to 20 percent among science students and 15 percent among arts and other majors.

Regressions in Table 4.3 confirm that economics and business majors were significantly ($p<.01$) more likely to participate than the other majors when estimated alone (Column 1) or with the other intellectual curiosity measures (Column 5).

Saving consistency: Figure 4.5 and Table 4.3 Columns 2 and 5 investigate the consistency of the saving decisions on lab participation. Figure 4.5 categorizes students into three groups: 'consistent' in both savings decision sets, consistent in one set, or 'inconsistent' in both. Figure 4.5 shows that 26 percent of the population participated among those consistent in both decision sets whereas only 18 percent of those inconsistent in both decision sets participated. Coding the variable "consistent" equal to 0 if the student was inconsistent in both sets, equal to 1 if consistent in one of the sets, and equal to

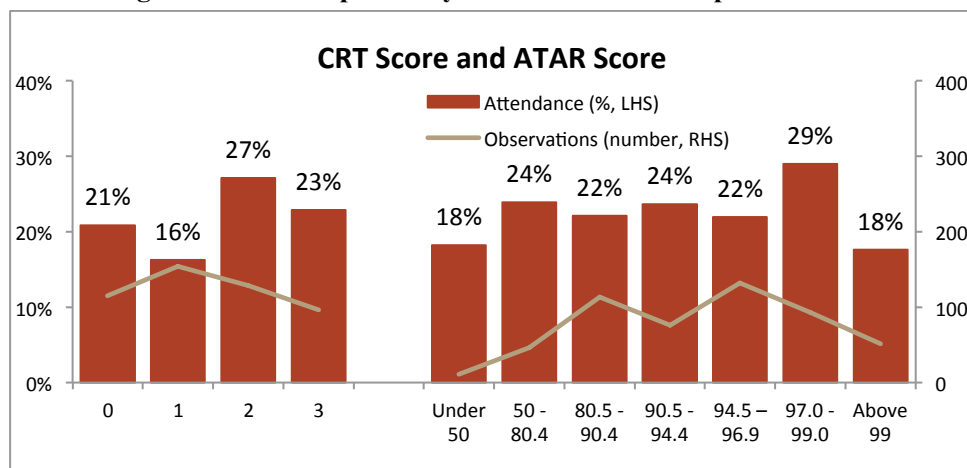
2 if consistent for both sets, regressions in Columns 2 and 5 confirm that more consistent individuals were significantly more likely to participate in the lab experiment.

Figure 4.5: Participation by major and consistency



CRT score: Figure 4.6 and Table 4.3 Columns 3 and 5 investigate whether lab attendance differs based on students' Cognitive Reflection Test (CRT) score. Figure 4.6 shows that students who answered two or more CRT questions correctly are directionally more likely to participate than those who answered less than two correctly. Although the estimated CRT effect on participation does not reach a conventional level of significance, it is marginally significant in a one-tailed test in the direction hypothesized ($p < 0.10$) and in the full model (Table 4.7) controlling for other variables the CRT variable becomes significant ($p < 0.05$).

Figure 4.6: Participation by CRT and academic performance



ATAR score: Figure 4.6 and Table 4.3 Columns 4 and 5 investigate whether lab attendance differs based on students' university admission ranking ATAR. Figure 4.6 shows no strong pattern of participation across the ATAR scores.³⁸ Estimates in Table 4.3 indicate academic performance

³⁸ Under 50 refers to below average in academic performance and likewise above 99 refers to above the top one percentile in academic performance.

measured by the ATAR score did not significantly affect lab participation when estimated alone (Column 4) or with the other intellectual curiosity measures (Column 5).

Result 3: *Students who major in economics and business, made more consistent decisions and had a higher CRT score were more likely to attend a laboratory economics experiment. However, relative academic performance upon entering the university does not predict participation*

Table 4.3: Participation by intellectual curiosity

| | (1) | (2) | (3) | (4) | (5) | Marginal Effect |
|--|---------------------|---------------------|--------------------|--------------------|----------------------|----------------------|
| Economics/Business | 0.352*** (0.118) | | | | 0.387*** (0.123) | 0.112*** (0.0345) |
| Consistent Saving | | 0.138** (0.0536) | | | 0.136** (0.0556) | 0.0398** (0.0167) |
| CRT Score | | | 0.102^ (0.0658) | | 0.100^ (0.0701) | 0.0295^ (0.0204) |
| ATAR Score | | | | 0.0153 (0.0444) | 0.00331 (0.0471) | 0.000973 (0.0138) |
| Constant | -1.239** (0.612) | -1.069* (0.564) | -1.102* (0.577) | -1.011* (0.596) | -1.581*** (0.601) | |
| Obs. | 885 | 885 | 885 | 885 | 885 | 885 |
| Log Likelihood | -460.1 | -458.6 | -461.9 | -463.8 | -452.0 | -452.0 |
| Probit regressions with robust standard errors at tutorial level in parentheses | | | | | | |
| *** p<0.01, ** p<0.05, * p<0.1; ^ p<0.1 (one tailed test); | | | | | | |
| Regressions include dummy variables for tutors, tutorial days & recruitment conditions | | | | | | |

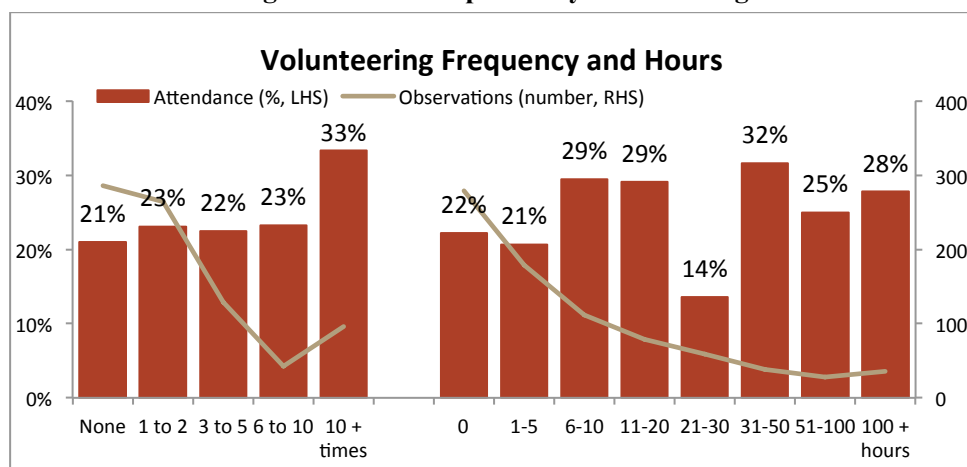
Discussion: Result 3 indicates a non-representative bias based on interests in economics or business, consistent with *Hypothesis 3a* that people were more likely to participate in experimental studies related to their major field of interest. In our case, the ‘economics decision-making’ task advertised in the recruitment invitations likely attracted more economics and business students than had we advertised another discipline-specific type of experiment, or no specific field.³⁹ In addition, we may have under-estimated the participation bias compared to recruiting those who have never taken an economics class, since the non-econ/bus majors in our sample have shown some interest in economics by taking an (optional) economics class. The results on broader intellectual curiosity also generally support our hypothesis (H3). Although we find that academic performance measured by ATAR scores does not predict lab attendance, evidence from the more direct measures of decision consistency and accuracy on the CRT suggests that students with higher interests or ability in intellectually challenging activities are over-represented among the lab attendees.

4.1.3 Pro-social preferences (H4, H4a)

³⁹ Psychology studies show that the description and title of an experiment could impact on subjects’ self-selection into the experiment (Jackson et al. 1989, Senn and Desmarais 2001, Saunders et al. 1985, Silverman and Margulis 1973). An alternative explanation for the stronger participation effect among economics and business majors could be that the lab’s location was in the economics and business building, thus potentially making the location more convenient for economics and business students. However, since virtually all (73 of the 77) tutorials were held in the same location in the economics and business building, the students in the population would be in the lab building at least twice during the time of the experiment (lecture and tutorial), thus the location is not likely to have played a major role.

Volunteering (frequency and total hours): Figure 4.7 and Table 4.4 Columns 1, 2, 6 and 7 examine participation based on the population's volunteering behavior. Figure 4.7 presents the participation rates by the number of times students volunteered in the past year in the left panel and by the total hours volunteered in the right panel. Students who volunteered more than 10 times in the past year were 10 to 12 percentage points more likely to participate in the lab experiment than students who volunteered fewer than 10 times. Regressions show that students who volunteered more frequently were significantly more likely to participate when estimated alone (Column 1) or with controls for other charitable behaviors (Column 6), consistent with H4a. Students volunteering more hours were also directionally more likely to attend the lab; for instance, 27 percent of students who volunteered six or more hours participated in the lab experiment whereas only 22 percent of students who volunteered less than 6 hours participated. However, this does not reach significance alone (Column 2, $t=1.26$), or controlling for other pro-social behaviors (Column 6).

Figure 4.7: Participation by volunteering

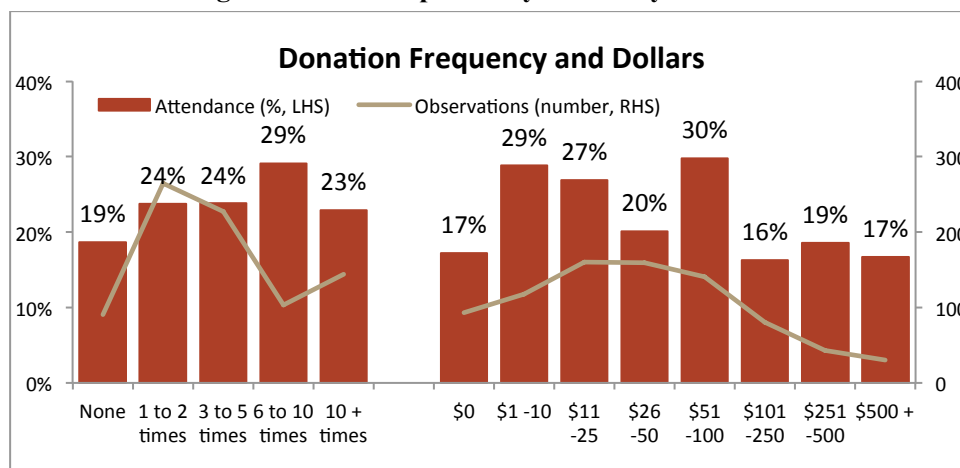


Donation (frequency and total dollars): Figure 4.8 and Table 4.4 Columns 3, 4, 6 and 7 examine participation based on the monetary donation frequency and total dollars donated. The left and right panels of Figure 4.8 present participation by the frequency of monetary donations in the past year and by the total dollars donated, respectively. We observe no strong pattern with the number of donations or with total dollars donated, but Figure 4.8 suggests directionally that students who donated money more frequently or gave fewer total dollars were more likely to participate. For instance, 19 percent of students who never donated participated whereas 24 percent and 26 percent of students who donated 1 to 5 times and more than 5 times, respectively, participated. On the other hand, 25 percent of students who donated less than \$100 participated, while only 17 percent of students donating more than \$100 participated.

Regressions with either monetary donation frequency or total dollars donated alone (Columns 3 and 4) indicate that neither is significant. However, Column 6 shows that when controlling for the other pro-social measures, donation frequency becomes marginally significant indicating that students who donate money more frequently are more likely to participate (consistent with H4) while students

who donate *less* money are significantly more likely to participate. While the donation frequency may reflect how often students think about acting pro-socially, consistent conceptually with the number of times they volunteer, donation dollars as discussed earlier may be positively correlated with wealth which we hypothesized and showed negatively affects lab attendance (Result 1). Adding in controls for the wealth measures, Column 7 shows indeed that donation dollars is no longer significant. Finally, the full model (Table 4.7) shows that when controlling for all of the measures, neither the frequency nor the total amount of monetary donations have a significant effect on participation.

Figure 4.8: Participation by monetary donations



Dictator game decision: Figure 4.9 shows participation rates based on the dictator game decision between each student and the Australian Red Cross (ARC). Participation was highest, over 28 percent, for those who donated \$160 or more, around 23 percent for those who donated between \$40 and \$120 and 17 percent for those who donated \$0. Regressions in Table 4.4 show that students who gave more money were significantly more likely to participate when estimated alone (Column 5) or with controls for the other pro-social measures (Column 6) and controls for wealth (Column 8, $p < .06$). Unlike the total monetary donation (outside the classroom experiment) effect that depends on controlling for wealth, the dictator game donation effect is unaffected when we controlled for wealth, consistent with Andersen et al.'s (2009) finding that subjects only partially integrate wealth when making lab decisions.

Result 4: *Lab participants were not representative of the target population based on pro-social preferences. The lab participants more frequently volunteered their time, but not money, and also donated more in the experimental dictator game than the population from which they were recruited.*

Figure 4.9: Participation by dictator game decision

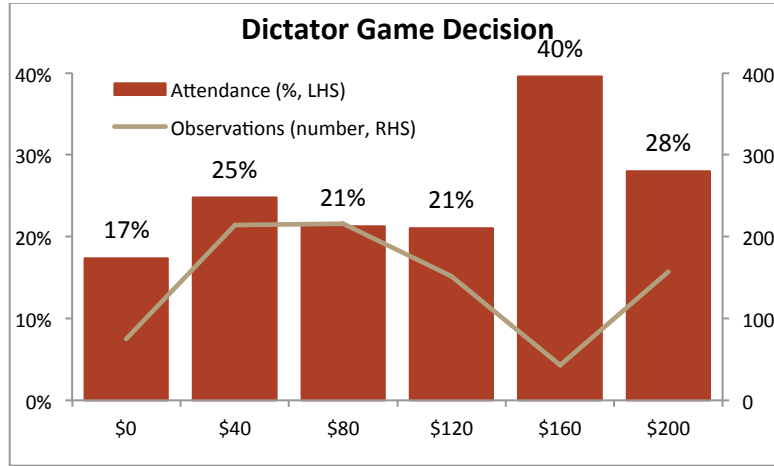


Table 4.4 Participation by pro-social behaviors

| | (1) | (2) | (3) | (4) | (5) | (6) | Marginal Effect | (7) | (8) |
|------------------------|--------------------|--------------------|--------------------|-------------------|--------------------|---------------------|----------------------|----------------------|----------------------|
| Volunteering Frequency | 0.095** (0.037) | | | | | 0.159** (0.076) | 0.045** (0.0215) | 0.148* (0.077) | |
| Volunteering Hours | | 0.029 (0.023) | | | | -0.037 (0.046) | -0.011 (0.013) | -0.037 (0.047) | |
| Donation Frequency | | | 0.030 (0.040) | | | 0.053 (0.045) | 0.015 (0.013) | 0.068 (0.049) | |
| Donation Dollars | | | | -0.022 (0.028) | | -0.074** (0.033) | -0.021** (0.0093) | -0.057 (0.035) | |
| Dictator Game (x100) | | | | | 0.143** (0.067) | 0.146** (0.072) | 0.0414** (0.0203) | | 0.142* (0.075) |
| Weekly Spending | | | | | | | | -0.145*** (0.036) | -0.152*** (0.036) |
| Working Hours | | | | | | | | -0.087** (0.036) | -0.079** (0.0356) |
| Household Income | | | | | | | | -0.044 (0.032) | -0.052 (0.032) |
| Constant | -1.115* (0.574) | -1.000* (0.579) | -1.079* (0.599) | -0.893 (0.585) | -1.076* (0.580) | -1.307** (0.608) | | -0.328 (0.607) | -0.0979 (0.579) |
| Obs. | 885 | 885 | 885 | 885 | 885 | 885 | 885 | 885 | 885 |
| LL | -460.7 | -462.6 | -462.9 | -463.5 | -458.9 | -449.3 | -449.3 | -438.1 | -442.5 |

Probit regressions with robust standard errors at tutorial level in parentheses *** p<0.01, ** p<0.05, * p<0.1; ^ p<0.1 (one tailed test); Regressions include dummy variables for tutors, tutorial days and recruitment conditions

Discussion: We find a significant positive correlation between participation and time-based pro-social behavior but no significant relationship between participation and monetary-based pro-social behavior outside the lab. Money- and time-based pro-social behaviors are not perfectly correlated and in fact can be fairly distinct. For example, the highest correlation between the two volunteering and two donation behavior measures is only 0.37 between volunteer hours and donation dollar amount. We anticipated that time-based pro-social preferences would be critical for the *participation decision* since participation does not explicitly involve donating money but instead involves earning money in exchange for giving up time. Therefore people who are more willing to volunteer their time would be

more likely to participate in the lab experiment while people who donate more money are not equally generous with their time. This distinction may explain the insignificant results trying to link money-based charitable behavior with lab participation in previous studies (Cleave et al. 2013; Falk et al. 2013)⁴⁰.

The result from the dictator game donation decision indicates that lab participants over-represent individuals who are more generous with money received in an experiment. The contrast between the positive effect between the dictator game and participation, and the insignificant (and directionally negative) donation dollars and participation is interesting. One possibility is that the dictator game may reflect the charitable feeling of the population at the closest time to the participation decision, and is thus capturing the population's temporal pro-social preferences and therefore manifest themselves on the participation decision. Further, by measuring the dictator donation decision over the same options and same charitable entity (the Australian Red Cross) at the same time, it might provide a more parsimonious measure of charitable behavior than the other two donation measures. Further, since the dictator game decision was over "house money," the population may not treat the decision in the same manner as donating money they have earned outside the lab; the correlation between the dictator game decision and the two monetary donation dollars was just 0.12. For instance, Andersen et al. (2009) find that lab subjects only partially integrate outside wealth with experimental decisions. Thus, it is possible that a combination of the dictator game's temporal proximity to the participation decision, parsimony across the charitable decision and the abstraction from outside wealth may result in a measure that captures pro-social behavior related to the pro-social aspect of the participation decision.⁴¹

4.1.5 Time and Risk perceptions (H5, H6)

Risk perception: Figure 4.10 shows participation rates by risk perception in the right panel and by each of the six lottery choices in the left panel. Both panels suggest directionally that *more* risk-averse individuals are more likely to participate. For instance, excluding the small sample of the least and most risk taking individuals, 32, 24 and 21 percent of the below average, average and above average risk takers, respectively, participated. Likewise, 19 percent of the population that chose the two riskiest lotteries participated, whereas 24 percent of that chose the four least risky lotteries participated. Regressions indicate that both risk attitudes and lottery choice are directionally negative (Table 4.5), with risk perceptions marginally significant. However, controlling for all the variables in

⁴⁰ Several studies have also compared students with non-students and found students are no more pro-social than non-students. (Fehr and List (2004), List (2004), Cardenas (2005), Carpenter et al. (2004), Bellemare et al. (2008), Carpenter et al. (2008), Burks et al. (2009), Baran, et al. (2010), Cardenas (2011), Falk, et al. (2013). However, all of these studies reported monetary-based pro-social preferences. It would be interesting to see whether those results change under time-based pro-social preference measures.

⁴¹ In both Cleave et al. (2013) and Falk et al. (2013) the pro-social monetary decision and the participation decision were several months apart. In Falk et al. (2013) the pro-social decision involved sacrificing their own money.

the full model (Table 4.7), neither risk perception nor lottery choice reach even marginal significance ($p > .20$).⁴²

Figure 4.10 Participation by risk perception and lottery choice

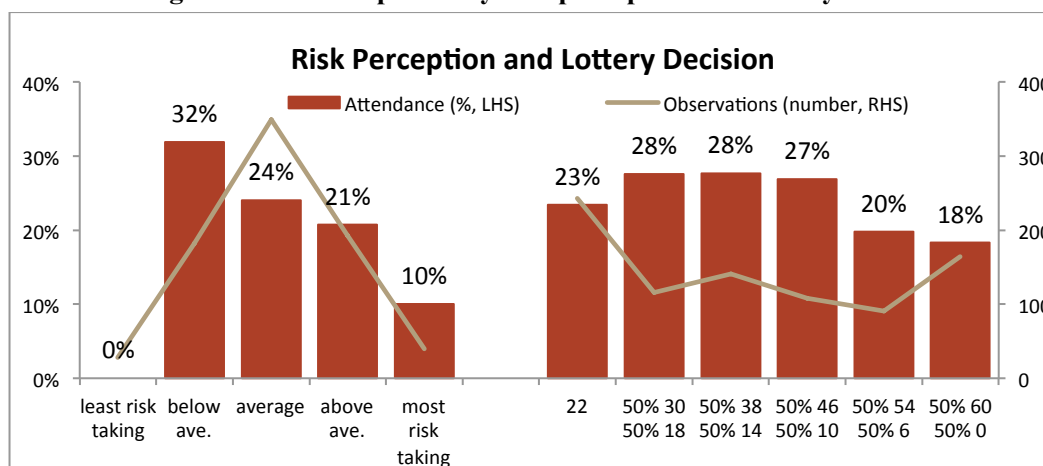


Table 4.5 Participation by risk perception and lottery choice

| | (1) | (2) | (3) | Marginal Effect |
|------------------|----------------------|---------------------|---------------------|-----------------------|
| Risk Attitude | -0.0947* (0.0542) | | -0.0828 (0.0543) | -0.0246 (0.0162) |
| Lottery Decision | | -0.0311 (0.0239) | -0.0237 (0.0238) | -0.00705 (0.00709) |
| Constant | -0.640 (0.601) | -0.847 (0.574) | -0.601 (0.594) | |
| Observations | 885 | 885 | 885 | 885 |
| Log Likelihood | -462.3 | -461.2 | -460.2 | -460.2 |

Probit regressions with robust standard errors at tutorial level in parentheses
 *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$; ^ $p < 0.1$ (one tailed test)
 Regressions include dummy variables for tutors, tutorial days & recruitment conditions

Patience: Figure 4.11 shows participation rates based on patience perceptions in the left panel and for the average savings amount across the six savings decisions in the right panel. Both panels show directionally that more patient individuals were more likely to participate. For instance, 16 percent of students who regarded themselves as less patient than their peers participated, whereas 24 percent of those assessing their patience as average or above average participated. Similarly, 18, 23 and 30 percent of those who chose to save less than \$20, between \$20 and \$99, and \$100, respectively, participated. The regressions in Table 4.6 show that greater perceived patience marginally significantly ($p < .10$) increased participation (Column 1), while higher saving in the experimental task significantly ($p < .05$) increased participation (Column 2), and the significance level for both variables is the same when estimated together (Column 3).

⁴² It is interesting that H1 was confirmed suggesting diminishing marginal utility of wealth whereas H5 was not confirmed despite also testing for risk aversion from diminishing marginal utility. One potential explanation to reconcile these two results is that H1 was examined over a much larger wealth range in the tens of thousands of dollars whereas H5 was examined over a much smaller scale.

Result 5: Lab participants saved significantly more in the saving decisions and view themselves to be more patient than the population they were recruited from.

Figure 4.11 Participation by patience perception and average savings

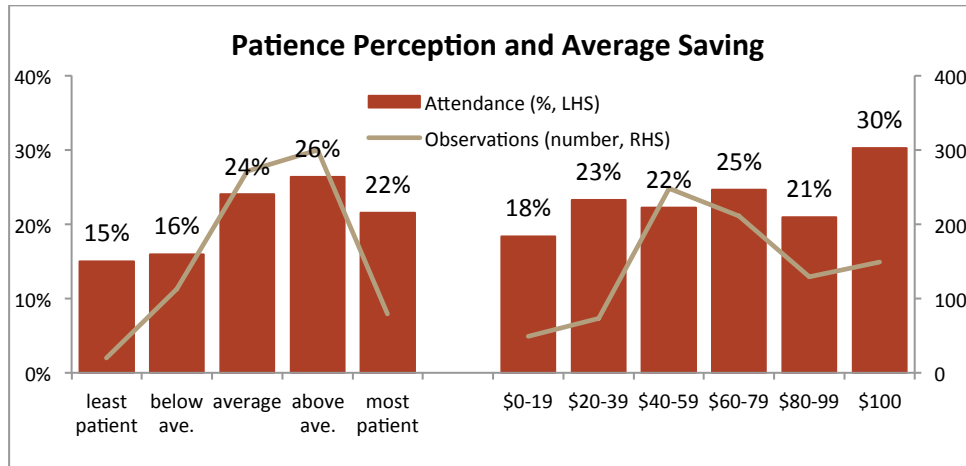


Table 4.6 Participation by patience perception and savings choices

| | (1) | (2) | (3) | Marginal Effect |
|---------------------------|---------------------------------|---------------------|---------------------------------|---------------------|
| Patience | 0.0882 [^] (0.0572) | | 0.0799 [^] (0.0582) | 0.0237 (0.0171) |
| Saving Decision (x100) | | 0.383** (0.184) | 0.381** (0.182) | 0.113** (0.0545) |
| Constant | -1.274** (0.632) | -1.139** (0.563) | -1.436** (0.618) | |
| Observations | 885 | 885 | 885 | 885 |
| Log Likelihood | -462.6 | -459.0 | -457.7 | -457.7 |

Probit regressions with robust standard errors at tutorial level in parentheses

*** p<0.01, ** p<0.05, * p<0.1; [^] p<0.1 (one tailed test)

Regressions include dummy variables for tutors, tutorial days and recruitment conditions

Discussion: We anticipated that lab participants would be less risk averse (H5) and more patient (H6) than the population they were recruited from. Our evidence confirms the patience hypothesis, but rejects the risk hypothesis. It is possible that the lab experiment we invited our population to attend was perceived to have minimum financial risk since we advertised earnings “on average of at least \$30,” that is nearly twice the minimum wage. There may also have been other dimensions with little perceived risk to participation since turn-aways and delayed starting times almost never occur.

4.1.6 Full model: implications for representative biases

Table 4.7 shows the estimates of the model including all the measures we collected (Column 1) and their marginal effects (Column 2). The estimates indicate that the core non-representative biases are robust to the inclusion of all the measures with most of the significant results reported above remaining significant when controlling for all other variables.

We thus focus here on the magnitude of non-representative biases in terms of the marginal effects (Column 3) and the implied large ratio of disproportionate representation of the characteristics of the lab participants relative to the population (Column 4). Consider the variable ‘spending per week;’ for every \$20 more a student spent per week (one level shift in the survey), students were 4.0 percentage

points less likely to participate in the lab experiment, which amounts to a 16 percentage point difference in participation between students with the highest and lowest weekly spending (H1 income). Column 3 shows similar large differences in participation for all the core hypotheses: a 9.1 percentage point overall difference in participation for ‘hours worked’ (H2 leisure time), 11.6 percentage point for ‘economics major’ (H3 intellectual interests) and 17.9 percentage point for ‘volunteering frequency’ (H4 pro-social preferences).

The disproportionate representation of lab participants in Column 4 reports the ratio of the over-represented to under-represented group, assuming for simplicity an equal number of people in each response category in the population. Consider again weekly spending; the raw participation rate for each weekly spending response (Figure 4.2) show a ratio of 34 to 13 for lab participants in the lowest to highest income categories, which is approximately a **2.6 to 1** over-representation of the lowest to highest income group instead of a 1 to 1 ratio in the population. Column 4 shows a larger ratios of disproportionate representation for all core non-representative biases: **2.6 to 1** for students not working to working 16-20 hours a week, **1.5 to 1** for students majoring in economics and business to other majors, and **1.6 to 1** for students who volunteer 10 or more times a year compared to students who did not volunteer. We also include the disproportionate ratios for intellectual curiosity overall of **2.9 to 1** for students majoring in business who were both consistent in the savings decision and correctly answered all of the CRT questions correctly compared to non business and economics majors who were inconsistent in the savings decisions and answered all of the CRT questions incorrectly; and for more pro-social preferences **2.8 to 1** for students who volunteered more than 10 times and gave \$200 in the dictator game compared to those who never volunteered and gave nothing in the dictator game.

To test whether any of the variables led to significant differences in participation across the recruitment conditions, we re-estimated the full model in Table 4.7 with interaction terms for each variable by each recruitment condition. The model thus produces 51 pair-wise tests consisting of the 17 variables with three comparisons each: (1) Appointment vs. Drop-in; (2) Appointment vs. Option; and (3) Drop-in vs. Option. The results indicate that none of the 51 comparisons are significant at the $p = .05$ level, and only one of the 51 tests is significant at the $p = .10$ level.⁴³ Therefore, we cannot reject the null hypothesis that non-representative biases are the same across scheduling conditions. This result suggests that switching from the standard appointment recruiting procedures to either a drop-in or option procedure would not alleviate the participation biases.

⁴³ Students who volunteered more hours were less likely to participate in the appointment than drop-in condition ($p < .10$).

Table 4.7 Participation by all characteristics

| | (1) Probit Est. | (2) Marginal Effects | (3) Percentage point difference Top v. Bottom Category | (4) Non-repres. Bias Top v. Bottom Cat. |
|---------------------------------|------------------------------|-------------------------------|--|---|
| Income H1 | | | | |
| Spending per week | -0.147*** (0.0380) | -0.0399*** (0.0101) | -16.0% \$0-40 v. > \$100 | 2.6 to 1 |
| Household Income (per year) | -0.0397 (0.0365) | -0.0108 (0.00992) | -6.5% < \$30,000 v. > \$200,000 | |
| Leisure Time H2 | | | | |
| Work Hour (per week) | -0.0839** (0.0392) | -0.0227** (0.0106) | -9.1% no work v. 16-20 hours | 2.6 to 1 |
| Intellectual Interest H3 | | | | All three: 2.9 to 1 |
| Econ/Business | 0.434*** (0.130) | 0.116*** (0.0327) | 11.6% Econ/bus v. Other majors | 1.5 to 1 |
| Saving Consistency | 0.136** (0.0638) | 0.0368** (0.0174) | 7.4% inconsistent v. consistent | 1.4 to 1 |
| CRT Score | 0.137* (0.0740) | 0.0372* (0.0197) | 11.2% 0 v. 3 Correct | 1.4 to 1 |
| ATAR Score | -0.0285 (0.0462) | -0.00774 (0.0125) | -4.6% Under 50 v. Above 99 | |
| Pro-social Pref. H4 | | | | Both: 2.8 to 1 |
| Volunteering Freq. | 0.165** (0.0738) | 0.0447** (0.0200) | 17.9% Never v. > 10 times | 1.6 to 1 |
| Volunteering Hours | -0.0427 (0.0446) | -0.0116 (0.0122) | -9.3% 0 v. > 100 hours | |
| Donation Freq. | 0.0500 (0.0485) | 0.0135 (0.0132) | 5.4% 0 v. > 10 times | |
| Donation Dollars | -0.0559 (0.0357) | -0.0152 (0.00957) | -10.6% 0 v. > \$500 | |
| Dictator Game (x100) | 0.145* (0.0753) | 0.0394* (0.0205) | 7.8% 0 v. \$200 | 1.8 to 1 |
| Risk Attitude | -0.0250 (0.0558) | -0.00677 (0.0152) | -2.7% least v. most risk taking | |
| Lottery Decision | -0.0250 (0.0257) | -0.00677 (0.00699) | -3.4% certainty v. risk seeking | |
| Patience | 0.0592 (0.0579) | 0.0160 (0.0155) | 6.4% least v. most patient | |
| Saving Decision (x100) | 0.317* (0.184) | 0.086* (0.051) | 8.5% 0 v. \$100 | |
| Female | -0.155 (0.137) | -0.0407 (0.0345) | -4.1% female v. male | |
| Caucasian | -0.0270 (0.129) | -0.00730 (0.0349) | -0.7% Caucasian v. Asian | |
| Constant | -1.200* (0.710) | | | |
| Observations | 881 | 881 | | |
| Log Likelihood | -416.3 | -416.3 | | |

Probit regressions with robust standard errors at tutorial level in parentheses, *** p<0.01, ** p<0.05, * p<0.1
Regressions include dummy variables for tutors, tutorial days and recruitment conditions

4.2 Appointment vs. Drop-in choices

This section briefly investigates students' decision to make an appointment or drop-in if given the option. Of the 60 students in the option condition who participated in the lab experiment, 43 made an appointment and 17 dropped in. We can thus easily reject that students who participated in the lab when given a choice were equally likely to make an appointment or drop-in at the $p = 0.001$ level. While this behavior signifies that the majority of students prefer to make an appointment when given an option, understanding what individual characteristics explain this preference is unfortunately difficult to infer since only 17 students chose to drop-in. To understand this choice given the small sample, we estimated probit regressions on the students who participated where the dependent variable equals 1 if they made an appointment and 0 if they dropped in, including only one independent variable at a time from the classroom tasks.

The estimates from each regression indicate that only one measure was significant, and no other measure was even marginally significant at the $p = .10$ level. Consistent with our hypothesis (H7a), we found that more risk-averse participants on the lottery decision were more likely to make an appointment when given the option ($p < 0.06$). Table 4.8 shows that students were 6.9 percentage points more likely to make an appointment for each additional less risky choice, thus a student who chose the sure \$22 payoff was almost 35 percentage points more likely to make an appointment than someone who chose the riskiest option.

Result 7: *Among students given the option to make an appointment or drop-in, participants preferred making an appointment, and more risk-averse participants were more likely to make an appointment.*

| Table 4.8 Chose to make an appointment given option condition and participated | | |
|---|----------|-----------------|
| | (1) | Marginal Effect |
| Lottery Decision | -0.205* | -0.0685** |
| | (0.105) | (0.0347) |
| Constant | 1.220*** | |
| | (0.388) | |
| Observations | 59† | 59† |
| Log Likelihood | -33.44 | -33.44 |
| Probit regressions with robust standard errors in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$ | | |
| †One lab participant in the option condition did not make a choice for classroom lottery decision. | | |

Discussion: Result 7 may in part be due to the sentence we included in the option recruitment flyer in which we justified the option by writing, “appointments are helpful since spaces may be limited,” which may suggest risks (e.g., being turned away or longer delays) with dropping in than having an appointment. Moreover, we found that subjects' lottery choice on participation was not significantly different across the recruitment conditions suggesting that while risk-aversion might affect how subjects choose to participate (appointment or drop-in), it does not affect whether they participate.

5. Addressing non-representative biases

The results indicate that the characteristics of lab participants are not representative of the characteristics of the population they were recruited from. We hypothesized and found several over

represented characteristics among lab participants including having less income, more leisure time, greater interest in economics lab activities and more pro-social over volunteering time. Researchers can address the potential concerns in both recruitment procedures and econometric analyses. Indeed, several actions with respect to recruitment procedures are already in practice by some researchers. These procedures can reduce the potential bias B in making an inference from the lab to a more general population, and thus can increase the confidence in the external validity of the qualitative results.

5.1 Recruitment procedures

Our hypotheses were based on a standard model of individual utility (see Section 2 above) that was substantiated by our results. This model has direct implications for procedures experimenters can follow to reduce bias including increasing payments, reducing participation time, increasing convenience and altering task information.

5.1.1 Reward based procedures

For biases caused by monetary rewards, **increasing experimental payments** could alleviate over-representation of *low income* groups in the lab. Although expensive, researchers have an option to offer higher payments if this bias would substantially affect the lab results. Our model and empirical finding suggest that higher anticipated earning will increase the likelihood of participation for everyone, thus potentially reducing the *low income* participation bias.⁴⁴ For biases caused by monetary rewards or the opportunity cost of time, experimenters may **reduce the lab time**, thus raising the hourly earnings rate $r(a)/t(a)$ has the same effect as increasing the monetary rewards. **Reducing the lab time** also allows more individuals with *higher value of time* to attend the lab experiment. Several additional procedures are possible to increase participation by **improving flexibility and convenience**, which reduces the *total* time and increases the ease for participants. For instance, the experimenter may 1) run experiments in more convenient locations to reduce the transit time to the lab, 2) offer more convenient or more flexible lab times when most of the population would be free, or 3) run experiments on-line if the study design permits, which allows people to choose the time and location. The use of the Internet to run ‘traditional’ lab studies has been growing increasingly common (e.g., Bellemare et al. 2008, 2011; Slonim and Garbarino 2006; Garbarino and Slonim 2009; Horton et al. 2011).

Another reward, potentially as powerful as monetary payments, to attract students to participate is **course credits**. Many business school and psychology departments create ‘subject pools’ and offer modest course credits for participation. To avoid coercion, students are typically given multiple

⁴⁴ While the experimental economics literature has looked extensively at the effects of varying the stakes on behavior within a study, to our knowledge no study has directly varied the advertised earnings in the recruitment procedures in order to test non-representative biases. Some early psychology studies suggest that paying volunteering subjects might increase their representativeness (Rush et al. 1978, Wagner and Schubert 1976).

options for earning the extra course credit besides participating in a study, and students are also free to choose none of the options. This approach often generates very high levels of participation, for instance the course credit offer by the Marketing Discipline at the University of Sydney typically has over 90 percent of students choosing to participate in a study during the term. Importantly, studies offering course credit can still be incentivized for the decisions within the study identically to current economic laboratory studies.⁴⁵

5.1.2 Information based procedures

For biases caused by intrinsic motivations over the nature of experiments, carefully minimizing relevant signals in the recruitment information (by withholding or framing of the task information) can help recruiting participants with more neutral interests. Specific suggestions follow.

Not mentioning economics in the recruitment process can address over-represented *interest in economic lab tasks* among economics or business students. Our explicit indication in the recruitment flyer of an ‘economics decision-making experiment’ could be partly responsible for this ‘economics’ student bias we identified. If it is not possible to conceal a connection with economics, for example due to either ethics considerations or reputation, the experiments can be held in more convenient times and locations for non-economics and business students, for instance in locations near engineering, science and humanities buildings, or using a mobile lab.⁴⁶ Another approach is to run a lab in which a broader set of researchers beyond economists run experiments such that the recruited population would not know in advance what kind of lab activities might occur. Feasibility of this approach may depend on whether the standards for recruitment can be unified across the research communities (e.g., over compensation and deception).

Similarly, **not suggesting social value** of the lab experiment, e.g. never mention helping researchers or the broader community, can reduce participation bias based on *Pro-social preferences*. However, since most experiments are specifically run to enhance knowledge, experimenters can only go so far to minimize the communication of the value of the research without outright deception. Moreover, in our experiment the recruitment material never mentions helping researchers or the broader community, yet we still found significant participation bias on pro-social volunteering time.

5.2 Econometric analyses

Experimenters can also take several approaches to econometrically address non-representative biases. First, researchers can measure participants’ characteristics on which there is anticipated bias (e.g., income, work hours, major areas of study, pro-social volunteering behavior) and then control for their influence in the analyses. If the researchers are making quantitative inferences, then weighted analyses can be reported for average population inferences. If researchers are making qualitative

⁴⁵ It is possible though that offering course credits may cause a different set of participation biases such as attracting students who are more concerned about course grades.

⁴⁶ The ‘economics’ bias could also be due to potential participants believing knowledge of economics is important. To address this bias, recruitment materials can explicitly state that no knowledge of economics is necessary.

inferences, they can control for bias by controlling for the interaction of the within experiment manipulations by the participant's characteristics and/or can report weighted analyses for population inferences. However, this approach assumes the experimenters are able to find reliable population weights.

Second, experimenters can collect information on the population they recruit from. In many labs, this means collecting information on the population they invite into their recruitment databases, not just into the lab; Cleave et al. (2013) report that only 25 percent of the population invited joined the subject pool database, and Krawczyk (2011) reports that less than 2.5% of his population joined the subject pool, suggesting that participation bias could mainly occur before an invitation to a specific experiment occurs. If information on participants who do and do not participate is available or can be collected, then standard approaches to selection (e.g., IV strategies) are possible (Heckman 1979; Heckman et al. 1998).

Third, experimenters can manipulate recruitment procedures to econometrically estimate the nature and extent of potential participation bias. Andersen et al. (2009), to our knowledge, is one of the rare papers to have taken this approach. Their study held the expected payoffs constant and manipulated the variability of earnings in their recruitment advertisement. As hypothesized, they found greater risk aversion among the participants recruited with the lower variance. In this method, experimenters can vary the expected earnings, for instance recruiting subjects for three earnings conditions: $r(a)$ and $M_1r(a)$ and $M_2r(a)$, where $M_2 > M_1 > 1$. Experimenters can then compare the behavior of the three distinctly recruited groups to test whether their behavior systematically differs, and use any differences to extrapolate for greater external validity.⁴⁷ Likewise, experimenters could vary the advertised time to be $t(a)$, $N_1t(a)$ and $N_2t(a)$, with $0 < N_1 < N_2 < 1$, and then in all conditions run an experiment that only lasts for $N_1t(a)$. In this setup, the experimenter can anticipate higher turnout the shorter the advertised experimental time, and can compare behavior to test whether the participants in the higher turnout condition (presumably with the shorter advertised lab time) behave differently than those in the longer advertised lab time conditions. If any differences occur, the experimenter can then extrapolate to improve external validity.

Fourth, a common technique used in survey work to address response bias involves examining subjects' behavior based on the temporal order of participation. The temporal order can be measured by either the sequential time in which subjects sign up or show up, or by the researchers sending advertisements multiple times to the same individuals (removing those who have participated from the subsequent advertisements). The implicit assumption with this approach is that those who sign up to participate sooner or with fewer announcements are more likely to exhibit the participation biases than those who sign up later, and if so, researchers can then calibrate the extent of the bias among

⁴⁷ One difficult challenge with this approach is that in the lab, whatever stakes actually get used, $r(a)$, $M_1r(a)$ or $M_2r(a)$, in the lab only one amount will reflect the lab stakes, and thus this amount will be a surprise in the other conditions, and so any difference in behavior in the lab across the groups could be due to the surprise or the variance in the advertised payments.

those who participate. There are also several additional methods that experimentalists can consider adopting that are common to address participation bias in survey work (Miller and Smith 1983; Groves 2006).

5.3 Disclosing recruitment procedures

Experimenters can adopt a convention to report recruitment materials and procedures either in manuscripts or in on-line supplemental material like the current convention to provide experimental instructions. We believe this will not only enable readers to better assess the potential concern for participation bias, but will also help disseminate state of the art recruitment techniques and further standardize and facilitate comparison of results across labs.

6. Conclusion

Lab experiments are an increasingly common source of empirical data for economic research. We modeled the decision to participate in an experiment as a rational decision over costs and benefits, and derived several hypotheses regarding the characteristics of the people who would be more likely to participate. Consistent with our hypotheses, we found that recruited lab participants were not representative of the target population they were recruited from; participants had lower income, more leisure time, more interests in economics and lab activities, and were more pro-social on the dimension of volunteering time. Our estimates indicate that the rational participation decision led to an over-representation of most of the hypothesized characteristics by a ratio of more than 2 to 1 among the participants compared to the target population.

Any behavior measured in an experiment that is correlated with any non-representative characteristic may result in biased estimates. In such cases, researchers could follow two simple steps to address participation bias. First, researchers can adopt a convention of reporting recruitment procedures, both into subject pools as well as into specific studies, to allow readers to understand and compare results across labs for potential participation biases. It is also important to report the percent of individuals in the population invited who attend the lab study to allow readers to assess the potential for participation bias. Second, researchers can collect individual characteristics within their lab studies to control for potentially biased characteristics that would be correlated with outcome behaviors; indeed many researchers already routinely collect and control for socio-economic and demographic data. A third step, but more involved, would be to collect socio-economic and demographic data on individuals in the population before recruitment, either using existing administrative sources and or by collecting it themselves as we did in the current study. Researchers can then use standard econometric procedures to estimate and control for participation bias.

The most common approach on the more general question of generalization of lab studies has been to compare the behavior of subjects recruited from one population with subjects recruited from

another population.⁴⁸ This approach allows researchers to directly test the robustness of results across different subject populations. However, the recruitment procedures, which are typically the same across the subject populations, likely “homogenize” the participants between the populations so that their characteristics are more similar than the populations they were recruited from, and hence comparing participants could under-estimate differences in the populations they were recruited from. The potential for this homogenization will likely increase in studies with lower participation; in the current study, 23% of the population contacted ultimately participated in our lab study. Cleave et al. (2013) and Falk et al. (2013) report approximately 12% participation in their lab studies, and Krawczyk (2011) reports that only 2% joined the subject pool among those who were sent a mass email invitation.⁴⁹

This paper focuses on the recruitment procedures and presents the first systematic and comprehensive study motivated by theory to examine the voluntary participation decision. Our study used university students as the target population, which likely under-estimated the magnitude of participation biases since the characteristics of this population (e.g., age, income, education) are more homogeneous than a more general population. Beyond students, we hope to raise a general concern that experiment samples from a well-chosen population could potentially be biased due to recruitment. Nonetheless, given that many lab studies still primarily recruit from student populations, the results presented here are immediately relevant for a large body of research.

Lab research has made tremendous contributions to the economics literature. Its advantages for empirical study, including control, measurement, and replication, are well known. Perhaps one of the current remaining challenges for further influence involves addressing questions regarding robustness and generalizability. The current work suggests that the characteristics of the participants in lab studies are not representative of the population they were recruited from.⁵⁰ Well-known techniques are available to address bias, and this paper takes the first step to identify the sources and magnitudes of potential biases.

⁴⁸ Cleave et al. (2013) review this literature: example include comparing results across occupation (Cooper et al. 1999; Hannah et al. 2002; Fehr and List 2004; Carpenter et al. 2004; Güth et al. 2007; Carpenter et al. 2008; Andersen et al. 2009; Anderson et al. 2010), across age (Harbaugh et al. 2003), across nationality/culture (Roth et al. 1991; Henrich et al. 2001; Herrmann et al. 2008; Cameron et al. 2009; Henrich et al. 2010) and between student and a representative sample of the population (Bellemare and Kröger 2007, Anderson et al. 2010 and Falk et al. 2013).

⁴⁹ The current experiment was run one week after the initial recruitment, whereas Cleave et al. (2013) and Falk et al. (2013) ran their studies several weeks to months after the initial recruitment, which could explain the difference in lab participation rates.

⁵⁰ This conclusion should not seem shocking; we similarly do not assume professional athletes, entrepreneurs, truck drivers, data entry workers, bicycle messengers, sports card dealers, academics, blue collar workers, teachers or almost any other specific population we study would be perfectly representative of the broader population they come from.

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