

# The External Validity of Experimental Social Preference Games

by

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# Abstract

The external validity of experimental games is a growing topic of interest because researchers commonly use such games to study social preferences. Many papers have conducted within-subjects experiments, comparing in-lab game decisions to real-world decisions. However, the current accumulated evidence have yielded mixed conclusions. Some papers have found statistically significant correlations between game and field behavior, while other papers have not. In this research, I compared behavior in various social preference games and self-reported measures regarding past pro-social behavior to a natural, far-removed field measure: donations to Wesleyan University. Donations were recorded as binary (whether individuals donated or not) and continuous (individuals' average yearly donations) metrics. To examine the explanatory power of social preference games on donations behavior, I ran several logistic and linear regression models. I also compared how well the games predict donations behavior relative to a baseline model. My results show that the social preference games do a poor job explaining donations behavior. On the other hand, the games have modest additional predictive power given the baseline model's predictions. Most notably, the self-reported measures seem to perform just as well, if not better, than the social preference games in both explaining and predicting the field measure.

# 1 Introduction and Literature Review

The standard economic model assumes that individuals' actions are motivated purely by self-interest. However, from simple observation it is clear that people also care about the well-being of others: people volunteer<sup>1</sup>, people donate<sup>2</sup>, and social welfare programs exist. If someone is not solely motivated by material self-interest but also cares about the well-being of others, we say that they have social preferences.

A common approach in studying social preferences is to conduct experiments in a laboratory setting. Subjects play experimental games, where they receive monetary incentives. The benefit is that researchers are able to control prices, information, and actions available to the participants, allowing researchers to rigorously target different aspects of social behavior<sup>3</sup>.

The study of social preferences with experimental games goes back over twenty years. Kahneman et al. (1986) recruited undergraduate students to play the first dictator game experiment in economics. The dictator game involves a single player (the dictator) who receives an endowment and must then choose how to split the amount between themselves and a second player (the receiver). In their study, the dictator was given two choices on how to split the endowment: either an even split or an uneven split. The authors found that a majority of the subjects favored the equal split option, contrary to the basic economic theory of self-maximizing interests. Forsythe et al. (1994) also recruited undergraduate students from the University of Iowa to play the dictator game, but this time the dictators had free range over how to split the endowment. They found that the average contribution

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<sup>1</sup>The Corporation for National & Community Service reported 63.6 million volunteers and 7.9 billion hours of service in the U.S. in 2015.

<sup>2</sup>According to Giving USA, individual giving in 2016 was reported to be \$281.86 billion, a 3.9 percent increase from the previous year.

<sup>3</sup>Many papers have identified various aspects of social preferences such as altruism, social welfare, inequality aversion, and reciprocity. See, e.g., Charness and Rabin (2002); Rabin (1993); Fisman et al. (2014).

was about 20% of the endowment.

Forsythe et al. additionally had subjects play the ultimatum game. The ultimatum game is a two-player game in which two players, a proposer and a responder, bargain over a fixed endowment: the proposer divides the endowment, and the responder either accepts or rejects the offer. If accepted, the proposal is implemented; if rejected, both players receive nothing. The authors found that most proposers shared their endowments and responders rarely rejected offers.

Berg et al. (1995) recruited undergraduate students from the University of Minnesota to play the trust game. Similar to the ultimatum game, the trust game is a two-player game in which the proposer proposes how to divide the given endowment between themselves and the responder. The offered amount is multiplied by a factor, and the responder decides how much of the multiplied contribution to return to the proposer. The authors found that participants showed high levels of trust and reciprocity: 94% of the proposers sent money, and over one-third of the responders returned an amount greater than what was given to them.

Marwell and Ames (1981) conducted public goods experiments with high school and college students in Madison, Wisconsin. The public goods game is an N-player game where each player receives the same sum of money and simultaneously decides how much to contribute into a public fund. The total amount in the public fund is multiplied by a factor, and divided evenly amongst the players. The authors found that subjects generally sent 40%–60% of their endowment, showing ‘weak’ free riding behavior: the amount contributed into the public fund was between the Pareto efficient level and the free riding level.

Using social preference games to infer real-world behavior has become one of the building blocks of experimental and behavioral economics. However, pro-social behavior may be unintentionally influenced by non-monetary factors, leading to

variation in game behavior. One such factor is that the subjects' actions are often under the scrutiny of the researcher. Hoffman et al. (1994) found that almost half of their subjects donated at least \$3 (out of a \$10 pie) when playing the dictator game. However, when the authors implemented a "double-blind" treatment where both the experimenter and other subjects could not observe the dictators' actions, only 16% of subjects gave at least \$3.

Individuals may also be influenced by the framing and context of the situation. Burnham et al. (2000) conducted the trust game in which they switched between calling the responder as "partner" or "opponent". The authors found that trustworthiness with a "partner" was over twice than that for an "opponent". Similarly, Ross and Ward (1996) found that participants showed higher levels of cooperation when playing a prisoner's dilemma game called a "community" game and lower levels when the game was called a "Wall Street" game.

These examples demonstrate that non-monetary factors can yield significant variations in lab behavior. On a larger scale, experimental games conducted in a lab setting are abstract and remote from realistic situations; such non-monetary factors are expected to also lead to differences in behavior between a lab setting and a real-world setting. For example, people know that their actions are being watched and recorded during an experiment, but their decisions are usually made in private when making real-life choices. Similar to the study by Hoffman et al. where higher levels of scrutiny led to more pro-social behavior, people may behave more pro-socially in the lab for the same reason than they are in real life. Another example is that in the studies by Burnham et al. and Ross and Ward, subjects were more pro-social when the games were framed collaboratively – that is, the context of the situation is important. Likewise, individuals' actions in the lab may not reflect their real-world pro-social behavior since real-life decisions may hold different personal meaning to the individual than experimental games

do. Indeed, there are many non-monetary factors that can lead to deviations in behavior<sup>4</sup>. Therefore, an important question to ask is the external validity of social preference games – to what extent can decisions made in experimental games be generalized to decisions made in the field?

Some studies have concluded that lab behavior does explain field behavior. Baran et al. (2010) recruited MBA alumni and found that their reciprocity behavior when playing the trust game predicted their donations to their university. Franzen and Pointner (2012) compared decisions from university students participating in dictator games to their actions when receiving a misdirected letter containing money; subjects who showed pro-social behavior in the lab returned the letters more often than subjects who were selfish in the lab. Englmaier and Gebhardt (2011) conducted a field experiment where they compared university students’ free riding behavior at the library to free riding behavior in a public goods game. The authors found a statistically significant correlation between the field and lab measures.

There are also studies that used non-student subjects. Fehr and Leibbrandt (2011) recruited Brazilian fishermen to play the public goods game, and found that fishermen who were more cooperative in the games were less likely to exploit the communal fishing grounds. Karlan (2005) compared behavior to loans repayment behavior in a Peruvian microfinance program: subjects who displayed “trustworthy” behavior were less likely to default on their loans.

To the contrary, however, a number of papers found that lab behavior had no explanatory power over field behavior. Goeschl et al. (2015) examined university students’ actions in two tasks: the public goods game and contributions to a field situation about reducing CO<sub>2</sub> emissions. The authors found that behavior in both tasks were uncorrelated. Hill and Gurven (2004) carried out the ultimatum

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<sup>4</sup>See Levitt and List (2007) for a full discussion of non-monetary factors, with supporting literature.



game and public goods game on Paraguay Ache Indians. They compared the game decisions to observed food production and sharing patterns with individuals outside of the nuclear family, and found no significant relationship. Gurven and Winking (2008) recruited Tsimane forager-horticulturalists in Bolivia, and compared the behavior when playing the dictator game and ultimatum game to their food-sharing behavior. The authors likewise found no relation between the two measures. Voors et al. (2012) studied farmers in Sierra Leone, and found no meaningful correlation in behavior between actions in the public goods game and actions when asked to contribute to a real community public good.

Galizzi and Navarro-Martinez (2017) summarized that about 40% of reported correlations between experimental games and field behavior found statistically significant associations<sup>5</sup>. Therefore it is clear that the current evidence for the external validity of experimental games is mixed. The authors argued, however, that the previous studies compared only one social preference game to one specific field measure – it is crucial to have a more systematic approach. The authors proposed using multiple experimental games and self-reported questionnaires to compare to multiple field responses.

Galizzi and Navarro-Martinez conducted their own study in which participants answered questions about social behaviors exhibited in the past, played various social preference games, and then encountered naturalistic field situations. The possible field situations included a research assistant asking for help carrying boxes down the stairs, asking to use the participant’s phone to make a brief phone call, asking for donations to a children’s charity, asking for donations to an environmental charity, or asking for donations to the lab’s research fund. The authors’ overarching conclusion was that the experimental games did a poor job of explaining the field behavior. However, they asserted that more systematic studies like

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<sup>5</sup>See Galizzi and Navarro-Martinez for their full systematic review and meta-analysis of literature on within-subjects studies comparing lab and field behavior.

theirs are needed in order to draw a definite conclusion. This is where my thesis contributes.

My research provides another systematic study to add to the ongoing discussion on the external validity of social preference games. I recruited Wesleyan University seniors and recent alumni (those who graduated within the last five years) to participate in various experimental games. I also collected self-reported questionnaires regarding past pro-social behavior as a supplementary layer to analyze the explanatory and predictive ability of the games.

In order to further inform my experiment design, it is critical to think about why some previous studies found correlations between the experimental game and field measures while other studies did not. While playing the experimental games for the study by Hill and Gurven, participants expressed worry that their choices would upset the receiver. Given that the tribal group's culture was heavily focused on community, perhaps the participants didn't want to risk making any choices that would create any tension. Likewise, in the studies by Gurven and Winking and Voors et al., participants were subject to high scrutiny and low anonymity since it was easy for community members to find out the choices each subject made. It is possible that such factors skewed results. Therefore an important feature in my research design was that participants played the games remotely. This set-up ensured minimal scrutiny and higher anonymity, reducing the possibility of influenced behavior.

When deciding on my field measure, one criticism of the experimental design by Galizzi and Navarro-Martinez is how the authors executed their field measures. The field situations occurred as the participants were exiting the lab session, so it is likely that the participants were able to connect the encounters to the research lab, especially since both events were about pro-social behavior and occurred in such close time proximity. This may have led to actions that participants would

not have done if they were unaware of the scrutiny. This is called the experimenter demand effect, which is a common problem in experimental design: if participants know their actions are being examined, they may change their behavior towards what constitutes appropriate behavior. Therefore, it is more desirable to use a natural, far-removed situation as the field measure: in this research, I used the participants' donations to Wesleyan University.

Overall, my thesis adopted the systematic approach of Galizi and Navarro-Martinez while refining and enhancing the experimental and field responses to reduce the experimental response bias.

I first examined how well the social preference games explain donations. Donations were defined as whether the participant had ever donated (binary) and the participant's average yearly donations (continuous), so I ran several logistic and linear regression models. I found that the games explain only a small portion of the variation in donations behavior. In fact, the self-reported measures explain the field measure just as well as the games, as seen by the  $R^2$  values from the regression models. I then analyzed how well the games and self-reported measures predict donations. I used the lab behavior from older alumni class year participants to build prediction models, and the donations behavior from the newest alumni class year participants to test the models' performance. I found that the games and self-reported measures do a good job of predicting if individuals will donate, but not the amount donated. In addition, the self-reported measures seem to play a more important role than the social preference games in predicting the field behavior.

## 2 Methods

Wesleyan University seniors and recent alumni received an email that explained my research and invited them to participate in my study (2,004 emails were provided by Wesleyan University Relations). Participants were informed that upon their completion of the study, their college major, class year, and Wesleyan donations information would be collected.

Each participant was presented with two tasks to complete: (i) incentivized social preference games, and (ii) self-reported questionnaires regarding past pro-social behavior. Online links to both the experimental games and survey questions were included in the email<sup>6</sup>. The field measure used to compare to the participants' lab results was their donation status and amount to Wesleyan University, provided by Wesleyan University Relations<sup>7</sup>.

To incentivize participation as well as elicit honest game behavior, participants were informed that completing the entire study made them eligible for a lottery prize. Each social preference game used “tickets” as the experimental currency unit, where the total tickets each participant earned in the games equaled how many lottery tickets they owned. At the end of the study, ten tickets were randomly drawn, and the winners were contacted and instructed on how to receive their \$100 prize.

### 2.1 Incentivized social preference games

Participants first played four social preference games (in random order): the generalized dictator game, the ultimatum game, the trust game, and the public goods game. They received detailed instructions for each game along with an example to illustrate how the game worked. For the ultimatum game and the trust game,

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<sup>6</sup>The entire study was computerized, programmed and implemented using Qualtrics. Those who chose to take part completed the study remotely.

<sup>7</sup>All donations information were cumulative as of January 2018.

participants played as both the proposer and responder in separate rounds. At the end of the participation deadline, all participant responses were randomly paired and ticket payoffs were calculated.

Below are descriptions of each game the participants played, along with examples. See Appendix C for screenshots of each game, along with respective instructions and examples, from the online study. In addition, I describe the decisions individuals are expected to have made depending on the various preferences they may have.

### 2.1.1 Generalized dictator game

Each participant played nine different rounds of the generalized dictator game. In each round, the participants were given various endowments of tickets and prices of giving, and were asked how they would like to divide the endowment with an anonymous, random Player 2. The budget constraint is given by  $\pi_s + p\pi_o = m$ , where  $\pi_s$  is how many tickets were kept,  $\pi_o$  is how many tickets were given,  $p$  is the relative price of giving, and  $m$  is the endowment. The endowment in each round was either 10, 12, or 15 tickets. Every ticket the participant kept was multiplied by 1, 2, 3, or 4 (hold price), and every ticket given to Player 2 was multiplied by 1, 2, 3, or 4 (pass price) so that the price of giving was  $\frac{\text{hold price}}{\text{pass price}}$ . Below are the nine sets of endowments and prices of giving used in the study, based on the design by Andreoni and Miller (2002):

Round	Ticket Endowment	Hold Price	Pass Price	Relative Price of Giving
1	15	1	2	$\frac{1}{2}$
2	10	1	3	$\frac{1}{3}$
3	15	2	1	2
4	12	1	2	$\frac{1}{2}$
5	10	3	1	3
6	15	1	1	1
7	12	2	1	2
8	10	4	1	4
9	10	1	4	$\frac{1}{4}$

Participants were given the endowments and prices for each round, and were presented an interactive slider bar that displayed the different ticket amounts each player would earn. The slider bar ensured choices fulfilled the budget constraint, and eliminated the need to perform calculations by directly showing how many tickets each player would receive.

*Example:* Suppose the endowment was 10 tickets, the hold price was 1, and the pass price was 3 (so that the relative price of giving was  $\frac{1}{3}$ ). That is, however many tickets the player decided to keep was multiplied by 1, and however many tickets given to Player 2 was multiplied by 3. The player was presented a slider bar, ranging from giving 0 tickets to giving 10 tickets. With each possible offer amount, the player was told the total ticket amounts received by both players in the form (total tickets received, total tickets given). For example, if the player decided to give 4 tickets to Player 2, they saw (6, 12), i.e. they would receive 6 tickets ( $10 - 4 = 6$ ) and Player 2 would receive 12 tickets ( $4 * 3 = 12$ ).

The utility function for individuals with selfish preferences is represented by

$U(\pi_s, \pi_o) = \pi_s$ . Selfish individuals will prefer to maximize their own payoff, so their optimal allocation is to keep their entire endowment.

The utility function for Rawlsian preferences is given by  $U(\pi_s, \pi_o) = \min(\pi_s, \pi_o)$ . If the individual has Rawlsian preferences, their optimal allocation is to evenly split the endowment. For example, if the price of giving was 1 and the endowment was 10 tickets,  $\pi_s = \pi_o = 5$  tickets. Or if the price of giving was  $\frac{1}{2}$  and the endowment was 15 tickets, the dictator gave 5 tickets: they received 10 tickets and the other player received  $5 * 2 = 10$  tickets.

Individuals with utilitarian preferences have the utility function  $U(\pi_s, \pi_o) = \pi_s + \pi_o$ . Such individuals will allocate all payoffs to whichever  $\pi_s$  or  $\pi_o$  is cheaper. That is, if  $p$  was less than 1, they sent their entire endowment to the other player, and if  $p$  was greater than 1, they kept their endowment.

### 2.1.2 Ultimatum game

**Player 1:** Each participant was endowed with 10 tickets, and were told to decide how much of their endowment to send to an anonymous, random responder (Player 2) so that  $\pi_s + \pi_o = 10$ . They were informed that the responder may or may not reject the proposed allocation: if the allocation was accepted, then the proposal was implemented (Player 1 received  $\pi_s$  and Player 2 received  $\pi_o$ ), but if the allocation was rejected, neither player received any tickets.

*Example:* Suppose the participant chose to give 3 tickets to Player 2. If Player 2 accepted the proposal, the participant received 7 tickets ( $10 - 3 = 7$ ) and Player 2 received 3 tickets. However, if Player 2 rejected the proposition, then both players received 0 tickets.

**Player 2:** Each participant was informed that the proposer (Player 1) was given an endowment of 10 tickets. They were then presented a list from 0 tickets to 10 tickets (in 1-ticket increments), which represented the different amounts

that Player 1 could choose to send. The participants were instructed to indicate whether they accept or reject each hypothetical proposal, and were told that accepting means they agree to receiving the offered amount, and rejecting means they do not agree and instead both players will receive 0 tickets.

*Example:* Suppose the participant chose to reject all offered amounts below 5 tickets, and accept all offered amounts equal to or greater than 5 tickets. If Player 1 chose to offer 6 tickets, then Player 1 received 4 tickets ( $10 - 6 = 4$ ) and the participant received 6 tickets. But if Player 1 chose to offer 3 tickets, then both players received 0 tickets.

Since selfish individuals seek to maximize their own payoffs, selfish responders should never reject a non-zero offer. If selfish proposers assume responders are also selfish, they will offer the smallest non-zero amount (in this case, 1 ticket). However, if selfish proposers think the responder will be indifferent between being offered 1 ticket or 0 tickets, i.e. the responder will accept an offer of 0 tickets, then the proposer will offer 0 tickets.

However, responders may care about both inequality and total welfare. They may have Fehr-Schmidt difference-aversion preferences<sup>8</sup>:

$$U(\pi_s, \pi_o) = \begin{cases} \pi_s - \alpha(\pi_s - \pi_o) & \text{if } \pi_s > \pi_o \\ \pi_s - \beta(\pi_o - \pi_s) & \text{if } \pi_s \leq \pi_o \end{cases}$$

where  $0 \leq \alpha \leq \beta \leq 1$ . That is, the responder dislikes inequality but dislikes it even more if they have the smaller allocation. For example, say  $\alpha = \frac{1}{2}$  and  $\beta = 1$ . Compared to the utility of rejecting ( $U(\$0, \$0) = 0$ ), the responder will accept payoffs  $(\$4, \$6)$  since  $U(\$4, \$6) = 4 - 1(6 - 4) = 2$ , but reject payoffs  $(\$3, \$7)$  since  $U(\$3, \$7) = 3 - 1(7 - 3) = -1$ .

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<sup>8</sup>See Fehr and Schmidt (1999).



### 2.1.3 Trust game

**Player 1:** Each participant was endowed with 10 tickets. They were prompted to decide how much of their endowment to send to an anonymous, random responder (Player 2) so that  $\pi_s + \pi_o = 10$ . The participants were told that the amount sent over would be multiplied by 3, i.e. Player 2 would receive  $3\pi_o$ . Player 2 would then decide how many tickets,  $r \leq 3\pi_o$ , they would like to return. Overall, Player 1 received  $\pi_s + r$  tickets and Player 2 received  $3\pi_o - r$  tickets.

*Example:* If the participant chose to send 5 tickets, then Player 2 received 15 tickets ( $5 * 3 = 15$ ). If Player 2 returned 3 tickets, then Player 1 earned a total of 8 tickets ( $5 + 3 = 8$ ) and Player 2 earned a total of 12 tickets ( $15 - 3 = 12$ ).

**Player 2:** Each participant was informed that the proposer (Player 1) received an endowment of 10 tickets. They were then given a list of all ten possible multiplied amounts that Player 1 could have chosen to send, ranging from 3 tickets to 30 tickets in 3-ticket increments. For each possible offered amount, the participants entered the number of tickets they would like to return back to Player 1. They were given clear instructions that their input could not exceed what was given to them. For example, if Player 1 sent a multiplied amount of 15 tickets, then the maximum number of tickets the participant could return was 15 tickets.

Example: Suppose the participant's return scheme was as below:

Possible Offer Amounts (Multiplied)	Tickets Returned
3	0
6	1
9	3
12	3
15	5
18	5
21	5
24	5
27	5
30	5

where the first column is a list of all possible multiplied amounts that Player 1 could choose to send, and the second column indicates how many tickets the participant would like to return. If Player 1 decided to send 7 tickets, then the participant received a multiplied amount of 21 tickets ( $7 * 3 = 21$ ). As indicated by the participant's return scheme, the participant chose to send back 5 tickets. Thus Player 1 earned 8 tickets ( $3 + 5 = 8$ ), and the participant earned 16 tickets ( $21 - 5 = 16$ ).

Similar to the ultimatum game, selfish responders should return nothing; if selfish proposers assume responders are also purely selfish, then they will pass nothing. However, proposers with utilitarian preferences will prefer to maximize the sum of payoffs. Since the amount sent to the responder is multiplied by a positive factor, they will send everything to the responder. This can also be seen mathematically:  $U(\pi_s, \pi_o) = \pi_s + \pi_o = \pi_s + r + 3\pi_o - r = \pi_s + 3\pi_o$ . The amount sent to the responder increases the proposer's utility more than the amount kept, and so the proposer will choose to send their entire endowment to the responder.

#### 2.1.4 Public goods game

Participants were each given 10 tickets, and were told that they would be randomly matched with one other player. They were then prompted to decide how much of their endowment to contribute to a public fund, and that the other player was told to do the same task. The total tickets in the public fund was multiplied by 2, and divided evenly between the two players.

The payoff function is given by  $P_i = 10 - g_i + \sum_{n=1}^2 g_n$  where  $g_i$  is the amount that player  $i$  donated to the fund, and  $\sum_{n=1}^2 g_n$  is the sum of both players' donations to the public fund. Therefore Player 1's payoff function is  $P_1 = 10 - g_1 + \sum_{n=1}^2 g_n = 10 + g_2$ , and likewise Player 2's payoff function is  $P_2 = 10 - g_2 + \sum_{n=1}^2 g_n = 10 + g_1$ .

*Example:* Suppose the participant contributed 3 tickets, and the second player sent 5 tickets. The total donated amount,  $\sum_{n=1}^2 g_n$ , was 8 tickets. Therefore the participant received  $P_1 = 10 + 5 = 15$  tickets, and the second player received  $P_2 = 10 + 3 = 13$  tickets.

As seen in the payoff functions, each player's payoff depends on the other player's contribution. Therefore selfish players will not send any tickets into the public fund. But if the player has utilitarian preferences, from the perspective of Player 1, their utility is:  $U_1 = P_1 + P_2 = 20 + g_1 + g_2$ . Their utility depends on both players' contributions, so individuals with utilitarian preferences will send their entire endowment into the public fund.

#### 2.1.5 Strategy Method

Participants completed the games at their own availability, and were randomly matched with other participants after all data had been collected. In the two-player games which required both a proposer and responder (the ultimatum game and the trust game), each participant played both roles. When playing as the re-

sponder, the participant saw a list of all possible offer amounts and was prompted for their choice given each offer. This is called the strategy method.

There are several reasons why the strategy method is advantageous. First, it is useful to have all of the responder’s potential choices so that payoffs can be calculated after the fact. Most importantly, the strategy method gives more information. If players were matched with other players live, then we would only have the responder’s response given the proposer’s offer. The strategy method, however, provided all returned amounts for all possible donated amounts in the trust game, and provided participants’ minimum accepted amount in the ultimatum game.

#### **2.1.6 Payment**

After all experimental data was collected, participants were randomly matched. In each pair, one participant was randomly selected to be Player 1 (i.e. they were the dictator in the generalized dictator game, and proposer in the ultimatum game and the trust game), and the other was Player 2 (i.e. they were the receiver in the generalized dictator game, and the responder in the ultimatum and the trust game). I ran through each game and calculated ticket payoffs for each participant. Since the generalized dictator game consisted of nine rounds, one round was randomly selected; participants received tickets from that round.

Once all participants’ total lottery tickets were allocated, ten tickets were drawn. Each ticket owner was emailed instructions on how to receive their \$100 prize through direct deposit or by check.

## **2.2 Self-reported measures of past pro-social behaviors**

Participants then reported on past pro-social behavior. The questions were adapted from the Self-Report Altruism (SRA) scale introduced by Rushton et al. (1981).

The survey was comprised of 10 items, and participants reported how frequently they had done each item. Participants rated each statement as either “Never”, “Once”, “More than once”, “Often”, or “Very often”. Examples included “I have donated money at the cash register when buying groceries” and “I have pointed out a clerk’s error (at the supermarket, at a restaurant) in undercharging me.” A full list of the items from the online study is displayed in Appendix D.

## 2.3 Field Measure

Wesleyan University Relations provided a dataset that contained each participant’s Wesleyan donations information.

There are several reasons why I used donations as my field measure. First, many behavioral economics papers that explored the relationship between lab behavior and field behavior used donations<sup>9</sup>. Falk et al. (2013) justified that donations are an accurate field measure because they do not rely on self-reported responses but on actual decisions. Furthermore, donations are made in private and never made public, and students/alumni are unaware that their actions will be analyzed in a future research study. The lack of scrutiny therefore indicates donations should reflect the donors’ genuine altruism. The authors then pointed out the most important reason for their decision to use donations: all students and alumni are solicited, so everybody has to make the decision about donating.

In addition, donations are a more accurate field measure than creating a scenario at the end of the online session. In the experiment by Galizzi and Navarro-Martinez, participants were subject to the experimenter demand effect: because participants encountered the field experiments shortly after completing the lab experiments, it would not be difficult for participants to link the two situations together. Therefore, participants could have acted more pro-socially than they

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<sup>9</sup>See, e.g., Benz and Meier (2006); Baran et al.; Falk et al.

would usually. At Wesleyan University, seniors are solicited for donations around once per semester; alumni are solicited at the end of November / beginning of December, March, and June. The online study in this research was released between solicitation cycles (early January 2018), and participants' donations information were provided as of January 2018. Therefore participants' donations are not influenced by the experimenter demand effect.

### **2.3.1 Theoretical Correspondences Between Games and Donations**

The social preference games used in my study tap into different aspects of pro-social behaviors that are also related to donating. All first movers in each game can keep their endowment to themselves, but may also choose to share their endowment with the other player. Therefore the actions in each of the four games can be explained by altruism: those who choose to keep their endowment exhibit lower levels of altruism, and those who choose to share their endowment demonstrate higher levels of altruism. Likewise, altruism is the most common representation for donating since the donors choose to give a portion of their income to the university.

Proposers' decisions in the trust game indicate their trust levels. The offered amount is multiplied by a factor, so they may exhibit trust by sharing their endowment with the hopes of the responders sending back an amount larger than what was given. Correspondingly, donating may also represent trust since donors are trusting that the University will use their donations to benefit future students.

Responders' actions in the trust game can be interpreted by reciprocity: if the proposers decide to share their endowment, the responders then have the opportunity to give back. The responders display higher levels of reciprocity if they return tickets, and display lower levels of reciprocity if they do not. The responders' actions can also be represented by trustworthiness: the proposers

may contribute some of their endowment in hopes of the responders returning a larger amount than what was offered. Thus responders who return tickets indicate higher levels of trustworthiness. Equivalently, donations may explain reciprocity and trustworthiness since seniors and alumni may donate to the university as thanks for providing them invaluable resources and opportunities.

Players' responses in all of the games can also correspond with inequality aversion, that is, they may choose to share their endowment so that the other player will not be left with nothing. Donations can also potentially be explained by inequality aversion: people may donate because they believe their donations will help students receive opportunities they would not be able to obtain otherwise. Donors are also able to target what area their donations can go towards: for example, if the donor targets their donations to Financial Aid, then they are displaying inequality averse preferences.

Lastly, players' decisions in the public goods game can be explained by their cooperation levels. Players may choose to contribute a portion of their endowment because they believe the other players are doing the same thing. In the case for donations, people may exhibit cooperation by donating because the University solicits for donations (i.e. they are cooperating with what the University is asking for), or donating because they believe other seniors/alumni are also donating.

## **2.4 Participants and Sessions**

Wesleyan University Relations provided a random sample of 2,004 emails (334 emails for each class year from 2013 to 2018), and I sent an invitation email in early January 2018 asking for participation in my study. Participants were informed that the study consisted of several experimental games and non-incentivized survey questions. The participants were volunteers who opened the link to the online study, provided consent for me to receive their major, class year, and Wesleyan

donations data, and completed both the social preference games and survey questions. The deadline for participation was mid-February 2018; a total of 397 people completed the online study. Shortly after the participation deadline, all participants were randomly paired, ticket payoffs were calculated, and 10 winners were randomly selected. The winners were emailed in the beginning of March 2018 with instructions on how to receive their prizes.

### 3 Results

The results are presented in four distinct sections. I start by describing the results obtained in the three main elements (social preference games, self-reported measures, and donations). The last section focuses on the main question of this paper: the extent to which the games explain and predict donations. Appendix A contains all figures and tables; Appendix B contains the variables definition table.

#### 3.1 Social Preference Games

Since the generalized dictator game consisted of 9 rounds with varying sets of endowments and prices of giving, I assumed each participant’s giving preferences was a member of the constant elasticity of substitution (CES) utility function<sup>10</sup>. The CES utility function is written as:  $U_s = [\alpha(\pi_s)^\rho + (1 - \alpha)(\pi_o)^\rho]^{1/\rho}$ .

The first parameter,  $\alpha$ , measures the relative weight on the payoff to self. Holding  $\rho$  constant, as  $\alpha \rightarrow 1$ ,  $U_s \rightarrow \pi_s$ , i.e. the individual’s utility depends only on the amount they keep for themselves. As  $\alpha \rightarrow 0$ ,  $U_s \rightarrow \pi_o$ , i.e. the individual’s utility depends only on the amount the other person receives. Therefore as  $\alpha \rightarrow 1$ , the individual exhibits selfish preferences, and as  $\alpha \rightarrow 0$ , the individual exhibits displays preferences.

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<sup>10</sup>Andreoni and Miller and Fisman et al. (2007) used the CES utility function to represent subjects’ preferences.



The second parameter,  $\rho$ , indicates the willingness to trade off payoffs to self and other in response to price changes. Holding  $\alpha$  constant, as  $\rho \rightarrow 1$ ,  $U_s \rightarrow \alpha\pi_s + (1 - \alpha)\pi_o$ , i.e. the individual's utility depends on the sum of payoffs. This means the individual exhibits perfect substitutes preferences for giving, or efficiency-minded preferences: they will prefer to give their entire endowment to the other player when the price of giving is cheap ( $p < 1$ ), and they will prefer to keep their entire endowment when the price of giving is expensive ( $p > 1$ ). As  $\rho \rightarrow -\infty$ ,  $U_s \rightarrow \min(\alpha\pi_s, (1 - \alpha)\pi_o)$ , that is, the individual's utility equals the minimum payoff between both players. These preferences are called Leontief preferences, or inequality-averse preferences: the individual prefers to split the endowment equally. Lastly, as  $\rho \rightarrow 0$ ,  $U_s \rightarrow A\pi_s^\alpha\pi_o^{1-\alpha}$ . In this case, the individual has Cobb-Douglas preferences.<sup>11</sup>

Maximizing utility subject to the budget constraint ( $p_s\pi_s + p_o\pi_o = m$ ) yielded the CES demand function given by:

$$\begin{aligned}\pi_s(p, m) &= \frac{[\alpha/(1-\alpha)]^{1/(1-\rho)}}{\rho^{-\rho/(\rho-1)} + [\alpha/(1-\alpha)]^{1/(1-\rho)}} m \\ &= \frac{A}{p^r + A} m\end{aligned}$$

where  $r = -\rho/(1 - \rho)$  and  $A = [\alpha/(1 - \alpha)]^{1/(1-\rho)}$ . This generated the following individual-level econometric specification for each participant  $i$ :

$$\pi_{s,i}^t = \frac{A_i}{(p_i^t)^{r_i} + A_i} m_i^t + \epsilon_i^t$$

where  $i$  represents each participant,  $t$  represents each independent decision-problems in the generalized dictator game, and  $\epsilon_i^t$  is assumed to be distributed normally with mean zero and variance  $\sigma_i^2$ . For each participant, I used the 9 combinations of  $\pi_s$ ,  $p$ , and  $m$  to calculate the estimates  $\hat{A}_i$  and  $\hat{r}_i$  using non-linear least squares. From the estimates, I then retrieved each participant's  $\hat{\rho}_i$  and  $\hat{\alpha}_i$ . I used  $\hat{\alpha}$  as the

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<sup>11</sup>See Arrow et al. (1961) on how the different preferences are derived from the CES function.

generalized dictator game parameter to indicate participants' selfishness, and  $\hat{\rho}$  as the second parameter to represent participants' efficiency levels.

Figure 1 consists of two panels (Panels A and B) that shows the distribution of  $\hat{\alpha}$  and  $\hat{\rho}$ . The parameter estimates varied dramatically across subjects, implying that preferences for giving were very heterogeneous. Panel A displays a high peak of 21% at  $\hat{\alpha}=1$ : a considerable amount of participants displayed extremely selfish preferences. There is a smaller peak of 12% at  $\hat{\alpha}=0.5$ , and there are more  $\hat{\alpha}$  observations above 0.5 than below 0.5. These results indicate that participants tended to have more selfish preferences.

To facilitate presentation of Panel B, participants with very negative  $\hat{\rho}$  values were combined into the leftmost bar. About 7% of subjects had efficiency-minded preferences for giving ( $\hat{\rho} \approx 1$ ): these subjects preferred to give their entire endowment to Player 2 when the price of giving was less than one, and preferred to keep their entire endowment when the price of giving was greater than one. A little over 20% of participants demonstrated inequality-averse preferences ( $\hat{\rho}$  far below 0): they preferred splitting the endowment equally. Roughly 15% of subjects possessed Cobb-Douglas preferences ( $\hat{\rho} \approx 0$ ). Many subjects also had intermediate values of  $\hat{\rho}$ : 24% had preferences for increasing total payoffs ( $0.1 \leq \hat{\rho} \leq 0.9$ ), and almost 20% had inequality-averse preferences ( $-0.9 \leq \hat{\rho} \leq 0.9$ ).

Results from the proposers in the ultimatum game ("ultimatum1") and trust game ("trust1") were represented by their pass rates (the percentage of the endowment passed to the other player). For example, if the proposer sent 6 tickets, the pass rate was 0.6. In the ultimatum game, higher pass rates indicated higher levels of altruism and/or fairness preferences. In the trust game, higher pass rates indicated higher levels of altruism, fairness preferences, and/or trust.

Similarly, outcomes for the players in the public goods games ("cooperation") were represented by their pass rates into the public fund. Larger amounts con-

tributed into the public fund signaled higher levels of cooperation.

Results from the responders in the ultimatum game (“ultimatum2”) were represented as the minimum pass rate the responder accepted. Since responders were presented an ascending list of all possible amounts the proposer could choose to send, minimum pass rates were obtained with the switch point where the responders changed from rejecting an offer amount to accepting an offer amount. Lower minimum accepted pass rates indicated lower levels of selfishness and negative reciprocity, whereas higher minimum accepted pass rates indicated higher levels of selfishness and negative reciprocity.

Figure 2 consists of four panels (Panels C, D, E, and F) which shows the distribution of responses in the ultimatum, trust, and public goods games. Panel C reports that 42% of proposers in the ultimatum game gave half of their endowment to the responders, and there was slightly more emphasis on those who gave contributions lower than half the endowment than contributions higher than half the endowment. These results are in line with the typical patterns in previous literature, which found that a majority of offers were in the range of 0.25-0.50. Correspondingly, Panel D shows the distribution of the minimum offers the responders accepted. With the exception of one participant who showed extreme negative reciprocity by only accepting 10 tickets, everyone accepted an amount less than or equal to half of the endowment. 27% of participants accepted an offer amount of 0 tickets.

Panel E shows the distribution of proposers’ pass rates in the trust game. Pass rates were scattered all across the range from offering none of their endowment to offering all of their endowment. There are two maxima, both around 22%, where participants gave either half the endowment or the entire endowment. Other contributions that had more than 10% are proposers who gave 0.3 or 0.4 of the given endowment. These results are also broadly in line with typical findings that

reported average transfers of roughly half of the endowment.

Panel F shows that almost half the participants in the public goods game sent their entire endowment into the public fund. The next most popular choice (20%) was to send half their endowment to the public pool, and only 4% of participants sent nothing into the public pool. Again, these findings match usual results in literature.

Lastly, the trust game asked for the responder's return amount given the proposer's 10 possible offer amounts. For each responder, I regressed their return amount on the offer amount, and retrieved the estimated slope. Thus the results from the responders in the trust game were represented by the estimated slope, which measured the participant's reciprocity, or trustworthiness level ("trust2"). Values closer to one represented more reciprocal behavior, and lower levels closer to zero represented more selfish behavior.<sup>12</sup> I also calculated the responders's average repayment rate: for each possible amount the proposer could have sent, the responder chose to send back a portion of the offer. I took the average of the responder's return rates.

Figure 3 contains two panels (Panels G and H) that displays the distribution of reciprocity levels and average repayment rate, respectively. Panel G shows that, with the exception of two participants who demonstrated negative reciprocity (perhaps they did not understand the game), reciprocity levels were very heterogeneous between 0 and 1. There was a maximum (27%) at reciprocity levels around 0.5, and a local maximum (14%) around 0.35. There was also a small local maximum (10%) at 0 – these individuals did not show any reciprocity. Panel H shows a strong peak of repayment rates of around 0.45, and participants showed slightly stronger preference in repaying less than half of what was received com-

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<sup>12</sup>There may be concern that some participant's decisions did not follow a linear trend. After plotting each participant's return amount in response to the offer amount, I found that with the exception of a few participants, each participant's data points followed a linear slope.

pared to repaying more than half of what was received. These results are in line with typical patterns found in previous literature, which reported average repayment rates of nearly half of the transfer.

Table 1 shows the pairwise correlations between the different game outcomes. A majority of the correlations were statistically significant at the 5% level (13 out of 21). All of the statistically significant negative correlations involved  $\hat{\alpha}$  from the generalized dictator game and responders' behavior in the ultimatum game. The negative correlations for  $\hat{\alpha}$  reflected that participants who were more selfish ( $\hat{\alpha} \rightarrow 1$ ) were more likely to make smaller contributions in the other games, and the negative correlations for the responders in the ultimatum game reflected that participants who accepted smaller contributions were more likely to make larger contributions in the other game decisions. Otherwise, decisions made in the other games had positive correlations with one another. Overall, these results show that participants generally demonstrated consistent behavior in all the games.

### 3.2 Self-Reported Measures of Past Pro-Social Behaviors

Total SRA scores were obtained by summing across each participant's responses for the 10 items in the SRA Scale ("Never" = 0, "Once" = 1, "More than once" = 2, "Often" = 3, "Very often" = 4). A higher SRA score indicated higher pro-social behavior. Figure 4 Panel I shows the distribution of total scores ("SRAtotal"). There was a wide variety in the total SRA scores obtained, ranging between scores of 20 and 48. Scores were centered around 33 and the shape was symmetric. Panel J displays the distribution of monetary SRA scores ("SRAmoney"), which were obtained by summing across each participant's responses for only the items related to money (items 2, 3, 4, and 7 in Appendix B). A large majority of the scores were between 9 and 12.

Table 2 contains pairwise correlations between the game responses and the

total/monetary SRA scores. None of the game results were significantly correlated with total SRA scores, and only the results from the responders in the trust game and players in the public goods game were significantly correlated with monetary SRA scores. Overall, there was a very weak relationship between the social preference games and self-reported measures.

### 3.3 Donations Behavior

Figure 5 shows the distribution of Wesleyan donations. Panel K shows the distribution of participants' total donation amounts (donations above \$100 are aggregated into the rightmost bar). Most of the total donation amounts were below \$20 (about 36%). There were 30 participants who each donated a total amount greater than \$100. All of these larger donations amounts were between \$100 and \$625, with the exception of two extremely large donations. Panel L displays the natural log of average donation amounts<sup>13</sup>. The distribution followed a symmetric shape.

Figure 6 shows that each class year had different donations behavior. Panel M shows that only about a quarter of the senior class participants donated. In contrast, at least 60% in each alumni class year donated. Panel N shows each class year's average yearly donations. Each class year consecutively had higher donations, from seniors' average donation of \$3 to the class of 2013's average donation of \$12<sup>14</sup>.

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<sup>13</sup>Older alumni have had more years to donate, so their total donations were expected to generally be larger than younger alumni. To find the average donation amount, I divided total donations by the number of years they have been solicited. For example, the class of 2018 has been solicited for 1 year, and the class of 2013 has been solicited for 6 years.

<sup>14</sup>Outliers were excluded when calculating each class year's average donations.

### 3.4 External Validity of Social Preference Games

#### 3.4.1 Do the Games Explain Donations Behavior?

I now turn to the question of whether the game decisions explain the field behavior. There were two ways that I represented donations behavior: (1) whether the participant has ever donated or not, and (2) the log of each participant's average donations. I included  $\hat{\alpha}$  and  $\hat{\rho}$  parameters from the generalized dictator game (which I will now refer to as “ $\alpha$ ” and “ $\rho$ ”), proposers' pass rates in the ultimatum and trust games (“ultimatum1” and “trust1”), responders' minimum accepted pass rates from the ultimatum game (“ultimatum2”), responders' reciprocity levels from the trust game (“trust2”), and players' pass rates in the public goods game (“cooperation”) as the explanatory game variables. I also included total and monetary SRA scores (“SRAtotal” and “SRAmoney”) as the explanatory self-reported variables. In addition, I included class year, gender, and college major dummy variables<sup>15</sup>. In the regression models, the baseline class year is the current senior class (class of 2018), and the baseline gender is male. I grouped college majors into three areas of study: arts and humanities, natural sciences and mathematics, and social sciences. The baseline area of study is social sciences. Appendix B contains the table of variable definitions.

Table 3a presents twelve logistic regression models using the binary donations representation as the response variable. The first seven columns present each of the game outcomes on their own, and the eighth column includes all of the game variables. The ninth and tenth columns contain only the total and monetary SRA scores, and the last two columns include all of the game outcomes along with the total and monetary SRA scores, respectively. All of the class year

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<sup>15</sup>Although I normalized each class year's average donations by dividing by the number of years they have been solicited, different class years may have different pro-social tendencies. This is supported by Figure 6 Panel N where average donations increase in class year. Males and females may have different social preferences, and different college majors are known to have different income levels which may affect their donations behavior.

dummy variables are statistically significant at the 1% level, showing that donation participation increased in class year. None of the games or SRA results are statistically significant on their own. When both the games and SRA results are used in the regression model, still none of the variables are statistically significant.

I then used ordinary least squares (OLS) to regress the same explanatory variables on the log of average donations. Table 4a presents the twelve linear regression models, presented in the same format as Table 3a. Most of the class year variables are statistically significant at the 5% level, and show that donation amounts generally increased in class year. None of the game outcomes or SRA scores are statistically significant at the 5% level, although trust2 is statistically significant at the 10% level.

It is also useful to look at the  $R^2$  statistic, which measures the proportion of variance explained by the regressors. For the logistic regressions, I calculated each model's McFadden's pseudo- $R^2$  values, displayed at the bottom of Table 3a<sup>16</sup>. Each model's pseudo- $R^2$  values are around 0.14, which means there is still about 85% of the variation in donations behavior left unexplained. The adjusted  $R^2$  values for the linear regression models are displayed at the bottom of Table 4a. Each value is roughly around 0.05, so there is still about 95% of the variation in donations that is unexplained. More interestingly, each model's  $R^2$  values are similar, whether the model includes all of the game variables, only SRA scores, or a combination of the two.

Even when combined with self-reported measures, social preference games explain only a small portion of the variability of donations behavior. However, perhaps different combinations of the explanatory variables can better explain the field measure. I performed best subset selection on both the logistic and

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<sup>16</sup>  $R_{McFadden}^2 = 1 - \frac{\log(L_c)}{\log(L_{null})}$  where  $L_c$  denotes the maximized likelihood for the current fitted model, and  $L_{null}$  denotes the maximized likelihood the model with no predictors.



linear regression models<sup>17</sup>. Since best subset selection tests all possible combinations of regressors, I included more variables: I added the responders’ average return outcome from the trust game (“average return”), and replaced SRAtotal and SRAmoney with each of the ten individual SRA items (“SRA1” - “SRA10”).

Table 5 displays the top five best subset logistic regression models along with the dummy variables. Notably, four SRA items (items 3, 4, 8, and 10) appear in each model, and items 3 and 4 are statistically significant at the 5% level. The pseudo- $R^2$  values are only slightly larger than the logistic models displayed in Table 3a.

Table 6 reports the five best subset linear regression models with the dummy variables. Three game variables (ultimatum1, ultimatum2, and trust2) as well as four SRA items (items 3, 4, 5, and 6) appear in all of the models. Trust2 and SRA items 3 and 4 are statistically significant at the 5% level. The adjusted  $R^2$  statistics are quite larger than in the models in Table 4a; each model explains almost 17% of the variability in donations behavior.

Overall, the  $R^2$  values in Tables 3–6 show that a majority of the variation in the field measure is still unexplained. Furthermore, some of the game variables have signs that are not expected. First, we would expect the coefficient on  $\alpha$  to be negative since higher levels of  $\alpha$  indicate more selfish behavior. Ultimatum1, trust1, and cooperation should have positive relationships with donations since higher pass rates signal more pro-social preferences. Ultimatum2 is expected to have a negative relationship with donations since higher minimum accepted pass rates signal higher negative reciprocity, and trust2 should have a positive relationship with donations. However, in Table 3a, the coefficients for  $\alpha$ , ultimatum1,

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<sup>17</sup>Best subset selection identifies all of the possible regression models derived from all of the possible combinations of the candidate predictors, and determines the model that does the best at meeting some well-defined criteria. In this case, the criteria I used is Mallows’  $C_p$ -statistic, which assesses model fits when models with different numbers of parameters are being compared. See Mallows (1973).

ultimatum2, and cooperation have opposite signs than expected. In Table 4a, the signs on the coefficients for  $\alpha$ , trust1, and trust2 are unexpected. Lastly, some of the game variable coefficients in the best subset regression models (Tables 5 and 6) have unexpected signs. Thus the low  $R^2$  values and unexpected direction of game coefficients suggest the external validity of social preference games is poor.

### 3.4.2 Do the Games Predict Donations Behavior?

Perhaps the social preference games and self-reported measures can still be a useful tool to predict donations behavior. That is, Wesleyan University can possibly use social preference game results and/or self-reported measures from older alumni to anticipate donations from incoming alumni.

In predictive modeling, a common approach is to split the data into a training set and testing set. The training set is used to build and train the model, and once the model is ready, the model is tested on the testing set to determine its accuracy and performance. I used the data from the older alumni participants (those who graduated in 2013, 2014, 2015, and 2016) to create the training set, and used the data from the most recent alumni (those who graduated in 2017) to create the testing set<sup>18</sup>.

Similar to the previous section, I used both the binary and continuous representation of donations behavior. Overall, the models I estimated from the training set included: the logistic/linear predictive models, the best subset logistic/linear predictive models, and the least absolute shrinkage and selection operator (lasso) models<sup>19</sup>. To compare how well the models performed, I tested each of the models

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<sup>18</sup>I did not use seniors as the testing set because they have very different donations behavior. Using the most recent alumni class as the testing set is satisfactory since the senior class participants will eventually become the newest alumni class year. Moreover, it is more interesting to predict their donations behavior since Wesleyan University focuses more on alumni donations than senior donations and, as seen in Table 6, there is a significant jump in donations.

<sup>19</sup>The lasso is a regression analysis method that performs both variable selection and regularization to enhance prediction accuracy. The lasso estimate is defined by

on the testing set. For the logistic models I calculated the mean-squared prediction error (MSPE)<sup>20</sup>, and for the linear models I calculated the root mean square error (RMSE)<sup>21</sup>. Smaller error values indicate better performing predictive models.

First, Table 7 reports the logistic predictive models. Each of the estimated models were tested on the testing set, and the bottom row reports the corresponding MSPE values. The lowest MSPE belongs to the model that includes only the monetary SRA score. Table 8 reports the top five best subset logistic models, and again, the MSPE values are displayed at the bottom. The model that includes  $\alpha$ , ultimatum2, and SRA items 3, 4, and 10 has the lowest MSPE. Lastly I used the lasso method, and all of the variables except for  $\alpha$ , ultimatum2, and SRA items 3 and 4 were truncated to zero. Table 9 shows the lasso penalized logistic model<sup>22</sup> and corresponding MSPE value.

I repeated the same steps for the linear models. Table 10 reports the linear predictive models; the lowest RMSE corresponds to the model that includes only trust2. Table 11 reports the top five best subset linear models, where the lowest RMSE belongs to the model that contains trust2, ultimatum1, cooperation, and SRA items 4, 5, and 6. Finally, the lasso method truncated most of the variables to zero, leaving  $\rho$ , average return, cooperation, and SRA items 4, 5, and 6. Table 12 displays the lasso model and RMSE value.

The table below reports the best performing logistic model, best subset logic model, and lasso penalized logistic model with respective MSPE values:

$$\beta^{lasso} = \underset{\beta}{\operatorname{argmin}} \left\{ \frac{1}{2} \sum_{i=1}^N (y_i - \beta_0 - \sum_{j=1}^p x_{ij} \beta_j)^2 + \lambda \sum_{j=1}^p |\beta_j| \right\}$$

where  $\lambda$  is a free parameter that minimizes the out of sample error. Certain coefficients are truncated to zero to effectively choose a simpler model. In other words, lasso regression picks out the most important coefficients, i.e. those that are most predictive (and have the lowest p-values). See Tibshirani (1996) for a full introduction on the lasso method.

<sup>20</sup> $MSPE = E[(g(x_i) - \hat{g}(x_i))^2]$ , i.e. the expected value of the squared difference between the fitted values implied by the predictive model  $\hat{g}$  and the values of the (unobservable) model  $g$ .

<sup>21</sup> $RMSE = \sqrt{\frac{\sum_{i=1}^n (\hat{y}_i - y_i)^2}{n}}$ , i.e. the square root of the average sum of squared residuals.

<sup>22</sup>Statistical significance tests were based on Lockhart et al. (2014). See Kyung et al. (2010) and Tibshirani for a full discussion on standard errors for lasso predictions.

Logistic model	Best subset logistic model	Lasso penalized logistic model
donated = SRAmoney	donated = $\alpha$ + ultimatum2 + SRA3 + SRA4 + SRA10	donated = $\alpha$ + ultimatum2 + SRA3 + SRA4
0.2465	0.2619	0.2518

The logistic model is the most accurate model. The MSPE value of roughly 0.25, indicates the model correctly predicts whether people will donate or not 75% of the time. As seen in Figure 6, about 60% of the alumni participants donated: we could randomly guess that the participants in the testing set would donate and be correct about 60% of the time. Thus the prediction model increased prediction accuracy by 15%.

The table below displays the best performing linear model, best subset linear model, and lasso penalized linear model with corresponding RMSE values:

Linear model	Best subset linear model	Lasso penalized linear model
$\log(\text{average donations}) = \text{trust2}$	$\log(\text{average donations}) = \text{trust2} + \text{ultimatum1} + \text{cooperation} + \text{SRA4} + \text{SRA5} + \text{SRA6}$	$\log(\text{average donations}) = \rho + \text{avgreturn} + \text{cooperation} + \text{SRA4} + \text{SRA5} + \text{SRA6}$
1.8962	1.8967	1.8811

The lasso penalized model is the best-performing model for predicting donation amounts. Since I used the natural log of average donations as the response variable, taking the inverse function allows us to better interpret the prediction error:  $e^{1.8811} = 6.5607$ , so the model predicted donations with an error of \$6.56. In order to draw conclusions about the performance of the model, a baseline model is needed for comparison. A reasonable guess is to use the older alumni class years' average donation. Testing the baseline model that includes only the average donation amount gives an RMSE of 1.9052:  $e^{1.9052} = 6.7208$ , so using the average donation of older alumni predicted the donations of the newest alumni class with an error of \$6.72.

Overall, using social preference games and self-reported measures increases the prediction accuracy of whether individuals will donate or not by 15%. However, when predicting the amount donated, the games and self-reported measures perform similarly as guessing the training set's average donation.

## 4 Conclusion and Discussion

Currently, the accumulated literature exploring the external validity of social preference games has mixed results. My thesis provided a systematic approach to this topic, where I collected decisions in four experimental social preference games along with self-reported pro-social behaviors performed in the past. Most importantly, I compared the lab behavior to a natural field measure that is far-removed from my study.

To examine the explanatory power of the social preference games, I ran regression models with different combinations of game outcomes and self-reported measures on donations. I observed low  $R^2$  values – there was still a lot of variation in the field measure left unexplained. Moreover, a majority of the game coefficients were not statistically significant, and had unexpected directions. Overall it seems that the experimental games did a poor job explaining the field behavior. These results are still very interesting because it suggests that social preference games may not generalize field behavior as much as it is anticipated to. Social preference games are thought to at least generally indicate individuals' pro-social behavior, but with the results from my research, this does not seem to be the case. However, there may be a considerable amount of noise in game behavior due to the experimenter demand effect. Thus there isn't a baseline  $R^2$  value to compare to, so perhaps the games do a sufficient job explaining donations behavior.

I then ran various prediction models on a training dataset of older alumni participants, and tested the models on a testing dataset of the newest alumni class. The baseline logistic model was using the proportion of those who donated in the training set to guess the proportion of those who will donate in the testing set. The baseline linear model was using the average donations from participants in the training set to guess the donations from participants in the testing set. The games and self-reported measures did a good job in predicting donations behavior:

using social preference games and self-reported measures increased the accuracy of predicting whether individuals will donate by 15%. On the other hand, the games and self-reported measures predicted donation amounts no better than the baseline model.

Most notably, the self-reported measures seemed to perform just as well as the games in both explaining and predicting donations behavior. Tables 3 and 4 showed each model's  $R^2$  values were very close to one another – the models that included only the total/monetary SRA score explained donations behavior just as well as the models that included multiple game variables. Tables 7 and 10 showed that all of the prediction models (whether they included only self-reported measures or multiple game variables) had very similar MSPE/RMSE values.

It can even be argued that the self-reported measures played a more important role than the games. The same SRA items were consistently included in the best subsets and lasso-penalized models (items 3 and 4 in the logistic models in Tables 8 and 9; and items 4, 5, and 6 in the linear models in Tables 11 and 12). Moreover, Table 7 showed that the models that contained only total/monetary SRA scores had error values that were smaller than the models that contained multiple social preference games.

This conclusion has a potential policy implication from a research perspective. Experimental games require significant resources: not only is it expensive paying participants for attending the lab session and providing money aligned with the payoffs of the games in order to elicit honest actions, but it also takes a lot of time to program the experimental games. Therefore since self-reported measures seem to explain and predict the field behavior just as well as social preference games, perhaps eliminating the games in favor of survey questions is more efficient.

However, there is a limitation to these results. Table 3b displays the same explanatory logistic models as Table 3a, but without the class year dummy vari-

ables. Similarly, Table 4b reports the explanatory linear models without the class year dummy variables. Comparing Table 3b and Table 4b to the logistic predictive models and linear predictive models in Table 7 and Table 10, respectively, the only difference is that the class of 2017 and 2018 were excluded in the predictive models. The game coefficients  $\alpha$ , ultimatum2, and trust2 are quite different between the logistic models, and the game coefficients  $\alpha$ , ultimatum2, trust1, and cooperation are different between the linear models. Moreover, the game coefficients are still quite different even when including the class year dummy variables (Tables 3a and 4a). These results suggest that the relationship between the game outcomes and donations behavior is significantly different for different class years. Perhaps this is why the games did not seem to explain donations behavior very well, even when controlling for class year effects, and only had modest additional predictive power.

There is additional limitation with the logistic models. Older class years have had more chances to donate, but given the provided data, there wasn't a way to normalize the binary donations representation. Therefore we must be cautious when discussing the explanatory power and prediction performance of the logistic models.

Nevertheless, this is just the beginning of a systematic approach to uncovering the external validity of experimental social preference games. There are a few things that further research can include. First, both Galizzi and Navarro-Martinez and my study used (recent) university students who self-selected into the experiments. It would be beneficial to use a different participant pool, since our subjects could be inherently different than the general population<sup>23</sup>. Further research should also use more field measures. Galizzi and Navarro-Martinez created five field situations; however, their subjects were likely influenced by the

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<sup>23</sup>See Levitt and List for a discussion on student participants.

experimenter demand effect. On the other hand, my study included only one field measure, but the measure was not influenced by the experimenter demand effect. Therefore further research should incorporate more field measures that can be theoretically mapped to various behavioral constructs, but are also far removed from the study itself. Lastly, perhaps using other social preference games and/or exploring repeated games could provide further insight into the topic.



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# Appendix A   Figures and Tables

Figure 1: Distribution of CES parameters from generalized dictator game

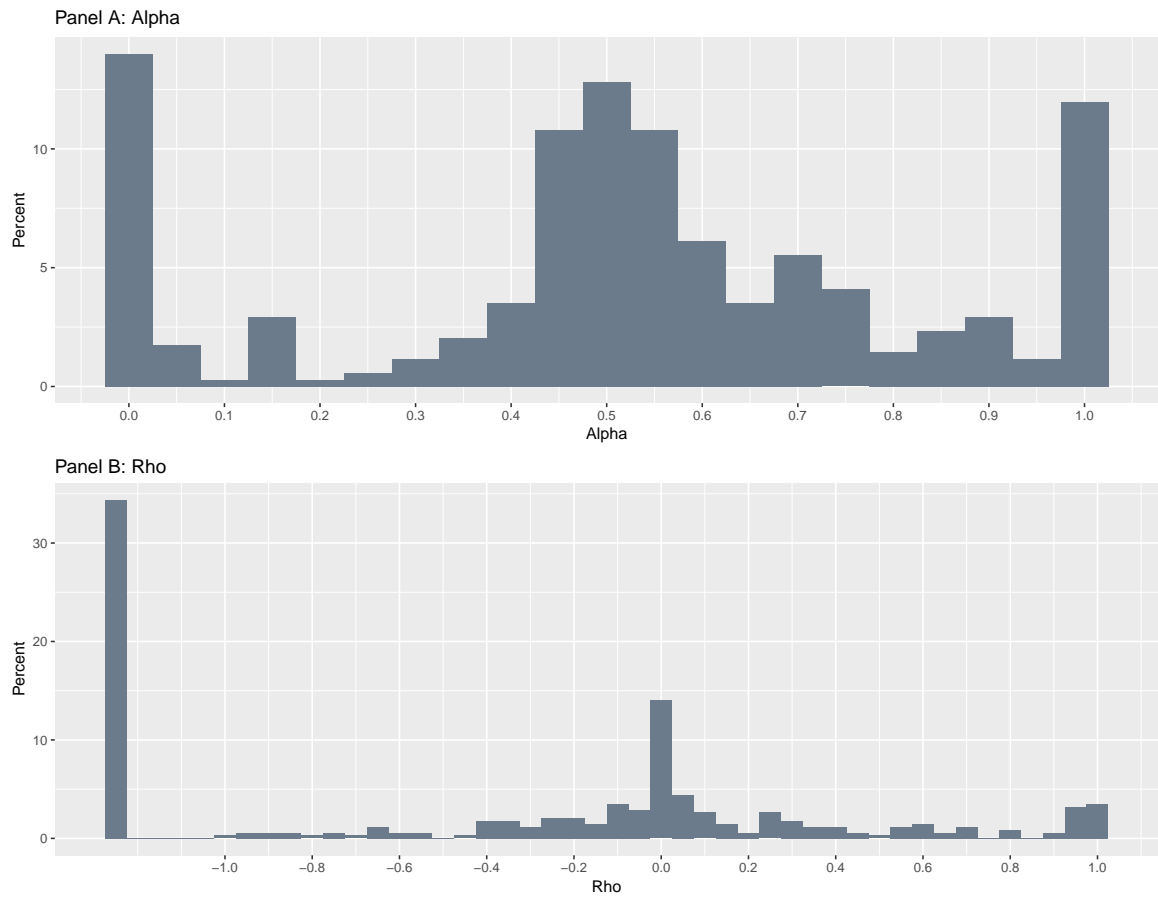


Figure 2: Distribution of responses in ultimatum, trust, and public goods games

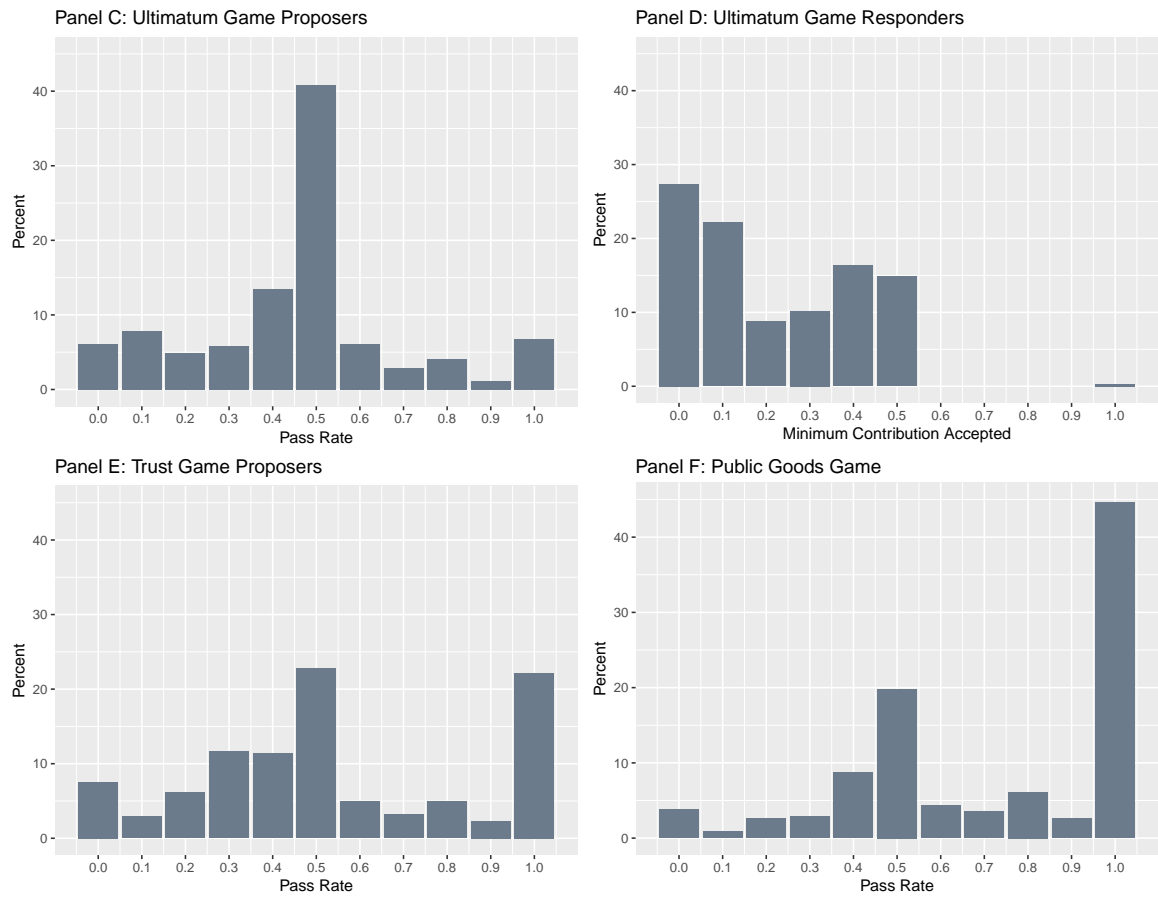


Figure 3: Distribution of responses from responders in trust game

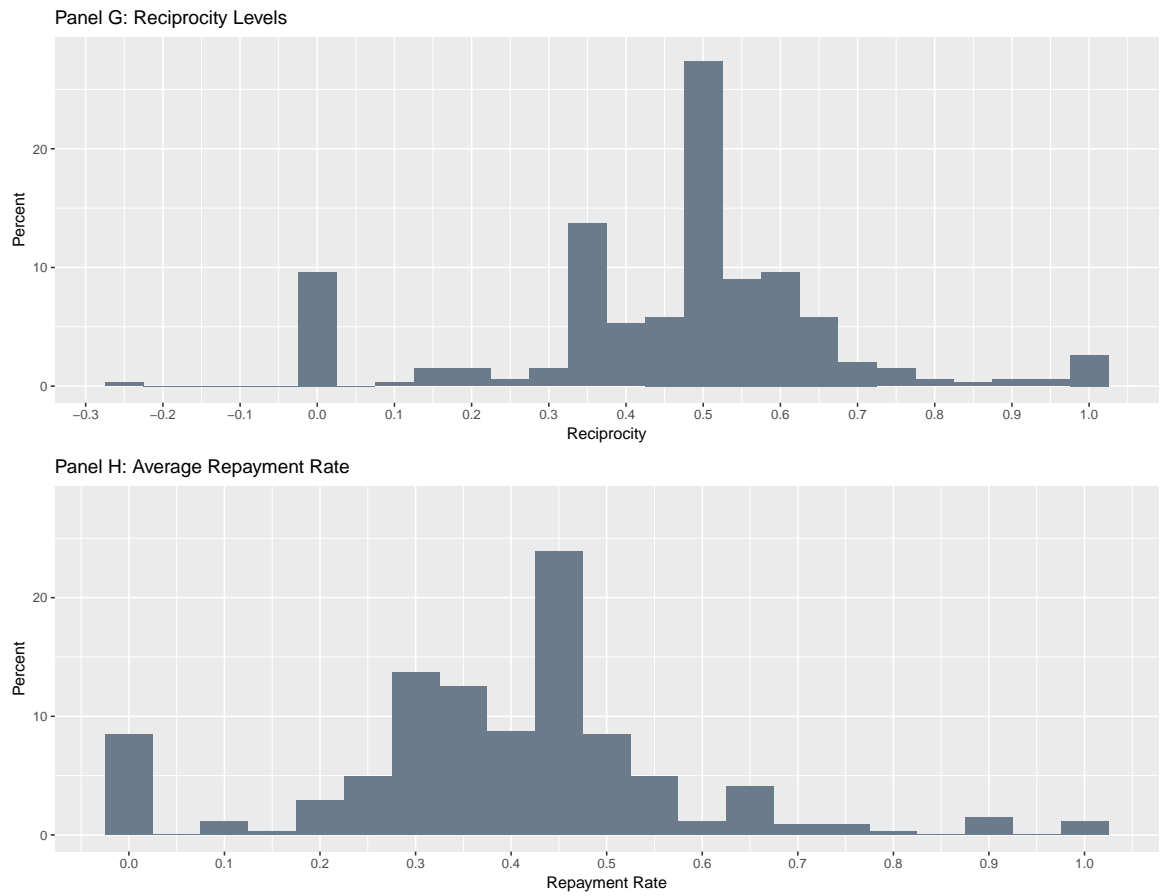


Figure 4: SRA scores

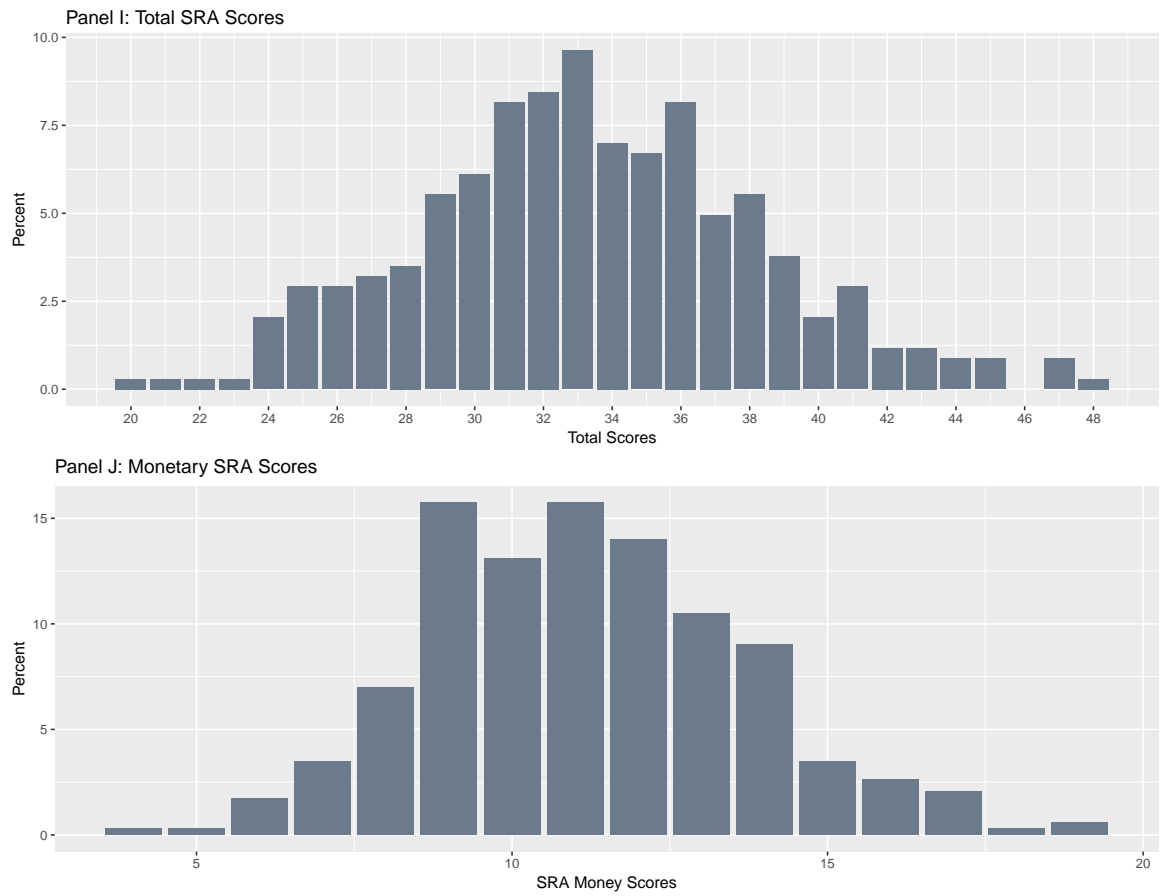




Figure 5: Donations behavior

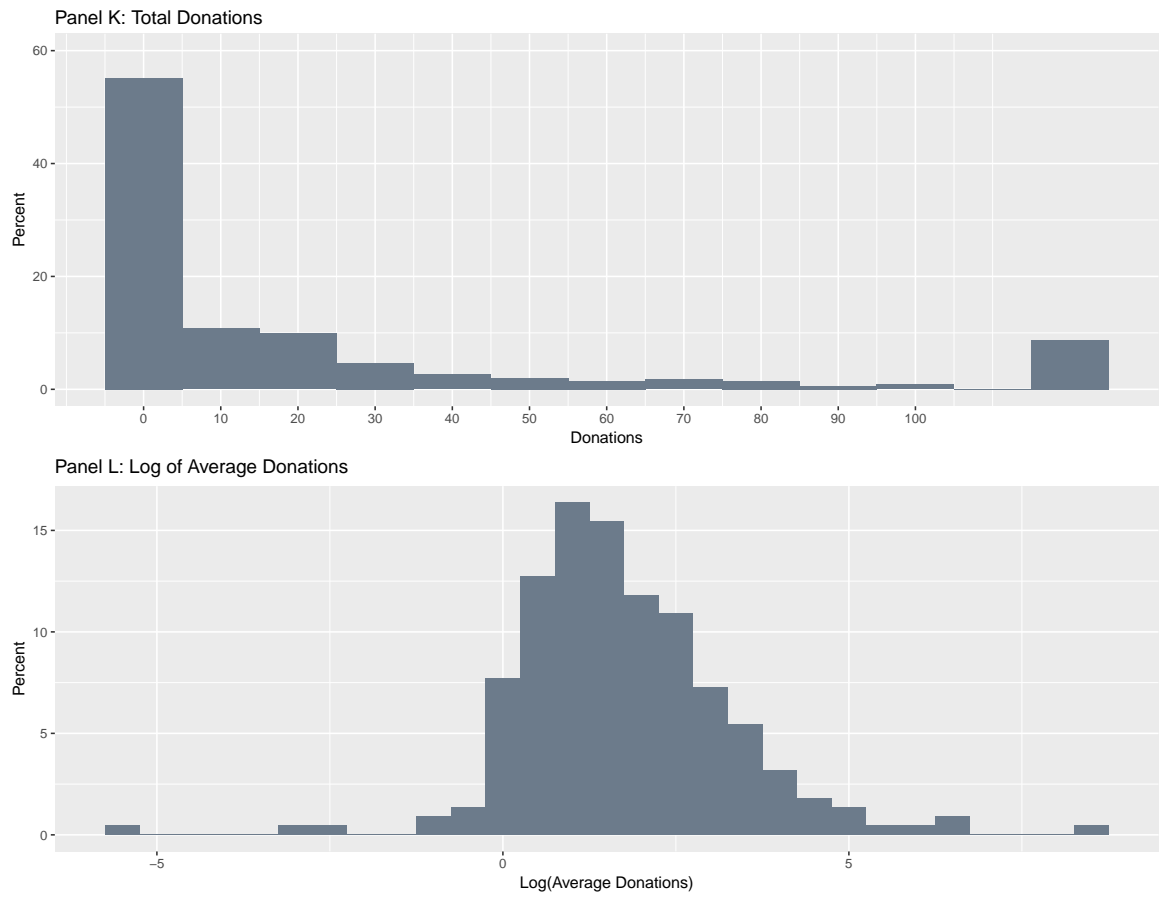


Figure 6: Donations behavior by class year

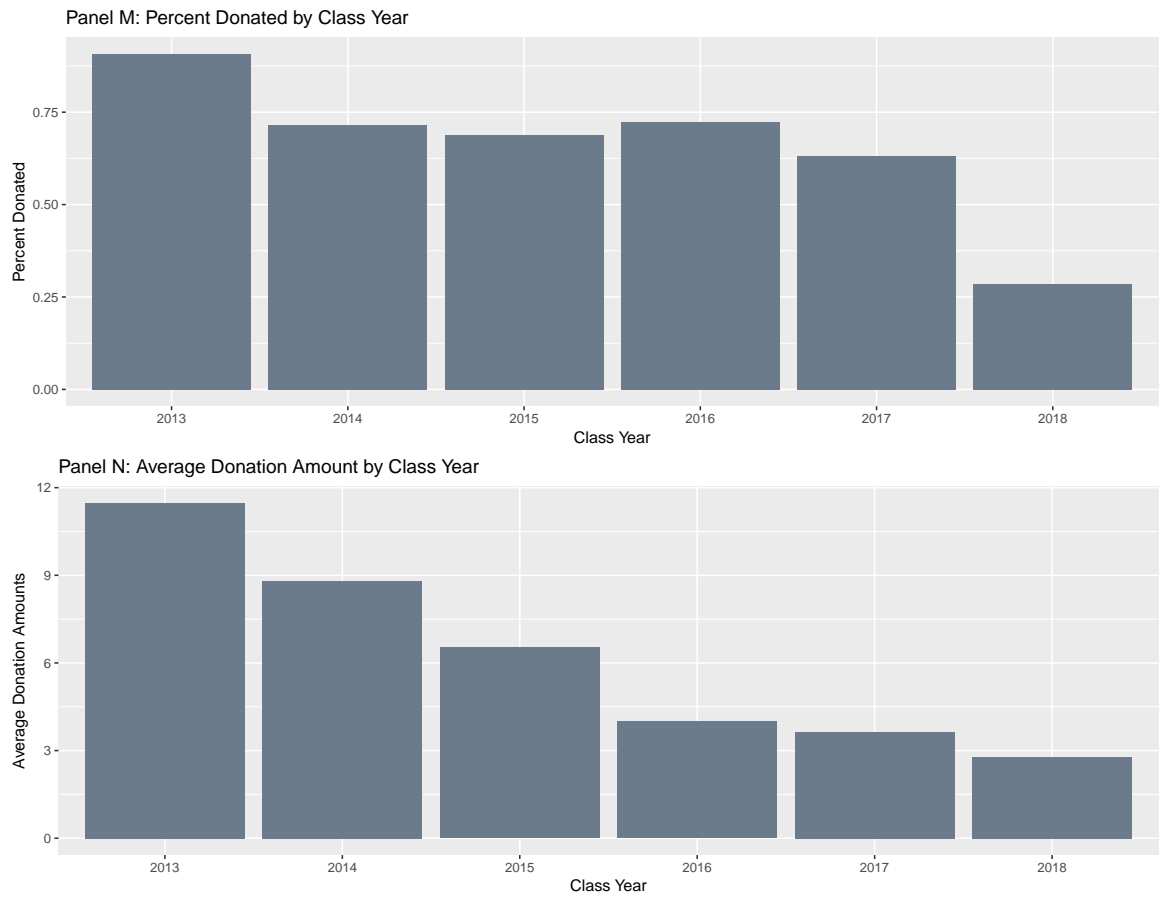


Table 1: Pairwise correlations between game results (Spearman's  $\rho$ )

	Alpha	Rho	Ultimatum1	Ultimatum2	Trust1	Trust2
Rho	0.54***					
Ultimatum1	-0.28***	-0.13**				
Ultimatum2	0.04	-0.04	0.09			
Trust1	-0.26***	0.04	0.41***	-0.10*		
Trust2	-0.30***	-0.10*	0.31***	-0.08	0.45***	
Cooperation	-0.16***	-0.05	0.30***	-0.16***	0.44***	0.21***
<i>Note:</i>				*p<0.1; **p<0.05; ***p<0.01		

Table 2: Correlations between game results and SRA scores (Spearman's  $\rho$ )

	SRAtotal	SRAmoney
Alpha	-0.01	-0.04
Rho	-0.03	-0.02
Ultimatum1	0.02	0.07
Ultimatum2	-0.05	-0.05
Trust1	0.07	0.08
Trust2	0.04	0.11**
Cooperation	0.06	0.10*
<i>Note:</i>	*p<0.1; **p<0.05; ***p<0.01	

Table 3a: Logistic regression models with class year dummy variables

	Dependent variable:											
	Donated											
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Alpha	0.085 (0.080)							0.088 (0.104)			0.084 (0.104)	0.088 (0.104)
Rho		0.004 (0.007)						-0.0002 (0.008)			0.0001 (0.008)	-0.0002 (0.008)
Ultimatum1			-0.060 (0.099)					-0.075 (0.116)			-0.073 (0.116)	-0.076 (0.116)
Ultimatum2				0.119 (0.127)				0.132 (0.132)			0.135 (0.132)	0.134 (0.132)
Trust1					0.001 (0.077)			0.046 (0.100)			0.041 (0.101)	0.046 (0.100)
Trust2						0.005 (0.113)		0.045 (0.131)			0.044 (0.131)	0.040 (0.131)
Cooperation							-0.025 (0.081)	-0.006 (0.092)			-0.008 (0.092)	-0.009 (0.092)
SRAtotal									0.004 (0.005)		0.004 (0.005)	
SRAmoney										0.004 (0.010)		0.005 (0.010)
2017	0.342*** (0.080)	0.338*** (0.080)	0.339*** (0.080)	0.336*** (0.080)	0.337*** (0.080)	0.337*** (0.080)	0.339*** (0.080)	0.343*** (0.081)	0.332*** (0.080)	0.335*** (0.080)	0.339*** (0.081)	0.342*** (0.081)
2016	0.431*** (0.076)	0.431*** (0.077)	0.432*** (0.077)	0.426*** (0.076)	0.429*** (0.077)	0.429*** (0.077)	0.430*** (0.077)	0.435*** (0.078)	0.425*** (0.077)	0.426*** (0.077)	0.430*** (0.078)	0.431*** (0.078)
2015	0.401*** (0.084)	0.393*** (0.083)	0.397*** (0.084)	0.390*** (0.083)	0.393*** (0.083)	0.393*** (0.083)	0.393*** (0.083)	0.405*** (0.085)	0.389*** (0.083)	0.388*** (0.084)	0.401*** (0.085)	0.399*** (0.085)
2014	0.424*** (0.083)	0.421*** (0.083)	0.423*** (0.083)	0.416*** (0.083)	0.420*** (0.083)	0.420*** (0.083)	0.422*** (0.083)	0.417*** (0.084)	0.416*** (0.083)	0.416*** (0.083)	0.414*** (0.084)	0.414*** (0.084)
2013	0.619*** (0.080)	0.621*** (0.080)	0.622*** (0.080)	0.619*** (0.080)	0.618*** (0.080)	0.618*** (0.080)	0.621*** (0.081)	0.623*** (0.082)	0.614*** (0.080)	0.613*** (0.081)	0.620*** (0.082)	0.618*** (0.082)
Female	0.079 (0.049)	0.077 (0.049)	0.074 (0.048)	0.076 (0.048)	0.073 (0.048)	0.073 (0.049)	0.072 (0.049)	0.083 (0.051)	0.072 (0.048)	0.072 (0.048)	0.082 (0.051)	0.082 (0.051)
Humanities	-0.020 (0.063)	-0.023 (0.063)	-0.022 (0.063)	-0.028 (0.064)	-0.024 (0.064)	-0.024 (0.064)	-0.023 (0.064)	-0.028 (0.064)	-0.019 (0.064)	-0.021 (0.064)	-0.024 (0.065)	-0.026 (0.065)
STEM	0.022 (0.055)	0.025 (0.055)	0.025 (0.055)	0.024 (0.055)	0.027 (0.055)	0.027 (0.055)	0.027 (0.055)	0.016 (0.056)	0.027 (0.055)	0.029 (0.055)	0.017 (0.056)	0.018 (0.056)
Constant	0.197** (0.078)	0.250*** (0.062)	0.272*** (0.075)	0.224*** (0.067)	0.246*** (0.074)	0.245*** (0.079)	0.264*** (0.083)	0.161 (0.130)	0.113 (0.170)	0.199* (0.119)	0.032 (0.201)	0.113 (0.161)
Observations	343	343	343	343	343	343	343	343	343	343	343	343
Log Likelihood	-201.351	-201.760	-201.744	-201.479	-201.929	-201.928	-201.880	-200.578	-201.558	-201.816	-200.201	-200.440
Akaike Inf. Crit.	422.702	423.521	423.488	422.957	423.858	423.857	423.761	433.155	423.115	423.631	434.402	434.880
Pseudo-R <sup>2</sup>	0.14617	0.14443	0.14450	0.14563	0.14371	0.14371	0.14392	0.14947	0.14529	0.14419	0.15108	0.15006

Note:

\*p&lt;0.1; \*\*p&lt;0.05; \*\*\*p&lt;0.01

Table 3b: Logistic regression models without class year dummy variables

	Dependent variable:											
	Donated											
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Alpha	0.067 (0.087)							0.107 (0.111)			0.102 (0.111)	0.106 (0.111)
Rho		0.0004 (0.008)						-0.004 (0.009)			-0.003 (0.009)	-0.004 (0.009)
Ultimatum1			0.013 (0.108)					-0.013 (0.125)			-0.010 (0.125)	-0.016 (0.125)
Ultimatum2				0.129 (0.137)				0.143 (0.143)			0.148 (0.143)	0.149 (0.143)
Trust1					0.024 (0.083)			0.044 (0.109)			0.035 (0.109)	0.043 (0.108)
Trust2						-0.004 (0.122)		-0.001 (0.141)			-0.002 (0.141)	-0.015 (0.141)
Cooperation							0.043 (0.087)	0.056 (0.099)			0.051 (0.099)	0.045 (0.099)
SRAtotal									0.007 (0.005)		0.007 (0.005)	
SRAmoney										0.016 (0.010)		0.016 (0.010)
Female	0.103* (0.053)	0.099* (0.053)	0.098* (0.052)	0.101* (0.052)	0.099* (0.052)	0.098* (0.053)	0.101* (0.052)	0.111** (0.055)	0.096* (0.052)	0.094* (0.052)	0.108** (0.055)	0.107** (0.055)
Humanities	0.030 (0.069)	0.027 (0.069)	0.027 (0.069)	0.022 (0.069)	0.026 (0.069)	0.027 (0.069)	0.025 (0.069)	0.021 (0.070)	0.034 (0.069)	0.034 (0.068)	0.028 (0.070)	0.028 (0.070)
STEM	0.051 (0.060)	0.054 (0.060)	0.054 (0.060)	0.050 (0.060)	0.054 (0.060)	0.054 (0.060)	0.055 (0.060)	0.047 (0.060)	0.054 (0.059)	0.059 (0.059)	0.047 (0.060)	0.051 (0.060)
Constant	0.523*** (0.069)	0.560*** (0.050)	0.554*** (0.070)	0.533*** (0.057)	0.547*** (0.068)	0.562*** (0.071)	0.528*** (0.082)	0.408*** (0.134)	0.328* (0.182)	0.383*** (0.125)	0.192 (0.216)	0.245 (0.171)
Observations	343	343	343	343	343	343	343	343	343	343	343	343
Log Likelihood	-232.985	-233.288	-233.282	-232.840	-233.246	-233.289	-233.165	-232.086	-232.399	-232.076	-231.245	-230.878
Akaike Inf. Crit.	475.970	476.576	476.563	475.681	476.492	476.577	476.331	486.171	474.798	474.153	486.490	485.757
Pseudo-R <sup>2</sup>	0.01136	0.01007	0.01010	0.01198	0.01025	0.01007	0.01439	0.01520	0.01386	0.01523	0.01878	0.02034

Note:

\*p&lt;0.1; \*\*p&lt;0.05; \*\*\*p&lt;0.01

Table 4a: Linear regression models with class year dummy variables

	<i>Dependent variable:</i>											
	Log(Average Donations)											
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Alpha	-0.152 (0.360)							0.035 (0.461)			0.016 (0.461)	0.036 (0.461)
Rho		-0.041 (0.030)						-0.041 (0.036)			-0.038 (0.036)	-0.040 (0.036)
Ultimatum1			0.226 (0.415)					0.420 (0.463)			0.446 (0.463)	0.425 (0.463)
Ultimatum2				-0.254 (0.548)				-0.346 (0.557)			-0.315 (0.558)	-0.330 (0.558)
Trust1					-0.266 (0.338)			-0.249 (0.435)			-0.291 (0.436)	-0.254 (0.435)
Trust2						-0.889* (0.480)		-0.991* (0.563)			-1.010* (0.563)	-1.022* (0.563)
Cooperation							0.489 (0.361)	0.534 (0.392)			0.543 (0.392)	0.520 (0.393)
SRAtotal									0.020 (0.020)		0.022 (0.021)	
SRAmoney										0.028 (0.040)		0.030 (0.040)
2017	-1.330*** (0.430)	-1.313*** (0.427)	-1.328*** (0.430)	-1.293*** (0.432)	-1.285*** (0.430)	-1.302*** (0.426)	-1.364*** (0.429)	-1.314*** (0.433)	-1.346*** (0.429)	-1.338*** (0.430)	-1.349*** (0.434)	-1.337*** (0.435)
2016	-0.847** (0.409)	-0.813** (0.408)	-0.859** (0.409)	-0.822** (0.413)	-0.842** (0.408)	-0.886** (0.406)	-0.885** (0.408)	-0.860** (0.414)	-0.873** (0.409)	-0.879** (0.410)	-0.892** (0.415)	-0.894** (0.416)
2015	-0.564 (0.432)	-0.519 (0.430)	-0.577 (0.433)	-0.520 (0.437)	-0.550 (0.431)	-0.545 (0.428)	-0.548 (0.429)	-0.494 (0.439)	-0.566 (0.430)	-0.601 (0.436)	-0.518 (0.440)	-0.548 (0.445)
2014	-0.553 (0.427)	-0.535 (0.425)	-0.569 (0.428)	-0.525 (0.432)	-0.518 (0.429)	-0.482 (0.426)	-0.607 (0.427)	-0.466 (0.434)	-0.563 (0.426)	-0.579 (0.428)	-0.476 (0.434)	-0.490 (0.436)
2013	-0.278 (0.403)	-0.280 (0.402)	-0.299 (0.405)	-0.261 (0.405)	-0.261 (0.403)	-0.261 (0.400)	-0.331 (0.404)	-0.317 (0.406)	-0.300 (0.403)	-0.320 (0.407)	-0.342 (0.406)	-0.360 (0.410)
Female	-0.158 (0.215)	-0.200 (0.215)	-0.142 (0.211)	-0.149 (0.212)	-0.168 (0.214)	-0.079 (0.212)	-0.097 (0.213)	-0.113 (0.227)	-0.146 (0.211)	-0.147 (0.211)	-0.117 (0.227)	-0.117 (0.228)
Humanities	-0.386 (0.276)	-0.394 (0.275)	-0.380 (0.276)	-0.376 (0.276)	-0.370 (0.276)	-0.357 (0.274)	-0.399 (0.275)	-0.353 (0.276)	-0.369 (0.276)	-0.368 (0.277)	-0.335 (0.276)	-0.336 (0.277)
STEM	-0.449* (0.237)	-0.445* (0.235)	-0.452* (0.236)	-0.446* (0.238)	-0.460* (0.236)	-0.473** (0.234)	-0.419* (0.237)	-0.381 (0.240)	-0.452* (0.236)	-0.444* (0.237)	-0.373 (0.240)	-0.367 (0.241)
Constant	2.819*** (0.425)	2.685*** (0.370)	2.637*** (0.408)	2.759*** (0.375)	2.870*** (0.410)	3.088*** (0.415)	2.372*** (0.453)	2.669*** (0.623)	2.076*** (0.766)	2.432*** (0.561)	1.971** (0.902)	2.370*** (0.738)
Observations	220	220	220	220	220	220	220	220	220	220	220	220
R <sup>2</sup>	0.090	0.098	0.091	0.090	0.092	0.104	0.097	0.129	0.093	0.092	0.133	0.131
Adjusted R <sup>2</sup>	0.051	0.059	0.052	0.051	0.053	0.066	0.059	0.064	0.055	0.053	0.065	0.062
Residual Std. Error	1.507 (df = 210)	1.501 (df = 210)	1.507 (df = 210)	1.507 (df = 210)	1.506 (df = 210)	1.496 (df = 210)	1.501 (df = 210)	1.497 (df = 204)	1.504 (df = 210)	1.506 (df = 210)	1.496 (df = 203)	1.498 (df = 203)
F Statistic	2.312** (df = 9; 210)	2.522*** (df = 9; 210)	2.326** (df = 9; 210)	2.316** (df = 9; 210)	2.366** (df = 9; 210)	2.709*** (df = 9; 210)	2.514*** (df = 9; 210)	2.006** (df = 15; 204)	2.406** (df = 9; 210)	2.351** (df = 9; 210)	1.953** (df = 16; 203)	1.912** (df = 16; 203)

Note:

\*p&lt;0.1; \*\*p&lt;0.05; \*\*\*p&lt;0.01

Table 4b: Linear regression models without class year dummy variables

	<i>Dependent variable:</i>											
	Log(Average Donations)											
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Alpha	-0.037 (0.363)							0.222 (0.460)			0.211 (0.461)	0.227 (0.461)
Rho		-0.043 (0.030)						-0.052 (0.036)			-0.049 (0.036)	-0.051 (0.036)
Ultimatum1			0.237 (0.421)					0.504 (0.408)			0.521 (0.469)	0.501 (0.469)
Ultimatum2				-0.427 (0.549)				-0.536 (0.558)			-0.518 (0.559)	-0.528 (0.559)
Trust1					-0.336 (0.341)			-0.350 (0.441)			-0.380 (0.443)	-0.351 (0.441)
Trust2						-0.800* (0.484)		-0.815 (0.568)			-0.824 (0.569)	-0.845 (0.570)
Cooperation							0.419 (0.365)	0.478 (0.397)			0.483 (0.397)	0.463 (0.397)
SRAtotal									0.015 (0.021)		0.016 (0.021)	
SRAmoney										0.029 (0.040)		0.030 (0.040)
Female	-0.245 (0.216)	-0.301 (0.216)	-0.241 (0.213)	-0.250 (0.213)	-0.272 (0.215)	-0.186 (0.214)	-0.206 (0.214)	-0.237 (0.227)	-0.246 (0.213)	-0.246 (0.213)	-0.242 (0.228)	-0.241 (0.228)
Humanities	-0.473* (0.280)	-0.482* (0.279)	-0.471* (0.280)	-0.456 (0.280)	-0.454 (0.280)	-0.448 (0.279)	-0.487* (0.279)	-0.425 (0.280)	-0.463* (0.280)	-0.460 (0.280)	-0.414 (0.281)	-0.410 (0.281)
STEM	-0.419* (0.242)	-0.404* (0.239)	-0.414* (0.240)	-0.398 (0.242)	-0.423* (0.240)	-0.433* (0.239)	-0.384 (0.242)	-0.337 (0.245)	-0.415* (0.240)	-0.405* (0.241)	-0.330 (0.245)	-0.322 (0.246)
Constant	2.184*** (0.290)	2.129*** (0.205)	2.050*** (0.287)	2.248*** (0.232)	2.360*** (0.286)	2.496*** (0.286)	1.828*** (0.356)	2.026*** (0.562)	1.666** (0.731)	1.829*** (0.509)	1.502* (0.888)	1.695** (0.713)
Observations	220	220	220	220	220	220	220	220	220	220	220	220
R <sup>2</sup>	0.028	0.037	0.029	0.030	0.032	0.040	0.033	0.069	0.030	0.030	0.071	0.071
Adjusted R <sup>2</sup>	0.009	0.019	0.011	0.012	0.014	0.022	0.015	0.024	0.012	0.012	0.022	0.022
Residual Std. Error	1.540 (df = 215)	1.533 (df = 215)	1.539 (df = 215)	1.538 (df = 215)	1.537 (df = 215)	1.530 (df = 215)	1.535 (df = 215)	1.529 (df = 209)	1.538 (df = 215)	1.538 (df = 215)	1.530 (df = 208)	1.530 (df = 208)
F Statistic	1.523 (df = 4; 215)	2.056* (df = 4; 215)	1.602 (df = 4; 215)	1.676 (df = 4; 215)	1.769 (df = 4; 215)	2.224* (df = 4; 215)	1.860 (df = 4; 215)	1.539 (df = 10; 209)	1.650 (df = 4; 215)	1.652 (df = 4; 215)	1.449 (df = 11; 208)	1.448 (df = 11; 208)

Note:

\*p&lt;0.1; \*\*p&lt;0.05; \*\*\*p&lt;0.01

Table 5: Best subset logistic regressions

	<i>Dependent variable:</i>				
	Donated				
	(1)	(2)	(3)	(4)	(5)
Alpha	0.101 (0.078)	0.104 (0.078)			
Ultimatum2			0.100 (0.124)		
SRA3	−0.097*** (0.027)	−0.099*** (0.027)	−0.094*** (0.027)	−0.096*** (0.027)	−0.098*** (0.027)
SRA4	0.099*** (0.029)	0.097*** (0.029)	0.097*** (0.029)	0.097*** (0.029)	0.096*** (0.029)
SRA7		0.015 (0.020)			0.014 (0.020)
SRA8	0.047 (0.033)	0.046 (0.033)	0.048 (0.033)	0.046 (0.033)	0.046 (0.033)
SRA10	−0.019 (0.024)	−0.022 (0.024)	−0.018 (0.024)	−0.017 (0.024)	−0.019 (0.024)
2017	0.326*** (0.078)	0.329*** (0.078)	0.318*** (0.078)	0.320*** (0.078)	0.322*** (0.078)
2016	0.410*** (0.075)	0.410*** (0.075)	0.405*** (0.076)	0.408*** (0.075)	0.408*** (0.075)
2015	0.399*** (0.083)	0.395*** (0.083)	0.386*** (0.082)	0.389*** (0.082)	0.386*** (0.083)
2014	0.405*** (0.081)	0.403*** (0.081)	0.398*** (0.081)	0.401*** (0.081)	0.399*** (0.081)
2013	0.578*** (0.079)	0.572*** (0.080)	0.579*** (0.080)	0.579*** (0.080)	0.573*** (0.080)
Female	0.036 (0.049)	0.032 (0.050)	0.032 (0.049)	0.030 (0.049)	0.026 (0.049)
Humanities	−0.009 (0.062)	−0.011 (0.062)	−0.017 (0.062)	−0.013 (0.062)	−0.014 (0.062)
STEM	0.037 (0.054)	0.038 (0.054)	0.040 (0.054)	0.043 (0.054)	0.043 (0.054)
Constant	0.058 (0.158)	0.048 (0.158)	0.086 (0.156)	0.112 (0.152)	0.105 (0.152)
Observations	343	343	343	343	343
Log Likelihood	−189.537	−189.223	−190.062	−190.399	−190.142
Akaike Inf. Crit.	407.075	408.445	408.124	406.797	408.284
Pseudo-R <sup>2</sup>	0.19652	0.19786	0.19428	0.19285	0.19394

*Note:*

\*p&lt;0.1; \*\*p&lt;0.05; \*\*\*p&lt;0.01



Table 6: Best subset linear regressions

	<i>Dependent variable:</i>				
	Log(Average Donations)				
	(1)	(2)	(3)	(4)	(5)
Ultimatum1	0.783* (0.442)	0.877** (0.439)	0.757* (0.416)	0.796* (0.415)	0.755* (0.416)
Ultimatum2	-0.731 (0.533)	-0.826 (0.531)	-0.745 (0.527)	-0.715 (0.527)	-0.769 (0.527)
Trust1	-0.523 (0.405)	-0.340 (0.389)			
Trust2	-1.162** (0.535)	-1.238** (0.535)	-1.388*** (0.487)	-1.419*** (0.486)	-1.434*** (0.485)
Cooperation	0.587 (0.371)				
SRA1			-0.164 (0.154)	-0.186 (0.153)	
SRA2	-0.145 (0.106)	-0.140 (0.106)	-0.122 (0.107)		-0.136 (0.106)
SRA3	-0.274** (0.116)	-0.266** (0.117)	-0.243** (0.117)	-0.261** (0.116)	-0.260** (0.116)
SRA4	0.639*** (0.134)	0.647*** (0.134)	0.647*** (0.134)	0.627*** (0.133)	0.641*** (0.134)
SRA5	-0.235* (0.128)	-0.239* (0.129)	-0.213 (0.131)	-0.224* (0.131)	-0.240* (0.128)
SRA6	0.283** (0.138)	0.266* (0.138)	0.286** (0.140)	0.271* (0.140)	0.253* (0.137)
2017	-1.093*** (0.416)	-1.061** (0.417)	-1.068** (0.416)	-1.129*** (0.412)	-1.101*** (0.415)
2016	-0.773* (0.399)	-0.744* (0.400)	-0.740* (0.400)	-0.812** (0.395)	-0.769* (0.399)
2015	-0.351 (0.429)	-0.374 (0.431)	-0.384 (0.430)	-0.470 (0.424)	-0.380 (0.430)
2014	-0.461 (0.416)	-0.421 (0.416)	-0.419 (0.415)	-0.467 (0.414)	-0.453 (0.414)
2013	-0.351 (0.393)	-0.312 (0.393)	-0.305 (0.393)	-0.354 (0.391)	-0.327 (0.393)
Female	-0.088 (0.217)	-0.120 (0.217)	-0.109 (0.212)	-0.124 (0.212)	-0.069 (0.209)
Humanities	-0.318 (0.262)	-0.300 (0.263)	-0.290 (0.263)	-0.278 (0.263)	-0.315 (0.262)
STEM	-0.196 (0.229)	-0.238 (0.228)	-0.226 (0.229)	-0.235 (0.229)	-0.251 (0.228)
Constant	1.245 (0.866)	1.610* (0.838)	1.778** (0.852)	1.848** (0.850)	1.607* (0.837)
Observations	220	220	220	220	220
R <sup>2</sup>	0.238	0.228	0.230	0.225	0.225
Adjusted R <sup>2</sup>	0.170	0.163	0.165	0.164	0.164
Residual Std. Error	1.410 (df = 201)	1.415 (df = 202)	1.414 (df = 202)	1.415 (df = 203)	1.414 (df = 203)
F Statistic	3.485*** (df = 18; 201)	3.517*** (df = 17; 202)	3.546*** (df = 17; 202)	3.680*** (df = 16; 203)	3.693*** (df = 16; 203)

Note:

\*p&lt;0.1; \*\*p&lt;0.05; \*\*\*p&lt;0.01

Table 7: Logistic predictive models on 2013-2016 alumni

	<i>Dependent variable:</i>											
	Donated											
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Alpha	0.212** (0.094)							0.214* (0.119)			0.218* (0.119)	0.222* (0.119)
Rho		0.011 (0.008)						0.003 (0.010)			0.003 (0.010)	0.003 (0.010)
Ultimatum1			-0.049 (0.121)					-0.054 (0.138)			-0.054 (0.138)	-0.059 (0.138)
Ultimatum2				0.276* (0.150)				0.291* (0.154)			0.301* (0.154)	0.308** (0.154)
Trust1					-0.033 (0.093)			-0.008 (0.116)			-0.016 (0.116)	-0.005 (0.116)
Trust2						0.028 (0.129)		0.160 (0.151)			0.172 (0.152)	0.161 (0.151)
Cooperation							-0.037 (0.099)	0.005 (0.109)			0.001 (0.109)	-0.007 (0.109)
SRAtotal									0.003 (0.006)		0.005 (0.006)	
SRAmoney										0.011 (0.012)		0.016 (0.012)
Constant	0.650*** (0.056)	0.776*** (0.032)	0.783*** (0.064)	0.699*** (0.044)	0.777*** (0.058)	0.746*** (0.066)	0.786*** (0.077)	0.543*** (0.138)	0.662*** (0.199)	0.635*** (0.140)	0.359 (0.243)	0.367* (0.194)
Observations	216	216	216	216	216	216	216	216	216	216	216	216
Log Likelihood	-121.414	-123.035	-123.866	-122.244	-123.885	-123.927	-123.879	-119.047	-123.827	-123.536	-118.605	-118.183
Akaike Inf. Crit.	246.828	250.069	251.733	248.488	251.770	251.853	251.758	254.095	251.655	251.072	255.211	254.365
MSPE	0.26410	0.25548	0.24911	0.24984	0.24999	0.24837	0.24903	0.26641	0.24726	0.24649	0.26513	0.26493

Note:

\*p&lt;0.1; \*\*p&lt;0.05; \*\*\*p&lt;0.01

Table 8: Best subsets logistic predictive models on 2013-2016 alumni

	<i>Dependent variable:</i>				
	Donated				
	(1)	(2)	(3)	(4)	(5)
Alpha	0.283*** (0.093)	0.281*** (0.094)	0.244*** (0.090)	0.246*** (0.089)	0.249*** (0.090)
Average Return	0.203 (0.151)	0.177 (0.151)			
Ultimatum2	0.225 (0.144)		0.208 (0.143)	0.203 (0.143)	
SRA3	-0.086*** (0.032)	-0.094*** (0.031)	-0.091*** (0.031)	-0.091*** (0.031)	-0.098*** (0.031)
SRA4	0.137*** (0.032)	0.140*** (0.032)	0.143*** (0.033)	0.139*** (0.032)	0.141*** (0.032)
SR10			-0.022 (0.025)		
Constant	0.284* (0.170)	0.361** (0.163)	0.450*** (0.158)	0.399*** (0.147)	0.455*** (0.142)
Observations	216	216	216	216	216
Log Likelihood	-107.722	-108.970	-108.264	-108.649	-109.672
Akaike Inf. Crit.	227.444	227.940	228.528	227.298	227.345
MSPE	0.26557	0.26473	0.26193	0.26468	0.26419

*Note:*

\*p&lt;0.1; \*\*p&lt;0.05; \*\*\*p&lt;0.01

Table 9: Lasso penalized logistic predictive model on 2013-2016 alumni

	<i>Dependent variable:</i>
	Donated
Alpha	0.13728
Ultimatum2	0.07993
SRA3	-0.05163*
SRA4	0.09403***
Constant	0.51105
Observations	216
MSPE	0.25177
<i>Note:</i>	*p<0.1; **p<0.05; ***p<0.01

Table 10: Linear predictive models on 2013-2016 alumni

	<i>Dependent variable:</i>											
	Log(Average Donations)											
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Alpha	-0.283 (0.382)							0.043 (0.466)			0.067 (0.466)	0.120 (0.465)
Rho		-0.053 (0.033)						-0.058 (0.038)			-0.054 (0.038)	-0.057 (0.038)
Ultimatum1			0.525 (0.455)					0.444 (0.499)			0.445 (0.498)	0.415 (0.496)
Ultimatum2				0.249 (0.580)				0.124 (0.584)			0.196 (0.587)	0.232 (0.584)
Trust1					0.113 (0.370)			0.080 (0.447)			0.026 (0.449)	0.081 (0.444)
Trust2						-0.674 (0.502)		-1.093* (0.579)			-1.051* (0.580)	-1.093* (0.575)
Cooperation							0.924** (0.384)	0.898** (0.409)			0.908** (0.409)	0.860** (0.407)
SRAtotal									0.031 (0.023)		0.026 (0.023)	
SRAmoney										0.088* (0.046)		0.080* (0.046)
Constant	1.956*** (0.236)	1.731*** (0.120)	1.555*** (0.242)	1.745*** (0.175)	1.741*** (0.230)	2.112*** (0.257)	1.134*** (0.299)	1.273** (0.555)	0.760 (0.784)	0.784 (0.537)	0.372 (0.974)	0.330 (0.773)
Observations	164	164	164	164	164	164	164	164	164	164	164	164
R <sup>2</sup>	0.003	0.016	0.008	0.001	0.001	0.011	0.035	0.076	0.011	0.023	0.084	0.094
Adjusted R <sup>2</sup>	-0.003	0.010	0.002	-0.005	-0.006	0.005	0.029	0.035	0.005	0.017	0.036	0.047
Residual Std. Error	1.444 (df = 162)	1.435 (df = 162)	1.440 (df = 162)	1.445 (df = 162)	1.446 (df = 162)	1.438 (df = 162)	1.421 (df = 162)	1.416 (df = 156)	1.438 (df = 162)	1.430 (df = 162)	1.415 (df = 155)	1.407 (df = 155)
F Statistic	0.548 (df = 1; 162)	2.577 (df = 1; 162)	1.335 (df = 1; 162)	0.184 (df = 1; 162)	0.092 (df = 1; 162)	1.802 (df = 1; 162)	5.791** (df = 1; 162)	1.834* (df = 7; 156)	1.801 (df = 1; 162)	3.751* (df = 1; 162)	1.765* (df = 8; 155)	2.005** (df = 8; 155)
RMSE	1.91565	1.90468	1.91318	1.91622	1.9158	1.89620	1.98669	1.99186	1.90721	1.92767	1.98337	1.99968

Note:

\*p&lt;0.1; \*\*p&lt;0.05; \*\*\*p&lt;0.01

Table 11: Best subset linear predictive models on 2013-2016 alumni

	<i>Dependent variable:</i>				
	Log(Average Donations)				
	(1)	(2)	(3)	(4)	(5)
Rho	-0.051* (0.031)	-0.049 (0.031)	-0.054* (0.031)	-0.053* (0.031)	
Trust2	-1.267*** (0.486)	-1.258** (0.487)	-1.115** (0.472)	-1.108** (0.473)	-1.163** (0.485)
Ultimatum1	0.570 (0.445)	0.568 (0.446)			0.625 (0.446)
Cooperation	0.611* (0.368)	0.630* (0.369)	0.706* (0.361)	0.724** (0.362)	0.629* (0.371)
SRA1	-0.214 (0.165)		-0.213 (0.166)		
SRA4	0.614*** (0.141)	0.600*** (0.141)	0.619*** (0.141)	0.605*** (0.141)	0.604*** (0.141)
SRA5	-0.301** (0.126)	-0.332*** (0.124)	-0.298** (0.126)	-0.329*** (0.124)	-0.318** (0.124)
SRA6	0.363** (0.149)	0.312** (0.144)	0.341** (0.148)	0.290** (0.143)	0.331** (0.144)
Constant	-0.349 (0.879)	-0.706 (0.837)	-0.153 (0.868)	-0.509 (0.824)	-0.857 (0.836)
Observations	164	164	164	164	164
R <sup>2</sup>	0.215	0.206	0.207	0.198	0.193
Adjusted R <sup>2</sup>	0.174	0.171	0.171	0.167	0.162
Residual Std. Error	1.310 (df = 155)	1.313 (df = 156)	1.313 (df = 156)	1.315 (df = 157)	1.319 (df = 157)
F Statistic	5.303*** (df = 8; 155)	5.796*** (df = 7; 156)	5.801*** (df = 7; 156)	6.466*** (df = 6; 157)	6.269*** (df = 6; 157)
RMSE	1.89726	1.89975	1.90965	1.91352	1.89668

*Note:*

\*p&lt;0.1; \*\*p&lt;0.05; \*\*\*p&lt;0.01

Table 12: Lasso penalized linear predictive model on 2013-2016 alumni

	<i>Dependent variable:</i>
	Log(Average Donations)
Rho	−0.00057
Average Return	−0.3853
Cooperation	0.3020
SRA4	0.3183***
SRA5	−0.0228
SRA6	0.1136
Constant	0.1977
Observations	164
RMSE	1.88109
<i>Note:</i>	*p<0.1; **p<0.05; ***p<0.01

## Appendix B Variables Definition Table

Alpha	Player's $\alpha$ level derived from the generalized dictator game
Rho	Player's $\rho$ level derived from the generalized dictator game
Ultimatum1	Player 1's pass rate in the ultimatum game
Ultimatum2	Player 2's minimum pass rate accepted in the ultimatum game
Trust1	Player 1's pass rate in the trust game
Trust2	Player 2's reciprocity level in the trust game
Cooperation	Player's pass rate into public pool in the public goods game
SRAmoney	Player's monetary SRA score
SRAtotal	Player's total SRA score
2013–2017	Class year dummy variables, where the baseline class year is 2018 (current senior class)
Female	Gender dummy variable, where the baseline gender is male
Humanities	Arts and humanities dummy variable (the baseline area of study is social sciences)
STEM	Natural sciences and mathematics dummy variable (the baseline area of study is social sciences)
Average Return	Player 2's average return rate in the trust game
SRA1–SRA10	Each of the individual SRA items (see Appendix B)



# Appendix C Computerized Social Preference Games

## Generalized Dictator Game:

You are **Player 1**. You will decide how to divide a given number of tickets between yourself and an anonymous, random Player 2.  
Each ticket you keep will be multiplied by either 1, 2, 3, or 4, and similarly for Player 2.

For each question, there is a slider that indicates how many tickets you would like to give Player 2.  
Above each amount are the tickets you and Player 2 will receive, represented as **(tickets you receive, tickets other player receives)**.

For example, say you are given 10 tickets, hold @ 1 ticket each and pass @ 2 tickets each. If you decided to pass 3 tickets, then you keep  $(10-3)*1 = 7$  tickets and Player 2 receives  $3*2 = 6$  tickets.

Instead, if hold @ 2 tickets each and pass @ 1 ticket each, you keep  $(10-3)*2 = 14$  tickets, and Player 2 receives  $3*1 = 3$  tickets.

Please choose how you would like to divide the tickets.

Divide 15 tickets: Hold @ 1 ticket each, Pass @ 2 tickets each. How many tickets do you want to send?

(15, 0)	(14, 2)	(13, 4)	(12, 6)	(11, 8)	(10, 10)	(9, 12)	(8, 14)	(7, 16)	(6, 18)	(5, 20)	(4, 22)	(3, 24)	(2, 26)	(1, 28)	(0, 30)
0	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15



Divide 10 tickets: Hold @ 1 ticket each, Pass @ 3 tickets each. How many tickets do you want to send?

(10, 0)	(9, 3)	(8, 6)	(7, 9)	(6, 12)	(5, 15)	(4, 18)	(3, 21)	(2, 24)	(1, 27)	(0, 30)
0	1	2	3	4	5	6	7	8	9	10



Divide 15 tickets: Hold @ 2 tickets each, Pass @ 1 ticket each. How many tickets do you want to pass to the other player?

(30, 0)	(28, 1)	(26, 2)	(24, 3)	(22, 4)	(20, 5)	(18, 6)	(16, 7)	(14, 8)	(12, 9)	(10, 10)	(8, 11)	(6, 12)	(4, 13)	(2, 14)	(0, 15)
0	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15



Divide 12 tickets: Hold @ 1 ticket each, Pass @ 2 tickets each. How many tickets do you want to pass to the other player?

(12, 0)	(11, 2)	(10, 4)	(9, 6)	(8, 8)	(7, 10)	(6, 12)	(5, 14)	(4, 16)	(3, 18)	(2, 20)	(1, 22)	(0, 24)
0	1	2	3	4	5	6	7	8	9	10	11	12



Divide 10 tickets: Hold @ 3 tickets each, Pass @ 1 ticket each. How many tickets do you want to pass to the other player?

(30, 0)	(27, 1)	(24, 2)	(21, 3)	(18, 4)	(15, 5)	(12, 6)	(9, 7)	(6, 8)	(3, 8)	(0, 10)
0	1	2	3	4	5	6	7	8	9	10



Divide 15 tickets: Hold @ 1 ticket each, Pass @ 1 ticket each. How many tickets do you want to pass to the other player?

(15, 0)	(14, 1)	(13, 2)	(12, 3)	(11, 4)	(10, 5)	(9, 6)	(8, 7)	(7, 8)	(6, 9)	(5, 10)	(4, 11)	(3, 12)	(2, 13)	(1, 14)	(0, 15)
0	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15



Divide 12 tickets: Hold @ 2 tickets each, Pass @ 1 ticket each. How many tickets do you want to pass to the other player?

(24, 0)	(22, 1)	(20, 2)	(18, 3)	(16, 4)	(14, 5)	(12, 6)	(10, 7)	(8, 8)	(6, 9)	(4, 10)	(2, 11)	(0, 12)
0	1	2	3	4	5	6	7	8	9	10	11	12



Divide 10 tickets: Hold @ 4 tickets each, Pass @ 1 ticket each. How many tickets do you want to pass to the other player?

(40, 0)	(36, 1)	(32, 2)	(28, 3)	(24, 4)	(20, 5)	(16, 6)	(12, 7)	(8, 8)	(4, 9)	(0, 10)
0	1	2	3	4	5	6	7	8	9	10



Divide 10 tickets: Hold @ 1 ticket each, Pass @ 4 tickets each. How many tickets do you want to pass to the other player?

(10, 0)	(9, 4)	(8, 8)	(7, 12)	(6, 16)	(5, 20)	(4, 24)	(3, 28)	(2, 32)	(1, 36)	(0, 40)
0	1	2	3	4	5	6	7	8	9	10



## Ultimatum Game Player 1:

### You are Player 1.

You are endowed with 10 tickets. Please decide how much of your 10 ticket you would like to send to an anonymous, random Player 2.

After receiving your donated amount, Player 2 may choose to accept or reject the offer. **If your offer is rejected, you both will receive 0 tickets.**

Please decide how many of the 10 tickets you will give to Player 2:

## Ultimatum Game Player 2:

### Now you are Player 2.

Player 1 was endowed with 10 tickets and can choose to share their endowment with you.

You can choose to accept or reject Player 1's offer. **If you reject the offer, you both will receive 0 tickets.**

For example, say Player 1 offers you 4 tickets (i.e. Player 1 keeps 6 tickets). If you agree to the split, then click "Accept". If you do not like the split, then you can click "Reject" and you both will get 0 tickets.

Now for each possible offer, please state whether you accept or reject.

	Reject	Accept
Player 1 offers you 0 tickets (they keep 10 tickets)	<input type="radio"/>	<input type="radio"/>
Player 1 offers you 1 ticket (they keep 9 tickets)	<input type="radio"/>	<input type="radio"/>
Player 1 offers you 2 tickets (they keep 8 tickets)	<input type="radio"/>	<input type="radio"/>
Player 1 offers you 3 tickets (they keep 7 tickets)	<input type="radio"/>	<input type="radio"/>
Player 1 offers you 4 tickets (they keep 6 tickets)	<input type="radio"/>	<input type="radio"/>
Player 1 offers you 5 tickets (they keep 5 tickets)	<input type="radio"/>	<input type="radio"/>
Player 1 offers you 6 tickets (they keep 4 tickets)	<input type="radio"/>	<input type="radio"/>
Player 1 offers you 7 tickets (they keep 3 tickets)	<input type="radio"/>	<input type="radio"/>
Player 1 offers you 8 tickets (they keep 2 tickets)	<input type="radio"/>	<input type="radio"/>
Player 1 offers you 9 tickets (they keep 1 tickets)	<input type="radio"/>	<input type="radio"/>
Player 1 offers you 10 tickets (they keep 0 tickets)	<input type="radio"/>	<input type="radio"/>

## Trust Game Player 1:

### You are Player 1.

You are endowed with 10 tickets. Please decide how many of your 10 tickets to send to an anonymous, random Player 2. **The amount sent over will be multiplied by 3. Player 2 will then decide how much of the multiplied amount they will return back to you.**

For example, if you decide to offer 2 tickets, then Player 2 will receive  $2 \times 3 = 6$  tickets. Player 2 will then decide if they would like to send back any of their 6 tickets to you.

Now please decide how many of the 10 tickets you would like to offer:

## Trust Game Player 2:

### Now you are Player 2.

Player 1 was endowed with 10 tickets, and can choose to share their endowment with you. **The amount Player 1 donates to you will be multiplied by 3. You will be given the opportunity to return some of the tickets back to Player 1.**

For example, if Player 1 gives you 3 tickets, then you receive  $3 \times 3 = 9$  tickets. You can then decide whether you would like to send any of the 9 tickets back to player 1.

Now for each possible offer, please state how many tickets you would like to send back to Player 1.

How many tickets you would like to return:

Player 1 passes 1 ticket, i.e. you receive 3 tickets	<input type="text"/>
Player 1 passes 2 tickets, i.e. you receive 6 tickets	<input type="text"/>
Player 1 passes 3 tickets, i.e. you receive 9 tickets	<input type="text"/>
Player 1 passes 4 tickets, i.e. you receive 12 tickets	<input type="text"/>
Player 1 passes 5 tickets, i.e. you receive 15 tickets	<input type="text"/>
Player 1 passes 6 tickets, i.e. you receive 18 tickets	<input type="text"/>
Player 1 passes 7 tickets, i.e. you receive 21 tickets	<input type="text"/>
Player 1 passes 8 tickets, i.e. you receive 24 tickets	<input type="text"/>
Player 1 passes 9 tickets, i.e. you receive 27 tickets	<input type="text"/>
Player 1 passes 10 tickets, i.e. you receive 30 tickets	<input type="text"/>

## Public Goods Game:

You will be randomly matched with one other anonymous, random player. You each are endowed with 10 tickets, and will decide how much of your respective endowments to contribute to a common group fund. **The overall tickets in the fund will be multiplied by 2, and divided evenly between the both of you.**

For example, if you contribute 6 tickets and Player 2 contributes 4 tickets, the total tickets contributed is  $(6+4)*2 = 20$  tickets. You and Player 2 will then both receive  $20/2 = 10$  tickets. Therefore you will earn your remaining tickets  $(10-6 = 4)$  plus the extra 10 tickets from the pool for a total of 14 tickets.

Now please decide how many of your 10 tickets to put into the common group fund:

## Appendix D Self-Report Altruism (SRA) Items

1. I have allowed someone to go ahead of me in line.
2. I have donated money at the cash register when buying groceries.*
3. I have given money to a stranger (or an acquaintance I don't know too well) in need.*
4. I have donated to a charity.*
5. I have done volunteer work for a charity/organization.
6. I have delayed an elevator/held door open for stranger(s).
7. I have pointed out a clerk's error (at a supermarket, restaurant) in undercharging me.*
8. I have gone out of my way to meet with someone to help them with a task (e.g. help proofread their paper, listen to their presentation, etc).
9. I have offered my seat on a bus/train to a stranger who was standing.
10. I have helped an acquaintance with moving in/ moving out of their dorm/apartment/house.

Note: \* indicates SRA item is related to money.