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Roman M. Sheremeta
Chapman University

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Impulsive Behavior in Competition: Testing Theories of Overbidding in Rent-Seeking Contests

Roman M. Sheremeta [a,b,*]

[a] Weatherhead School of Management, Case Western Reserve University
11119 Bellflower Road, Cleveland, OH 44106, USA
[b] Economic Science Institute, Chapman University
One University Drive, Orange, CA 92866, USA

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Abstract

Contests are commonly used in the workplace to motivate workers, determine promotion, and assign bonuses. Although contests can be very effective at eliciting high effort, they can also lead to inefficient effort expenditure (overbidding). Researchers have proposed various theories to explain overbidding in contents, including mistakes, systematic biases, the utility of winning, and relative payoff maximization. Using an eight-part experiment, we test and find significant support for the existing theories. Also, we discover some new explanations based on cognitive ability and impulsive behavior. Out of all explanations examined, we find that impulsivity is the most important factor explaining overbidding in contests.

JEL Classifications: C72, C91, D01, D72
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* Corresponding author: Roman Sheremeta, rms246@case.edu and rshereme@gmail.com
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1. Introduction

Contests can be powerful at incentivizing performance and eliciting high effort. Empirical studies in economics (Prendergast, 1999), management (Connelly et al., 2014) and sports (Szymanski, 2003) show that tournament-like incentives increase individual performance of workers, managers and athletes. Contests are also used to accelerate economic development (Masters, 2005) and encourage innovation (Harris and Vickers, 1985; Terwiesch and Xu, 2008). Despite many advantages and widespread applications, however, contests often lead to inefficient overbidding (Dechenaux et al., 2015).

One prominent example of inefficient overbidding is rent-seeking contests (Krueger, 1974; Tullock, 1980). In such contests, firms or individuals engage in unproductive competition in order to increase one's share of existing wealth without creating new wealth. For example, a firm may choose to spend money on lobbying for government to impose regulations on competitors in order to increase market share. Such competitive behavior is costly, but it creates no value, resulting in a negative-sum contest game. Other examples include "office politics" (Carpenter et al., 2010), inefficient crowdsourcing (Liu et al., 2014), economic conflicts (Kimbrough et al., 2018), and wars between nations (Lopez and Johnson, 2018). Theoretical models of contests predict substantial welfare losses resulting from inefficient competition (see the review by Konrad, 2009). Experimental studies examining rent-seeking contests show that inefficiencies arising in laboratory contests are even higher than predicted (see the review by Dechenaux et al., 2015).[1]

[1] Empirical studies also suggest that costs of rent-seeking are high (see the review by Del Rosal, 2011). To provide some examples, Krueger (1974) calculates that 7% of India's 1964 and 15% of Turkey's 1968 gross national product were wasted in rent-seeking activities. Posner (1975) uses industry sales to estimate that the rent-seeking costs may range from 5% to 32% of all industry sales. Laband and Sophocleus (1992) use indirect measures of rent-seeking and find that the cost of rent-seeking in the US was about 23% of 1985 gross national product. Mauro (1995) uses corruption as a proxy for rent-seeking to show how it is detrimental to economic growth.

Consider the following experimental game: You are competing against an opponent in a lottery contest for a prize of $100. The probability of winning equals the ratio of your bid to the sum of your and the opponent's bids, and all bids are forgone. In such a rent-seeking contest, while it is socially optimal to bid $0 (no resources wasted in unproductive competition), the Nash equilibrium bids are $25. Moreover, a deliberate consideration shows that any bid above $25 is strictly dominated. Therefore, one would expect the actual behavior of participants to fall somewhere between $0 and $25. Despite such predictions the vast majority of participants in contest experiments routinely overbid by choosing strictly dominated strategies (Dechenaux et al., 2015), creating a puzzle for behavioral economists. In many studies, overbidding is so high that participants receive negative expected payoffs.[2]

Over the past decade, various theories have been proposed to explain overbidding in contests (see the reviews by Sheremeta, 2013, 2015). For example, a common explanation proposed by behavioral economists is that people are prone to mistakes (Camerer, 2003) and such mistakes lead to overbidding in contests (Chowdhury et al., 2014). A related explanation is that behavior in contests could be significantly impacted by systematic biases, such as loss-aversion (Kahneman and Tversky, 1979), leading to sub-optimal behavior. Another explanation is that, in addition to a monetary prize, participants derive a utility of winning the contest (Sheremeta, 2010). Finally, it could be the case that, instead of maximizing absolute payoffs, participants are motivated by relative payoffs (Fehr and Schmidt, 1999) or spite (Hamilton, 1970), which could lead to overbidding in contests (Mago et al., 2016).

Although some of the above mentioned theories found empirical support in the literature, their relative impact on individual behavior remains unknown. It is possible that some of the

[2] Here the welfare losses from rent seeking are born by the rent seekers themselves. However, in other cases of rent-seeking, in particular, in the case of the imposition of regulations on competitors, the welfare losses are incurred both by customers and the competitor firms.

factors contributing to overbidding are correlated. For example, the utility of winning may be driven by relative payoff maximization, or systematic biases may be driven by mistakes. Moreover, an open question is whether there is an underling theory which potentially could unify all of the existing explanations of overbidding. To answer these questions, we conduct a controlled laboratory experiment.

The purpose of our experiment is to test simultaneously different theories of overbidding and to provide a unified explanation for overbidding in contests. The key innovation of our paper is that we study simultaneously all major existing, as well as some new theories of overbidding in the same group of subjects. This has a number of advantages. First, we test different theories on the same dataset. Second, we can examine the relationship between different factors contributing to the same overbidding phenomenon. Third, we are able to control for some factors while examining the relationship between others. Finally, we can estimate the relative importance of each explanatory factor, allowing us to evaluate which factors are most important in explaining overbidding.

Our empirical findings can be summarized as follows: First, we find significant support for the existing theories of overbidding. For example, we show that participants who better understand the rules of the contest overbid less, suggesting that mistakes could be one of the reasons for overbidding. Related to mistakes, we find that behavior in contests is driven by systematic biases grounded in prospect theory. Also, we provide evidence that participants care not only about the prize, but also about winning itself, and such non-monetary utility of winning could partially explain overbidding.

Second, besides the existing theories of overbidding, we discover some new explanations. For example, we show that participants who display competitive preferences (in a separate task) by choosing to sacrifice social welfare to have a higher payoff than others choose significantly higher bids than participants with prosocial preferences. This suggests that bidding is a competitive phenomenon. Also, we find that participants who have lower cognitive ability, measured through a cognitive test based on the Graduate Record Examination, make significantly higher bids. This suggests that overbidding in contests is driven in part by limited cognitive ability.

Third, out of all explanations examined, we find that impulsivity, measured through a Cognitive Reflection Test, is the most important factor explaining overbidding in contests. Impulsivity is also correlated with competitive preferences and cognitive ability, as well as the utility of winning. However, when putting together in a joint multivariate analysis, only impulsivity remains significant, suggesting that overbidding is primarily driven by impulsive behavior.

We describe our research methods and behavioral predictions in Section 2. Our results are presented in Section 3. Implications of our results are discussed in Section 4.

2. Methods

2.1. Standard Theoretical Model

Consider a standard rent-seeking contest of Tullock (1980) in which two players compete for a prize value of v. The probability that player i wins the prize depends on player i's bid b_i relative to player j's bid b_j, and it is defined by a lottery contest success function:

$$p_i(b_i, b_j) = b_i/(b_i + b_j). \tag{1}$$

If $b_i = b_j = 0$ then $p_i(b_i, b_j) = 1/2$. The expected payoff for player i is equal to the probability of winning the prize $p_i(b_i, b_j)$ times the prize value v minus the cost of bid b_i, plus the probability of losing times the cost of bid:

$$\pi_i(b_i, b_j) = p_i(b_i, b_j)(v - b_i) + (1 - p_i(b_i, b_j))(-b_i). \tag{2}$$

Differentiating (2) with respect to b_i gives the following best-response function for player i (similarly player j):

$$b_i(b_j) = \sqrt{vb_j} - b_j. \tag{3}$$

By solving best-response functions $b_i(b_j)$ and $b_j(b_i)$ simultaneously, we receive equilibrium bids:

$$b_i^* = b_j^* = b^* = v/4. \tag{4}$$

The symmetric pure-strategy Nash equilibrium (4) is unique and there are no asymmetric or mixed-strategy equilibria (Szidarovszky and Okuguchi, 1997). Moreover, bids higher than b^* are strictly dominated and therefore should not be chosen by rational economic agents.[3] Despite such stark predictions, the vast majority of participants in contest experiments overbid relative to the Nash equilibrium. By examining a sample of 30 contest experiments, Sheremeta (2013) finds that the median overbidding rate is 72%. The magnitude of overbidding is so high that many participants receive negative expected payoffs (Abbink et al., 2010; Price and Sheremeta, 2011, 2015; Chowdhury et al., 2014; Lim et al., 2014; Mago et al., 2016). To explain such behavior a number of theories have been proposed, including mistakes, systematic biases, the utility of winning, and relative payoff maximization. We discuss predictions of these theories in the following section.

[3] Note that the best-response function (3) reaches its maximum at $v/4$ given any positive bid b_j.

2.2. Behavioral Predictions

The standard theoretical contest model is based on the assumption that individuals are perfectly rational. However, research shows that people are prone to mistakes and their rationality is bounded (Camerer, 2003). One way of modeling bounded rationality is through a quantal response equilibrium (QRE) suggested by McKelvey and Palfrey (1995). In the Nash equilibrium (4), player i is playing a pure strategy b_i^*, given that player j is playing the equilibrium strategy b_j^*. In the QRE, player i is playing a mixed strategy σ_i^* in which the probability of playing a pure strategy b is increasing in the expected payoff $\pi_i(b, \sigma_j^*)$, given that player j is playing the equilibrium mixed strategy σ_j^*. The most commonly used specification of the QRE is the logistic QRE, where the equilibrium probability of choosing b is given by:

$$\sigma_i^*(b) = \frac{\exp\left(\pi\left(b,\sigma_j^*.\right)/\mu\right)}{\int_x \exp\left(\pi\left(x,\sigma_j^*.\right)/\mu\right)}, \tag{5}$$

where $\mu > 0$ is an error parameter describing the level of noise in the decision making process. If $\mu \to 0$, then the Nash equilibrium bid b^* is chosen with probability one, i.e., $\sigma^*(b^*) = 1$. If $\mu \to \infty$, then each bid b between 0 and the maximum allowed bid (usually v) is equally likely to be chosen. One prediction of the QRE is that if individuals can bid between 0 and v, then any level of mistakes, i.e., $\mu > 0$, will lead to overbidding.[4] Therefore, our first behavioral prediction is that:

Prediction 1: Higher level of mistakes leads to higher bids in contests.

According to the prospect theory of Kahneman and Tversky (1979), when dealing with probabilistic outcomes and losses (as it is the case in contests), people exhibit systematic biases.

[4] The intuition is simple. Consider an individual who is completely confused and does not understand the rules of the game, i.e., $\mu \to \infty$. According to the QRE, such an individual will randomly choose a bid b between 0 and v. Therefore, such an individual on average will bid $v/2$, which is higher than the Nash equilibrium effort $b^* = v/4$. There are several studies that have examined implications of the QRE in contests, including Sheremeta (2011), Chowdhury et al. (2014), and Lim et al. (2014).

Perhaps the best documented bias suggested by the prospect theory is loss aversion (Kahneman, 2011).[5] To incorporate loss-aversion into a contest model assume that players place a weight $\lambda > 1$ on losses and a weight 1 on gains.[6] Thus, the payoff function (2) for player i can be rewritten as:

$$\pi_i(b_i, b_j) = p_i(b_i, b_j)(v - b_i) + (1 - p_i(b_i, b_j))\lambda(-b_i). \quad (6)$$

Differentiating (6) and solving for the equilibrium gives the equilibrium bids:

$$b_i^\lambda = b_j^\lambda = b^\lambda = v/(3 + \lambda). \quad (7)$$

This analysis shows that bids decrease in the loss-aversion parameter λ.[7] This is unlike first-price auctions, where overbidding increases with loss-aversion (Lange and Ratan, 2010). Therefore, our second behavioral prediction is that:

Prediction 2: Higher loss-aversion leads to lower bids in contests.

The standard economic assumption is that individuals care only about the monetary prize v associated with winning the contest. However, individuals may also care about winning itself (Parco et al., 2005; Sheremeta, 2010). The utility of winning could be incorporated into the contest by assuming that, in addition to the prize value v, players have an additive non-monetary utility of winning w. Therefore, the updated expected payoff of player i can be written as:

$$\pi_i^w(b_i, b_j) = p_i(b_i, b_j)(v + w - b_i) + (1 - p_i(b_i, b_j))(-b_i). \quad (8)$$

In such a case, the new equilibrium bids derived from (8) are:

$$b_i^w = b_j^w = b^w = (v + w)/4. \quad (9)$$

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[5] Studies show that when the contest success function is replaced by a share function, eliminating possible probability distortion and losses, behavior in contests is closer to the Nash equilibrium (e.g., Fallucchi et al., 2013; Shupp et al., 2013; Chowdhury et al., 2014).

[6] An implicit assumption here is that both players have the same loss-aversion parameter λ. The model could be easily extended to the case of different loss-aversion parameters.

[7] Similar calculations could be done to demonstrate that the equilibrium bid decreases in risk-aversion (Hillman and Katz, 1984). However, experimental evidence on the impact of risk-aversion on behavior in contests is much weaker than that of a loss-aversion (Eisenkopf and Teyssier, 2013; Shupp et al., 2013; Dechenaux et al., 2015).

Note that bids (9) increase in the non-monetary utility of winning w, and for any $w > 0$, are higher than the standard equilibrium (4).[8] Therefore, our third behavioral prediction is that:

Prediction 3: Higher non-monetary utility of winning leads to higher bids in contests.

Finally, it has been suggested that overbidding may be driven by relative payoff maximization (Herrmann and Orzen, 2008; Fonseca, 2009; Eisenkopf and Teyssier, 2013; Mago et al., 2016). Many preference structures are consistent with relative payoff maximization. For example, it may be the case that individuals are spiteful (Hamilton, 1970), have social preferences (Fehr and Schmidt, 1999), or that they behave in a manner predicted by evolutionary game theory (Leininger, 2003; Hehenkamp et al., 2004). Irrespective of its origin, one could model relative payoff maximization into a contest by assuming that the expected utility of player i depends on the difference between own payoff $\pi_i(b_i, b_j)$ and the weighted payoff of the opponent $r\pi_j(b_i, b_j)$:[9]

$$u_i(b_i, b_j) = \pi_i(b_i, b_j) - r\pi_j(b_i, b_j), \tag{10}$$

where r is a relative payoff parameter, with $r < 0$ reflecting preferences of a prosocial player seeking to increase the payoff of the opponent, and $r > 0$ reflecting preferences of a competitive player seeking to obtain a higher relative payoff than the opponent.

Differentiating (10) with respect to b_i (similarly b_j) and solving for the equilibrium gives the equilibrium bids:

$$b_i^r = b_j^r = b^r = (1 + r)v/4. \tag{11}$$

[8] Similar to the utility of winning, Delgado et al. (2008) suggest that another explanation for overbidding is a disutility of losing. They provide evidence for the disutility of losing in the context of a first-price auction. Currently, there is no study examining the disutility of losing as an explanation for overbidding in contests. What is even a more interesting question is how to distinguish the utility of winning from the disutility of losing. These questions are worth pursuing for future research.

[9] The utility function (10) is most commonly used in evolutionary contest theory (Leininger, 2003; Hehenkamp et al., 2004). The idea is that the objective of a contestant is not necessarily to maximize the expected payoff, but to "survive" by outperforming the rival.

This analysis shows that competitive players (i.e., $r > 0$) should bid more than prosocial players (i.e., $r < 0$), leading us to our fourth behavioral prediction:

Prediction 4: Higher competitiveness leads to higher bids in contests.

Recently, behavioral economists have examined how individual behavior is affected by cognitive abilities. It has been shown that participants who are less cognitively constrained in general are better at figuring out the equilibrium play (Branas-Garza and Smith, 2016; Gill and Prowse, 2016). A prominent theory of decision making under cognitive constraints is the dual-system theory, suggesting that people make their decisions using "System 1" or "System 2". Kahneman (2011) describes System 1 as impulsive and effortless, while System 2 as reflective and calculative (resembling a standard economic thinking). The predictions of the standard contest model described in Section 2.1 rest on the assumptions that individuals use reflective System 2 when bidding in rent-seeking contests. However, as Kahneman points out, most choices are usually made by impulsive System 1. Therefore, we should expect less impulsive participants to behave more in line with the standard Nash equilibrium.[10]

Prediction 5: Lower impulsivity leads to bids that are more in line with the standard Nash equilibrium prediction.

2.3. Experimental Design and Procedures

In order to test different theories of overbidding, we collected data on a number of different economic behaviors. The data came from a computerized experiment (Fischbacher, 2007), conducted at the Economic Science Institute laboratory. A total of 184 undergraduate students participated in 11 experimental sessions. Each session lasting between 70 and 90

[10] Note this is a different prediction from Prediction 1, since it pertains not to the actual understanding of the game, but rather to the general capacity of not being an impulsive decision-maker.

minutes had between 16 and 24 participants. The currency used in the experiment was U.S. Dollars. Upon completion of the experiment, earnings from the experiment were added to a participation fee of $10. Participants received their payments in private and in cash, ranging from $7.50 to $33.

The experiment proceeded in eight parts, summarized in Table 1. Participants were told that there would be eight independent parts and that the new set of instructions (available in Appendix A) would be given to them at the beginning of each part. The experimenter read the instructions for each part aloud. In part 1, participants were given the instructions explaining the rules of a simple two-player lottery contest. Each participant was randomly and anonymously matched with another participant. Both matched participants could bid for a reward of $8 by choosing any number between $0 and $10 (including increments of $0.25). Instructions clearly stated that regardless of who receives the reward, both participants would have to pay their bids and that they could receive negative earnings that would be subtracted from their participation fee. After reading the instructions, but before making their decisions, participants completed an incentivized quiz on the computer to verify their understanding of the game. Participants had 5 minutes to answer 5 quiz questions, and they received $0.50 for each correct answer. After answering all quiz questions, participants were asked to submit their bids. The computer chose the winner by implementing a simple lottery rule: the probability of receiving the reward was calculated as the number of dollars a participant bids divided by the total number of dollars both participants bid. However, the results of this part of the experiment were not presented until the very end of the experiment, after all parts of the experiment were completed.

In part 2, participants were asked to provide a guess about the bid of the other paired participant in part 1. Participants were not aware of part 2 until after they finished part 1.[11] Participants received an additional $2 if their guess was equal to the bid made by the other participant. The actual earnings for this part were determined at the end of the experiment.

In part 3, each participant was randomly and anonymously matched with another participant. The rules for part 3 were exactly the same as the rules for part 1 with an exception that the winner of the contest received a prize of $0 (Sheremeta, 2010). Participants were told that they would be informed whether they won the contest or not and that all participants would have to pay their bids. This procedure was used to measure how important it is for participants to win when winning is costly and there is no monetary reward for winning the contest. The actual results for this part were determined at the end of the experiment.

In part 4, similar to Charness and Rabin (2002), participants made 12 binary choices measuring social preferences. The choices involved additional income for themselves and another participant with whom they were randomly and anonymously paired. Each choice offered the option of $3 to both "self" and "other" or an unequal amount with total value between $3.50 and $8.50. One of the 12 choices was randomly selected to be paid out at the end of the experiment (and one of the paired participants was randomly selected as a decision maker, while the other was selected as a receiver).

In part 5, participants made two decisions similar to those described by Ellsberg (1961). Participants were told that the computer would randomly draw a ball from a virtual bag containing 30 red balls and 60 other balls that are either blue or green. The first decision was between option A ($5 if a red ball is drawn) and option B ($5 if a blue ball is drawn). The second

[11] We intentionally chose to elicit a belief about the bid of the other paired participant after eliciting the actual bidding strategy (but before revealing outcomes) in order to circumvent hedging issues that may arise when eliciting behavior and beliefs. It is documented, however, that hedging confounds are not problematic (Blanco et al., 2010).

decision was between option A ($5 if a red or green ball is drawn) and option B ($5 if a blue or green ball is drawn). Participants also made two incentivized decisions similar to those described by Allais (1953). The decision was between option A (receiving $5 for sure) and option B (89% chance of receiving $5, 1% chance of receiving nothing, and 10% chance of receiving $25). The next decision was between option A (89% chance of receiving nothing, and 11% chance of receiving $5) and option B (90% chance of receiving nothing, and 10% chance of receiving $25). One of the 4 choices was randomly selected to be paid out at the end of the experiment. These tasks were used to elicit systematic violations of the expected utility theory, thus providing us with a measure of systematic biases that could be linked to overbidding.

In part 6, following Shupp et al. (2013), we simultaneously elicited participants' preferences toward risk and losses. In the first 15 decisions, participants were asked to choose between a risky option A ($0 or $5 with 50% chance each) and a safe option B (increasing monotonically from $0.50 to $4). In the next 15 decisions, participants chose between a risky option A (50% chance of receiving $5 or losing a certain amount between -$0.50 to -$7.50) and a safe option B of $0. One of the 30 choices was randomly selected to be paid out at the end of the experiment. As in previous parts, participants were not aware of this part until after they finished the preceding part.

In part 7, participants completed a three-question Cognitive Reflection Test (CRT) measuring impulsivity of behavior (Frederick, 2005). The three questions involved making simple calculations and were designed to have an appealing but incorrect answer. For example, the first question was "A bat and a ball cost $1.10 in total. The bat costs $1.00 more than the ball. How much does the ball cost?" The appealing but incorrect answer is $0.10. The correct answer is $0.05. All three questions were incentivized, with participants receiving $0.50 per each correct answer.

In part 8, participants completed a 10-minute cognitive test consisting of 7 multiple-choice mathematical questions. The questions were drawn from a Graduate Record Examination (GRE) test preparation book (Seltzer, 2009). The test was used to elicit cognitive ability of participants. Participants received $0.50 per each correct answer.

At the end of the experiment, participants filled out a demographic questionnaire. After this the computer displayed outcomes from all parts of the experiment and calculated individual earnings, participants received their payments in private and in cash.

3. Results

We begin with an overview of bidding behavior in our experiment. Then we discuss one by one how different theories and corresponding measures can explain the observed bidding behavior. Finally, we perform a joint analysis which allows us to examine the relative importance of each explanatory factor and provide a unified explanation for overbidding in contests.

3.1. Bidding Behavior in Contests

Figure 1 displays the distribution of bids in our experiment. There are two noticeable deviations from the theoretical predictions. First, instead of a unique pure-strategy equilibrium of $2, bids are distributed between $0 and $10. Second, 79.3% of bids are higher than the equilibrium, indicating significant overbidding (Wilcoxon signed-rank test, p-value < 0.01). On average, participants bid $3.62, which is $1.62 higher than the equilibrium. As a result of overbidding, participants earn only \$0.38 on average, which is significantly less than the predicted \$2 (Wilcoxon signed-rank test, p-value < 0.01).

Result 1: There is significant overbidding and heterogeneity of behavior in contests.

Although these findings are consistent with dozens of other experimental studies reviewed by Dechenaux et al. (2015), they create a puzzle for behavioral economists: Why participants choose dominated strategies to the detriment of their own earnings?[12] The first explanation that we consider is mistakes.

3.2. Mistakes

One potential explanation for overbidding, stated as behavioral Prediction 1, is that higher level of mistakes leads to more overbidding in contests. There are two types of mistakes that one could make when making a bid in a contest. First, participants can make mistakes when evaluating behavior of others. Given that the value of the prize is \$8, according to the best-response function (3) any bid higher than \$2 is strictly dominated. Therefore, if participants believe that others are not going to play the equilibrium, we should observe underbidding. However, this is clearly not the case. Figure 2 displays a scatterplot of individual bids versus beliefs about the other participant's bid, as well as the best-response function. Note that instead of an inverted U-shaped best-response function, there is a positive and significant correlation between bids and beliefs (Spearman's correlation coefficient is 0.33, p-value < 0.01). Given the

[12] Recall that there are no asymmetric or mixed-strategy equilibria in the two-player lottery contest, and the symmetric pure-strategy equilibrium is unique. Therefore, variation in bids and systematic overbidding by participants cannot be explained by other equilibria.

stated beliefs, 90.8% of bids are greater than the best response. This suggests that overbidding cannot be simply explained by incorrect beliefs about the behavior of others.[13]

Another possibility is that participants simply do not understand the contest game. Recall from Section 2.3 that after reading the instructions, but before making their decisions, participants completed an incentivized quiz to verify their understanding of the game. Participants answered five quiz questions testing their understanding of the rules of the game as well as the ability to calculate simple best responses (see Appendix A). We find that 89.9% of participants answered at least three questions correctly. Figure 3 displays the average bid and relative overbidding (i.e., the difference between the actual bid and the best-response calculated based on the stated belief about the other bid) by correct quiz answers. The average bid decreases as participants answer more quiz questions correctly (Spearman's correlation coefficient is -0.21, p-value < 0.01).[14] The same is true for the relative overbidding (Spearman's correlation coefficient is -0.21, p-value < 0.01).

Together, these findings provide support for Prediction 1, suggesting that participants who make more mistakes are more likely to overbid in contests.

Result 2: Participants who make more mistakes overbid more in contests.

3.3. Systematic Biases

To examine how systematic biases impact behavior in contests, and to test Prediction 2, we elicited a number of relevant behaviors. Following Shupp et al. (2013), we elicited

[13] One may argue that participants use the belief question to diversify their risk since both the payoff from belief elicitation and the payoff from the contest depend on the same action of the opponent. However, such hedging is uncommon (Blanco et al., 2010). Moreover, there are no beliefs that a participant could hold that would make overbidding optimal.

[14] We have also tried to look at the average bid separately by each quiz question and found that participants who answer a given quiz question correctly on average bid less.

participants' preferences toward risk and losses using 30 binary lottery choices (see Section 3 and Appendix A for details). Each choice offered a risky lottery A or a safe option B. Choices were structured in such a way that participants would first choose option A and then switch to option B, with the switching point indicating the degree of aversion to risk and losses. Most participants had one switching point, and less than 3% made inconsistent choices. Based on our sample, we find that 67.4% of participants are risk-averse and 95.7% are loss-averse. Figure 4 shows a weak and insignificant correlation between bids and risk-aversion (Spearman's correlation coefficient is -0.04, p-value = 0.59). On the other hand, there is a negative and significant correlation between bids and loss-aversion (Spearman's correlation coefficient is -0.16, p-value = 0.02), indicating that more loss-averse participants bid less in the contest.[15]

Besides loss-aversion and risk-aversion, we also elicited participants' propensity to violate the expected utility theory. Specifically, we asked participants to make two choices between option A and option B corresponding to the Ellsberg paradox (Ellsberg, 1961) and two choices corresponding to the Allais paradox (Allais, 1953), see Section 3 for details. In both paradoxes, choosing AA or BB is consistent with the expected utility theory. Based on our sample, we find that 73.9% of participants facing the Ellsberg paradox and 9.8% of participants facing the Allais paradox violate the expected utility theory by choosing AB.[16] However, we find that violation of the expected utility theory is not correlated with overbidding in contests. Figure 5 shows that participants who do not violate the expected utility theory on average bid $3.52, which is similar to the bid of $3.60 by participants who display one violation (either Ellsberg or

[15] It is important to emphasize, however, that even the most loss-averse participants on average bid more than $3, which is still 50% higher than the Nash equilibrium prediction.

[16] Other laboratory experiments also have shown that participants violate the expected utility theory by commonly choosing AB when facing the Ellsberg paradox (Camerer and Weber, 1992; Binmore et al., 2012) or the Allais paradox (Kahneman and Tversky, 1979; Conlisk, 1989; Starmer and Sugden, 1991). The relatively low violation rate in the Allais paradox in our experiment is likely due to small payoffs and real monetary payments (Huck and Müller, 2012).

Allais), and similar to the bid of $3.98 by participants who display both violations. None of these pairwise comparisons is significant (Wilcoxon rank-sum test, all p-values > 0.61).

Therefore, it appears that, consistent with Prediction 2, loss-aversion is a significant predictor of behavior in contests.

Result 3: Participants who are more loss-averse bid less in contests.

3.4. The Utility of Winning

To examine how important winning is to participants, and to test Prediction 3, we elicited a non-monetary utility of winning. Following Sheremeta (2010), participants were asked to bid in a contest with a prize of $0.[17] Participants were told that they would be informed whether they won the contest or not and that all participants would have to pay their bids. This procedure was used to measure how important it is for participants to "win" when winning is costly and there is no monetary reward for winning the contest.

We find that 46.7% of participants bid in the contest with a zero prize, indicating that participants derive a utility from winning apart from monetary incentives. Moreover, Figure 6 shows that there is a positive and significant correlation between bids for a prize of $0 and bids for a prize of $8 (Spearman's correlation coefficient is 0.31, p-value < 0.01), suggesting that, consistent with Prediction 3, the utility of winning is predictive of overbidding in contests.[18]

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[17] Other ways of measuring the utility of winning include using questionnaires (Altmann et al., 2012; Kräkel and Nieken, 2015) or content analysis (Sheremeta and Zhang, 2010; Cason et al., 2012, 2017).

[18] Part of this correlation could be because participants who are confused when bidding for a prize of $0 are also confused when bidding for a prize of $8. Indeed, we find that the average bid for a prize of $0 decreases as participants answer more quiz questions about the contest game correctly (Spearman's correlation coefficient is -0.16, p-value = 0.02). Nevertheless, the weak correlation suggests that bidding for zero is measuring not only confusion but also the utility of winning. Indeed, when estimating an OLS regression in which the dependent variable is a bid for a prize and the independent variables are a bid for zero and a number of correctly answered quiz questions, we find that both variables are significant in predicting bidding behavior. We perform a more general analysis of all explanatory factors in Section 3.7.

Result 4: Participants who have higher non-monetary utility of winning overbid more in contests.

3.5. Relative Payoff Maximization

Our behavioral Prediction 4 states that participants who are more competitive should bid more in contests. To test this prediction, following Charness and Rabin (2002), we elicited social preferences using 12 binary choices as shown in Table 2. Each choice offered an option A of $3 to both self and other or an option B of unequal amount. We use these choices to distinguish participants who always maximize social welfare from those who are competitive.

Note that choosing B over A in 1-6 implies that a participant is competitive, since such a participant chooses to sacrifice social welfare to have a higher payoff than the opponent. Interestingly, participants who choose B in 1-6, indicating competitive behavior, make significantly higher bids in the contest than participants who choose A (see columns five and six in Table 2).[19] Similarly, we find that participants who choose A in 7-12, indicating competitive behavior, make significantly higher bids in the contest than participants who chose B.

Next, we create a measure of competitive social preferences as the number of choices in which a participant chooses to sacrifice social welfare to be ahead the other participant (i.e., choosing B over A in 1-6) or not to be behind the other participant (i.e., choosing A over B in 7-12). Using this measure, we find that there is a positive and significant correlation between competitiveness and bidding (Spearman's correlation coefficient is 0.19, p-value < 0.01). Similarly, we find a positive and significant correlation between competitiveness and relative overbidding (Spearman's correlation coefficient is 0.17, p-value = 0.02). Together, these findings

[19] There are very few participants choosing B in choices 4-6, so the differences are not significant.

show that competitiveness is related to overbidding in rent-seeking contests, providing support for Prediction 4 and suggesting that overbidding is a competitive phenomenon.

Result 5: Participants who are more competitive ovebid more in contests.

3.6. Impulsive Behavior and Cognitive Ability

Our novel behavioral Prediction 5, based on the dual-system theory, states that participants who are less impulsive should bid more in line with the standard Nash equilibrium prediction. There are several methods to test the implications of the dual-system theory by isolating impulsive and reflective cognitive processes. For the purpose of our study, we chose to assess participants' impulsivity using a Cognitive Reflection Test (CRT), which measures the ability to override impulsive responses and to engage in further reflection before making a decision (Frederick, 2005).[20] Specifically, participants completed three math questions (see Section 3 and Appendix A for details). The simple math questions were easily solvable, yet had intuitively compelling incorrect answers. To reach the correct answer, the participant had to engage reflective System 2 in order to override the impulsive response of System 1.[21]

We find that only 16.8% of participants were able to answer all three CRT questions correctly, while 33.1% answered all three questions incorrectly. The top histogram in Figure 7 shows the average bid by CRT. It is apparent that the average bid decreases as participants answer more CRT questions correctly (Spearman's correlation coefficient is -0.33, p-value <

[20] Using the CRT to study impulsive and reflective behavior is a trait-based approach which relies on the assumption that individuals with an impulsive cognitive style are more likely to make decisions guided by System 1, whereas reflective individuals are more likely to be driven by System 2 (Oechssler et al., 2009; Corgnet et al., 2015; Peysakhovich and Rand, 2016). Other methods used by behavioral researchers rely on the analysis of reaction time (e.g., Rubinstein, 2007, 2013; Piovesan and Wengström, 2009; Rand et al., 2012), and the use of experimental manipulations, such as cognitive load (e.g., Cornelissen et al., 2011; Benjamin et al., 2013; Duffy and Smith, 2014; Deck and Jahedi, 2015) or time pressure (e.g., Rand and Kraft-Todd, 2014; Rand et al., 2015).

[21] The CRT responses are a good proxy for the individuals' tendency to make impulsive versus reflective decisions, since the CRT correlates with one's ability to delay gratification (Frederick, 2005) and predicts one's ability to refrain from using inaccurate heuristics in a variety of situations (Oechssler et al., 2009, Toplak et al., 2011).

0.01). Moreover, participants who answer all three CRT questions correctly on average bid \$2.56, which is relatively close to the equilibrium prediction of \$2. On the other hand, participants who answer all three CRT questions incorrectly on average bid \$4.38. Given the observed empirical distribution of bids in the rent-seeking contest, the expected payoff of the most reflective participants is \$0.77, while the expected payoff of the most impulsive participants is only \$0.07. Therefore, it appears that, consistent with Prediction 5, more reflective and less impulsive participants overbid less and earn higher expected payoffs in rent-seeking contests.

Result 6: Participants who are more impulsive overbid more in contests.

One could argue that the CRT simply captures the cognitive ability of participants to solve math problems, and participants who have higher cognitive ability in general are better at figuring out the equilibrium play in other games (Gill and Prowse, 2016). To test this hypothesis, we elicited a different measure of participants' cognitive ability to solve math problems. Specifically, participants completed a 10-minute cognitive test consisting of 7 multiple-choice mathematical questions drawn from a GRE test preparation book (Seltzer, 2009). The bottom histogram in Figure 7 shows the average bid by GRE. Although there is a negative correlation between the average bid and the number of correct GRE answers, the trend is somewhat weaker and less significant (Spearman's correlation coefficient is -0.14, p-value = 0.05) than the correlation between bids and CRT answers.

To summarize, both CRT and GRE predict bidding behavior in contests. Moreover, there is a positive and significant correlation between the number of correct CRT and GRE answers (Spearman's correlation coefficient is 0.34, p-value < 0.01), which is not surprising since cognitive abilities are required to answer both tests. The fact that the correlation is moderate suggests that the CRT and the GRE are measuring somewhat different cognitive skills (Stanovich, 2009). While the GRE measures participants' cognitive ability to solve math problems, the CRT measures the tendency to resist the impulsive behavior and reflect on the task. In order to examine whether cognitive ability or impulsivity is more important in explaining behavior in rent-seeking contests, we employ a multivariate analysis.

3.7. Joint Analysis of Measured Behaviors

Table 3 shows the correlation matrix of our measured behaviors, with colored cells indicating statistically significant correlations. Consistent with our previous observations, *bid* is significantly correlated with *belief* (belief about the other bid), *quiz* (number of correct quiz answers), *loss-averse* (number of options B), *bid-zero* (bid for a prize of $0), *competitive* (number of antisocial competitive choices), *gre* (number of correct GRE answers), and *crt* (number of correct CRT answers). However, it is clear from Table 3, that some of these variables are also correlated with each other. For example, *loss-averse* is correlated with *bias* (number of decisions violating the expected utility) and *risk-averse* (number of safe options B), which is expected since all three measures are designed to capture systematic biases.

The variable that has the strongest correlation with other variables, besides *bid*, is *crt*. Previously, in Section 3.6, we discussed that besides impulsivity, the CRT is measuring cognitive ability, and thus it is not surprising that *crt* is positively correlated with *gre*. For the same reason, it is not surprising that *crt* is positively correlated with *quiz*, since both tasks require cognitive ability. Surprisingly, however, *crt* is negatively and significantly correlated with *competitive*, suggesting that more impulsive participants (i.e., participants who score less on the CRT) are more competitive (i.e., participants who choose to sacrifice social welfare to be ahead or not to be behind of others).[22] Given that *crt* is correlated with both *competitive* and *bid,* it is possible that the correlation between *competitive* and *bid* is mainly driven by *crt*. Of course, the reverse could be true as well. Therefore, we employ a multivariate analysis.

Table 4 shows the estimation results of different OLS regressions in which the dependent variable is *bid*, and the independent variables are measured behaviors reported in Table 3. Specification (1) supports the findings from Section 3.2, by showing that *bid* is positively correlated with *belief* and negatively correlated with *quiz*. Specification (2) supports the findings from Section 3.3, by showing that out of different measures of systematic biases only *loss-averse* is significantly correlated with *bid*. Similarly, specifications (3) and (4) support the findings from Sections 3.4 and 3.5, by showing that *bid* is positively correlated with *bid-zero* and *competitive*. Recall from Section 3.6 that *bid*, *gre*, and *crt* are all correlated (this can also be seen in Table 3). Specification (5), however, shows that when we include both *gre* and *crt* as explanatory variables, only *crt* is significant. Therefore, we conclude that it is mainly impulsivity, and not cognitive ability to do mathematical computations, that influences behavior in rent-seeking contests.

To further explore the joint effect of all measured behaviors on bidding behavior we estimate specification (6), in which we include all of the explanatory variables. Interestingly, most of the variables, including *quiz, loss-averse, bid-zero,* and *competitive*, that previously were significant in specifications (1) through (4) become insignificant. The only variables that remain significant are *belief* and *crt*. To see which of these two variables captures most of the explanatory power from other variables, we re-estimate all specifications in Table 4 controlling separately for *belief* and *crt*. When we control for *belief*, as shown in Table 5, all of the results

[22] This result is also robust when we consider alternative definitions of competitiveness (see Table B1 and the corresponding discussion in Appendix B).

reported in specifications (2) through (5) in Table 4 are virtually unchanged. On the other hand, when we control for *crt*, as shown in Table 6, most of the explanatory variables, including *quiz*, *loss-averse*, *bid-zero*, and *competitive*, become insignificant. Therefore, it appears that *crt* captures most of the explanatory variance for bidding behavior in the rent-seeking contest. On average, one correctly answered CRT question reduces the bid by $0.43-$0.58, depending on the exact regression in Table 6. This translates into a gap of $1.29-$1.74 between the most impulsive participants (who answer zero CRT questions correctly) and the most reflective participants (who answer all three CRT questions correctly).[23]

We have also checked the robustness of these results, by using *overbidding* (i.e., the difference between the actual bid and the best-response calculated based on the stated belief about the other bid), instead of *bid*, as a dependent variable. The results reported in Table B2 in Appendix B are very similar qualitatively to those reported in Table 4. In addition, we used *expected payoff* (i.e., the average expected payoff calculated based on the individual bid and the empirical distribution of all other bids in our sample) as a dependent variable. Again, the results reported in Table B3 in Appendix B are very similar qualitatively.

Combined, these estimation results tell a consistent story. Specifications (1) through (5) in Table 4 provide evidence that overbidding in contests is correlated with mistakes (specification 1), systematic biases (specification 2), the utility of winning (specification 3), relative payoff maximization (specification 4), and impulsive behavior (specification 5). However, when putting together in a joint multivariate analysis (specification 6), only impulsivity remains significant, suggesting that overbidding is primarily driven by impulsive behavior. Estimations reported in Table 6 further confirm that impulsivity is correlated with

[23] Recall that the equilibrium bid is $2.

other explanatory factors and thus it is the main moderating factor explaining overbidding in rent-seeking contests.

Result 7: Impulsivity is the most important factor, out of all factors examined, explaining overbidding in contests.

4. Discussions and Conclusion

In this paper, we have examined the predictive power of different theories to explain overbidding in rent-seeking contests. For this purpose, we conducted an eight-part experiment. Our results showed significant support for the existing theories of overbidding, such as mistakes, systematic biases, the utility of winning, and relative payoff maximization. Besides the existing theories of overbidding, we discovered some new explanations, such as cognitive ability and impulsive behavior. Out of all explanations examined, we found that impulsive behavior, measured through a Cognitive Reflection Test, is the most important factor explaining the overbidding phenomenon.

Besides providing an explanation for a long standing puzzle about overbidding in rent-seeking contests, our results also explain why some studies find less overbidding than others. Fallucchi et al. (2013) and Chowdhury et al. (2014), for example, show that there is less overbidding when the rules of the contest are simplified and when participants receive more feedback. Similarly, Sheremeta and Zhang (2010) find that overbidding is reduced when, instead of individuals, groups of two participants make decisions in contests. All these manipulations reduce cognitive load, allowing participants to make more deliberate and less impulsive choices, thus reducing overbidding in contests.

Our results have important implications for social science in general. Specifically, our findings indicate that participants with more competitive preferences (e.g., participants who choose to sacrifice social welfare to be ahead of others) are more impulsive. Furthermore, our findings also indicate that bidding behavior in rent-seeking contests is a competitive phenomenon driven by impulsive behavior. An important implication of this is that individuals who are better at controlling their impulsive behavior (i.e., using System 2 instead of System 1), should be less likely to engage in irrational competitions.[24] This interpretation is also consistent with research examining evolution of prosocial behavior of children (Bloom, 2013; Fehr et al., 2008, 2013). The main conclusion from this literature is that children (who are most likely guided by System 1) display very competitive and spiteful behavior in their early years of life; however, as they grow older (and thus become more capable of using System 2) they display more cooperative behavior.

Our results also have implications for economic theory. The standard economic theory is based on the assumption that economic agents are perfectly rational and they do not make mistakes. However, as research suggests, this is not necessarily the case (Camerer, 2003).[25] Kahneman (2011) argues that one reason why individuals make "irrational" choices is that they often ignore the reflective System 2 (needed to make rational economic decisions) and instead use the impulsive System 1 (inclined to biases and errors).[26] An important implication of this is that if by obtaining a good indicator whether an individual is indeed using System 2 in economic

[24] This result contrasts the "social heuristics hypothesis," claiming that cooperative behavior is more intuitive (Rand et al., 2014). In fact, we find exactly the opposite: Individuals who are more impulsive (i.e., use intuitive System 1) are more competitive and bid more aggressively in contests than individuals who are more reflective (i.e., use System 2). Therefore, our results align with the literature suggesting that cooperative behavior is not impulsive (Piovesan and Wengström, 2009; Tinghog et al., 2013; Verkoeijen and Bouwmeester, 2014).

[25] Cason and Plott (2014), for example, show that even in the simplest laboratory experiments individuals routinely make mistakes which cannot be explained neither by standard nor by nonstandard preference theories.

[26] Rubinstein (2016) suggest a new typology of players based on the classification of actions as either instinctive (impulsive) or contemplative (reflective).

decision-making, one could reliably test the economic theory. We find that the CRT is one of such indicators. In our experiment, the most impulsive participants who answer all three CRT questions incorrectly on average bid $4.38 (which is 119% higher than the theoretical prediction), while the most reflective participants who answer all three questions correctly bid $2.56 (which is only 28% away from the theoretical prediction). Thus, we can conclude that the behavior of participants who score higher on the CRT, indicating better use of System 2, is more in line with the economic theory; and researchers who want to test other theoretical models of rent-seeking should use this information to make their conclusions about the predictive power of the theory.

There are, of course, a number of avenues for future research. Although our experimental results provide significant evidence that impulsivity is an important factor in explaining behavior in contests, the exact mechanism is unknown. It could be the case that impulsive participants are more likely to form incorrect beliefs about the behavior of others or that they are more likely to be influenced by focal points (i.e., bid half the value of the prize).[27] Experimental studies, directly manipulating cognitive load (e.g., Cornelissen et al., 2011; Benjamin et al., 2013; Duffy and Smith, 2014; Deck and Jahedi, 2015) and time pressure (e.g., Rand and Kraft-Todd, 2014; Rand et al., 2015), could provide more insights into how impulsivity affects overbidding in rent-seeking contests.

Also, our laboratory results have limited external validity (Creswell, 2008), and it would be important to replicate our findings in more field-like settings. Such extensions could include giving participants more feedback, repeating the contest multiple times, and increasing stakes. These manipulations might help participants to think harder and overcome their impulsivity.

[27] Examining our data, we do not find significant support for these hypotheses, as participants with different CRT scores have similar beliefs and similar frequencies of biding $4 (half the prize value of $8).

Finally, we conjecture that our findings potentially could be applied to explain overbidding in winner-pay auctions. There is a long-standing debate about what could explain overbidding in first-price and common value auctions. Some of the explanations are similar to the ones proposed to explain overbidding in rent-seeking contests. For example, Cox et al. (1992) suggest that part of the overbidding in auctions is caused by the joy of winning. Goeree et al. (2002) and Crawford and Iriberri (2007) suggest that overbidding is due to mistakes. Risk aversion and systematic biases are also cited as possible explanations for overbidding in winner-pay auctions (Cox et al., 1988; Goeree et al., 2002). However, even after a heated discussion by Cox et al. (1992), Friedman (1992), Kagel and Roth (1992), and Merlo and Schotter (1992), which followed Harrison's (1989) critique of Cox et al. (1982), the debate has not been resolved. We hypothesize that impulsivity, measured through a Cognitive Reflection Test, potentially, could explain overbidding in winner-pay auctions.

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Figure 1: Distribution of bids.

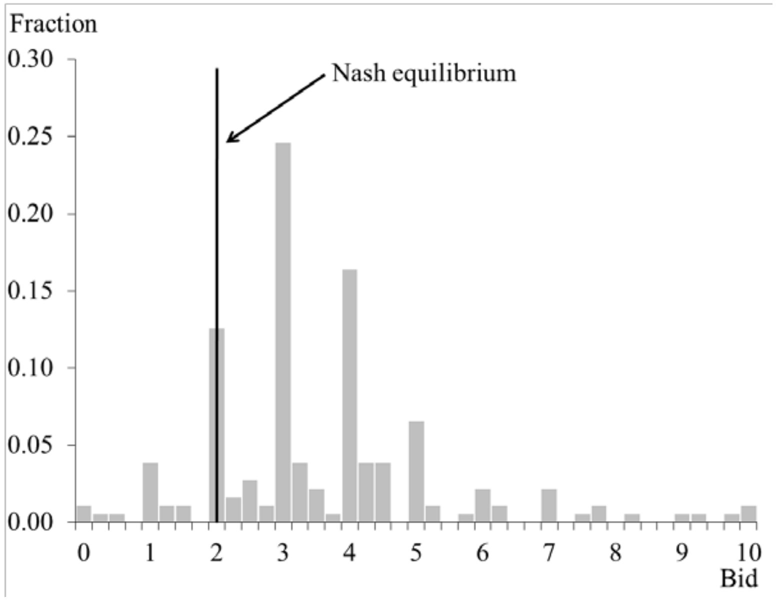

Figure 2: Bids, beliefs and best-responses.

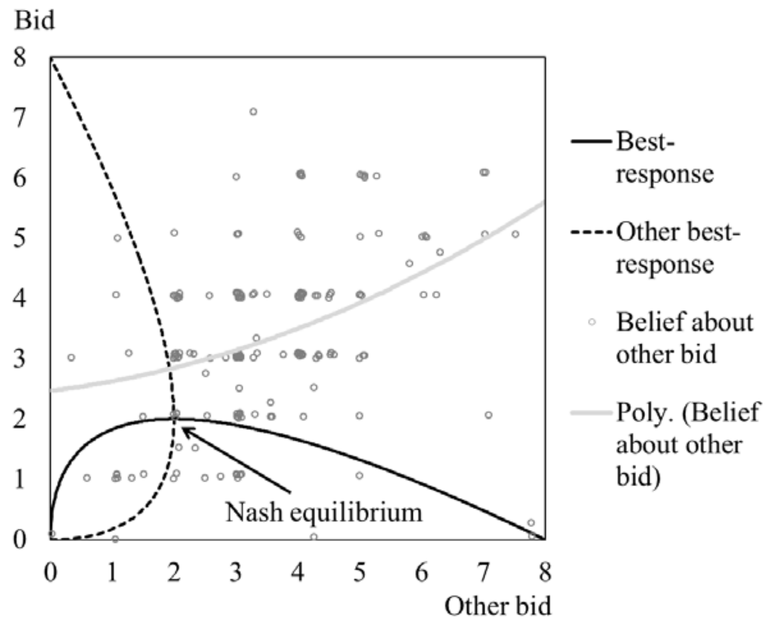

Figure 3: Average bid and relative overbidding by correct quiz answers.

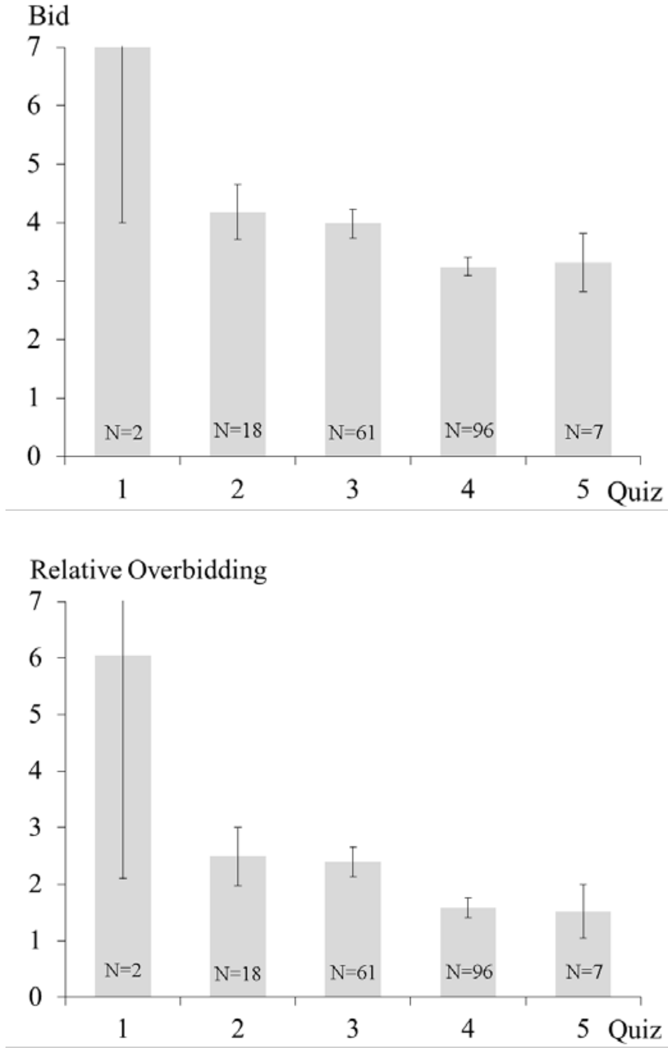

Figure 4: Average bid versus risk-aversion and loss-aversion.

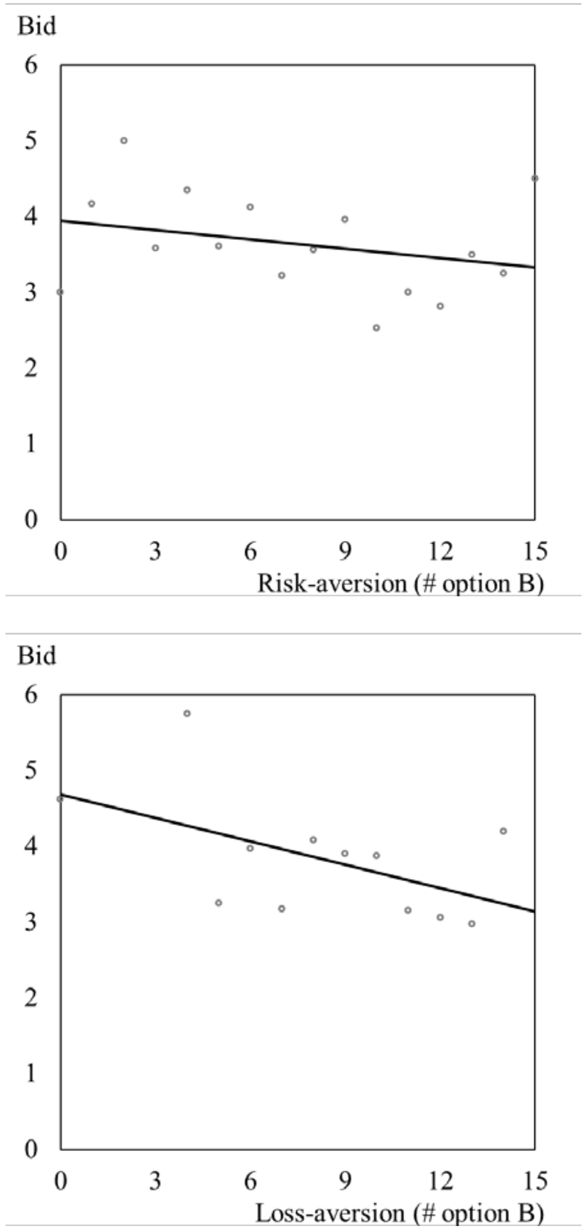

Figure 5: Average bid by violation of the expected utility theory.

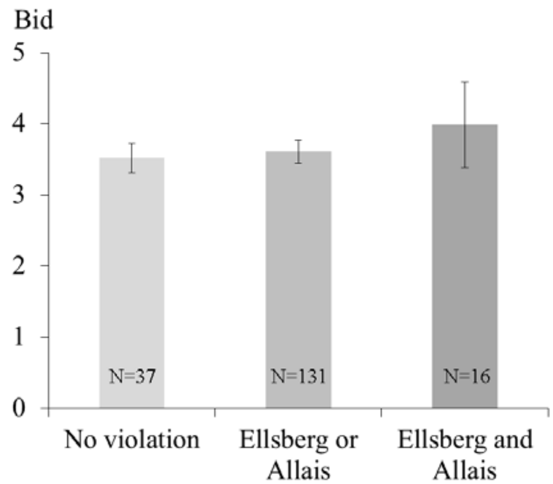

Figure 6: Bid for a zero prize versus bid for a positive prize.

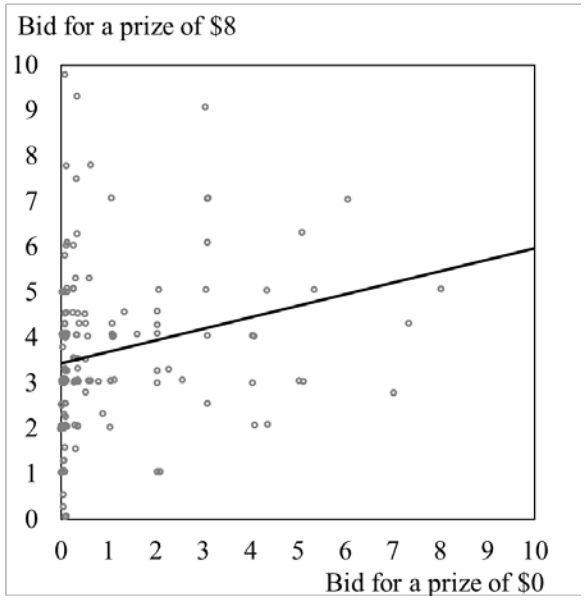

Figure 7: Average bid by CRT and GRE.

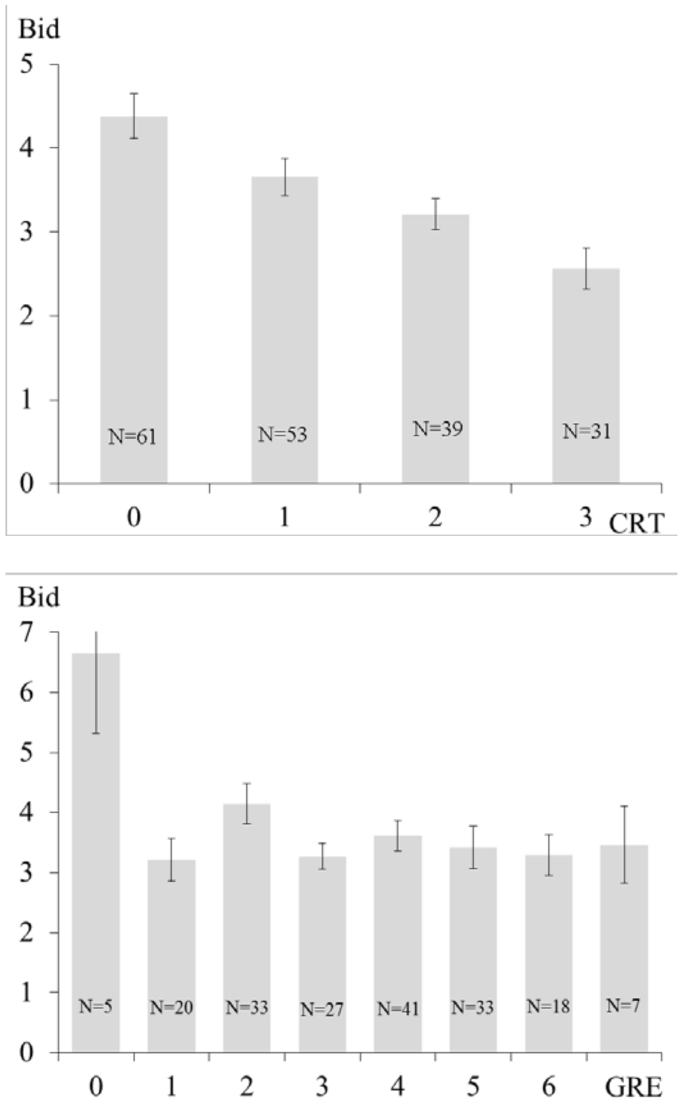

Table 1: Summary of the experimental design.

Part	Measure	How measured
1	Quiz	5 quiz questions about the contest, receiving $0.50 for each correct answer.
	Bid	Bid between $0 and $10 (including increments of $0.25) in a two-payer contest for a reward of $8.
2	Belief	Guess about the bid of the other participant, receiving $2.00 for a correct guess.
3	Bid for zero	Bid between $0 and $10 (including increments of $0.25) in a two-payer contest for a reward of $0.
4	Social preferences	12 binary choices measuring social preferences, with each choice offering the option of $3 to both self and other or an unequal amount with total value between $3.50 and $8.50.
5	Ellsberg	Two decision, First, between option A ($5.00 if a red ball is drawn) and option B ($5.00 if a blue ball is drawn). Second, between option A ($5.00 if a red or green ball is drawn) and option B ($5.00 if a blue or green ball is drawn).
	Allais	Two decisions. First, between option A (receiving $5.00 for sure) and option B (89% chance of receiving $5.00, 1% chance of receiving nothing, and 10% chance of receiving $25.00). Second, between option A (89% chance of receiving nothing, and 11% chance of receiving $5.00) and option B (90% chance of receiving nothing, and 10% chance of receiving $25.00).
6	Risk aversion	15 binary choices between a risky option A ($0 or $5 with 50% chance each) and a safe option B (increasing monotonically from $0.50 to $4)
	Loss aversion	15 binary choices between a risky option A (50% chance of receiving $5 or losing a certain amount between -$0.50 to -$7.50) and a safe option B of $0.
7	CRT	3 cognitive reflection questions, receiving $0.50 for each correct answer.
8	GRE	7 multiple-choice GRE mathematical questions during 10 minutes, receiving $0.50 for each correct answer.

Table 3: Correlation matrix.

	bid	*belief*	*quiz*	*Bias*	*risk-averse*	*loss-averse*	*bid-zero*	*competitive*	*gre*
belief	0.31								
	(0.00)								
quiz	-0.25	-0.16							
	(0.00)	(0.02)							
bias	0.05	-0.00	-0.09						
	(0.45)	(0.98)	(0.20)						
risk-averse	-0.03	0.09	0.08	0.03					
	(0.66)	(0.20)	(0.24)	(0.60)					
loss-averse	-0.13	-0.02	-0.02	0.14	0.19				
	(0.06)	(0.72)	(0.75)	(0.05)	(0.00)				
bid-zero	0.22	0.11	-0.22	-0.01	-0.13	-0.18			
	(0.00)	(0.12)	(0.00)	(0.89)	(0.06)	(0.01)			
competitive	0.17	0.04	-0.06	0.00	-0.02	-0.17	0.02		
	(0.01)	(0.56)	(0.40)	(0.93)	(0.68)	(0.01)	(0.72)		
gre	-0.14	-0.14	0.15	-0.07	-0.08	0.01	-0.04	-0.19	
	(0.04)	(0.05)	(0.03)	(0.31)	(0.24)	(0.80)	(0.55)	(0.00)	
crt	-0.35	-0.09	0.26	-0.06	0.05	0.05	-0.28	-0.31	0.35
	(0.00)	(0.20)	(0.00)	(0.40)	(0.43)	(0.42)	(0.00)	(0.00)	(0.00)

p-values are in parentheses.

Table 4: OLS regression of bid on measured behaviors.

Specification	(1)	(2)	(3)	(4)	(5)	(6)
Dependent variable, *bid*						
belief	0.31**					0.28**
[belief about the other bid]	(0.13)					(0.12)
quiz	-0.49***					-0.29*
[number of correct quiz answers]	(0.19)					(0.18)
bias		0.26				0.15
[violation of the expected utility]		(0.25)				(0.20)
risk-averse		0.00				0.00
[number of safe options B]		(0.05)				(0.04)
loss-averse		-0.12**				-0.08
[number of options B]		(0.06)				(0.05)
bid-zero			0.21***			0.07
[bid for a prize of $0]			(0.07)			(0.08)
competitive				0.10**		0.03
[number of antisocial choices]				(0.04)		(0.04)
gre					-0.02	0.03
[number of correct GRE answers]					(0.09)	(0.08)
crt					-0.58***	-0.43***
[number of correct CRT answers]					(0.13)	(0.13)
constant	4.29***	4.56***	3.43***	3.35***	4.41***	4.61***
[the constant term]	(0.91)	(0.50)	(0.14)	(0.16)	(0.35)	(1.10)
N	184	184	184	184	184	184
R-squared	0.14	0.02	0.05	0.03	0.13	0.25
R-squared adjusted	0.13	0.01	0.05	0.03	0.12	0.21

* significant at 10%, ** significant at 5%, *** significant at 1%. Robust standard errors are in parenthesis.

Table 5: OLS regression of bid on measured behaviors, controlling for belief.

Specification	(1)	(2)	(3)	(4)	(5)	(6)
Dependent variable, *bid*						
belief	0.31**	0.34***	0.32**	0.34**	0.31**	0.28**
[belief about the other bid]	(0.13)	(0.13)	(0.13)	(0.13)	(0.12)	(0.12)
quiz	-0.49***					-0.29*
[number of correct quiz answers]	(0.19)					(0.18)
bias		0.26				0.15
[violation of the expected utility]		(0.21)				(0.20)
risk-averse		-0.03				0.00
[number of safe options B]		(0.04)				(0.04)
loss-averse		-0.11**				-0.08
[number of options B]		(0.05)				(0.05)
bid-zero			0.18**			0.07
[bid for a prize of $0]			(0.08)			(0.08)
competitive				0.10**		0.03
[number of antisocial choices]				(0.04)		(0.04)
gre					0.02	0.03
[number of correct GRE answers]					(0.08)	(0.08)
crt					-0.56***	-0.43***
[number of correct CRT answers]					(0.13)	(0.13)
constant	4.29***	3.45***	2.37***	2.24***	3.20***	4.61***
[the constant term]	(0.91)	(0.76)	(0.43)	(0.46)	(0.44)	(1.10)
N	184	184	184	184	184	184
R-squared	0.14	0.13	0.14	0.13	0.21	0.25
R-squared adjusted	0.13	0.11	0.13	0.12	0.2	0.21

* significant at 10%, ** significant at 5%, *** significant at 1%. Robust standard errors are in parenthesis.

Table 6: OLS regression of bid on measured behaviors, controlling for CRT.

Specification	(1)	(2)	(3)	(4)	(5)	(6)
Dependent variable, *bid*						
belief	0.29**					0.28**
[belief about the other bid]	(0.12)					(0.12)
quiz	-0.31*					-0.29*
[number of correct quiz answers]	(0.17)					(0.18)
bias		0.18				0.15
[violation of the expected utility]		(0.24)				(0.20)
risk-averse		0.01				0.00
[number of safe options B]		(0.04)				(0.04)
loss-averse		-0.10*				-0.08
[number of options B]		(0.05)				(0.05)
bid-zero			0.13*			0.07
[bid for a prize of $0]			(0.08)			(0.08)
competitive				0.04		0.03
[number of antisocial choices]				(0.04)		(0.04)
gre					-0.02	0.03
[number of correct GRE answers]					(0.09)	(0.08)
crt	-0.50***	-0.58***	-0.53***	-0.56***	-0.58***	-0.43***
[number of correct CRT answers]	(0.10)	(0.11)	(0.12)	(0.12)	(0.13)	(0.13)
constant	4.33***	5.09***	4.15***	4.20***	4.41***	4.61***
[the constant term]	(0.85)	(0.50)	(0.25)	(0.27)	(0.35)	(1.10)
N	184	184	184	184	184	184
R-squared	0.23	0.15	0.15	0.13	0.13	0.25
R-squared adjusted	0.21	0.13	0.14	0.12	0.12	0.21

* significant at 10%, ** significant at 5%, *** significant at 1%. Robust standard errors are in parenthesis.

Table 2: Social preferences and bids.

Decision number	Option A (self, other)	Option B (self, other)	Percentage choosing A	Average bid conditional on A	Average bid conditional on B	Wilcoxon rank-sum test
1	\$3.00, \$3.00	\$3.00, \$2.50	87.0%	3.57 (0.14)	4.00 (0.30)	p-value = 0.08
2	\$3.00, \$3.00	\$3.00, \$2.00	83.2%	3.52 (0.15)	4.13 (0.25)	p-value = 0.01
3	\$3.00, \$3.00	\$3.00, \$1.50	83.2%	3.51 (0.15)	4.16 (0.24)	p-value = 0.01
4	\$3.00, \$3.00	\$2.50, \$2.00	95.7%	3.65 (0.14)	3.00 (0.46)	p-value = 0.33
5	\$3.00, \$3.00	\$2.50, \$1.50	96.2%	3.60 (0.14)	4.14 (0.59)	p-value = 0.30
6	\$3.00, \$3.00	\$2.50, \$1.00	94.6%	3.58 (0.14)	4.35 (0.56)	p-value = 0.15
7	\$3.00, \$3.00	\$3.00, \$3.50	45.7%	3.88 (0.21)	3.41 (0.16)	p-value = 0.14
8	\$3.00, \$3.00	\$3.00, \$4.00	46.7%	3.90 (0.20)	3.39 (0.17)	p-value = 0.05
9	\$3.00, \$3.00	\$3.00, \$4.50	46.7%	3.87 (0.20)	3.41 (0.17)	p-value = 0.09
10	\$3.00, \$3.00	\$3.50, \$4.00	17.9%	4.25 (0.40)	3.49 (0.13)	p-value = 0.05
11	\$3.00, \$3.00	\$3.50, \$4.50	21.7%	4.18 (0.35)	3.47 (0.14)	p-value = 0.06
12	\$3.00, \$3.00	\$3.50, \$5.00	22.3%	4.19 (0.34)	3.46 (0.14)	p-value = 0.04

Appendix A (For Online Publication) – Experimental Instructions

GENERAL INSTRUCTIONS

This is an experiment in the economics of decision-making. Various research agencies have provided funds for this research. The instructions are simple.

The experiment will proceed in 8 parts. Each part contains decision problems that require you to make a series of choices that determine your total earnings. The currency used in all parts of the experiment is U.S. Dollars. You have already received a $10.00 participation fee. Your earnings from 8 parts of the experiment will be added to your participation fee. At the end of today's experiment, you will be paid in private and in cash.

It is very important that you remain silent and do not look at other people's work. If you have any questions, or need assistance of any kind, please raise your hand and an experimenter will come to you. If you talk, laugh, exclaim out loud, etc., you will be asked to leave and you will not be paid. We expect and appreciate your cooperation.

At this time we proceed to PART 1 of the experiment.

PART 1

In PART 1 of the experiment you will be randomly and anonymously matched with another participant. You and the other participant will choose how much to bid for a reward of $8. You may bid any integer number of dollars between $0 and $10 (including increments of $0.25).

After both participants have made their decisions, your earnings will be calculated. Regardless of who receives the reward, both participants will have to pay their bids. Thus, your earnings will be calculated as follows:

If you receive the reward: Earnings = reward – your bid = $8 – your bid

If you do not receive the reward: Earnings = no reward – your bid = $0 – your bid

Remember, you have received a $10 participation fee. In this part of the experiment, you may receive either positive or negative earnings. If the earnings are negative, we will subtract them from your participation fee. If the earnings are positive, we will add them to your participation fee.

The more you bid, the more likely you are to receive the reward. The more the other participant bids, the less likely you are to receive the reward. Specifically, for each dollar you bid you will receive one lottery ticket. After both participants make their bids, the computer will draw randomly one ticket among the tickets purchased by you and the other participant. The owner of the drawn ticket will receive the reward of $8. Thus, your chance of receiving the reward is given by the number of dollars you bid divided by the total number of dollars you and the other participant bid.

$$\text{Your chance of receiving a reward} = \frac{\text{your bid}}{\text{your bid + the other participant's bid}}$$

If both participants bid zero, the reward is randomly assigned to one of the two participants.

After both participants make their bids, the computer will make a random draw based on these bids and determine who receives the reward. Then the computer will calculate your earnings based on your bid and whether you received the reward or not.

Example: Assume that you bid $1 and the other participant bids $3. Therefore, the computer assigns 1 lottery ticket to you and 3 lottery tickets to the other participant. Then the computer randomly draws one lottery ticket out of 4 (1 + 3). Thus, your chance of receiving the reward is 0.25 = 1/4 and the other participant's chance is 0.75 = 3/4. Also, assume that the computer made a random draw and the other participant has received the reward. Therefore, your earnings = $0 – $1 = – $1, since you did not receive the reward and your bid was $1. The other participant's earnings = $8 – $3 = $5, since the reward was $8 and the other participant's bid was $3.

Important notes: You will not be told which of the participants in this room are matched with you. You can never guarantee yourself the reward. However, by increasing your bid, you can increase your chance of receiving the reward. Regardless of who receives the reward, both participants will have to pay their bids.

The actual earnings for this part of the experiment will be determined at the end of the experiment, and will be independent of other parts of the experiment.

QUIZ

Before you make your bid, you will be asked to answer 5 quiz questions during 5 minutes to check your understanding of the instructions. You will receive $0.50 for each correct answer. All 5 questions are given to you below. However, you have to enter your final answers into the computer before the 5 minutes end to be able to get your earnings.

Question 1: Assume that you bid $4 and the other participant bids $1. How many total lottery tickets will the computer use for drawing? ______

Question 2: Assume that you bid $4 and the other participant bids $1. What is your chance of receiving the reward? ______

Question 3: Assume that you bid $4 and the other participant bids $1. Also, assume that the computer made a random draw and the other participant has received the reward. What are your earnings? ______

Question 4: If you knew that the other participant bid $0, which bid would bring you the highest earnings for sure: $0, $1, $2, $3, $4, $5, $6, $7, $8, $9 or $10? ______

Question 5: If you knew that the other participant bid $2, which bid would bring you the highest expected earnings: $0, $1, $2, $3, $4, $5, $6, $7, $8, $9 or $10? ______

PART 2

In PART 2 of the experiment, you will be asked to provide a guess about what was the bid made by the other participant in PART 1. You will receive $2 if your guess is equal to the bid made by the other participant.

The actual earnings for this part of the experiment will be determined at the end of the experiment, and will be independent of other parts of the experiment.

Please enter your guess on your screen.

PART 3

In PART 3 of the experiment you will be randomly and anonymously matched with another participant. The rules for PART 3 are the same as the rules for PART 1. You and the other participant will choose how much to bid in order to be a winner. The only difference is that in PART 3 the winner does not receive the reward. Therefore, the reward is worth $0 to you and the other participant. After both participants have made their decisions, your earnings will be calculated as follows.

Earnings = $0 – your bid

After both participants make their bids, the computer will make a random draw based on these bids and determine who the winner is. At the end of the experiment, the computer will display the results of this part of the experiment (that is, whether you won or not), and will calculate your earnings.

Please make your decision on your screen.

PART 4

In PART 4 of the experiment, you will be asked to make a series of choices in decision problems. You will see a table with 12 lines. You will state whether you prefer Option A or Option B in each line. You should think of each line as a separate decision you need to make. However, only one line will be the 'line that counts' and will be paid out. In particular, at the end of the experiment, the computer will randomly draw an integer number between 1 and 12. The number chosen indicates which line will be paid out.

Your earnings for the selected line depend on which option you chose: if you chose A in that line, you will receive $3.00 and the other participant who will be matched with you will also receive $3.00. If you chose B in that line, you and the other participant will receive earnings as indicated in the table for that specific line. For example, if you chose B in line 2 and this line is selected for payment, you will receive $3.00 and the other participant will receive $2.00. Similarly, if you chose B in line 3 and this line is selected for payment, you will receive $3.00 and the other participant will receive $1.50.

After you have completed all your choices the computer will randomly draw an integer numbered between 1 and 12 to determine which line is going to be paid. Then the computer will randomly and anonymously match you with another participant in the experiment. While matching you with another participant, the computer will also randomly determine whose decision to implement. If the computer chooses your decision to implement, then the earnings to you and the other participant will be determined according to your choice of A or B. If the computer chooses the other participant decision to implement, then the earnings will determined according to the other participant choice of A or B.

Decision Number	Option A (you, the other participant)	Option B (you, the other participant)	Choose A or B
1	$3.00 to you, $3.00 to other	$3.00 to you, $2.50 to other	
2	$3.00 to you, $3.00 to other	$3.00 to you, $2.00 to other	
3	$3.00 to you, $3.00 to other	$3.00 to you, $1.50 to other	
4	$3.00 to you, $3.00 to other	$2.50 to you, $2.00 to other	
5	$3.00 to you, $3.00 to other	$2.50 to you, $1.50 to other	
6	$3.00 to you, $3.00 to other	$2.50 to you, $1.00 to other	
7	$3.00 to you, $3.00 to other	$3.00 to you, $3.50 to other	
8	$3.00 to you, $3.00 to other	$3.00 to you, $4.00 to other	
9	$3.00 to you, $3.00 to other	$3.00 to you, $4.50 to other	
10	$3.00 to you, $3.00 to other	$3.50 to you, $4.00 to other	
11	$3.00 to you, $3.00 to other	$3.50 to you, $4.50 to other	
12	$3.00 to you, $3.00 to other	$3.50 to you, $5.00 to other	

The actual earnings for this part of the experiment will be determined at the end of the experiment, and will be independent of other parts of the experiment.

Please make your decision on your screen.

PART 5

In PART 5 of the experiment, you will be asked to make a series of choices in decision problems. How much you receive will depend partly on chance and partly on the choices you make.

You will see two tables with 2 lines each. You will state whether you prefer Option A or Option B in each line. You should think of each line as a separate decision you need to make. You will make 4 decisions in total. However, only one line will be the 'line that counts' and will be paid out. In particular, at the end of the experiment, the computer will randomly draw an integer number between 1 and 4. The number chosen indicates which line will be paid out. You will be paid according to the option you selected on that line.

The decisions you make in the first table (lines 1-2) correspond to the following problem: There is bag containing 30 red balls and 60 other balls that are either blue or green. You don't know how many blue or green balls there are, but that the total number of blue balls plus the total number of green equals 60. The balls are well mixed so that each individual ball is as likely to be drawn as any other. In line 1, you are asked to choose between A or B. If you chose A in line 1, you will receive $5.00 if a red ball is drawn from the bag. If you chose B in line 1, you will receive $5.00 if a blue ball is drawn from the bag. In line 2, you are asked to choose between A or B. If you chose A in line 2, you will receive $5.00 if a red or green ball is drawn from the bag. If you chose B in line 2, you will receive $5.00 if a blue or green ball is drawn from the bag.

Decision Number	Option A	Option B	Choose A or B
1	$5.00 if a red ball is drawn from the bag	$5.00 if a blue ball is drawn from the bag	
2	$5.00 if a red or green ball is drawn from the bag	$5.00 if a blue or green ball is drawn from the bag	

The decisions you make in the second table (lines 3-4) are following: In line 3, you are asked to choose between A or B. If you chose A in line 3, you will receive $5.00 for sure. If you chose B in line 3, there is an 89% chance that you will receive $5.00, a 1% chance that you will receive nothing, and a 10% chance that you will receive $25.00. In line 4, you are asked to choose between A or B. If you chose A in line 4, there is an 89% chance that you will receive nothing, an 11% chance that you will receive $5.00. If you chose B in line 4, there is a 90% chance that you will receive nothing, a 10% chance that you will receive $25.00.

Decision Number	Option A	Option B	Choose A or B
3	$5.00 for sure	$5.00 with an 89% chance, nothing with a 1% chance, and $25.00 with a 10% chance	
4	nothing with an 89% chance, and $5 with an 11% chance	nothing with a 90% chance, and $25.00 with a 10% chance	

The actual earnings for this part of the experiment will be determined at the end of the experiment, and will be independent of other parts of the experiment.

Please make your decisions on your screen.

PART 6

In PART 6 of the experiment, you will be asked to make a series of choices in decision problems. How much you receive will depend partly on chance and partly on the choices you make.

You will see two tables with 15 lines each. You will state whether you prefer Option A or Option B in each line. You should think of each line as a separate decision you need to make. You will make 30 decisions in total. However, only one line will be the 'line that counts' and will be paid out. In particular, at the end of the experiment, the computer will randomly draw an integer number between 1 and 30. The number chosen indicates which line will be paid out. You will be paid according to the option you selected on that line.

Your earnings for the selected line depend on which option you chose: In the first table (lines 1-15), option A always offers a 50% chance to receive $5.00 and a 50% chance to receive nothing, while option B offers a certain amount of money for sure (between $0.50 and $4.00, depending on the line). If you choose B, you will receive a certain amount of money for sure specified by that line. If you chose A in that line, you will receive either $5.00 or nothing. To determine your earnings in the case you chose A we will randomly draw a ball from a bag containing ten orange balls and ten white balls. That means that when we draw a ball, there is a 50% chance that it is white and a 50% chance that it is orange. If the drawn ball is white and you selected A in that line, you will receive $5.00, otherwise you will receive $0.00.

Decision Number	Option A		Option B	Choose A or B
1	$5.00 with a 50% chance	nothing with a 50% chance	$0.50 for sure	
2	$5.00 with a 50% chance	nothing with a 50% chance	$0.75 for sure	
3	$5.00 with a 50% chance	nothing with a 50% chance	$1.00 for sure	
4	$5.00 with a 50% chance	nothing with a 50% chance	$1.25 for sure	
5	$5.00 with a 50% chance	nothing with a 50% chance	$1.50 for sure	
6	$5.00 with a 50% chance	nothing with a 50% chance	$1.75 for sure	
7	$5.00 with a 50% chance	nothing with a 50% chance	$2.00 for sure	
8	$5.00 with a 50% chance	nothing with a 50% chance	$2.25 for sure	
9	$5.00 with a 50% chance	nothing with a 50% chance	$2.50 for sure	
10	$5.00 with a 50% chance	nothing with a 50% chance	$2.75 for sure	
11	$5.00 with a 50% chance	nothing with a 50% chance	$3.00 for sure	
12	$5.00 with a 50% chance	nothing with a 50% chance	$3.25 for sure	
13	$5.00 with a 50% chance	nothing with a 50% chance	$3.50 for sure	
14	$5.00 with a 50% chance	nothing with a 50% chance	$3.75 for sure	
15	$5.00 with a 50% chance	nothing with a 50% chance	$4.00 for sure	

In the second table (lines 16-30), option A offers a 50% chance to receive $5.00 and a 50% chance to lose a certain amount of money (between -$0.50 and -$7.50, depending on the line), while option B offers $0.00 for sure. If you chose B, you will receive $0.00. If you chose option A in that line, you can receive either a loss between -$0.50 and -$7.50, depending on the line, or a gain of $5.00. To determine your earnings in the case you chose option A we will randomly draw a ball from a bag containing ten orange and ten white balls. If the drawn ball is white and you selected A in that line, you will receive $5.00, otherwise you will receive -$x (the exact amount depends on the line chosen).

Decision Number	Option A		Option B	Choose A or B
16	$5.00 with a 50% chance	-$0.50 with a 50% chance	$0.00 for sure	
17	$5.00 with a 50% chance	-$1.00 with a 50% chance	$0.00 for sure	
18	$5.00 with a 50% chance	-$1.50 with a 50% chance	$0.00 for sure	
19	$5.00 with a 50% chance	-$2.00 with a 50% chance	$0.00 for sure	
20	$5.00 with a 50% chance	-$2.50 with a 50% chance	$0.00 for sure	
21	$5.00 with a 50% chance	-$3.00 with a 50% chance	$0.00 for sure	
22	$5.00 with a 50% chance	-$3.50 with a 50% chance	$0.00 for sure	
23	$5.00 with a 50% chance	-$4.00 with a 50% chance	$0.00 for sure	
24	$5.00 with a 50% chance	-$4.50 with a 50% chance	$0.00 for sure	
25	$5.00 with a 50% chance	-$5.00 with a 50% chance	$0.00 for sure	
26	$5.00 with a 50% chance	-$5.50 with a 50% chance	$0.00 for sure	
27	$5.00 with a 50% chance	-$6.00 with a 50% chance	$0.00 for sure	
28	$5.00 with a 50% chance	-$6.50 with a 50% chance	$0.00 for sure	
29	$5.00 with a 50% chance	-$7.00 with a 50% chance	$0.00 for sure	
30	$5.00 with a 50% chance	-$7.50 with a 50% chance	$0.00 for sure	

The actual earnings for this part of the experiment will be determined at the end of the experiment, and will be independent of other parts of the experiment.

Please make your decisions on your screen.

PART 7

In PART 7 of the experiment, you will be asked to answer 3 questions. You will receive $0.50 per each correct answer, and there is no penalty for incorrect answers.

Question 1: A bat and a ball cost $1.10 in total. The bat costs $1.00 more than the ball. How much does the ball cost? _____ cents

Question 2: It takes 5 machines 5 minutes to make 5 widgets. How long does it take 100 machines to make 100 widgets? _____ minutes

Question 3: In a lake, there is a patch of lily pads. Every day, the patch doubles in size. It takes 48 days for the patch to cover the entire lake. How long does it take for the patch to cover half of the lake? _____ days

PART 8

In PART 8 of the experiment, you will take a 10-minute cognitive test containing 7 questions. You may use the margins of this booklet to work out your answer if needed. You may ONLY use pencil and paper provided. No other aids are permitted.

You will receive $0.50 per each correct answer, and there is no penalty for incorrect answers.

All 7 questions are given to you in paper sheets. However, you have to enter your final answers into the computer before the 10 minutes end to be able to get your earnings.

Question 1: If the average (arithmetic mean) of 12 numbers is 25 and the average (arithmetic mean) of 11 of the numbers is 20 then what is the remaining number?

1. 5
2. 55
3. 60
4. 70
5. 80

Question 2: If $bc \neq 0$, and $3b + 2c = 18$, then which of the following is NOT a possible value of c ?

1. $5\frac{3}{5}$
2. 6
3. $8\frac{2}{5}$
4. 9
5. 12

Question 3: If x is a positive integer greater than one, which of the following has the greatest value?

1. $\frac{1}{x}$
2. $\frac{1}{x+1}$
3. $\frac{x}{x+1}$
4. $\frac{x}{\left(\frac{1}{x+1}\right)}$
5. $\frac{x}{\left(\frac{x}{x+1}\right)}$

Question 4: A hat contains 18 raffle tickets, numbered 1 through 18. If two raffle tickets are chosen at random from the hat, what is the probability that both tickets are even numbers?

1. $\frac{2}{9}$
2. $\frac{4}{17}$
3. $\frac{1}{4}$
4. $\frac{1}{2}$
5. $\frac{33}{34}$

Question 5: What is the value of $\frac{3}{\left(\frac{3}{4}\right)} - \frac{\left(\frac{3}{2}\right)}{3}$?

1. -1.75
2. -0.75
3. 1
4. 2
5. 3.5

Question 6: A number divisible by a positive even prime number must be

1. prime
2. odd
3. even
4. the square of a prime
5. the square an odd number

Question 7: Which of the following inequalities is true?

1. $\frac{1}{11} < 0.08 < \frac{1}{9}$
2. $\frac{1}{10} < 0.11 < \frac{1}{8}$
3. $\frac{1}{7} < 0.17 < \frac{1}{6}$
4. $\frac{1}{5} < 0.26 < \frac{1}{4}$
5. $\frac{1}{3} < 0.30 < \frac{1}{2}$

Appendix B (For Online Publication) – Additional Analysis

Table B1 shows the 12 choices which we used to elicited social preferences and the corresponding CRT measures conditional on choosing A or B. Examining choices 1-6, we see that participants who choose option B, indicating competitive behavior (i.e., choosing to sacrifice social welfare to have a higher payoff than the opponent), are more impulsive (i.e., they score less on the CRT). Similarly, participants who choose A in 7-12, again indicating more competitive preferences, are more impulsive.

Table B1: Social preferences and CRT.

Decision Number	Option A (self, other)	Option B (self, other)	Percentage choosing A	CRT conditional on A	CRT conditional on B	Wilcoxon rank-sum test
1	\$3.00, \$3.00	\$3.00, \$2.50	87.0%	1.25 (0.08)	0.95 (0.22)	p-value = 0.17
2	\$3.00, \$3.00	\$3.00, \$2.00	83.2%	1.28 (0.08)	0.87 (0.18)	p-value = 0.04
3	\$3.00, \$3.00	\$3.00, \$1.50	83.2%	1.29 (0.08)	0.83 (0.19)	p-value = 0.02
4	\$3.00, \$3.00	\$2.50, \$2.00	95.7%	1.23 (0.08)	0.75 (0.25)	p-value = 0.25
5	\$3.00, \$3.00	\$2.50, \$1.50	96.2%	1.24 (0.08)	0.42 (0.20)	p-value = 0.05
6	\$3.00, \$3.00	\$2.50, \$1.00	94.6%	1.27 (0.08)	0.30 (0.15)	p-value < 0.01
7	\$3.00, \$3.00	\$3.00, \$3.50	45.7%	0.85 (0.10)	1.52 (0.11)	p-value < 0.01
8	\$3.00, \$3.00	\$3.00, \$4.00	46.7%	0.86 (0.10)	1.53 (0.11)	p-value < 0.01
9	\$3.00, \$3.00	\$3.00, \$4.50	46.7%	0.86 (0.10)	1.53 (0.11)	p-value < 0.01
10	\$3.00, \$3.00	\$3.50, \$4.00	17.9%	0.66 (0.14)	1.33 (0.08)	p-value < 0.01
11	\$3.00, \$3.00	\$3.50, \$4.50	21.7%	0.72 (0.14)	1.35 (0.09)	p-value < 0.01
12	\$3.00, \$3.00	\$3.50, \$5.00	22.3%	0.75 (0.14)	1.34 (0.09)	p-value < 0.01

Table B2 shows the estimation results of different OLS regressions in which the dependent variable is *overbidding* (i.e., the difference between the actual bid and the best-response calculated based on the stated belief about the other bid), and the independent variables are measured behaviors reported in Table 3. The estimation results are very similar qualitatively to those reported in Table 4.

Table B2: OLS regression of overbidding on measured behaviors.

Specification	(1)	(2)	(3)	(4)	(5)	(6)
Dependent variable, *overbidding*						
quiz	-0.65***					-0.42*
[number of correct quiz answers]	(0.23)					(0.22)
bias		0.24				0.10
[violation of the expected utility]		(0.31)				(0.27)
risk-averse		-0.01				0.02
[number of safe options B]		(0.05)				(0.05)
loss-averse		-0.11*				-0.08
[number of options B]		(0.06)				(0.06)
bid-zero			0.22***			0.10
[bid for a prize of $0]			(0.07)			(0.08)
competitive				0.10**		0.03
[number of antisocial choices]				(0.05)		(0.05)
gre					-0.06	-0.04
[number of correct GRE answers]					(0.10)	(0.10)
crt					-0.58***	-0.42***
[number of correct CRT answers]					(0.13)	(0.14)
constant	4.26***	2.91***	1.78***	1.73***	2.90***	4.54***
[the constant term]	(0.85)	(0.54)	(0.15)	(0.18)	(0.40)	(1.06)
N	184	184	184	184	184	184
R-squared	0.06	0.02	0.05	0.02	0.11	0.17
R-squared adjusted	0.06	0	0.04	0.02	0.11	0.13

* significant at 10%, ** significant at 5%, *** significant at 1%.
Robust standard errors are in parenthesis.

Table B3 shows the estimation results of different OLS regressions in which the dependent variable is *expected payoff* (i.e., the average expected payoff calculated based on the individual bid and the empirical distribution of all other bids in our sample), and the independent variables are measured behaviors reported in Table 3. The estimation results are very similar qualitatively to those reported in Table 4.

Table B3: OLS regression of expected payoff on measured behaviors.

Specification	(1)	(2)	(3)	(4)	(5)	(6)
Dependent variable, *expected payoff*						
belief	-0.16**					-0.15**
[belief about the other bid]	(0.06)					(0.06)
quiz	0.26**					0.17*
[number of correct quiz answers]	(0.10)					(0.10)
bias		-0.20				-0.15
[violation of the expected utility]		(0.15)				(0.11)
risk-averse		0.00				-0.01
[number of safe options B]		(0.03)				(0.02)
loss-averse		0.05*				0.04
[number of options B]		(0.03)				(0.02)
bid-zero			-0.10**			-0.03
[bid for a prize of $0]			(0.04)			(0.05)
competitive				-0.04**		-0.01
[number of antisocial choices]				(0.02)		(0.02)
gre					0.03	0.00
[number of correct GRE answers]					(0.05)	(0.04)
crt					0.24***	0.16**
[number of correct CRT answers]					(0.06)	(0.07)
constant	-0.20	-0.15	0.24***	0.27***	-0.25	-0.27
[the constant term]	(0.46)	(0.26)	(0.07)	(0.08)	(0.21)	(0.55)
N	184	184	184	184	184	184
R-squared	0.15	0.02	0.04	0.02	0.09	0.21
R-squared adjusted	0.14	0.01	0.03	0.02	0.08	0.17

* significant at 10%, ** significant at 5%, *** significant at 1%.
Robust standard errors are in parenthesis.