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When a risky prospect is valued more than its best possible outcome

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Abstract

In this paper, we document a violation of normative and descriptive models of decision making under risk. In contrast to uncertainty effects found by Gneezy, List and Wu (2006), some subjects in our experiments valued certain lotteries more than the best possible outcome. We show that the likelihood of observing this effect is positively related to the probability of winning the lottery and negatively related to the value of the maximum outcome. We also demonstrate that this effect can be partially attributed to subjects' competitiveness and level of comprehension of the lottery mechanism; the competitiveness effects far outweighing comprehension effects.

JEL codes: D81, D44
Keywords: lottery, Vickrey auction, risk, competitiveness

Introduction

Decision making often involves choices between risky properties. Prospect theory and expected utility theory both posit that individuals balance outcomes and their (potentially weighted) probability of occurrence, which then means that the value or certainty equivalent of a binary lottery will lie somewhere between the lowest and the highest outcomes. However, Gneezy, List and Wu (2006) document cases where individuals value a risky prospect less than its worst possible realization. They call this phenomenon the uncertainty effect and demonstrate its existence in various laboratory experiments (including real and hypothetical pricing tasks and inter-temporal choice tasks) as well as in a field experiment (a sportscard market). This uncertainty effect, however, disappears in within-subject designs and is only observed in lotteries that do not involve cash.

In this note, we document cases of the polar opposite of the uncertainty effect, where individuals value the outcome of a risky prospect more than its best possible realization. We demonstrate cases where subjects are willing to pay as much as three times the value of the best possible realization of a lottery in a second price auction. We term this effect the overbidding effect.

It is tempting to attribute the result to the particulars of the value elicitation mechanism. For example, in Kagel and Levin's (1993) non-risky induced value experiments, subjects tended to slightly overbid in a second price auction. Kagel and Levin (1993) attributed this overbidding to either the dominant bidding strategy not being transparent to subjects or to weak learning feedback mechanisms in the second price sealed bid auction. Although this result is often taken as a stylized fact associated with second price auctions, Lusk and Shogren (2007) document that several more recent induced value studies that focus on all bidders' values (not just the market price) tend to find behaviour more in-line with theoretical predicted bidding behaviour in the second price auction. Even if we accept the Kagel and Levin's (1993) result of over-bidding in the second price auction, it is difficult to conclude that this is the primary cause of the behaviour observed here. Although subjects in our experiments "overbid," we would expect people's bids to lie somewhere close to the expected payoff, *not* close to the maximum payoff of the lottery.

Hence, in addition to documenting the overbidding effect, we sought to identify the causes of the effect. Two non-exclusive possible causes of the observed effect are confusion or comprehension (i.e. subjects did not understand the payoff mechanism of a lottery) and/or utility from winning and being the “top dog” of the experiment (i.e. to walk out of the experiment as the “top dog” among their peers) (Shogren et al. 2001). Regarding the first issue, Plott and Zeiler (2005) show that the often-reported WTP-WTA disparity is likely a result of subject confusion with the elicitation mechanism – suggesting the WTP-WTA divergence is not an underlying feature of preference *per se* but rather a result of misunderstanding with the bidding mechanism.

Our results suggest that the overbidding effect can, in part, be attributed to comprehension of how lotteries work, but that training with the second price auction does not eliminate the overbidding effect. While we find that comprehension negatively influences the probability of overbidding, competitiveness positively affects this probability. Our results also suggest that the overbidding effect tends to attenuate when the maximum payoff of the lottery increases and accentuates when winning becomes more likely.

This paper is structured as follows: The next section discusses the design of our auction experiments followed by the econometric analysis and results. The last section contains the conclusions.

Experimental design

A conventional lab experiment was conducted using the z-Tree software (Fischbacher 2007). Subjects consisted of undergraduate students of the Agricultural University of Athens in Greece. During the recruitment, the nature of the experiment and the expected earnings were not mentioned.

We used a 2nd price Vickrey auction to determine the selling price of the lotteries. A 2x2 design was adopted varying the extent of training (minimal vs. extensive training) and posting of market clearing prices (posting vs. no posting of the 2nd highest price). Each subject participated in only one treatment. The size of the groups varied from 17 to 18 subjects per treatment. Each treatment lasted no more than an hour. In total, 71 subjects participated in our experiments, which were conducted in March 2009.

Each session included four phases: the training phase, the choice task, the lottery auction phase and the post-experimental phase. Data from the choice task are analyzed elsewhere. Subjects were given prior instructions on the overall layout of the session and were also reminded on the procedures at the beginning of each phase.

The training phase

We used a 2nd price Vickrey auction, a commonly used elicitation method in experimental auction studies, to elicit subjects’ prices of lotteries. After arriving at the lab, subjects were randomly seated in front of a computer. Subjects were given a fifteen Euros (15€) participation fee at the end of the experiment. We emphasized that although they were not given the money at the beginning of the experiment, the 15€ was theirs to use as they please and that they should think that they have this money already. To control for possible monetary endowment effects, subjects were also told that a random amount of money between 0.5€ and 3€ was going to be randomly assigned to each one of them[1]. Everyone then received this random fee, which was added to their participation fee, as soon as the computerized phase of the experiment began. We emphasized to the subjects that the endowment they received was private information and that they should not communicate this information to other subjects in the lab. All transactions were completed at the end of the experiment. No information about this additional endowment was given during recruitment.

Subjects were then shown a short presentation about how the auctions work to familiarize them with the procedure. All instructions were in PowerPoint and were projected onto a screen in the front of the lab. The instructions emphasized that the participants should not communicate with each other. Subjects were given a short introduction on how the 2^{nd} price Vickrey auction works, a short example on how bids are sorted in a descending order and on how the 2^{nd} highest bid and the winner are selected. In addition, a numerical example was given to indicate to respondents why it is in their best interest to bid exactly the amount the product is worth to them and to demonstrate the incentive compatibility of the auction. Subjects were then asked to take a short computerized test regarding the procedure. The correct answers were presented on their screen after everyone completed the test. The questions and the correct answers were read aloud and explained to subjects as well.

The set of instructions included a short section on what the subjects will see on their computer screen to familiarize them with the computerized part of the experiment. Instructions were also given on how subjects should submit their bids in the appropriate fields of their screen. We did not find it necessary to include a computer-training phase since all the subjects were students and already had computer experience.

The first part of the training included five *hypothetical* multi-product[2] auction rounds. We emphasized to the subjects that these rounds were intended to familiarize them with the auction procedure and although they would not have to pay any money to buy any product they should bid as if they were in a real auction and as if they really intended to buy the product. We also told them that one round and one product would be randomly chosen at the end of these rounds as binding. A screen with subjects' hypothetical payoffs was displayed after these rounds.

In the second part of the training, we included five *real* multi-product[3] auction rounds. We emphasized to the subjects that these rounds were real and that if they chose to buy a product they would actually have to pay for it. Similar to the previous hypothetical rounds, one round and one product were randomly chosen as binding at the end of these rounds. A screen with subjects' payoffs was displayed after these rounds.

Subjects who participated in the minimal training treatment were not exposed to the full training as described above. Subjects in the minimal training treatment were not provided with a numerical example on how a 2^{nd} price auction works, were not given a computerized test and were not explicitly informed about the incentive compatibility of the auction. They also participated only in the hypothetical rounds, not in the *real* ones.

The choice phase

[1] In every step that involved random drawings by the computer, we reassured subjects that the drawing was fair and that extra care was taken by the programmer to make sure that this is the case.

[2] The products were a packet of gums, a bag of cookies and a bag of potato chips.

[3] The products we used were a Tobleron chocolate, a pack of Soft Kings cookies and Kraft's Lacta chocolate.

After the training phase, the experiment on choice between lotteries was performed. We asked subjects to indicate their preference for each of three pairs of lotteries with the understanding that each pair has an equal chance of being randomly selected as binding and that their decision or choice in each pair will be applied. Subjects were also informed that at the end of the choice phase and the lottery auction phase, a randomly generated number by the computer would determine which of the two phases would be selected as binding. Subjects during the training phase were shown numerical examples on what exactly would happen depending on the payoff of the lottery under winning and losing scenarios.

The three pairs of lotteries with their corresponding chances and expected payoffs are exhibited in Table 1. To avoid any order effect, bet pairs and lotteries in each pair were randomly shown in each subject's screen and thus were presented to each subject in different order.

Bet pairs 1 and 3 were adopted from Cox and Grether (1996)[4]. Bet pair 2 was added as a medium expected payoff category to the high and low expected payoff lotteries of Cox and Grether. Notice that for bet pair 1, the bad outcome for the $-bet is worse than that for the P-bet[5]. The opposite exists for bet pair 3, while for bet pair 2, the bad outcomes are equal.

Table 1. Lotteries used in the experiment

Lottery	Bet type	Bet pair	Probability of win	Amount of win	Probability of loss	Amount of loss	Expected payoff
A	P-bet	1	90%	4	10%	1	3.50
B	$-bet		28%	16	72%	1.5	3.40
C	P-bet	2	80%	3	20%	1	2.20
D	$-bet		24%	12	76%	1	2.12
E	P-bet	3	75%	2	25%	1	1.25
F	$-bet		18%	9	82%	0.5	1.21

The lottery auction phase

In the lottery auction phase, we presented subjects with the same six lotteries and asked subjects to indicate how much, if any, they are willing to pay to buy each of the lotteries. The appearance of the lotteries was ordered randomly for each subject. Subjects repeated the bidding task for ten consecutive rounds and were informed that if the lottery auction phase was chosen as binding, only one lottery and one round would then be randomly chosen as binding. In the treatment with posted market clearing prices, subjects were able to observe the 2nd highest price and winner's ID (which could not identify the winner since these were anonymously assigned by the computer), while in the no posted market clearing prices treatment, subjects were only observing the winner's ID.

The post-experimental phase

After the experiment, we collected standard socio-demographic information about subjects' age, household size and economic position of their household

[4] We had to modify the chances into a percentage form since in the original paper these were given in a different format. The expected payoffs are very close to the ones reported in the original paper.

[5] The P-bet lottery involves a bet with a high probability of winning a modest amount and a low probability of losing an even more modest amount and the $-bet involves a bet with a modest probability of winning a large amount and a high probability of winning a modest amount.

(evaluated at a 5-likert scale). We further contacted subjects for a short telephone interview. In this interview, subjects were asked two sets of questions. The first set was composed of four questions seeking to determine subject's comprehension of a lottery's payoff. The purpose was to investigate if subjects understood well what the payoff of a lottery meant and to assess if they were bidding out of confusion in the auction phase. We asked subjects to imagine themselves in a situation where they are given a lottery with 78% probability of winning 6€ and 22% probability of losing 2€. We then asked subjects to indicate the maximum payoff and the maximum loss of this lottery. We also asked subjects their overall profit (loss) if they bought this lottery for 4€ and then won (lost) the lottery. These questions were given in random order to each subject. We then summed up the correct answers to derive a "comprehension score" for each individual.

The second set of questions was aimed at determining subjects' competitiveness trait. We adopted the scale developed by Brown, Cron and Slocum (1998). We asked subjects to indicate if they agree or disagree with four statements (given in random order) on a 7 Likert-scale ranging from totally disagree to totally agree. A competitiveness score was created by summing people's answers to the following four statements: (a) I enjoy working in situations involving competition with others; (b) It is important to me to perform better than others on a task; (c) I feel that winning is important in both work and games; and (d) I try harder when I am in competition with other people.

Experimental results

Out of the six lotteries auctioned, we observed that subjects bid more than the best (but uncertain) outcomes for lotteries A, C, E and F (with maximum payoffs of 4€, 3€, 2€ and 9€ respectively, see table 1)[6]. We did not observe similar behavior, however, for lotteries B and D (with maximum payoffs of 16€ and 12€ respectively, see table 1). Table 2 shows the mean, median and maximum bid observed by round for the six lotteries. It also exhibits the percentage of subjects overbidding by round and lottery. As evident in the table, the mean bid is increasing through the rounds, mainly due to a few subjects bidding high for the lotteries. The median bid is relatively constant across rounds.

Table 2. Mean, median and maximum bids by rounds

		Rounds									
		1	*2*	*3*	*4*	*5*	*6*	*7*	*8*	*9*	*10*
Lottery A	Mean	1.54	1.96	2.17	2.29	2.25	2.35	2.31	2.29	2.42	2.39
	Median	1.00	1.70	2.00	2.00	2.00	2.00	2.00	2.00	2.00	2.00
	Maximum bid	5.00	5.00	5.00	5.00	5.00	5.40	5.80	6.00	6.80	7.00
	% of overbidders	4.23	1.41	2.82	9.86	15.5	14.08	12.68	14.08	15.49	14.08
Lottery B	Mean	1.28	1.96	2.26	2.55	2.83	2.94	3.29	3.19	3.57	3.36
	Median	0.80	1.50	1.50	2.00	2.00	2.00	2.80	2.00	3.00	2.00
	Maximum bid	10.00	8.00	8.99	8.99	10.00	10.00	11.00	11.00	15.99	15.50
	% of	0	0	0	0	0	0	0	0	0	0

[6] Although the number of cases for lottery F was very small (2 cases).

	overbidders										
Lottery C	Mean	1.02	1.29	1.46	1.50	1.55	1.65	1.68	1.67	1.70	1.79
	Median	1.00	1.00	1.20	1.10	1.10	1.20	1.50	1.49	1.50	1.50
	Maximum bid	3.00	3.50	4.00	4.00	5.00	6.00	6.80	5.00	5.69	6.10
	% of overbidders	0	2.82	2.82	4.23	9.86	12.68	11.27	12.67	14.08	12.68
Lottery D	Mean	1.21	1.72	1.88	2.43	2.62	2.82	2.85	3.06	3.16	2.99
	Median	1.00	1.50	1.30	2.00	2.00	2.00	2.00	2.00	2.00	2.00
	Maximum bid	10.00	7.00	7.50	8.00	9.00	9.00	9.00	10.00	11.99	11.90
	% of overbidders	0	0	0	0	0	0	0	0	0	0
Lottery E	Mean	0.61	0.91	0.99	0.99	1.05	1.05	1.09	1.14	1.25	1.26
	Median	0.50	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00
	Maximum bid	2.00	2.56	2.50	2.98	5.00	3.55	4.39	4.76	5.99	6.23
	% of overbidders	0	2.82	5.63	7.04	11.27	7.04	5.63	9.86	11.27	11.27
Lottery F	Mean	0.97	1.42	1.76	1.94	2.18	2.47	2.52	2.59	2.76	2.57
	Median	0.50	1.00	1.60	1.50	1.90	2.00	1.50	1.90	2.00	1.50
	Maximum bid	8.00	6.00	7.00	7.00	7.00	7.30	7.10	10.00	9.00	10.00
	% of overbidders	0	0	0	0	0	0	0	1.41	0	1.41

Overbidding behavior was simultaneously observed for multiple lotteries. Table 3 shows the number of overbidders for 1, 2 and 3 lotteries in any given round. Overbidding tended to begin for one lottery in the early rounds but overbidding became more prevalent for other lotteries as the number of rounds increased.

Table 3. Number of overbidders by rounds

	Rounds									
	1	*2*	*3*	*4*	*5*	*6*	*7*	*8*	*9*	*10*
Overbid for 1 lottery	3	5	5	7	8	3	3	6	6	3
Overbid for 2 lotteries	0	0	0	1	3	3	3	3	4	2
Overbid for 3 lotteries	0	0	1	2	4	5	4	5	5	7
Total	**3**	**5**	**6**	**10**	**15**	**11**	**10**	**14**	**15**	**12**

Table 4 shows the number of distinct overbidders per round (this is the same as the row total in Table 3) and the total number of overbids in each round (aggregated over all lotteries). Note that when these figures deviate from each other, it is an indication that the extra overbids come from the same subjects that overbid on multiple lotteries. As shown in this table, subjects also tend to overbid for more than one lottery as the rounds progress. This can be seen in the third row of Table 4, which shows the ratio of total overbids over distinct overbidders (TMO/DMO). In the first two rounds, subjects-overbid for just one lottery out of six (ratio equals 1) while in the 10th round, subjects overbid on average for more than two lotteries.

Table 4. Number of overbidders and overbids by rounds

	Rounds									
	1	*2*	*3*	*4*	*5*	*6*	*7*	*8*	*9*	*10*
Distinct overbidders (DMO)	3	5	6	10	15	11	10	14	15	12
Total overbids (TMO)	3	5	8	15	26	24	21	27	29	28
Ratio TMO/DMO	1.00	1.00	1.33	1.50	1.73	2.18	2.10	1.93	1.93	2.33

Table 5 shows the number of new overbidders (based on their id's and aggregated over lotteries) that are added in every round. Results indicate that up to round 5, new subjects tend to imitate the overbidding behavior of subjects from earlier rounds. Hence, it appears that five rounds in our experiments are sufficient for the overbidding effect to arise and stabilize. In all, the documented overbidding behavior is caused by roughly one third (25 subjects) of the participants in our experiments.

Table 5. Number of new overbidders by rounds

	Rounds										**Total**
	1	*2*	*3*	*4*	*5*	*6*	*7*	*8*	*9*	*10*	
Number of new overbidders	3	4	3	5	8	0	0	1	1	0	**25**

To explore why subjects tend to bid higher than the best possible outcome of the lotteries, we created dummy variables taking the value of one when a subject bid more than the best outcome of a lottery. We then estimated random effects probit models that included as covariates the dummies for the treatments, a variable indicating the round, gender, age, perceived economic position of the household, household size, total fee (to control for money endowment effects), a variable indicating comprehension of the payoff mechanism of a lottery, and a variable indicating competitiveness traits of the subject. Some descriptive statistics of the associated variables are exhibited in Table 6[7].

Table 6. Variables and variable description

Variable	**Description**	**Mean**	**Std. Dev.**
WinLovLotA	Dummy, 1=subject bid over the best outcome for lottery A, 0=otherwise	0.11	0.31
WinLovLotC	Dummy, 1=subject bid over the best outcome for lottery C, 0=otherwise	0.08	0.26
WinLovLotE	Dummy, 1=subject bid over the best outcome	0.09	0.28

[7] Since in the telephone interviews we were unable to establish contact with 6 subjects, Table 6 and subsequent tables refer to a sample size of 65 subjects out of the 71 that participated in the experimental auctions.

	for lottery E, 0=otherwise		
TreatPrice	Dummy, 1=subject participated in the posted market clearing price treatment, 0= subject participated in the no-posted market clearing price treatment	0.51	0.50
TreatTrain	Dummy, 1=subject participated in the extensive training treatment, 0= subject participated in the minimal training treatment	0.51	0.50
Gender	Dummy, 1=male, 0=female	0.38	0.49
TotFee	Total endowment fee for participation	16.76	0.81
*EconPosition$_1$**	Dummy, 1=economic position of the household is good or very good, 0=otherwise	0.34	0.47
EconPosition$_2$	Dummy, 1=economic position of the household is above average, 0=otherwise	0.26	0.44
EconPosition$_3$	Dummy, 1=economic position of the household is average or worse, 0=otherwise	0.40	0.49
Age	Subject's age	20.74	1.54
Hsize	Household size	4.45	1.11
Comprehension	Score of comprehension of lottery's payoff mechanism	2.75	1.07
Competitiveness	Subject's competitiveness traits	21.05	4.25

* Removed from estimation

Table 7 exhibits the semi-elasticities of the form of $\mathrm{d}\ \ln \mathrm{Prob}Y \ / \mathrm{d}\ X$ which indicate the percentage change in the probability of the dependent variable Y resulting from a unit change in X. We can see from Table 7[8] that both comprehension and competitiveness have a statistically significant effect on the probability of bidding more than the best outcome of the lottery. Specifically, competitiveness positively affects the probability of being an overbidder but the effect attenuates, in terms of statistical significance, as the maximum possible payoff of the lottery increases (i.e., moving from lottery A to C and then to E). On the other hand, comprehension of the lottery's payoff negatively affects the probability of being an overbidder but the effect is statistically significant for only one lottery (lottery C). One could therefore conclude that the observed behavior in the lab of bidding more than the best outcome of a lottery can be explained more by competitiveness traits and less by comprehension of the payoff mechanism of the lotteries.

Table 7. Estimated semi-elasticities from random effects probit models and pooled probit model (overbidders)

	Lottery A Coef. (Std. Error)	Lottery C Coef. (Std. Error)	Lottery E Coef. (Std. Error)	Pooled model Coef. (Std. Error)
Round	**0.409**** **(0.119)**	**1.258**** **(0.406)**	**0.833**** **(0.319)**	**0.359**** **(0.059)**
TreatPrice	1.575	**12.978***	5.605	**2.323****

[8] We could not estimate a random effects probit model for lottery F due to small variability in the dependent variable.

	(1.321)	**(7.117)**	(4.038)	**(0.377)**
TreatTrain	1.68 (1.395)	10.961 (6.932)	7.467 (4.954)	**2.007**** **(0.383)**
Gender	**3.112**** **(1.453)**	5.042 (4.178)	1.082 (3.233)	**1.608**** **(0.326)**
TotFee	-0.106 (0.827)	4.711 (3.418)	-1.306 (2.337)	0.175 (0.205)
EconPosition$_2$	**4.432**** **(2.038)**	8.972 (5.901)	2.674 (4.989)	**2.816**** **(0.473)**
EconPosition$_3$	1.275 (1.645)	0.271 (4.416)	7.338 (5.291)	**1.466**** **(0.414)**
Age	-0.312 (0.411)	-1.583 (1.321)	**-3.538**** **(1.771)**	**-0.576**** **(0.108)**
Hsize	0.024 (0.513)	0.609 (1.901)	0.642 (1.589)	0.067 (0.146)
Comprehension	-0.897 (0.632)	**-4.730*** **(2.746)**	-1.467 (1.639)	**-0.878**** **(0.162)**
Competition	**0.458**** **(0.222)**	**1.810*** **(1.085)**	1.225 (0.769)	**0.369**** **(0.059)**
Probability of win	-	-	-	**8.049**** **(1.528)**
Max payoff	-	-	-	**-0.246**** **(0.099)**
Min payoff	-	-	-	0.662 (2.221)

*(**) Statistically significant at the 10%(5%) level.

Our results further indicate that the overbidding effect is more likely to occur as the rounds evolve. For lottery C, posting the market clearing price between rounds did have an effect on the probability of being an overbidder. It is possible that posting of price information for the lottery exacerbated competitiveness. On the other hand, training did not have a statistically significant effect. As for the demographics, results suggest that males and younger subjects are more likely to be classified as overbidders than females and older subjects, respectively.

To further explore the issue of why subjects exhibited overbidding behavior only in specific lotteries, we estimated pooled probit regressions (last column in Table 7) where we used lottery characteristics (i.e., the probability of winning the lottery, the maximum payoff of the lottery and the minimum payoff of the lottery) as independent variables. Table 7 shows that the overbidding effect attenuates when we move to lotteries with high maximum payoffs, which explains why we did not observe such an effect for lotteries B and D. In addition, the probability of winning is positively associated with the probability of overbidding in any given lottery. It appears that moving from uncertain to certain outcomes (i.e., increasing the probability of winning) reduces the costs of misbehaving with respect to optimality.

To complement our analysis and further investigate behavior under risk, we categorized the subjects as risk lovers (risk averters) if they bid more (less) than the expected payoff of a lottery. We then estimated random effects probit models. The results are presented in Tables 8 and 9, respectively. The last column in Tables 8 and 9 shows the results from a pooled probit regression.

Table 8. Estimated semi-elasticities from random effects probit models and pooled probit model (risk lovers)

	Lottery A Coef. (Std. Error)	Lottery B Coef. (Std. Error)	Lottery C Coef. (Std. Error)	Lottery D Coef. (Std. Error)	Lottery E Coef. (Std. Error)	Lottery F Coef. (Std. Error)	Pooled model Coef. (Std. Error)
Round	-0.014 (0.072)	**0.601**** **(0.123)**	0.070 (0.068)	**0.292**** **(0.069)**	0.061 (0.051)	**0.098**** **(0.030)**	**0.071**** **(0.010)**
TreatPrice	1.032 (1.090)	1.669 (1.282)	0.966 (1.016)	1.335 (0.946)	-0.051 (0.798)	0.276 (0.478)	**0.309**** **(0.062)**
TreatTrain	-0.528 (1.130)	2.009 (1.345)	-0.101 (1.057)	**1.947*** **(1.024)**	-0.010 (0.830)	**0.941*** **(0.524)**	**0.326**** **(0.064)**
Gender	0.524 (1.070)	1.852 (1.298)	1.722 (1.067)	**2.048**** **(1.011)**	0.765 (0.812)	0.692 (0.500)	**0.453**** **(0.062)**
TotFee	0.935 (0.702)	0.377 (0.808)	1.130 (0.702)	0.291 (0.590)	0.512 (0.526)	0.289 (0.311)	**0.234**** **(0.040)**
$EconPosition_2$	1.230 (1.503)	1.614 (1.665)	0.251 (1.405)	2.122 (1.291)	0.364 (1.091)	0.732 (0.642)	**0.199**** **(0.083)**
$EconPosition_3$	1.788 (1.392)	-0.171 (1.488)	1.283 (1.286)	0.237 (1.106)	1.661 (1.000)	0.563 (0.586)	**0.241**** **(0.075)**
Age	0.187 (0.345)	**0.955**** **(0.447)**	0.070 (0.320)	**0.528*** **(0.317)**	0.162 (0.252)	0.146 (0.159)	**0.102**** **(0.020)**
Hsize	0.317 (0.479)	0.321 (0.576)	0.418 (0.457)	0.227 (0.425)	**0.685*** **(0.375)**	0.032 (0.210)	**0.138**** **(0.028)**
Comprehension	-0.363 (0.511)	0.241 (0.589)	-0.260 (0.485)	-0.316 (0.432)	-0.307 (0.377)	-0.367 (0.234)	**-0.090**** **(0.029)**
Competition	0.207 (0.142)	0.200 (0.161)	0.064 (0.127)	0.088 (0.112)	0.160 (0.106)	0.055 (0.059)	**0.036**** **(0.008)**
Probability of win	-	-	-	-	-	-	**-2.526**** **(0.205)**
Max payoff	-	-	-	-	-	-	**-0.048**** **(0.011)**
Min payoff	-	-	-	-	-	-	0.049 0.107

Table 9. Estimated semi-elasticities from random effects probit models and pooled probit model (risk averters)

	Lottery A	Lottery B	Lottery C	Lottery D	Lottery E	Lottery F	Pooled model
	Coef. (Std. Error)	Coef. (Std. Error)	Coef. (Std. Error)	Coef. (Std. Error)	Coef. (Std. Error)	Coef. (Std. Error)	Coef. (Std. Error)
Round	-0.008 (0.005)	**-0.041* (0.022)**	-0.005 (0.004)	**-0.062** (0.025)**	**-0.016** (0.008)**	**-0.085** (0.027)**	**-0.037** (0.004)**
TreatPrice	-0.061 (0.053)	-0.114 (0.103)	-0.027 (0.028)	-0.282 (0.220)	-0.067 (0.085)	-0.273 (0.388)	**-0.175** (0.023)**
TreatTrain	0.000 (0.043)	-0.137 (0.111)	-0.008 (0.019)	-0.411 (0.251)	-0.045 (0.085)	**-0.718* (0.430)**	**-0.165** (0.024)**
Gender	-0.070 (0.057)	-0.126 (0.109)	-0.038 (0.035)	**-0.432* (0.253)**	-0.103 (0.090)	-0.622 (0.417)	**-0.226** (0.023)**
TotFee	-0.020 (0.030)	-0.026 (0.057)	-0.020 (0.019)	-0.062 (0.127)	-0.044 (0.055)	-0.265 (0.258)	**-0.085** (0.015)**
EconPosition$_2$	-0.093 (0.074)	-0.110 (0.124)	-0.024 (0.030)	-0.448 (0.299)	-0.085 (0.113)	-0.665 (0.524)	**-0.167** (0.031)**
EconPosition$_3$	-0.061 (0.061)	0.012 (0.102)	-0.026 (0.030)	-0.050 (0.234)	-0.184 (0.124)	-0.446 (0.476)	**-0.122** (0.029)**
Age	0.003 (0.014)	-0.065 (0.043)	0.002 (0.006)	-0.111 (0.076)	0.017 (0.027)	-0.127 (0.130)	**-0.013* (0.007)**
Hsize	-0.007 (0.018)	-0.022 (0.041)	-0.004 (0.008)	-0.048 (0.091)	-0.067 (0.047)	-0.007 (0.171)	**-0.045** (0.010)**
Comprehension	0.023 (0.024)	-0.016 (0.041)	0.011 (0.012)	0.067 (0.094)	0.038 (0.041)	0.286 (0.190)	**0.066** (0.011)**
Competition	-0.012 (0.008)	-0.014 (0.012)	-0.003 (0.003)	-0.019 (0.024)	**-0.022* (0.014)**	-0.047 (0.048)	**-0.022** (0.003)**
Probability of win	-	-	-	-	-	-	**0.721** (0.076)**
Max payoff	-	-	-	-	-	-	**0.019** (0.004)**
Min payoff	-	-	-	-	-	-	-0.010 (0.042)

For risk lovers, comprehension and competition do not significantly affect their risk taking behavior. On the other hand, older and male individuals are more likely to engage in risk taking behavior. Risk taking behavior is also more likely to evolve across rounds and in some lotteries, extensive training induced subjects to bid higher than the expected payoff of the lottery. It is worth noting that the pooled probit regression shows that when the winning outcome becomes more likely, the probability of behaving as a risk lover decreases. It is possible that when risk is taken out of a risky prospect, then the lottery looses its appeal for risk lovers. In addition, similar to overbidders, higher winning outcomes decrease the probability of behaving as a risk lover.

Interestingly, results for risk averse subjects follow an opposite trend. Male individuals and those exposed to extensive training are less likely to be risk averse. The effect is also less likely to evolve across rounds. Competition traits only marginally affect the probability of being a risk averter for one of the lotteries. The signs of the probability of win and maximum outcome variables in the pooled probit regressions show that they both positively affect the probability of behaving as a risk averter.

Conclusion

In this paper, we document violations in individuals' valuation of risky prospects. Subjects in our experiments valued some lotteries more than the best possible outcome of the lotteries (i.e., overbidder's effect). In some cases this can be as much as three times the maximum payoff of the lottery. Our results generally suggest that as the value of a risky prospect increases the likelihood of observing an overbidder's effect decreases. However, we do not observe an overbidder's effect in lotteries with higher maximum payoffs (i.e., lotteries with maximum payoffs more than 9€). Our results also suggest that the probability of observing an overbidder's effect is negatively related to the value of the maximum winning outcome and positively related to the likelihood of winning.

In this paper, we also showed that overbidder's effect can be partly attributed to individuals' competitiveness traits and, to some extent, comprehension of the lottery's payoff mechanism. Specifically, we find that competitiveness positively influences the probability of being an overbidder while comprehension negatively affects this probability. That competitiveness influences bids tends to suggest that the overbidding effect may be an artefact associated with eliciting values using auction-type rather than a fundamental feature of people's preference. However, we cannot rule out this latter case as it appears that characteristics of the lottery (not just characteristics of the individual) also influence the extent of over-bidding. Our results also suggest the possibility that confusion about how lotteries work (rather than with the elicitation mechanism) may be a reason for anomalous behaviour frequently observed in decision making under risk.

Our findings imply that for experiments that involve risky prospects, we should not only try to interpret the results in light of the behavioral theories that have been advanced regarding how people value risky prospects, but rather begin to develop theories of how people even understand lotteries and how the environments created by the elicitation mechanisms themselves (rather than "true" underlying references) may be responsible for "irrational" behavior.

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