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Buying and Selling Risk

An Experiment Investigating Evaluation Asymmetries

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Abstract

Experimental studies of the WTP-WTA gap avoid social trading by implementing an incentive compatible mechanism for each individual trader. We compare a traditional random price mechanism and a novel elicitation mechanism preserving social trading, without sacrificing mutual incentive compatibility. Furthermore, we focus on risky goods - binary monetary lotteries - for which asymmetries in evaluations are more robust with respect to experimental procedures. For both elicitation mechanisms, the usual asymmetry in evaluation by sellers and buyers is observed. An econometric estimation sheds new light on its causes: potential buyers are over-pessimistic and systematically underweight the probability of a good outcome.

JEL-Code: D810.

Keywords: WTP-WTA gap, risk, elicitation mechanisms, probability weighting.

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1 Introduction

Individuals appreciate uncertain outcomes in idiosyncratic ways which are, at best, privately known and this largely complicates the introduction of welfare enhancing regulation. Moreover, individual evaluations are subject to persistent biases which further question the success of external interventions aimed at improving welfare (Kahneman et al., 1991). Here, we focus on the most prominent of such biases, namely the gap between evaluations of sellers and buyers, commonly labeled WTP-WTA gap (see Plott and Zeiler, 2005, and the references therein). This bias not only creates problems for policy makers by questioning the existence of mutually profitable trade, but has also crucial implications for economic theory. As an example, in the presence of the gap, indifference curves depend on one's endowment and the usual considerations based on marginal rates of substitution become questionable (e.g., Knetsch, 1989).

Several interpretations have been suggested for this phenomenon, with most explanations relying on models of reference-dependent preferences. Thaler (1980) refers to the asymmetry in evaluations as *endowment effect*, a phenomenon originating in the loss aversion which is at the core of prospect theory (Kahneman and Tversky, 1979). The seller endowed with a good views selling as a loss, whereas purchasing the good is perceived as a gain. Focus on the loss, respectively the gain, of the physical commodity only, without taking into account the opposite effect of money, together with the asymmetry in evaluation of losses and gains postulated by prospect theory, makes sellers reluctant to give up a good. This implies that, ceteris paribus, sellers attach higher value to goods than buyers. Huck et al. (2005) propose an evolutionary argument to explain asymmetries in evaluations and suggest that endowment effects are hard-wired into preferences. Köszegi and Rabin (2006) adopt a different perspective and explain the endowment effect as originating from expectations about future trades and not from ownership of the good. This alternative interpretation is compatible with the lower levels of asymmetry observed among experienced traders (e.g., List, 2003).

While several experimental works have confirmed the existence of the WTP-WTA gap, its exact nature is still subject of dispute. Plott and Zeiler (2005) argue that the WTP-WTA gap usually observed in experiment is most likely an *experimental artifact* due to misconceived experimental procedures. In their carefully designed experiment, they try to ensure that participants fully understand the task they face and observe no significant WTP-WTA gap in a classic mug-trading experiment. However, Isoni et al. (2011) show that for a specific kind of goods, i.e. lotteries, the asymmetry in evaluations is resilient to strict experimental procedures aimed at minimizing misconceptions.[1]

The articles briefly reviewed above suggest that lotteries provide a more reliable medium to measure the WTP-WTA gap relative to physical goods. In light of this evidence, we employ a rich set of lotteries and test the robustness of the WTP-WTA gap across two distinct elicitation procedures, with participants choosing both as sellers and as buyers. In one condition, we adopt the standard Becker et al. (1964)'s random price mechanism (BDM), while in another condition we introduce a novel incentive-compatible mechanism of bilateral bargaining via subsidizing of possible price disagreements. In the latter mechanism, both the seller and the buyer state reservation prices, i.e. a lower and an upper price threshold, respectively. Only when reservation prices are consistent, i.e. the seller's threshold does not exceed that of the buyer, the commodity is sold with the buyer paying the seller's reservation price and the seller receiving the buyer's reservation price.

We find a systematic WTP-WTA gap for the set of lotteries investigated. The size of the gap does not differ substantially across the two elicitation protocols. Moreover, a simulation shows that the bargaining method requires lower implementation costs than the random price mechanism.

We exploit the nature of our lotteries to explore the causes of the WTP-WTA gap. The value of a lottery is given by the interaction of two distinct elements: the value attached to prospective outcomes and the perceived likelihood of these outcomes. To assess which of the two dimensions drives the gap, we adopt the procedure of Abdellaoui et al. (2011). Specifically, we test whether the WTP-WTA gap, observed for our set of lotteries, is due to higher risk aversion among buyers than among sellers or to differences in probability weighting. We show that whereas risk preferences of buyers and sellers do not differ substantially, probability weighting does. Specifically, buyers tend to systematically underweight probabilities. In contrast, sellers' probability weighting is in line with previous findings, namely crossing from overvaluation to undervaluation of experimentally induced objective probabilities at about 40% probability (as an example, see Prelec, 1998). Thus, we conclude that the WTP-WTA gap in our experiment is mainly due to pessimism of buyers. We will offer an interpretation of this finding and discuss some directions for future research inspired by our results.

The remainder of the paper is organized as follows: in section 2.1 we introduce the two mechanisms more formally as well as their costs. Section 2.2 describes the experimental protocols and specifies the lotteries to be evaluated.

[1] Also Plott and Zeiler employed, together with mugs, a series of lotteries, but only results about mugs are reported in the published paper. However, according to Isoni et al. the usual WTP-WTA gap is also present in Plott and Zeiler's lottery data.

In Section 2.3 we restate the robustness tests we are interested in and specify the rank-dependent utility model which is employed in our econometric analysis. Section 3 describes the data and the outcomes of the econometric analysis. Section 4 concludes.

2 Method

2.1 Experimental Choice Tasks

We consider simple lotteries in which x_l and x_h are, respectively, low and high monetary prizes and p_h is the probability associated to x_h, with $1-p_h$ being the complementary probability for x_l. We assume $x_h > x_l \geq 0$ and $0 < p_h < 1$. We elicit the value attached to each lottery twice: when selling and when buying the lottery. Elicitation is performed under two distinct protocols, one based on a random price mechanism (BDM) and one based on bilateral bargaining. The two mechanisms are labeled R-mechanism and B-mechanism, respectively.[2]

In the role of buyer, a participant is endowed with money and chooses the highest price which she is willing to pay for the $(x_l, 1-p_h; x_h, p_h)$ lottery (WTP). How WTP determines the outcome depends on the mechanisms as follows:

- in the R-mechanism, the randomly drawn price $v \in [x_l, x_h]$ is compared to the reported WTP: if $v >$ WTP, no trade occurs and the buyer keeps its monetary endowment; if $v \leq$ WTP, the buyer buys the lottery at the price v, i.e. she finally owns the lottery and her monetary endowment is diminished of v;

- in the B-mechanism what is compared with the reported WTP is the WTA-choice of another individual for the same $(x_l, 1-p_h; x_h, p_h)$ lottery. The payoff is computed like in the R-mechanism replacing v with the WTA of the other.

In the role of seller, a participant is endowed with the lottery and specifies the lowest price she is willing to accept to sell it (WTA). Depending on the mechanism adopted, outcomes are determined as follows:

- in the R-mechanism, $v \geq$ WTA is the condition for selling, meaning that if the condition is met the individual collects v and gives up the $(x_l, 1-p_h; x_h, p_h)$-lottery, else the individual keeps the lottery;

[2]The instructions (see Appendix B), carefully explain the two mechanisms and the nature of the lotteries.

- in the B-mechanism, the same procedure adopted in the R-mechanism is followed, except for the price v that is replaced by the WTP-choice of another individual for the same $(x_l, 1-p_h; x_h, p_h)$ lottery.

For opportunistic expected utility maximizers agents, the B-mechanism is incentive-compatible, but it offers a social context for mutually-beneficial cooperation among the buyer and the seller.[3] More specifically, by setting WTA as low as possible and WTP as high as possible the buyer and the seller can increase what they earn, what would increase the external costs of the B-mechanism.

When a contract is closed, the cost of the two mechanisms for the experimenter is defined by the price faced by buyers and sellers. Because of this, costs of guaranteeing mutual incentive compatibility may differ across the two mechanisms. For the R-mechanism, these "external" costs are either $x_h - v$ or $x_l - v$, depending on the chance move, specified by the probability p_h, respectively $1 - p_h$, of the WTP-task. For the WTA-task the costs in case of selling are either $v - x_h$ or $v - x_l$, respectively, depending on this chance move. For the B-mechanism, the external costs are similarly either $x_h - WTA$ or $x_l - WTA$ in the WTP-task and $WTP - x_h$ or $WTP - x_l$ in the WTA-task, where WTA and WTP in these payoff specifications are the choice of another individual in the opposite role for the same $(x_l, 1-p_h; x_h, p_h)$ lottery.

2.2 Experimental Protocol

Table 1 provides a summary of the 13 lotteries used in the experiment specifying the high and the low payoff and the associated probabilities (probability p_l of the low payoff is omitted in the table as it is always equal to $1-p_h$). Columns E_b and E_s identify the initial endowment of the buyer and the seller, respectively. The last column to the right captures the expected payoff of the lotteries for buyers and sellers.[4]

[Insert Table 1 about here]

[3] In the B-mechanism, declaration of the true reservation value is weakly dominant provided that the subjects' beliefs about other subjects evaluations assign positive probability to the values in the range $[x_l, x_h]$.However, the second price auction (Vickrey, 1961) is known to induce collusion in the form of cartel/ring formation (Fehl and Gueth, 1987).

[4] Expected values π_b and π_s are computed under the assumption of risk neutrality and a uniform distribution of the random price mechanism. For $EV = x_h p_h + x_l(1-p_h)$ and P as the choice variable, buyer's payoff is given by $\pi_b(P) = E_b + \int_{x_l}^{P} [EV - P] \frac{1}{x_h - x_l} \mathrm{d}P$, while seller's payoff is given by $\pi_s(P) = E_s + \int_{x_l}^{P} EV \frac{1}{x_h - x_l} \mathrm{d}P + \int_{P}^{x_h} P \frac{1}{x_h - x_l} \mathrm{d}P$. Both equations are maximal for $P^* = EV$, what implies that buyer's expected payoff is $\pi_b(P^*) = E_b + EV * \frac{EV - x_l}{x_h - x_l} - \frac{1}{2} \frac{EV^2 - x_l^2}{x_h - x_l}$. Similarly, seller's expected payoff is $\pi_s(P^*) = E_s + EV * \frac{EV - x_l}{x_h - x_l} + \frac{1}{2} \frac{x_h^2 - EV^2}{x_h - x_l}$. We set $E_b = x_h$ so that buyers can potentially afford any sensible price. Accordingly, we set E_s such that the expected payoff of the seller is equal to the one of the buyer, i.e., $E_s = E_b - \frac{x_h - x_l}{2}$.

As shown by the table, for lotteries 1–7 the probability associated to outcomes is kept constant and equal for the two outcomes. Differently, values associated to outcomes change across prospects, with high payoffs equal to 5, 10, 15 or 20 and low payoffs equal to 0, 5 or 10. For lotteries 8–13, the high payoff is always equal to 15 and the low payoff is always equal to 0. Probabilities of the high outcome differ across prospects, from 1/8 to 7/8.

The instructions of the R- and B-mechanism mainly differ in how prices, to be paid or received, are generated (see Appendix). Both in the R-mechanisms and in the B-mechanism, participants are asked for both the minimum price at which they are willing to sell the lottery and the maximum price at which they are willing to buy the lottery ticket, for each of the 13 lotteries in Table 1. In the R-mechanism, however, participants are matched with a (computerized) random number generator, while in B-mechanism they encounter a (human) bargaining partner. Thus, participants in the R-mechanism learn how the relevant price v is randomly drawn by the computer, while in the B-mechanism participants are told that the relevant price is the choice of another participant in the opposite role. Transactions are then executed following the rules of price matching. For a seller: when the price offered to the seller is greater or equal than her stated WTA, the lottery ticket is sold at the offered price; otherwise, the lottery is not sold and played out for the seller. For a buyer: when the price is lower or equal than her WTP, the lottery ticket is bought at that price and played out for the buyer; otherwise, the lottery is not bought.

2.3 Hypotheses

Standard benchmark analysis, based on common(ly known) monetary opportunism and well-behaved risk preferences, would predict no significant differences between the distributions of WTP and WTA. However, in light of the strong evidence in support of the WTP-WTA gap, we expect to reject this hypothesis. Concerning the two elicitation mechanisms employed, we test whether participants exploit the cooperation opportunities provided by the B-mechanism, which involves a social setting and thus can inspire other-regarding concerns. Actually, both parties, the buyer and the seller, can gain from voluntary cooperation (see Bolton et al., 2005, for evidence of cooperation based on expected gains only).[5] When actually cooperating, we expect to observe the usual WTP-WTA gap in the R-mechanism but the converse in the B-mechanism. Since trading partners cannot coordinate on how to arrange such voluntary cooperation, one may view this as a worst-case scenario for testing voluntary cooperation.

[5] The potential buyer can increase the potential seller's profit by choosing a higher WTP and, conversely, the seller can help the buyer by lowering her WTA.

We also compare the two mechanisms in terms of their implementation costs. In particular, we are going to tests whether the B-mechanism is more expensive than the familiar R-mechanism, namely because of voluntary cooperation.

In case a significant difference between the price posted by the buyer and the seller is observed, we try to assess the potential determinants of the gap econometrically. Specifically, we assume a rank-dependent utility specification estimated by using all choices by an individual participant. For our binary lotteries, the utility of a participant for each single lottery, when neglecting initial endowment, can be generally represented as $U(x_h, x_l, p_h) = w(p_h)u(x_h) + [1 - w(p_h)]u(x_l)$. We are going to estimate whether the gap between evaluations as buyer and seller originates mainly in the evaluation of outcomes or in the weighting of the objectively induced probabilities. Specifically, we are going to simultaneously test whether one differs as buyer or seller in risk perception or in pessimism about the likelihood of a favorable outcome.

A positive WTP-WTA gap is compatible both with higher risk aversion when being a buyer than when being a seller and with more pessimism of buyers relative to sellers. By our analysis we hope to shed light on which of the two sources, if any, is more relevant. Previous works have shown that the environment is likely to affect preferences in the long term (Bowles, 1998). However, we expect risk preferences to be quite robust across roles in our short-lived experiment. Differently, probability weighting seems to be more responsive to environmental stimuli and emotional states (e.g., Brandstätter et al., 2002). Thus, we expect the WTP-WTA gap in lottery evaluations to be mainly due to a difference in probability weighting rather than by swift changes in risk propensities.

2.4 Participants and Procedures

The experiment was conducted at the experimental laboratory of the Max Planck Institute of Economics (Jena, Germany). Participants were recruited among undergraduate students of the Friedrich-Schiller University of Jena using the ORSEE software (Greiner, 2004). A total of 254 participants took part in the experiment, 128 in the B-mechanism and 126 in the R-mechanism, over 8 distinct experimental sessions. Each sessions lasted about 70 minutes and average earnings amounted to €16.

Upon their arrival in the laboratory, participants were randomly assigned to computer terminals in isolated cubicles. The experiment was programmed and conducted using z-Tree software (Fischbacher, 2007). Participants received written instructions and before the start of the experiment had to answer a few control questions checking their understanding of the instructions.

Each participant took part in both roles, seller and buyer. To control for potential order effects, half of the participants were choosing first as seller and then as buyer, while the other half were choosing in the reversed order. Moreover, for each role and each individual, the order of the 13 lotteries was random. At the end of the experiment, 1 of the 26 choices was randomly chosen for payment, earnings computed, and payments were privately dispensed in cash.

3 Results

3.1 Description of Choices

Figure 1 provides a summary description of the distribution of the differences between the WTA of sellers and the WTP of buyers, for each lottery. Boxplots provide us with conventional information about the quantiles of the distributions, while the dashed horizontal line captures the average WTP-WTA gap across prospects.

[Insert Figure 1 about here]

As shown by the boxplots in Figure 1, median differences between WTA and WTP are positive for all prospects, both in the R-mechanism and in the B-mechanism. Furthermore, for most of the lotteries the interquartile range is defined over positive values. Average WTP-WTA gaps are equal to 2.233 for the R-mechanism and equal to 2.056 for the B-mechanism. Thus, our data support the existence of the usual gap between evaluations of sellers and buyers, with the former providing a higher evaluation for risky prospects than the latter. The existence of the gap is corroborated also by non-parametric tests. According to one-sample sign tests, averages of the WTP-WTA gap are significantly different from zero (for both elicitation mechanisms, p-values< 0.001).

Result 1 *The WTP-WTA gap is robustly confirmed for both elicitation mechanisms.*

Having shown a positive WTP-WTA for both elicitation conditions, we check whether the two differences significantly differ across the two elicitation mechanism. According to a Wilcoxon Rank Sum Test, the WTP-WTA gaps do not significantly differ between the two elicitation mechanisms (p-value=0.293).[6]

Result 2 *The WTP-WTA gap does not substantially differ between the two elicitation mechanisms.*

[6] The test is performed by taking individual-level averages.

3.2 Implementation Costs of the Mechanisms

The analysis above revealed no significant differences between prices posted in the two elicitation mechanisms. Still, their external costs may differ substantially. Here we compare the two mechanisms in terms of their cost for the experimenter via a Montecarlo simulation.

At each step, we calculate the payoff of each participant given her reported evaluations and the rules of the mechanism.[7]

[Insert Figure 2 about here]

Figure 2 provides a representation of the distribution of average payoffs in the two elicitation mechanisms (1000000 simulations). The figure clearly illustrates that in our simulation the implementation costs of the R-mechanism are higher than those of the B-mechanism: median payoffs are €16.5 and €15.4, respectively (Wilcoxon rank sum test's p-value< 0.001).

Result 3 *The implementation costs of the R-mechanism are higher than those of the B-mechanism.*

To gain in the understanding of the determinants of this difference, we consider both the number of transactions closed in the two mechanisms and the distribution of payoffs in correspondence to a closed transaction in the two mechanisms. In our simulation, we adopt the same algorithm adopted in the experiment to check whether a contract is closed or not.

The simulations show that significantly less transactions are closed in the B-mechanism than in the R-mechanism. Furthermore, transactions closed in the R-mechanism are definitely more valuable for the participants, and more expensive for the experimenter, than transactions closed in the B-mechanism.[8] These two pieces of information, together with the fact that a closed contract is always more expensive than a contract not closed, explain why the B-mechanism is less expensive for the experimenter than that the R-mechanism. This difference is mainly due to the differences in prices faced by participants in the two conditions. In particular, sellers in the B-mechanism face high random prices less often than sellers in the R-mechanism, in which prices are uniformly distributed. Furthermore, buyers in the B-mechanism face low random prices less often than buyers in the R-mechanism.

[7] See Appendix E for more details on the procedure and a robustness check

[8] In the R-mechanism, 41.3% of the contracts in the simulation are closed, while in the R-mechanism only 30.6% are closed. The average cost of a closed contract is equal to 18.360 and 16.550 in the R- and B- mechanism, respectively.

3.3 Econometric analysis

3.3.1 Model and Procedures

In the following, we assume that participants are Rank Dependent Utility (RDU) maximizers.[9] Thus, the utility $U(L)$ of each lottery $L = (x_1, p_1; \ldots; x_n, p_n)$ is given by the sum of weighted utilities of the two monetary prizes, with the weighting function $w(p)$ increasing in p, and subject to $w(0) = 0$ and $w(1) = 1$. Due to the restriction to binary lotteries $L = (x_l, (1-p_h); x_h, p_h)$, with $x_l < x_h$, the expected utility of a lottery is given by $U(L) = \big(w(1) - w(p_h)\big)u(x_l) + \big(w(p_h) - w(0)\big)u(x_h) = w(p_h)u(x_h) + \big(1 - w(p_h)\big)u(x_l)$.[10]

Given this utility specification, a seller endowed with E_s and asking a price P_s evaluates the lottery $L = (x_l, (1 - p_h); x_h, p_h)$ by

$$u(E_s + P_s) = w(p_h)u(E_s + x_h) + \big(1 - w(p_h)\big)u(E_s + x_l) \tag{1}$$

and a buyer endowed with E_b and paying a price P_b by

$$u(E_b) = w(p_h)u(E_b + x_h - P_b) + \big(1 - w(p_h)\big)u(E_b + x_l - P_b) \tag{2}$$

.

As a specification for the utility function, we adopt a conventional exponential specification capturing Constant Absolute Risk Aversion (CARA), $u(x) = \frac{1-\exp(-\rho x)}{\rho}$. Substituting this utility function in equations 1 and 2 one can obtain the prices P_s and P_b for a lottery L as a function of ρ and $w(p)$.[11]

$$P_s(L) = P_b(L) = -\frac{1}{\rho}\ln\Big(w(p)\exp(-\rho x_h) + \big(1 - w(p)\big)\exp(-\rho x_l)\Big) \tag{3}$$

We estimate the risk aversion parameter ρ and probability weighting $w(p)$ at $p \in \{\frac{1}{8}, \frac{2}{8}, \frac{3}{8}, \frac{4}{8}, \frac{5}{8}, \frac{6}{8}, \frac{7}{8}\}$ for each subject, both when choosing as a seller and as a buyer. At this aim, we follow the procedure suggested by Abdellaoui et al. (2011).[12] First, we obtain an estimate of ρ and $w(0.5)$ by minimizing the sum of squared distances between the WTAs and the prices P_s and between WTPs and

[9] For the present analysis, we assume that the WTAs and WTPs stated by the subjects are good approximations of the certain equivalents under RDU. Karni and Safra (1987) prove that this is not generally the case. However, Safra et al. (1990) show that prices collected relying on the BDM procedure can still be informative of underlying preferences of RDU agents.

[10] For the general case of more than two ordered monetary outcomes, the expected utility of a lottery is equal to $U(L) = \sum_i \left[w\left(\sum_{j=i}^{n} p_j\right) - w\left(1 - \sum_{j=1}^{i} p_j\right)\right] u(x_i)$, where $n(> 2)$ denotes the number of monetary payoffs.

[11] In Appendix D we replicate the same estimation with a Constant Relative Risk Aversion (CRRA) function. Results are robust across the two utility function specifications, overall.

[12] We adopt here a subject-by-subject estimation procedure similar to that adopted, as an example, by Hey and Orme (1994).

the prices P_b, for lotteries 1–7 (see Table 1). Second, we use the estimated ρ to obtain non-parametric estimates of the weights $w(p)$ for $p \neq 0.5$ from the WTAs and WTPs of lotteries 8–13.[13] Third, for each participant we fit Prelec (1998)'s weighting function $w(p) = \left[\exp\left(-\left(-\ln(p)\right)^{\alpha}\right)\right]^{\beta}$ to the non-parametric estimate of the weights via a NLS procedure (See Appendix C for details). Prelec's function captures attitudes toward probabilities by means of two parameters: α and β. Following the interpretation given by Abdellaoui et al. (2011), α captures sensitivity to probabilities and β pessimism.[14] To elaborate, the parameter α measures how much participants react to changes in probabilities, with a higher α representing higher sensitivity. With only two outcomes, the parameter β captures the under-weighting of the good outcome and, thus, directly measures pessimism, with a higher β capturing higher pessimism. In graphical terms, a higher α generates a steeper weighting function, while a higher β generates a more convex weighting function (see Appendix C for a graphical representation of the impact of a change in the parameters on the weighting function).

3.3.2 Estimation Outcomes

Table 2 displays median estimated values of ρ, α, and β from equation (3), in the B-mechanism and in the R-mechanism. Together with descriptive statistics, the table reports the outcomes of a series of non-parametric tests (i.e., p-values).[15]

[Insert Table 2 about here]

Concerning the level of risk aversion, the median estimated values of ρ are slightly negative, both when selling and buying and for both elicitation mechanisms. A series of Sign Tests fails to reject the hypothesis of risk neutrality ($\rho = 0$) only for the selling task in the BDM treatment (the same results are obtained when relying on a Wilcoxon Signed Rank Test). Thus, the representative participant of our experiment seems to be slightly risk-seeking. Moreover, attitudes towards risk are not strongly influenced by the role or by the elicitation procedure. This is confirmed by a series of tests comparing risk aversion when selling and when buying (ρ_s versus ρ_b) showing that the differences $\rho_s - \rho_b$ are not significantly different from zero (see the Sign Test $M(\theta_S - \theta_B) = 0$ in Table

[13] An individual point estimate of $w(p)$ for $p \neq 0.5$ is obtained by solving equation (3) for $w(p)$, i.e., $w(p) = \frac{\exp(-\rho P) - \exp(-\rho x_l)}{\exp(-\rho x_h) - \exp(-\rho x_l)}$, and substituting WTA (WTP) for P and $\hat{\rho}$ for ρ

[14] Wu and Gonzalez (1996) also consider these two dimensions of probability weighting, and use "discriminability" to capture sensitivity and "attractiveness" to capture pessimism. As the authors point out, the two parameters can be thought as measuring curvature and elevation of the weighting function, respectively.

[15] We avoid using the t-test because of strong non-normality of the distributions. We rely instead on the Sign Test, that is generally less powerful than the Wilcoxon Signed Rank Test (WSRT) but does not assume the symmetry of the distribution. Overall, the WSRT and the Sign Test deliver similar results.

2). When comparing risk attitudes across treatments, no significant differences are observed, neither as buyers (Kolgomorov-Smirnov Test, p-value = 0.148) nor as sellers (p-value = 0.357).

Result 4 *Risk attitudes are not significantly different across roles and elicitation mechanisms.*

Table 2 presents the median estimated values of parameters α and β in the weighting function $w(p) = \left[\exp\left(-\left(-\ln(p)\right)^{\alpha}\right)\right]^{\beta}$. Concerning the sensitivity parameter α, we fail to reject the hypothesis of the same sensitivity when selling and when buying (see Sign-test $M(\theta_S - \theta_B) = 0$ in Table 2). Furthermore, estimated parameters α do not significantly differ across the two elicitation methods, neither as buyers nor as sellers (Kolmogorov-Smirnov Test, p-value=0.989 and p-value=0.921, respectively).Thus, we can safely conclude that subjects show the same sensitivity in both treatments.

Result 5 *Buyers and sellers display similar sensitivities to a change in probabilities, for both elicitation mechanisms.*

When taking into account the pessimism parameter β, estimations strongly support the hypothesis of underweighting probabilities more when buying than when selling, in both treatments (see Sign Test $M(\theta_S - \theta_B) = 0$ in Table 2). Similar to what is reported above for the α parameter, no significant differences are observed when comparing estimated parameters across elicitation procedures (Kolmogorov-Smirnov Test, p-value=0.589 for choices as sellers and p-value=0.888 for choices as buyers).

Figure 3 graphically illustrates the probability weighting function $w(p)$ in correspondence to the median weights, for the B-mechanism and for the R-mechanism. The • dots (solid line) identify sellers, while the ▲ dots (dashed line) identify buyers.

[Insert Figure 3 about here]

The figure clearly illustrates the higher pessimism of buyers relative to sellers as captured by persistent underweighting of probabilities. The high pessimism of buyers results in a fixed point corresponding to p=0, while the estimated fixed point of sellers in Figure 3 is close to p=.40, a finding in line with estimates reported in the literature (e.g., Prelec, 1998; Abdellaoui et al., 2011). Overall, sellers in our experiment display a behavior that is consistent with previous estimates. In contrast, buyers persistently underweight probabilities and do not display the typical overweighting of small probabilities highlighted by previous contributions.

Result 6 *Buyers systematically underweight probabilities relative to sellers and to previous findings in the literature, for both elicitation mechanisms.*

4 Discussion and Conclusions

A persistent gap between willingness to pay and willingness to accept for physical goods has been documented in the literature. A possible explanation for this pattern is an asymmetry in preferences known as endowment effect. Recently, though, this explanation has been questioned by claiming that previous findings can be, at least partly, classified as mere experimental artifacts. Here, we focus on a class of goods, i.e. risky prospects, which seem to generate asymmetries in evaluations also when applying strict experimental procedures. We compare reservation values obtained under two elicitation mechanisms, a traditional random price mechanism and a novel bargaining setting in which the two parties directly interact with each other.

We show, in line with previous findings on WTP-WTA gap, that sellers tend to value lotteries more than buyers. Overall, the two elicitation mechanisms delivery very similar results in terms of evaluation gap. This shows that there has been no significant attempt to exploit the cooperative incentives in the B-mechanism. In our view, this does not allow to characterize the B-mechanism as cooperation-proof. Giving the opportunity to buyers ans sellers to communicate before bidding might foster voluntary cooperation.

When comparing the costs of the two mechanisms for guaranteeing mutual incentive compatibility, the mechanism based on a bargaining interaction is less expensive than the random price mechanism. This is surprising since bargaining introduces a social setup allowing participants to engage in voluntary cooperation, which would render experiments more expensive (for the experimenters).[16]

Altogether we shed new light on the reasons for the gap in evaluations. Specifically, we econometrically estimate parameters of risk aversion and of probability weighting, separately for the roles of sellers and buyers. Risk aversion is an idiosyncratic preference trait that is usually assumed to be quite stable at the individual level. Probability weighting instead is driven by cognition as it reflects how individuals process information.

Our estimation distinguishes between two components of probability weighting, sensitivity to a change in probability and under-weighting of probabilities. We find that risk preferences do not substantially depend on whether deciding as buyers or sellers, but probability weighting does. Specifically, buyers are

[16] This is true under the assumption of no WTP-WTA gap. In case of a price gap, the bargain mechanism offers a lower likelihood to observe a trade compared to the random price mechanism.

more pessimistic than sellers in our study and also more pessimistic than individuals in previous studies. Thus, the gap in evaluations seems to be driven by the anomalously under- (over-) weighting of probabilities associated to the best (worse) outcome in case of two outcome prospects.

Regarding further research into the determinants of buyers' behavior, Brandstätter et al. (2002) that probability weighting is affected by emotions, with expected disappointment prompting under-weighting and expected elation prompting over-weighting. It seems plausible that the emotional involvement of buyers exceeds that of sellers because only buyers "invest" in a risky prospect. Because of this, expected disappointment may loom larger for buyers than for sellers. Testing this conjecture should rely on an experimental setting eliciting or manipulating emotional involvement and goes beyond the scope of our study.

Our novel incentive-compatible elicitation protocol, placing individuals in a familiar bargaining setting of social trade, delivers consistent results and requires less subsidies than the quite artificial random price mechanism. Future studies will hopefully employ this elicitation mechanism to test its functionality also in other environments.

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A Figures and Tables

Figure 1: WTP-WTA gap across lotteries and elicitation methods

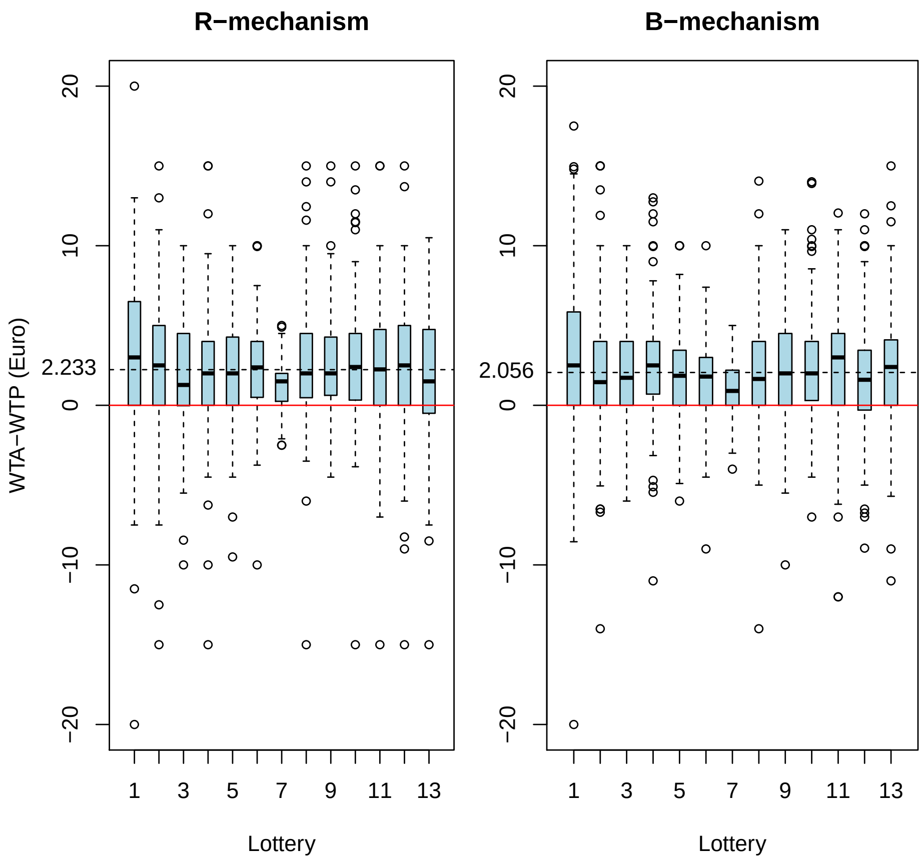


Figure 2: Distributions of average individual payoff

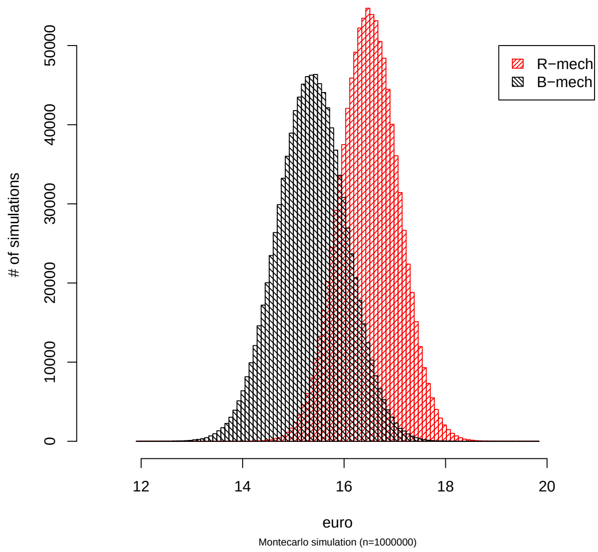
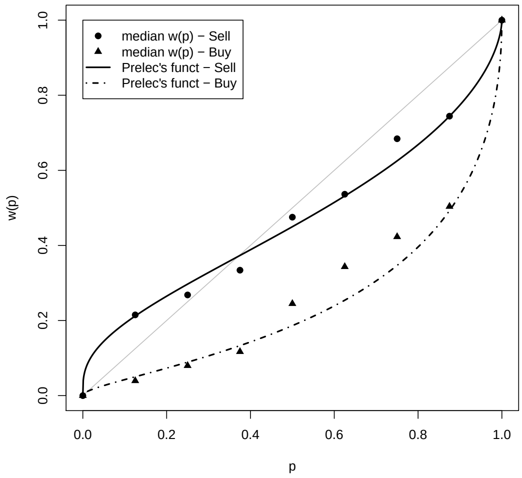


Figure 3: Prelec's weigthing function median weights (CARA)

R-mechanism



B-mechanism

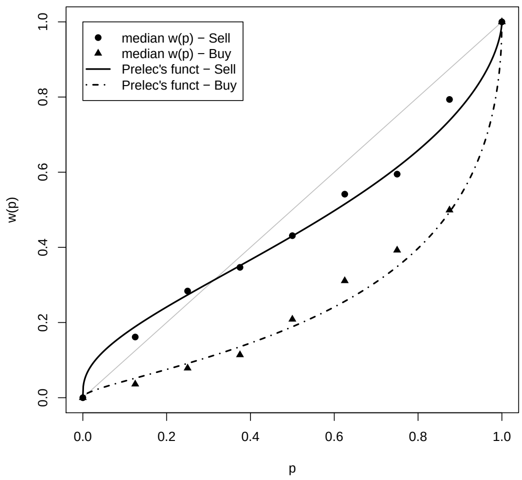


Table 1: Lotteries

#	x_h	x_l	p_h	E_b	E_s	$\pi_b = \pi_s$
1	20.00	0.00	4/8	20.00	10.00	22.50
2	20.00	5.00	4/8	20.00	7.50	21.87
3	20.00	10.00	4/8	20.00	5.00	21.25
4	15.00	0.00	4/8	15.00	7.50	16.87
5	15.00	5.00	4/8	15.00	5.00	16.25
6	10.00	0.00	4/8	10.00	5.00	11.25
7	5.00	0.00	4/8	5.00	2.50	5.62
8	15.00	0.00	1/8	15.00	7.50	15.12
9	15.00	0.00	2/8	15.00	7.50	15.47
10	15.00	0.00	3/8	15.00	7.50	16.05
11	15.00	0.00	5/8	15.00	7.50	17.93
12	15.00	0.00	6/8	15.00	7.50	19.21
13	15.00	0.00	7/8	15.00	7.50	20.74

Table 2: Estimated parameters (CARA)

Parameter θ	Role	Median	Interquartile Range	Sign Test $M(\theta) = \theta_0$	Sign Test $M(\theta_S - \theta_B) = 0$
			R-mechanism		
ρ	Seller	-0.011	[-0.114, 0.076]	0.185	0.063†
	Buyer	-0.044	[-0.159, 0.029]	*0.002*	
α	Seller	0.604	[0.330, 0.934]	*0.000*	0.331
	Buyer	0.525	[0.306, 0.840]	*0.000*	
β	Seller	0.997	[0.679, 1.655]	0.791	*0.000*
	Buyer	2.037	[1.251, 2.917]	*0.000*	
			B-mechanism		
ρ	Seller	-0.027	[-0.148, 0.044]	*0.010*	0.061
	Buyer	-0.081	[-0.169, 0.006]	*0.000*	
α	Seller	0.619	[0.366, 0.977]	*0.000*	0.061
	Buyer	0.522	[0.317, 0.881]	*0.000*	
β	Seller	1.059	[0.611, 1.860]	0.423†	*0.000*
	Buyer	2.019	[1.270, 2.805]	*0.000*	

† A Wilcoxon Signed Rank Test rejects the null hypothesis

B Instructions to Participants

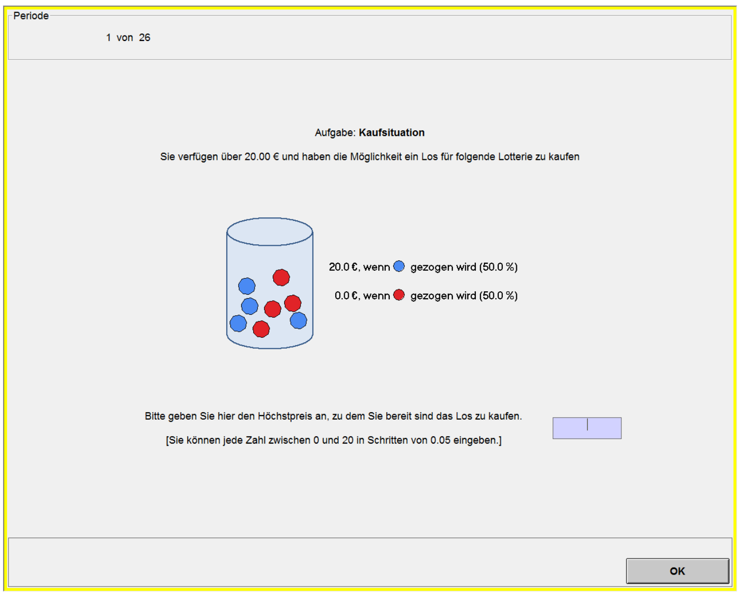
Welcome! This is an experiment founded by the Max Planck Institute of Economics. Please remain silent and switch off your mobile. If you have any questions during the experiment please raise your hand an experimenter will come to your place to answer.

You have the opportunity to earn an amount of money by participating in this experiment. Your earnings depend on your decisions during the experiment. There are no right or wrong ways to complete the experiment, however it is in your interest to read carefully these instructions in order to understand how your earnings depend on your decisions.

The experiment consists of two parts, in one part you will perform a series of selling tasks and in the other part you will perform a series of buying tasks. Below it is explained what a buying task and a selling task is. The order of the two parts is randomly determined at the beginning of the experiment. So you may either decide first as a buyer and then as a seller or first as a seller and then as a buyer. Your earnings will be determined according to **one** of the tasks you face during the experiment. The relevant task is randomly determined at the end of the experiment. Note that each task is equally likely to be the relevant one so is in your interest to treat each decision as if it were the one that determines your payment. Note that lottery prizes, endowment, and probability can vary from round to round.

Traded Items

The items you will buy and sell during the experiment are **lottery tickets**. A lottery ticket gives you the opportunity to win one out of two different money prizes according to the color of the ball that is drawn from an urn. As an example, consider an urn containing 4 red and 4 blue balls. The lottery ticket may give you the opportunity to win €20 in case a blue ball is drawn from an urn containing 4 red and 4 blue balls and to win €5 in case a red ball is drawn from the same urn. Figure 1 gives you an example of the screen used to describe and evaluate the lotteries.



Original Screenshot

Selling Task

When you decide as a **Seller** you will face a series of 13 selling tasks. In each task you are endowed with an amount of money and a lottery ticket. You have to decide the **minimum price at which you are willing to sell the lottery ticket**.

`R-mechanism starts here`

In order to determine if you sell or not the ticket the computer will make you a random offer. If the offer is greater than or equal to your price, then you sell the lottery ticket and receive the computer offer. If the computer offer is lower than your price then you do not sell the lottery ticket and you play the lottery.

> **Example:** Suppose you are endowed with 10.00 and that your minimum selling price is 12.50. If the computer offer is 14.00 you sell the ticket, keep the endowment, and receive the 14.00. If instead the computer offer is 9.50 you do not sell the ticket, keep the endowment, and obtain the outcome of the lottery.

`R-mechanism ends here`

`B-mechanism starts here`

In order to determine if you sell or not the lottery ticket the computer will randomly **match you with another participant** that was deciding as a buyer on that lottery. Buyers are asked to submit the maximum price at which they are willing to buy the lottery ticket. If the price submitted by the buyer is greater than or equal to your price, then you sell the lottery ticket and receive the price offered by the buyer. The buyer, on the other hand, buys the ticket and pays the price you submitted.

In case the price offered by the buyer is lower than your price then you do not sell and the buyer does not buy the lottery ticket.

> **Example:** Suppose you are endowed with 10.00 and that your minimum selling price is 12.50. If the buyer offer is 14.00 you sell the ticket to the buyer, keep the endowment, and receive 14.00. The buyer on the other hand buys the lottery ticket and pays 12.50. If instead the buyer offer is 9.50 you do not sell the ticket, keep the endowment of 10.00, and obtain the outcome of the lottery.

`B-mechanism ends here`

You should submit prices according to your preferences. There are no objectively "correct" values for submitting the prices. Personal values can differ from individual to individual.

Buying Task

When you decide as a **Buyer** you will face a series of 13 buying tasks. In each task you are endowed with an amount of money and are presented with a lottery. You have to decide the **maximum price at which you are willing to buy the lottery ticket**.

`R-mechanism starts here`

In order to determine if you buy or not the ticket the computer will make you a random offer. If this offer is less than or equal to your price, then you buy the lottery ticket and pay the computer offer. If the computer offer is higher than your price then you do not buy the lottery ticket.

> **Example:** Suppose you are endowed with 20.00 and your maximum buying price is 12.50. If the computer offer is 9.50 you buy the ticket, pay 9.50 from your endowment, and obtain the outcome of the lottery. If instead the the computer offer is 14.00 you do not buy the ticket and keep your endowment.

`R-mechanism ends here`

`B-mechanism starts here`

In order to determine if you buy or not the lottery ticket the computer will randomly **match you with another participant** that was deciding as a seller on that lottery. Sellers are asked to submit the minimum price at which they are willing to sell the lottery ticket. If the price asked by the seller is smaller than or equal to your price, then you buy the lottery ticket and pay the price offered by the seller. The seller, on the other hand, sells the ticket and receives the price you submitted.

In case the price asked by the seller is higher than your price then you do not buy and the seller does not sell the lottery ticket.

> **Example:** Suppose you are endowed with 20.00 and your maximum buying price is 12.50. If the seller offer is 9.50 you buy the ticket from the seller, pay 9.50 from your endowment, and obtain the outcome of the lottery. The seller on the other hand sells the lottery ticket and receives 12.50. If instead the seller offer is 14.00 you do not buy the lottery ticket and keep your endowment.

`B-mechanism ends here`

You should submit prices according to your preferences. There are no objectively "correct" values for submitting the prices. Personal values can differ from individual to individual.

`R-mechanism starts here`

How does the computer select the random offer?

In order to determine whether you buy/sell each the lottery ticket the computer will make you an offer that is independent of the price you submitted. The offer is determined by randomly drawing a number from the interval defined by the two prizes of the lottery. So, for instance, if the lottery you are trading gives the opportunity to win either €20 or €5, the computer offer will be a randomly drawn number between 20 and 5.

`R-mechanism ends here`

Your Earnings

As we have already mentioned your earnings are determined by the outcomes of only one of the 26 tasks you face in the experiment. How this works is as follows:

`R-mechanism starts here`

- The computer randomly selects one of the lotteries evaluated during the experiment and whether you are a seller or a buyer
- The computer then selects the random offer using the procedure described above

- The offer is then compared to your price

If you are a **Seller**

- If the computer offered less than your price you do not sell, keep the endowment, and play the lottery
- If the computer offered more than (or the same as) your price you sell the lottery, keep your endowment, and obtain the computer offer.

If you are a **Buyer**

- If the computer offered more than your price you do not buy the lottery and you keep your endowment
- If the computer offered less than (or the same as) your price you buy the lottery, pay the computer offer using your endowment, and play the lottery.

`R-mechanism ends here`

`B-mechanism starts here`

- The computer randomly matches you with another participant
- The computer randomly selects one of the lotteries evaluated during the experiment and who is the seller and the buyer in each couple of participants
- The offer of the other player is compared to your price

If you are a **Seller**

- If the buyer offered less than your price you do not sell, keep the endowment, and play the lottery
- If the buyer offered more than (or the same as) your price you sell the lottery, keep your endowment, and obtain the buyer offer.

If you are a **Buyer**

- If the seller asked more than your price you do not buy the lottery and keep your endowment
- If the seller asked less than (or the same as) your price you buy the lottery, pay the seller offer using your endowment, and play the lottery.

`B-mechanism ends here`

After trading, the outcome of the lottery is determined and earnings are paid out anonymously.

Warning: in this experiments your earnings may vary substantially. You can earn an amount of money between €2.50 and €40 depending on both your choices and chance.

Instructions are over. If you have any questions please raise your hand, an experimenter will come to your place to answer you. We will now ask you to answer some questions on your computer screen to ensure that you understand the instructions completely. Please raise your hand if you have any questions. Click "OK" (on your computer screen) when you are finished with the instructions.

C Econometric Estimation: Details

Our strategy is to estimate the risk aversion parameter ρ and the weights $w(p)$ at $p \in \{1/8, 2/8, 3/8, 4/8, 5/8, 6/8, 7/8\}$ for each subject, both when selling and buying. This way we obtain two parameters of risk aversion, ρ_s and ρ_b, and two vectors of weights, $(w_s(1/8), \ldots, w_s(7/8))$ and $(w_b(1/8), \ldots, w_b(7/8))$, for each subject. The procedure is as follows:

- we estimate ρ_s and $w_s(0.5)$ for selling tasks minimizing

$$\sum_L [\mathrm{WTA}(L) - P_s(L|\rho, w(0.5))]^2$$

  and ρ_b and $w_b(0.5)$ for buying tasks minimizing

$$\sum_L [\mathrm{WTP}(L) - P_b(L|\rho, w(0.5))]^2$$

- we use $\hat{\rho_s}$, $\hat{\rho_b}$, and the WTAs and WTPs of the lotteries 8 to 13 to compute

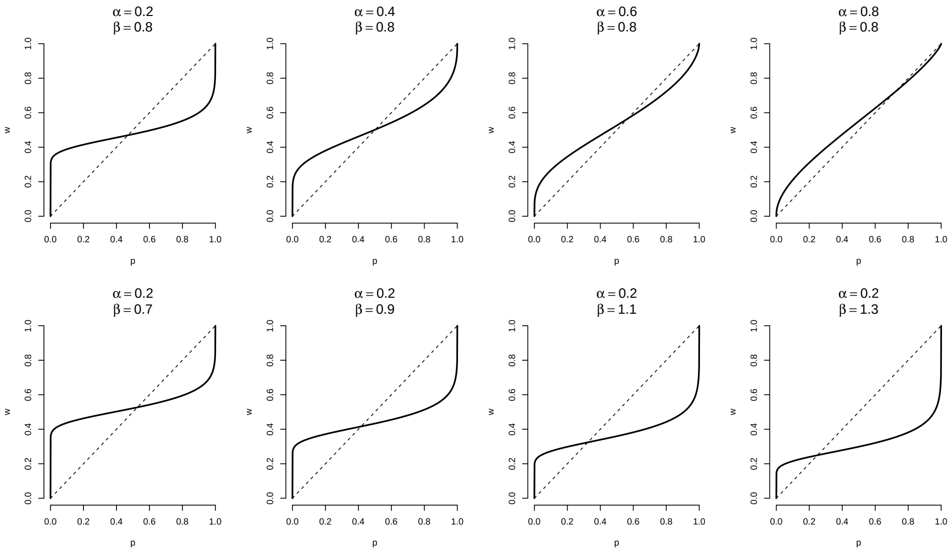
$$\hat{w_s}(p) = \frac{\exp(-\hat{\rho_s}\mathrm{WTA}) - \exp(-\hat{\rho_s}x_l)}{\exp(-\hat{\rho_s}x_h) - \exp(-\hat{\rho_s}x_l)}$$

  and

$$\hat{w_b}(p) = \frac{\exp(-\hat{\rho_b}\mathrm{WTP}) - \exp(-\hat{\rho_b}x_l)}{\exp(-\hat{\rho_b}x_h) - \exp(-\hat{\rho_b}x_l)}$$

  for $p \in \{1/8, 2/8, 3/8, 5/8, 6/8, 7/8\}$.

Using $\hat{w_b}(p)$ and $\hat{w_s}(p)$, we then estimate the parameters α and β of the Prelec's weighting function for each individual when selling and buying. For illustrative purposes, we provide below a graphical representation of how the parameters α and β impact on the shape of the weighting function $w(p)$. The figures illustrate how a higher α implies more sensitivity to a change in probabilities and a higher β more under-weighting of probabilities (i.e., higher pessimism).



For sellers, the parameters α_s and β_s are obtained by minimizing

$$\sum_p \left[\hat{w}_s(p) - \left(\exp\bigl(-(-\ln(p))^{\alpha_s}\bigr) \right)^{\beta_s} \right]^2$$

while for buyers the parameters α_b and β_b are obtained by minimizing

$$\sum_p [\hat{w}_b(p) - \left(\exp\bigl(-(-\ln(p))^{\alpha_b}\bigr) \right)^{\beta_b} \Big]^2$$

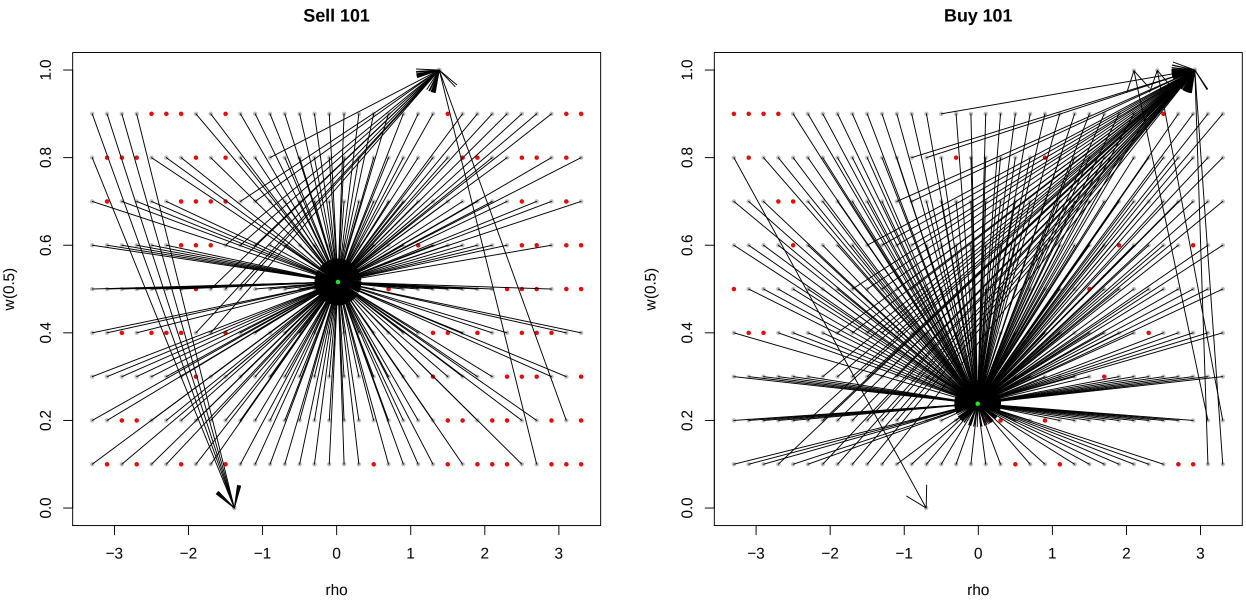
To minimize the chances of ending up in local minima, we run the minimization processes with about 300 different starting values drawn from a sensible parameter range. More precisely, we used the 306 values (ρ_0, w_0) in the grid $\{-3.3, -3.1, -2.9, \ldots 3.3\} \times \{0.1, 0.2, \ldots, 0.9\}$ to estimate ρ and $w(0.5)$ and the 289 values (α_0, β_0) in the grid $\{0.25, 0.75 \ldots, 8.25\} \times \{0.25, 0.75 \ldots, 8.25\}$ to estimate α and β. The robustness of the numerical minimization is testified by the fact that it converged to the same values for most of the starting values and for most of the subjects.

Figure 4 shows a sample graph of the estimation process of ρ and $w(0.5)$ for Subject 101. Black arrows connect each starting value with the estimated value of the parameters. Green points represent the best estimate of the parameter, i.e., the probable global optimum, and red points represent starting values for which the optimization algorithm failed to converge.

D Robustness Check

This appendix presents the results of our robustness check employing the utility function $u(x) = \frac{x^\rho}{\rho}$, where ρ is the constant coefficient of relative risk aversion. The estimation strategy is the same as for the CARA specification reported in

Figure 4: Convergence of optimization process Sbj 101 (CARA)



the paper. Substituting the CRRA utility function in equations 1 and 2 one can obtain the price P_s for a lottery L as an explicit function of ρ and $w(p)$

$$P_s = (w(p_h)(E + x_h)^\rho + (1 - w(p_h))(E + x_l)^\rho)^{1/\rho} - E$$

As P_b cannot be written as an explicit function of the parameters, we employ numerical methods to find the P_b solving

$$E^\rho - w(p_h)(E + x_h - P_b)^\rho + (1 - w(p_h))(E + x_l - P_b)^\rho = 0$$

for given ρ and $w(p)$.

Table 3 reports statistics and tests of the individual estimates of the parameters for the CRRA specification. Results are in line with those obtained for the CARA specification (See Table 2): (i) the median participant is risk seeking; (ii) there is no difference in risk attitudes and sensitivity to probability between roles (seller or buyer); and (iii) subjects are more pessimistic concerning probabilities when they buy than when they sell. Also in this case there are no differences in the estimated parameters when comparing elicitation methods.[17]

Notice that, as a consequence of the CRRA utility specification, subjects are slightly more risk seeking and more pessimistic compared to the CARA utility function. However, all the previous results concerning treatment differences are confirmed.

Concerning the optimization process, for the CRRA specification we used a grid of about 300 different staring values to obtain robust estimates of the

[17] KS tests for ρ_s: p-value= 0.855; KS tests for α_s: p-value= 0.231; KS tests for β_s: p-value= 0.295; KS tests for ρ_b: p-value= 0.318; KS tests for α_b: p-value= 0.816; KS tests for β_b: p-value= 0.784

Table 3: Estimated parameters (CRRA)

Parameter θ	Role	Median	Interquartile Range	Sign Test $M(\theta)=\theta_0$	Sign Test $M(\theta_S-\theta_B)=0$
			R-mechanism		
ρ	S	2.190	[0.057, 6.475]	0.000	0.659
	B	2.599	[-0.119, 6.155]	0.006	
α	S	0.580	[0.222, 0.948]	0.000	0.250
	B	0.516	[0.128, 0.852]	0.000	
β	S	1.367	[0.607, 2.615]	0.010	0.000
	B	2.076	[1.212, 3.390]	0.000	
			B-mechanism		
ρ	S	2.236	[0.205, 6.124]	0.003	0.090
	B	2.544	[-0.274, 8.204]	0.006	
α	S	0.612	[0.354, 1.050]	0.000	0.061*
	B	0.483	[0.163, 0.826]	0.000	
β	S	1.389	[0.635, 3.712]	0.010	0.000
	B	2.030	[1.329, 3.993]	0.000	

parameters. In particular, we adopted the same grid used for the CARA to estimate α and β (see Appendix B) and we used the 324 values (ρ_0, w_0) in the grid $\{-1.625, -1.375, -1.125, \ldots 7.125\} \times \{0.1, 0.2, \ldots, 0.9\}$ to estimate ρ and $w(0.5)$.

E Costs of the Elicitation Mechanisms

We compare the two methods in terms of how much they cost to the experimenter. In order to do so, we run a Montecarlo simulation in which, at each step, we calculate the payoff of each subject according to her evaluations and the rules in the experiment and compute the average payoff.

For the *R-mechanism*, at each step of the simulation we compute the payoff for each of the 128 subject as follows:

- we randomly choose one lottery and determine the role of the subject, i.e., whether she is buying or selling the lottery;
- we draw a random price for that lottery and compare it with the offer of the subject. If the role is seller and the random price is higher than the subject's evaluation, the subject sells the lottery and obtains the random price, else the subject keeps the lottery. If the role is buyer and the random price is lower than her evaluation, the subject buys the lottery and pays the random price, else the subject does not buy the lottery;
- if the subject does not sell or if she buys the lottery, we randomly draw the outcome of the lottery and add it to her payoff.

Finally we take the average of subjects' payoffs

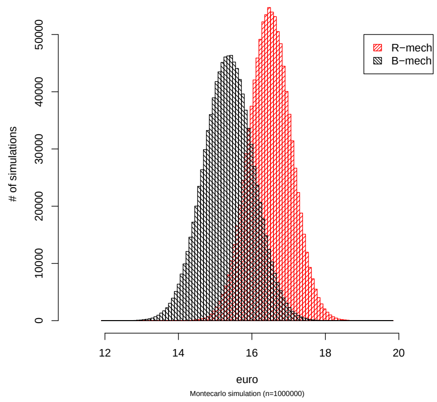
For the *B-mechanism*, at each step of the simulation we compute the payoff for each of the 126 subjects as follows:

- we randomly match two subjects, assign who of the pair is the the seller and who is the buyer, and then choose one lottery for each pair;
- we compare the WTA of the buyer and the WTP of the seller in the chosen lottery. If WTA$\leq$WTP, then the seller sells the lottery to the buyer and receives the buyer's offer, while the buyer receives the lottery and pays the seller's offer. If instead WTA>WTP, they do not trade and the seller keeps the lottery;
- we randomly draw the outcome of the lottery and add it to the payoff of the subject owning the lottery.

Finally we take the average of all payoffs.

Figure 5 reports the distribution of the average payoff in the two elicitation mechanisms based on 1000000 simulations. As apparent from the graph, the R-mechanism is more expensive than the B-mechanism: median payoffs are 16.5 and 15.4 euro respectively (Wilcoxon Rank Sum Test's p-value< 0.001).

Figure 5: Distributions of average individual payoff



To perform a robustness check we run two additional Montecarlo simulations where we keep the evaluations constant across the elicitation mechanism: in the first simulation we use only WTAs and WTPs obtained with the R-mechanism and in the second we use only WTAs and WTPs obtained with the B-mechanism. In both cases we compute individual payoffs with the rules of both elicitation mechanisms, keeping fixed subjects' evaluations. Figure 6 and 7 report the distribution of average payoffs under the two mechanisms using R-mechanism data and B-mechanism data, respectively. The analysis confirms that the R-mechanism generally is more expensive than the B-mechanism.

Figure 6: Distributions of average individual payoff (R-mechanism data)

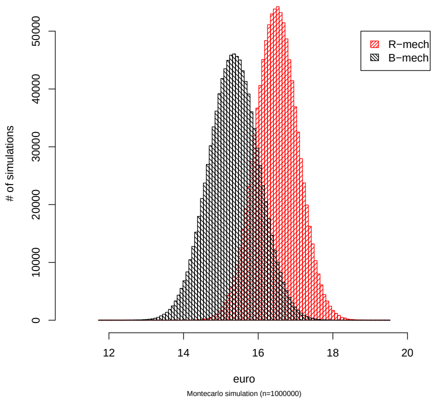


Figure 7: Distributions of average individual payoff (B-mechanism data)