Separating probability weighting and risk aversion in first-price auctions

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Abstract

In first price sealed-bid auctions, a power probability weighting function is observationally equivalent to a model with constant relative risk aversion. By comparing auctions with different ceilings on a computerized opponent's bid space, we can separate inverse S-shaped probability weighting as commonly used in the literature and risk-averse preferences from the distribution of observed bids. We find evidence to support both theories in the data. However, we also observe a significant number of violations after accounting for decision noise, which suggest that bidders' valuations may be malleable to cues of the auction environment.

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Keywords: bias; experiment; first-price auctions; probability weighting; risk aversion

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1 Introduction

In first-price sealed-bid auctions, a power probability weighting function is observationally equivalent to a model with constant relative risk aversion (Cox et al. 1985). Thus, it is difficult to separate probability weighting distortions and risk-averse preferences as drivers of observed bidding behaviour. Identifying a method to separate these effects in a competitive bidding environment with non-trivial equilibrium strategy is important for understanding the drivers and boundaries of previously observed behavioural biases.[4]

We design an experiment that enables us to separate inverse S-shaped probability weighting as commonly used in the literature (e.g., Prelec 1998, Tversky and Kahneman 1992) and risk-averse preferences directly from observed bidding behaviour. By implementing a ceiling on the bid interval, we can vary the beliefs about the opponent without changing the best response for a risk-neutral bidder. This is our identifying restriction.

To evaluate the restriction, we conduct an experiment in which human subjects bid against computerized opponents programmed to draw random numbers from one of three different uniform intervals. The treatments differ in the objective belief structure imposed on the opponent's bidding function; since this differentially influences expected payoffs, it is not a pure framing variation (see Dorsey and Razzolini 2003, Armantier and Treich 2009, Ratan 2015).

First, relative to the best response of a risk-neutral bidder, the best response of a risk-averse bidder diverges in one direction above a certain valuation threshold. Second, relative to the best response of a bidder who weights probabilities objectively, the best response of a bidder who overestimates (underestimates) low (high) probabilities of winning the auction (i.e., who uses an inverse S-shaped probability weighting function) diverges in the opposite direction for a certain valuation range.

[4] Both risk aversion and subjective probability weighting have been proposed as drivers of "overbidding" (e.g., Cox et al. 1988, Kagel and Levin 2011).

2 Experimental Design

Two bidders compete for an item at a first-price auction. Bidder i, with private valuation v_i in [100, 500], submits a continuous bid b_i from the same interval. A computerized opponent submits an independent draw $x_j \sim U[100, \bar{x}_j]$, where $\bar{x}_j$ is the ceiling on a uniformly distributed interval in auction j. This distribution is known in the experiment. If $b_i > x_j$, then i earns a profit of $v_i - b_i$; otherwise, i earns zero. Ties are broken randomly.

We implement three treatments using a within-subjects design: *Ceiling-300*, *Ceiling-400*, and *Ceiling-500*. In each treatment, the computerized opponent draws $x_j \sim U[100, \bar{x}_j]$, where the ceiling $\bar{x}_j$ corresponds to the treatment's name. Each subject completes *Ceiling-300* (low ceiling) and either *Ceiling-400* or *Ceiling-500* (high ceiling).

We elicit incentivized bid data from N=208 subjects using CloudResearch, a survey panel designed for academic research (Litman et al. 2017). The treatment order is randomized between subjects; 105 (103) subjects are confronted with the low (high) ceiling followed by the high (low) ceiling. In each treatment, bids are submitted using the strategy method for six pre-determined valuations, $v \in \{226, 306, 364, 418, 470, 500\}$.[5] We fixed these valuations across treatments to avoid confounding behavioural differences due to the ceiling with those due to differences in realized valuations. No feedback is provided until after all auctions are completed. Full details are provided in Online Appendix B.1.

[5] We also elicited switching points in a multiple price list lottery task to measure a subject's risk aversion (Holt and Laury 2002). See Online Appendix B.2 for details about the relationship of the pre-determined auction valuations to this task and within-subject analyses that relate the independent measure of risk aversion to bidding behaviour.

3 Theory

3.1 Benchmark model

Assume bidder *i* has constant relative risk aversion (CRRA) with utility

$$U_i(v_i - b_i) = (v_i - b_i)^{r_i}, \qquad (1)$$

where r_i is the risk preference parameter, with $r_i = 1$ corresponding to risk neutrality, and $r_i < 1$ to risk aversion. Notice that, in the maximization problem for bidder *i* in auction *j*, only *i*'s conditional (on winning) utility depends on r_i, and only *i*'s probability of winning depends on $\bar{x}_j$. For any bid $b_i \leq \bar{x}_j$ there is a constant probability of winning, $(b_i - 100) / (\bar{x}_j - 100)$. For any bid $b_i > \bar{x}_j$ there is an incentive to deviate to a lower bid equal to $\bar{x}_j$, which has a probability of winning equal to one. The optimal bid is then characterised as follows,

$$b^*_{i,RA}(v_i; \bar{x}_j) = min\left(\bar{x}_j, \frac{v_i + 100r_i}{(1 + r_i)}\right). \qquad (2)$$

Prediction 1. For any two first-price auctions L and H with commonly known ceilings $\bar{x}_L$ and $\bar{x}_H$, $\bar{x}_L < \bar{x}_H$, a bidder *i* who weights probabilities objectively bids $b_{i,L}(v_i) = \bar{x}_L$ in auction L and bids $b_{i,H}(v_i) > \bar{x}_L$ in auction H if $v_i > \bar{x}_L + r_i(\bar{x}_L - 100)$.

In our experiment, a risk neutral bidder does not bid above 300 and the ceiling does not influence the bid for any valuation. Thus, for a given valuation, a bidding function that maps to a bid more than 300 in the high ceiling auction and to a bid *equal* 300 in the low ceiling auction implies CRRA with objective probability weighting; if instead it maps to a bid *less than* 300 in the low ceiling auction it necessarily violates CRRA.

3.2 Inverse S-shaped probability weighting function

We now assume that bidders have an increasing probability weighting function (PWF) *w*(.) for which (i) *w*(0) = 0 and *w*(1) = 1, and (ii) there exists a unique threshold probability $\hat{p} \in (0,1)$ such that $w(\hat{p}) = \hat{p}$, $w(\hat{p}) > \hat{p}$ for all $p \in (0, \hat{p})$, $w(\hat{p}) < \hat{p}$ for all $p \in (\hat{p}, 1)$. This formulation produces an inverse S-shaped PWF, where the effect of a change in the probability of winning on the expected utility of a given bid diminishes with its distance from the ceiling.

To examine how diminishing sensitivity in the weighting function impacts bidding behaviour between auctions with different ceilings, we numerically compute the optimal bid for a bidder with CRRA utility using the inverse S-shaped PWF due to Prelec (1998):

$$w(p) = exp\{-(-\ln p)^{\gamma}\}. \quad (3)$$

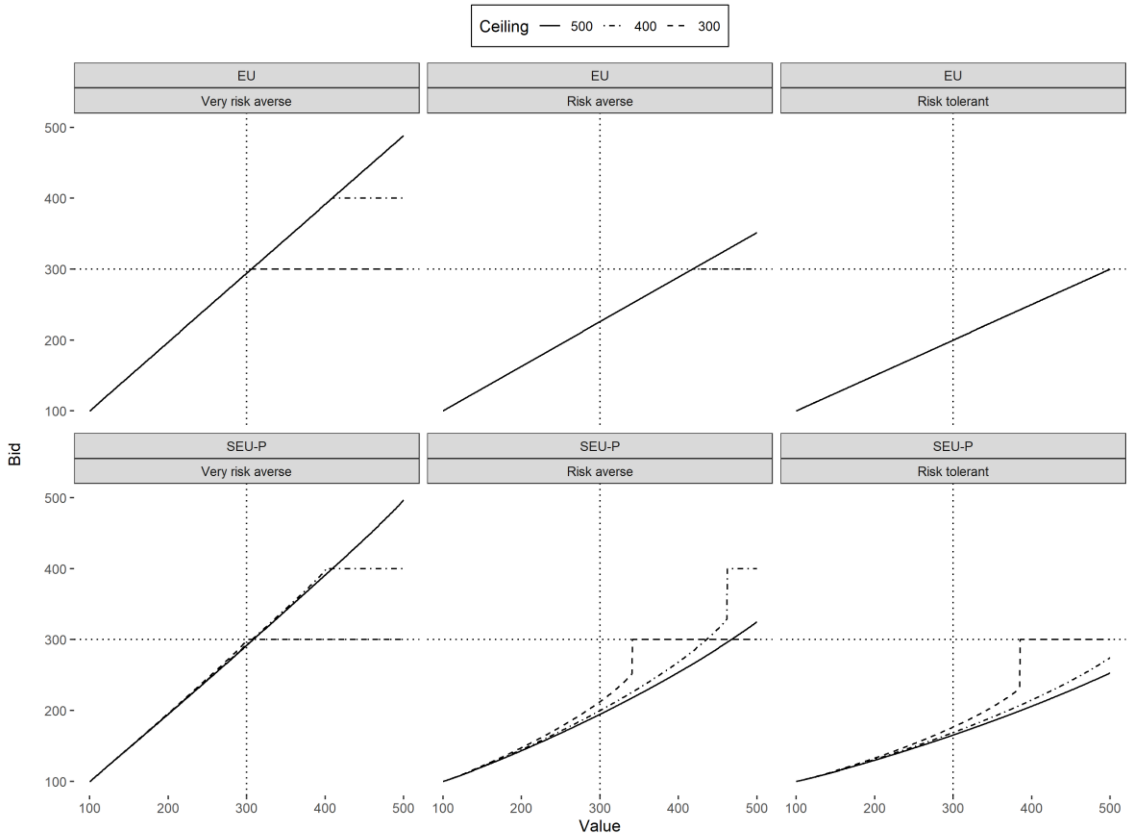
For fixed $\gamma < 1$, this function exhibits optimism for small probabilities and pessimism for large probabilities and produces a weighted utility for each prospective bid. In Figure 1 we present the bid that maximizes objective (top row) and subjective (bottom row) expected utility for $\gamma = 0.61$ and varying degrees of risk aversion in our three experimental treatments.[6] The parameter values selected for risk aversion (r = 0.59 and r = 0.03) reflect boundaries between switching points in a multiple price list lottery task which we used to elicit a bidder's independent measure of risk aversion (Holt and Laury 2002).

Prediction 2. For any two first-price auctions L and H with commonly known ceilings $\bar{x}_L$ and $\bar{x}_H$, $\bar{x}_L < \bar{x}_H$, a bidder i who weights the probability of winning using an inverse S-shaped PWF bids, for a subset of valuations, $b_{i,H}(v_i) < b_{i,L}(v_i) \leq \bar{x}_L$.

In our experiment, for a given valuation, a bidding function that maps to a bid less than 300 in the high ceiling auction and to a higher bid less than or equal 300 in the low ceiling auction implies subjective probability weighting using an inverse S-shaped PWF (SPW). Finally, notice that any bid strictly above the ceiling necessarily violates both theories.

[6] In Online Appendix A.1, we check that Prediction 2 is also satisfied for the commonly used inverse S-shaped PWF due to Tversky and Kahneman (1992).

Figure 1. Comparison of optimal bids using expected utility (EU) versus subjective expected utility with inverse S-shaped probability weighting due to Prelec (SEU-P).



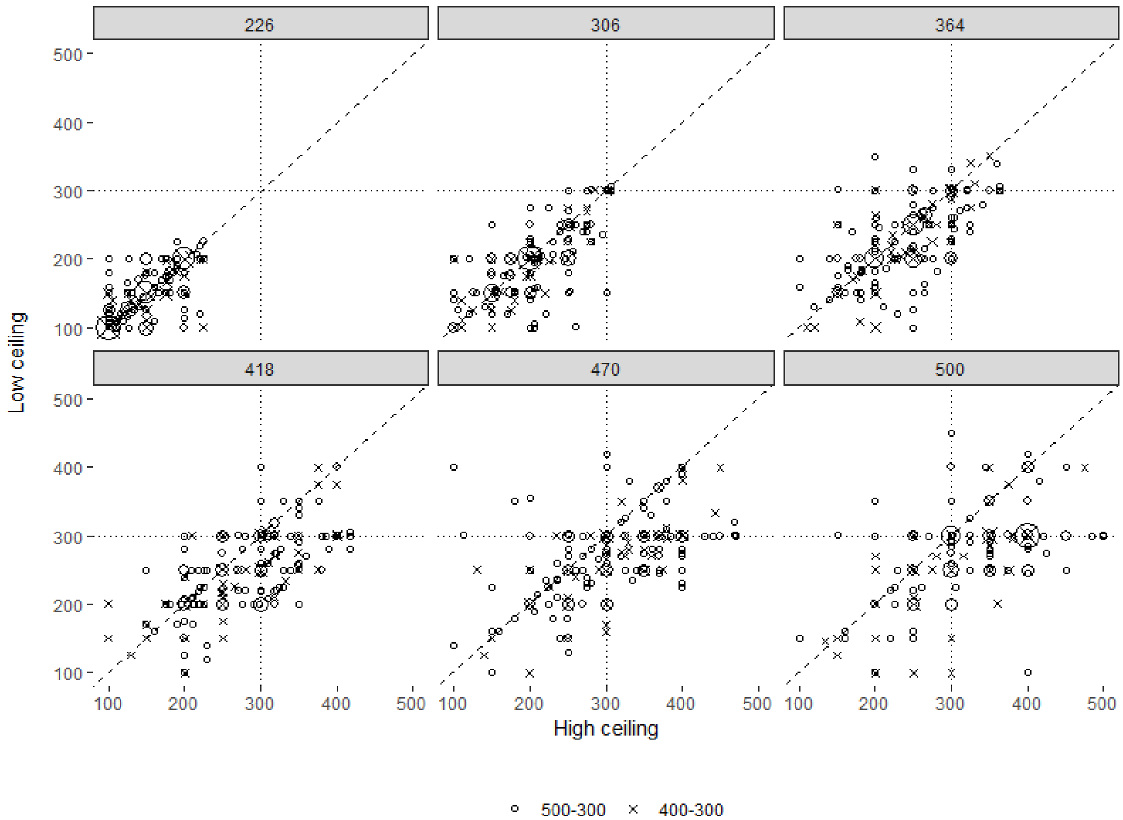
Notes: For SEU-P, we assume the Prelec PWF in (3), $\gamma = 0.61$. For risk tolerant subjects, we assume $r = 1$; for risk averse subjects, $r = 0.59$; for very risk averse subjects, $r = 0.03$.

4 Experimental Results

We observe 1,248 paired bids (208 bidders × 6 valuations) between auctions with high ceiling (*400, 500*) and low ceiling (*300*). The bid data are presented in Figure 2.

In the high ceiling auction, we find that 24% of bids are more than or equal 300; 85% of these bids are paired with a lower bid in the low ceiling auction, of which more than half equal 300 (we permit a margin of error of 5). Of the 76% of bids less than 300 in the high ceiling auction: 36% are paired with the same bid in the low ceiling auction; 24% are paired with a higher bid, of which 93% are less than or equal 300; and 40% are paired with a lower bid.

Figure 2. Paired bids, low ceiling (300) against high ceiling (400 or 500), by valuation.



Notes: The size is proportional to the number of observations.

Based on the theory, we categorize paired bids according to one of six mutually exclusive relations between the high and low ceiling auction separately for each valuation (Table 1). We make the following observations:[7]

(i) a substantial fraction of functions map to a bid less than 300 in the low ceiling auction and to a higher bid *less than* 300 in the high ceiling auction for low valuations;

(ii) a small fraction of functions map to a bid less than 300 in the low ceiling auction and to a higher bid *equal* 300 in the high ceiling auction for high valuations;

(iii) the probability of submitting the same bid in the two auctions is decreasing in valuation;

[7] In Online Appendix A.2, we corroborate the results using Logistic regression analyses that control for subject risk aversion, the treatment order, and the high ceiling level. None of the control variables are significant at the 5% level.

(iv) functions that map to a bid more than or equal 300 in the high ceiling auction and to a bid *less than* 300 in the low ceiling auction are observed across valuations;

(v) functions that map to a bid more than 300 in the high ceiling auction and to a bid *equal* 300 in the low ceiling auction are more likely at high valuations; and

(vi) bids above the 300 ceiling are rare and occur only at the highest valuations.

Table 1 – Paired bids in high ceiling auction (b_H) and low ceiling auction (b_L), by valuation.

	Valuation						*Implication*		
	226	*306*	*364*	*418*	*470*	*500*	*SPW*	*CRRA*	*Other*
(i) $b_H < b_L < 300 - \varepsilon$	19.7%	18.8%	16.3%	12.0%	5.3%	2.4%	Yes	-	-
(ii) $b_H < b_L = 300 \pm \varepsilon$	0.0%	2.4%	5.3%	6.3%	6.7%	4.8%	Yes	-	-
(iii) $b_H = b_L$	52.4%	38.9%	31.3%	20.2%	19.7%	19.7%	-	-	-
(iv) $b_L < 300 - \varepsilon < b_H$	27.9%	38.5%	40.9%	46.2%	42.3%	37.0%	-	-	Yes
(v) $b_L = 300 \pm \varepsilon < b_H$	0.0%	1.4%	3.4%	11.1%	17.8%	29.8%	-	Yes	-
(vi) $b_L > 300 + \varepsilon$	0.0%	0.0%	2.9%	4.3%	8.2%	6.3%	-	-	Yes

Notes: We permit a margin of error, ε = 5.

Observation (v) supports Prediction 1 (CRRA) and observations (i) and (ii) support Prediction 2 (SPW). Observation (iii) is consistent with risk neutral bidders who weight probabilities objectively.

However, CRRA and SPW do not provide a fully satisfactory description of behaviour: in addition to the small fraction of bids above the 300 ceiling (observation (vi)), the modal behaviour is captured by (iv), which violate both theories and suggests some other (unobserved) decision heuristic.

To investigate the extent to which this represents an anomalous behaviour, rather than decision noise, we harness the within-subjects structure of our data to classify each subject according to whether their bidding behaviour is consistent with CRRA or SPW. First, we obtain the vector of paired bids for each subject. Second, we classify each vector in accordance with whether it implies CRRA or SPW or violates either theory. We separately identify the number of subjects who submit the same bid between auctions. To permit decision noise, we consider a varying number of violations per vector (0, 1 and 2) in the classification.

The results are presented in Table 2. If we permit no violations from the theory, only a minority of the 208 subjects can be classified using this method: 16 subjects imply CRRA, 30 subjects imply SPW and 12 subjects exhibit no change in bids. If we permit up to two violations per subject, the numbers increase to 43 subjects (21%), 65 subjects (31%) and 19 subjects (9%), respectively; 21 subjects (10%) imply both CRRA and SPW. Thus, after allowing for decision noise, 102 of the 208 subjects are not well-described by either theory. However, 80 (78%) of those subjects exhibit bid functions that are weakly monotonic increasing in valuations, which suggests a systematic pattern of bids. One possibility is that the low ceiling acts as an anchor which distorts bids downwards in this treatment across the valuation interval, which would be consistent with observation (iv). For example, Ivanova-Stenzel and Seres (2021) find a positive correlation between the maximum bid limit and the bid submitted in first-price auctions.

Table 2 – Subject-level type classification.

	Implication			*Other*	
Num. violations	*CRRA*	*SPW*	*No change*	*Monotone*	*Non-monotone*
0	16	30	12	122	37
1	32	51	16	95	30
2	43	65	19	80	22

Notes: Values are number of subjects. The implications are not mutually exclusive; for 0 (1) [2] violations, the number of subjects who imply both CRRA and SPW is 9 (16) [21].

5 Conclusion

To separate inverse S-shaped probability weighting from constant relative risk aversion in first-price auctions, we studied subjects' bidding behaviour when confronted with a computerized opponent programmed to submit bids at random from the value support, or from the risk-neutral Nash equilibrium bid support. This is because a risk-neutral bidder behaves similarly in both auctions, whereas a risk-averse bidder and a bidder who exhibits inverse S-shaped probability weighting behave in diametrically opposed ways. We find evidence to support both theories in the data. However, we also observe a significant number of violations after accounting for decision noise, which suggest that bidders' valuations may be malleable to cues of the auction environment.

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Online Appendix A: Supplemental analysis.

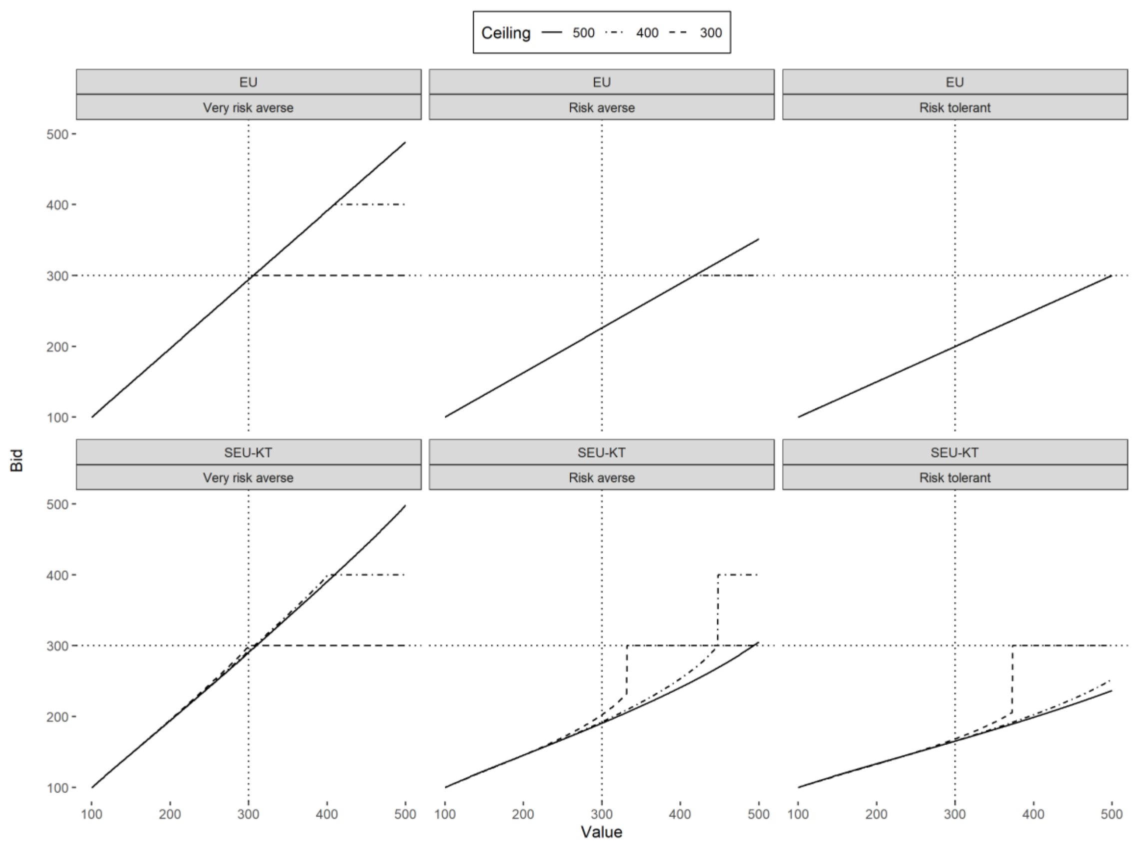
A.1 Inverse S-shaped PWF due to Tversky and Kahneman (1992).

We numerically compute the optimal bid for a bidder with CRRA utility using the following inverse S-shaped PWF due to Tversky and Kahneman (1992):

$$w(p) = \frac{p^{\gamma}}{(p^{\gamma} + (1-p)^{\gamma})^{1/\gamma}}. \qquad \text{(A1)}$$

In Figure A.1, we present the bid that maximizes objective (top row) and subjective (bottom row) expected utility for $\gamma = 0.61$ and varying degrees of risk aversion in our three experimental treatments.

Figure A. 1. Comparison of optimal bids using expected utility (EU) vs. subjective expected utility with inverse S-shaped probability weighting due to Tversky and Kahneman (SEU-KT).



Notes: For SEU-KT, we assume the PWF in (A1), γ = 0.61. For risk tolerant subjects, we assume r = 1; for risk averse subjects, r = 0.59*;* for very risk averse subjects, r = 0.03.

A.2 Additional experimental results.

In Table A.1, we corroborate observations (i) to (v) from Section 4 of the main text using Logistic regression analyses that control for subject risk aversion, the treatment order, and the high ceiling level.

Table A. 1 – Relationship between bid function and auction ceiling.

	Bid function between the high ceiling auction (b_H) and low ceiling auction (b_L)				
	$b_H < b_L < 300 - \varepsilon$	$b_H < b_L = 300 \pm \varepsilon$	$b_H = b_L$	$b_L < 300 - \varepsilon < b_H$	$b_L = 300 \pm \varepsilon < b_H$
Value	-0.006*	0.006*	-0.006*	0.002*	0.018*
	(0.001)	(0.002)	(0.001)	(0.001)	(0.002)
N	1,248	1,248	1,248	1,248	1,248
$\chi^2(7)$	53.040*	22.325*	85.812*	16.772*	162.287*

Notes: * $p < 0.05$. Logistic regressions with robust standard errors in parentheses clustered at the subject level (208 clusters). The dependent variable is a dummy variable = 1 for the specified bid pair, where $\varepsilon = 5$. All models include a constant term and the following control variables (not reported in the table): a continuous variable indicating the number of safe choices from the multiple price list lottery task; a dummy variable for the order in which the auctions were presented; and a dummy variable for *Ceiling-400*. None of the control variables are significant at the 5% level in any model.

Online Appendix B: Supplemental experiment details.

B.1 Recruitment and sampling protocols

The experiment recruitment was conducted via the CloudResearch platform (www.cloudresearch.com), a participant-sourcing tool designed purposely for academic research which extensively screens workers to improve data quality from online samples. Retakes were prevented, and for comparability, we restricted the location of subjects to the United States. We recruited a first wave of 122 subjects in the spring of 2020 and a second wave of 135 (new) subjects in the spring of 2021. The only difference between the two waves was that, in the second wave, we added a sentence to the auction instructions to mitigate ambiguity in interpretation over what constitutes a random number draw – see the instructions in Section B.3 below for the exact wordings used. There is no significant difference in bids (average or distribution) between waves in any treatment and so we pool the data across waves. The extent to which this change influenced bidding behaviour is unobserved and should be kept in mind when interpreting our results.

Subjects first completed a multiple price list task consisting of ten lottery pairs. Each pair offers a binary choice between a safe lottery A with payoff 200 or 160, and a risky lottery B with payoff of 385 or 10. In each row of the list, the probability of the higher payoff in each gamble increases, starting from 20% and finishing at 100% at which point the risky lottery strictly dominates the safe lottery. The first row in which a subject chooses to switch from the safe to the risky lottery provides a measure of own risk aversion. Subjects then completed the auctions as described in the main text. All subjects had to correctly answer a set of comprehension questions and pass an attention check to proceed. At the end of the experiment, subjects completed a questionnaire to collect information on demographics and self-reports of prior financial market trading and online auction participation. The self-report field experience data was collected for a separate research project investigating the relationship between trader experience and overbidding (see Heinrich and Walker 2022 for details).

The auctions and the lottery task were incentivized: upon completion, one decision from each was randomly selected for payment. Earnings were converted to US dollars (exchange rate: 100 points to 10 cents) and paid to subjects as a bonus, in addition to a participation fee of 30 cents. The median hourly-equivalent earnings for the experiment were $7.44. To enhance data reliability, we excluded any subject who exhibited straight-lining behaviour or chose a dominated action (the results are qualitatively unchanged by including these subjects). Based on these criteria, we excluded 49 subjects to obtain a final sample size of N = 208 (*500-300* n = 149, *400-300* n = 59). The *400-300* pair was only included in the second wave of sampling, hence the smaller sample size. A summary of demographic data for our experiment sample is contained in Table B. 2.

B.2 Relationship of pre-determined auction valuations and multiple price list lottery task

The auction valuations used in the experiment provide a one-to-one correspondence between the switching point from safe to risky lottery in the multiple price list task due to Holt and Laury (2002), and the valuation at which a CRRA bidder would switch to the "safe" bid of 300 in the *Ceiling-300* auction (see the top panels in Figure 1 of the main text; the bid function is kinked at the 300 ceiling). This information is summarized in Table B. 1. For example, a choice of 4 safe lotteries in the multiple price list task implies a maximum risk aversion parameter of $r_i = 0.85$. Substituting this parameter into the valuation threshold from Prediction 1 produces a value $v_i = 470$. Thus, if the auction ceiling is 300, a CRRA bidder with $r_i = 0.85$ would submit a bid equal 300 for $v_i \geq 470$. Notice that as the maximum bid for a risk neutral bidder in our experiment parametrization is 300, the CRRA model predicts that a risk neutral subject will submit the same bid in the high and low ceiling auctions for all valuations. In Figure 1 of the main text, we use the boundaries corresponding to $r = 0.59$ and $r = 0.03$.

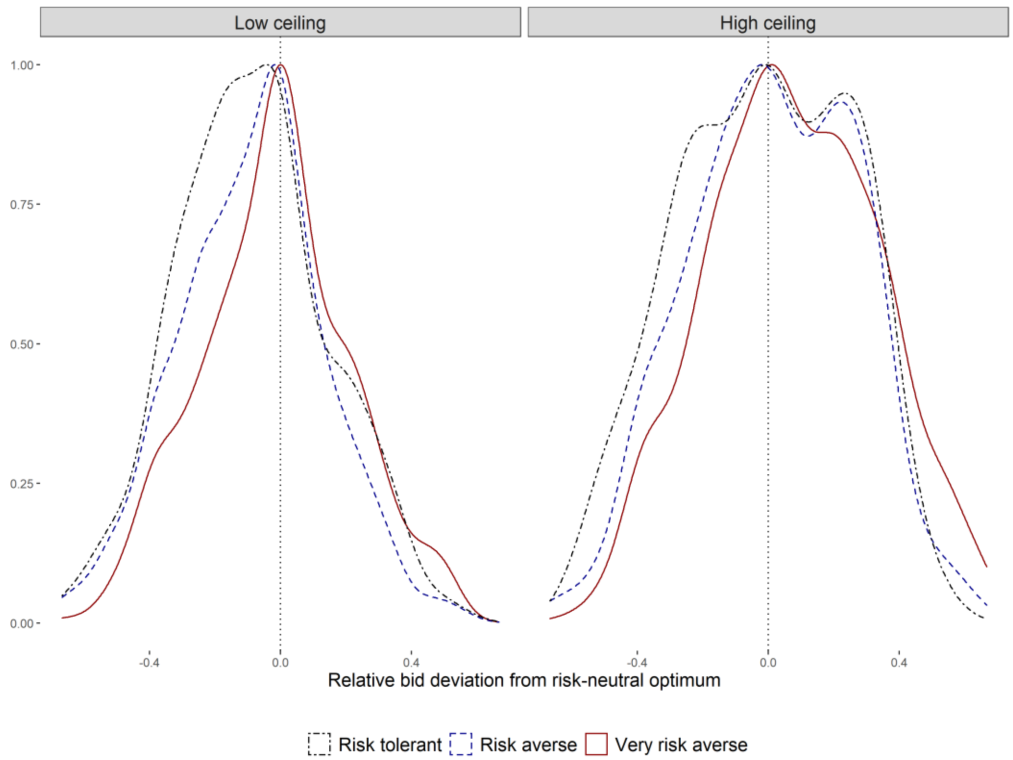
Table B. 1 – Correspondence between no. safe lottery choices and valuation (v-inverse) at which the optimal bid intersects the low ceiling (300).

No. safe lottery choices	Risk preference classification	No. subjects in experiment	Range of relative risk aversion $U(y) = y^{r_i}$	v-inverse $b_i^{*-1}(300)$[a]
Less than 4	Risk tolerant	45	$r_i > 1.15$	> 500
4			$0.85 < r_i < 1.15$	470
5	Risk averse	79	$0.59 < r_i < 0.85$	418
6			$0.32 < r_i < 0.59$	364
7	Very risk averse	84	$0.03 < r_i < 0.32$	306
More than 7			$r_i < 0.03$	< 300

Notes: [a] v-inverse bid for $\bar{x}_j = 300$, obtained by substituting the relevant r_i from column 4 into equation (2).

In Figure B. 1 below, we present the kernel density estimates of relative bid deviation from the optimal bid in equation (2) of the main text, assuming risk neutrality, decomposed by risk preference from the multiple price list lottery task. Those subjects who make less than or equal to four choices of the safe lottery are classified as "risk tolerant", which includes risk-neutral and riskloving subjects. Those subjects who make five or six choices of the safe lottery are classified as "risk averse". Those subjects who make more than or equal to seven choices of the safe lottery are classified as "very risk averse". Based on this classification, 45 subjects in our experiment are risk tolerant, 79 are risk averse, and 84 are very risk averse.

Figure B. 1. Kernel density estimates of relative bid deviation in low and high ceiling auctions, decomposed by risk preference classification from the lottery task.



Notes: Based on paired bid and lottery choice data from 208 subjects. Relative bid deviation from risk-neutral optimum is defined from equation (2) as $[2b_i/(v_i + 100) - 1]$.

Consistent with the stability of risk preferences between auction and lottery institutions, the distributions of relative bid deviation from the risk-neutral benchmark shift to the right in both the low and high ceiling auctions among subjects who exhibit greater risk aversion in the lottery task. That is, bidding is more aggressive among those subjects who made a greater number of safe choices in the lottery task. There is no robust statistical relationship within-subjects between risk aversion as measured in the multiple price list lottery task and the likelihood of any particular bid pair between low and high ceiling auctions (see the notes to Table A. 1).

Table B. 2 – Demographic data for our experiment sample.

N	208	
	Wave 1 (N = 94)	Wave 2 (N = 114)
Gender		
Female	29	28
Male	65	82
Other		2
Prefer not to say		2
Age		
18-25	7	11
26-30	16	23
31-35	26	14
36-40	18	25
41-50	17	18
51-60	8	15
61-70	2	5
71+		2
Prefer not to say		1
Employment status		
Full-time employed	75	76
Part-time employed	3	3
Retired	4	4
Self-employed	5	14
Student		6
Unemployed	6	9
Other	1	2
Occupation		
Construction, extraction, and maintenance	4	5
Farming, fishing, and forestry		
Government	7	8
Management, professional, and related	43	48
Production, transportation, and material moving	3	4
Sales and office	17	17
Services	8	15
Not applicable	12	17
Trading experience: How often do you trade financial products (such as stocks)?		
Never	9	5
Less than once a year	25	16
1-10 times a year	37	39
11-50 times a year	16	33
51-100 times a year	4	15
More	3	6
Auction experience: How often do you bid in online auctions (such as eBay)?		
Never	22	32
Less than once a year	23	33
1-10 times a year	47	33
11-50 times a year	1	13
51-100 times a year	1	3

B.3 Experimental instructions

Welcome to this web-based study that examines auction behavior. Before taking part in this study, please read the consent information below and click on the "I Agree" button at the bottom of the page if you understand the statements and freely consent to participate in the study.

Consent Information

The study is being conducted by [anonymised], and it has received ethical approval from xxxx. No deception is involved, and the study involves no more than minimal risk to participants (i.e., the level of risk encountered in daily life).

Participation in the study typically takes 5 to 10 minutes and is strictly confidential. Participants are expected to answer questions online. These questions pertain to participation in and preferences on economic decision-making.

All responses are treated as confidential, and in no case will responses from individual participants be identified. Rather, all data will be pooled and published in aggregate form only. Participants should be aware, however, that the study is not being run from a "secure" https server of the kind typically used to handle credit card transactions, so there is a small possibility that responses could be viewed by unauthorized third parties (e.g., computer hackers).

Your Mechanical Turk Worker ID will be used to distribute payment to you but will not be stored with your survey responses. Please be aware that your MTurk Worker ID can potentially be linked to information about you on your Amazon public profile page, depending on the settings you have for your Amazon profile. We will not be accessing any personally identifying information about you that you may have put on your Amazon public profile page.

Many individuals find participation in this study enjoyable, and no adverse reactions have been reported thus far.

Participants will receive payment of US $0.30 for completion plus a performance-dependent bonus payment. Please note that this study includes some comprehension questions and an attention check which, if answered incorrectly, will result in non-completion of the HIT.

Participation is voluntary, refusal to take part in the study involves no penalty or loss of benefits to which participants are otherwise entitled, and participants may withdraw from the study at any time without penalty or loss of benefits to which they are otherwise entitled.

If participants have further questions about this study, they may contact the investigators using the email address provided above.

After giving their consent to participate in the study, subjects completed a multiple price list lottery task followed by the two auction treatments. The lottery task consisted of a series of ten pairwise lottery choices. Subjects were informed that after they had made all their choices, one of the ten lottery pairs would be randomly chosen by the computer for payment and that their chosen lottery in this pair would be implemented. Any subject who chose the dominated lottery (lottery A in the final pair of the series) did not receive payment and subjects were informed of this. A screenshot of the lottery task is displayed below.

You will now face 10 decisions, listed below. Each decision is a paired choice between Lottery A and Lottery B. While the payoffs of the two lotteries are fixed for all decisions, the probability of the high payoff for each lottery varies.

After you have made all of your choices, one of the 10 decisions will be randomly chosen for payment. You will receive the outcome of the lottery you chose in that decision.

100 points will be exchanged to 10 U.S. cents.

	A	B	
A: 10% probability of 200, 90% probability of 160	○	○	B: 10% probability of 385, 90% probability of 10
A: 20% probability of 200, 80% probability of 160	○	○	B: 20% probability of 385, 80% probability of 10
A: 30% probability of 200, 70% probability of 160	○	○	B: 30% probability of 385, 70% probability of 10
A: 40% probability of 200, 60% probability of 160	○	○	B: 40% probability of 385, 60% probability of 10
A: 50% probability of 200, 50% probability of 160	○	○	B: 50% probability of 385, 50% probability of 10
A: 60% probability of 200, 40% probability of 160	○	○	B: 60% probability of 385, 40% probability of 10
A: 70% probability of 200, 30% probability of 160	○	○	B: 70% probability of 385, 30% probability of 10
A: 80% probability of 200, 20% probability of 160	○	○	B: 80% probability of 385, 20% probability of 10
A: 90% probability of 200, 10% probability of 160	○	○	B: 90% probability of 385, 10% probability of 10
A: 100% probability of 200, 0% probability of 160	○	○	B: 100% probability of 385, 0% probability of 10

Please note: if you choose a lottery which is sure to yield less than its pair (i.e., with 100% probability the non-chosen lottery in the pair would give you more points), the survey will end without payment.

Instructions for the auctions are presented below. Note that the highlighted sentences (not highlighted in the experiment) were included only for the second wave of data collection.

In the second part of the survey, you will bid against a random number. This random number is drawn from a specified interval. All numbers in this interval are equally probable. You will be paid for one of the tasks that you complete at random. Your earnings in that task are as follows:

- If your bid is higher than the random number, your earnings are *Your Value* minus *Your Bid.*
- If not, you earn 0.
- Ties are broken at random.
- *Your Bid* must be between 100 and 500.

100 points = 10 U.S. cents

Before they were able to proceed, subjects had to answer a set of three comprehension questions correctly (on the first attempt).

Your Value is 300, *Your Bid* is 200 and the random number drawn is 150. How much do you earn?

- 200
- 50
- 100
- 0

Your Value is 300, *Your Bid* is 200 and the random number drawn is 250. How much do you earn?

- 200
- 50
- 100
- 0

If the random number that you are bidding against is drawn from between 100 and 400, what is the highest possible bid you are competing with?

- 400
- 100

On successful completion of the comprehension questions, subjects were presented with two out of the below three auctions sequentially. The order in which the auctions were presented to subjects in the experiment was randomized.

Ceiling-300 auction:

You will now bid against a random number drawn from between **100 and 300**. All numbers between 100 and 300 are equally probable. You will be paid for one of the tasks below at random. Your earnings in that task are as follows:

- If your bid is higher than the random number, your earnings are *Your Value* minus *Your Bid.*
- If not, you earn 0.
- Ties are broken at random.
- *Your Bid* must be between 100 and 500.

100 points = 10 U.S. cents

Random number drawn from between 100 and 300

	Your Bid
1. *Your Value 500*	
2. *Your Value 470*	
3. *Your Value 418*	
4. *Your Value 364*	
5. *Your Value 306*	
6. *Your Value 226*	

Ceiling-500 auction:

You will now bid against a random number drawn from between **100 and 500**. All numbers between 100 and 500 are equally probable. You will be paid for one of the tasks below at random. Your earnings in that task are as follows:

- If your bid is higher than the random number, your earnings are *Your Value* minus *Your Bid*.
- If not, you earn 0.
- Ties are broken at random.
- *Your Bid* must be between 100 and 500.

100 points = 10 U.S. cents

Random number drawn from between 100 and 500

	Your Bid
1. *Your Value 500*	
2. *Your Value 470*	
3. *Your Value 418*	
4. *Your Value 364*	
5. *Your Value 306*	
6. *Your Value 226*	

Ceiling-400 auction:

You will now bid against a random number drawn from between **100 and 400**. All numbers between 100 and 400 are equally probable. You will be paid for one of the tasks below at random. Your earnings in that task are as follows:

- If your bid is higher than the random number, your earnings are *Your Value* minus *Your Bid*.
- If not, you earn 0.
- Ties are broken at random.
- *Your Bid* must be between 100 and 500.

100 points = 10 U.S. cents

Random number drawn from between 100 and 400

	Your Bid
1. *Your Value 500*	
2. *Your Value 470*	
3. *Your Value 418*	
4. *Your Value 364*	
5. *Your Value 306*	
6. *Your Value 226*	

After completing the lottery task and auctions, subjects passed through an attention filter (which required choosing the number 2 from a list of five single digit numbers). Attention filters are common in online experiments as an additional check that subjects are answering the survey questions carefully.

In the final part of the survey, subjects were asked to complete a questionnaire eliciting information about their experience trading financial products and bidding in online auctions, as well as standard demographic information, before their payment was processed.

B.4 Supplemental References

Heinrich, T. & Walker, M. J. (2022). From the Field to the Lab: Professionals and Bidding Aggression. In Handbook of Experimental Finance. Haruvy, E. & Fullbrunn, S. Edward Elgar.