Eliciting individual risk preferences in first-price auctions

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Abstract

Typically, in first-price auctions, a deviation of one's bid above the risk neutral Nash equilibrium (RNNE) is attributed to risk aversion and the degree of risk aversion attributed to that individual bidder is monotonically increasing in that individual's deviation from RNNE. A problem with that approach is that the deviation from RNNE could be due to any number of reasons that are not related to risk-preference. We propose a more robust method of identifying the role of individual risk preferences in first-price auctions. The method involves bidding against a computerized opponent (i.e., a random number generator) in a sequence of first-price auctions. Within-subject, comparing auctions with different upper bounds on the computerized opponent's bid space allows us to cleanly isolate risk-aversion as a driver of behaviour. This is because a risk-averse bidder is expected to behave differently in the two settings, and a risk-neutral bidder is expected to behave the same in both settings. We observe significantly lower bids when the opponent's bid space is restricted, which is consistent with the predicted best response functions given risk aversion. To establish robustness, we compare our characterizations to the theoretical predictions for bids that arise out of a separate Holt-Laury risk-elicitation task. We also provide evidence that related experience obtained in the field is associated with a fall in bidding aggression independently of risk preferences, but that this does not necessarily result in bids closer to the RNNE.

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Introduction

Bidding above the risk-neutral Nash equilibrium (RNNE) prediction in first-price sealed-bid auctions with independent private values, henceforth overbidding, is one of the most robust findings in the experimental auction literature (see overview in Kagel and Levin 2011). A series of seminal studies attribute overbidding to risk aversion, by fitting models to experimental data *ex post* (Cox et al., 1982; 1985; 1988). This explanation has been corroborated for different valuation and information structures (Chen and Plott 1998, Andreoni et al. 2007). Kirchkamp and Reiß (2011) provide experimental evidence to suggest that, consistent with the risk aversion explanation, equilibrium deviations are a result of incorrect best responses given correct expectations. Several works suggest that other behavioural explanations could be driving overbidding, implicitly undermining the role of risk-aversion.[1] Thus, there have been attempts to identify whether an association between risk aversion and overbidding really exists (Isaac and James 2000, Berg et al. 2005, Engel 2011). Füllbrunn et al. (2019) go beyond prior correlational studies and directly assign subjects to auction groups based on the distribution of risk preferences elicited *ex ante*. They observe a significant relationship between risk aversion and overbidding. These works, however, rely on the consistency of alternative risk preference elicitation instruments across institutions. The goal of the current study is to provide a more robust way to isolate risk-aversion.

We employ a new method of identifying individual risk preferences in first-price auctions. Our method is straightforward: to impose a price ceiling on the opponent's bid space. This is motivated by the observation that the risk-neutral best response is the same independent of whether the opponent submits a bid at random from the value interval, or from the interval of risk-neutral best responses (cf. Crawford and Irriberri 2007, p 1743, on level-*k* reasoning in first-price auctions). By doing so, we can vary the beliefs about the opponent without changing the strategic environment for a risk-neutral bidder. Our method is not a pure framing variation (cf. Dorsey and Razzolini 2003, Armantier and Treich 2009, Ratan 2015) because it influences expected payoffs. The best response of a risk averse bidder diverges from the best response of a risk neutral bidder. This is our identifying restriction.

To evaluate the identifying restriction, we administer an incentivized, multi-part experiment online. Online experiments enable access to a more diverse subject pool than the usual convenience student sample of the laboratory. The experiment consists of a multiple price risk elicitation task (Holt and

[1] Alternative explanations that assume correct expectations include regret (Loomes and Sudgen 1982, Engelbrecht-Wiggans 1989, Filiz-Ozbay and Ozbay 2007, Engelbrecht-Wiggans and Katok 2008), spiteful preferences (Morgan et al. 2003), decision-making errors (Goeree et al. 2002), and a concern for relative standing founded on learning direction theory (Ockenfels and Selten 2005, Neugebauer and Selten 2006). Other auction work has emphasized inconsistent expectations (e.g. Eyster and Rabin 2005, Crawford and Irriberri 2007).

Laury 2002), followed by two auction tasks. The auction tasks differ by the belief structure imposed about the opponent's bidding function. We uncover evidence of a reference price effect, which is strong enough to induce underbidding when the opponent's bid space is restricted. The Holt-Laury risk-elicitation task serves as a useful benchmark for comparison. We find support for the hypothesised correspondence between risk preferences and bid adjustments in response to a change in beliefs, particularly at low values.

An additional important finding from the experiment concerns the relationship between bidding and financial experience. It has been observed that related experience from the field can influence decision-making in auctions and economic games (e.g. List 2003, Alevy et al. 2007, Levitt et al. 2011, Garratt et al. 2012, Van Essen and Wooders 2015). Yet there is little consensus as to whether this is a context-specific effect or a form of "*theory absorption*" that generalizes to abstract settings (Kagel, 2015).[2] We observe that subjects who report more experience in trading financial products bid less aggressively in the experimental auction tasks, independently of risk preferences. This does not, however, lead more experienced subjects to bid closer to the risk-neutral Nash equilibrium. Thus, our data rejects the theory absorption explanation.

Experimental Design and Hypotheses

We conduct an online experiment consisting of three parts. Each subject completes all three parts. Part one is a standard Holt and Laury (2002) multiple price list task to elicit risk preferences. The safe lottery A is a gamble between 200 and 160; the risky lottery B is a gamble between 385 and 10.[3] 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 row in which a subject switches from the safe to the risky lottery provides a measure of own risk aversion.

Part two of the experiment is a forward first-price auction task in which a subject i bids against a computerised opponent, for a set of six items, with values $v_{ij},\ \ j \in \{1, \ldots, 6\}$, drawn from a uniform distribution with support [100, 500]. The values are presented on the screen from highest to lowest, and

[2] For example, with respect to common value auctions, Dyer et al. (1989) provide evidence that construction industry professionals are no less likely to bid overly aggressively in first-price common value procurement auctions than students. If the benefits of experience are situation-specific, this is perhaps unsurprising. By contrast, Harrison and List (2008) find that experienced sports card dealers are less prone to the winner's curse than non-dealers during laboratory auction experiments, when information on the common value is symmetric. Harrison and List interpret this result as confirmation that experienced subjects have developed generalizable rules of thumb that can "travel from problem domain to problem domain" (p. 824).

[3] All values are expressed in experiment points.

for each value the subject submits a bid, b_{ij} between 100 and 500.[4] A computerized opponent (i.e., a random number generator) draws a bid $x_j \sim U[100, \bar{u}]$, where $\bar{u}$ is the upper bound of the computerized opponent's support. If the bid b_{ij} is higher than the computerised opponent's bid x_j, then the subject earns a profit of $(v_{ij} - b_{ij})$; otherwise, the subject earns zero. Ties are broken randomly and subjects are informed of this.

Each subject completes two auction tasks sequentially, where in each auction task the subject submits bids for all six items. In total, each subject submits 12 bids. Across the two auction tasks, we vary the upper bound $\bar{u}$ of the computerised opponent's support, $\bar{u} \in \{300,500\}$, using a within-subjects design. The computerized opponent draws a uniform random bid either from the full value support [100, 500] or from the RNNE support [100, 300]. Since this design varies whether the opponent's bid space is unrestricted or restricted by a price ceiling, we call the two variants the *Unrestricted* support task (because the opponent's support spans the full range of possible valuations) and the *Restricted* support task, respectively. The tasks are completed sequentially and the order in which they are presented to subjects in the experiment is randomized.

To derive behavioural predictions for the auction task, we assume that bidders exhibit constant relative risk aversion (henceforth CRRA):

$$U\left(v_{ij} - b_{ij}\right) = (v_{ij} - b_{ij})^{r_i}, \tag{1}$$

where $r_i > 0$ is the private individual risk aversion parameter, with $r_i = 1$ indicating risk neutrality, $r_i < 1$ indicating risk aversion and $r_i > 1$ indicating risk loving preferences (Cox et al., 1988). The maximization function thus becomes:

$$Max\ U\left(v_{ij} - b_{ij}\right)\Pr\left(b_{ij} > x_j\right) = \left(v_{ij} - b_{ij}\right)^{r_i} \frac{(b_{ij} - 100)}{(\bar{u} - 100)}. \tag{2}$$

The first-order condition of the expected utility is:

$$(v_{ij} - b_{ij})^{r_i} - r_i\left(v_{ij} - b_{ij}\right)^{r_i - 1}\left(b_{ij} - 100\right) = 0. \tag{3}$$

In our *Unrestricted* task, the symmetric CRRA equilibrium bidding function given our value distribution is linear and standard:

[4] A limitation of our design is that the order in which the auction values are displayed was not randomized. We judged the benefits in terms of subject comprehension enough to favour a descending value approach.

$$b_{ij}^{*}(v_{ij}) = 100 + \frac{1}{1 + r_i}(v_{ij} - 100). \tag{4}$$

In our *Restricted* task, the opponent's bidding distribution is known and so the best response is known. Any solution to the maximization problem in (2) above the price ceiling of 300 is dominated by a bid equal to 300, which has a probability of winning equal to one. The same logic applies to a subset of risk-averse bidders for any price ceiling weakly above the upper bound RNNE support. Otherwise, (4) remains the best response.[5] Each bidder's best response in the *Restricted* task thus becomes:

$$b_{ij}^{*}(v_{ij}) = Min\left\{300, 100 + \frac{1}{1 + r_i}(v_{ij} - 100)\right\}. \tag{4'}$$

For a risk-neutral bidder, the best response functions in (4) and (4') coincide for all values in the support. For a risk-averse bidder, there is a value threshold at which choosing the "safe" bid of 300 yields the bidder a higher expected utility than the CRRA bid function in (4). This is similar in nature to the threshold row at which subjects' switch away from choosing the safe lottery in the Holt-Laury task.

We base our selection of auction values around this insight. To avoid confounding differences in bid adjustments by differences in values, the six auction values used in the experiment are fixed across subjects and tasks. These values are explicitly chosen to correspond to different switching points in the Holt-Laury task. The predicted correspondence between the number of safe lottery choices in the risk task and bidding behaviour in the auction task is presented in Table 1. We classify subjects into three categories based on their risk preference. Those subjects who make less than or equal to four choices of the safe lottery are classified as "risk tolerant". Those subjects who make five or six choices of the safe lottery are classified as "risk averse". Those subjects who make greater than or equal to seven choices of the safe lottery are classified as "risk intolerant". The risk preference classification implies a value support for the CRRA bid function in the *Restricted* auction task. The more risk averse is an individual, the smaller is the value support.

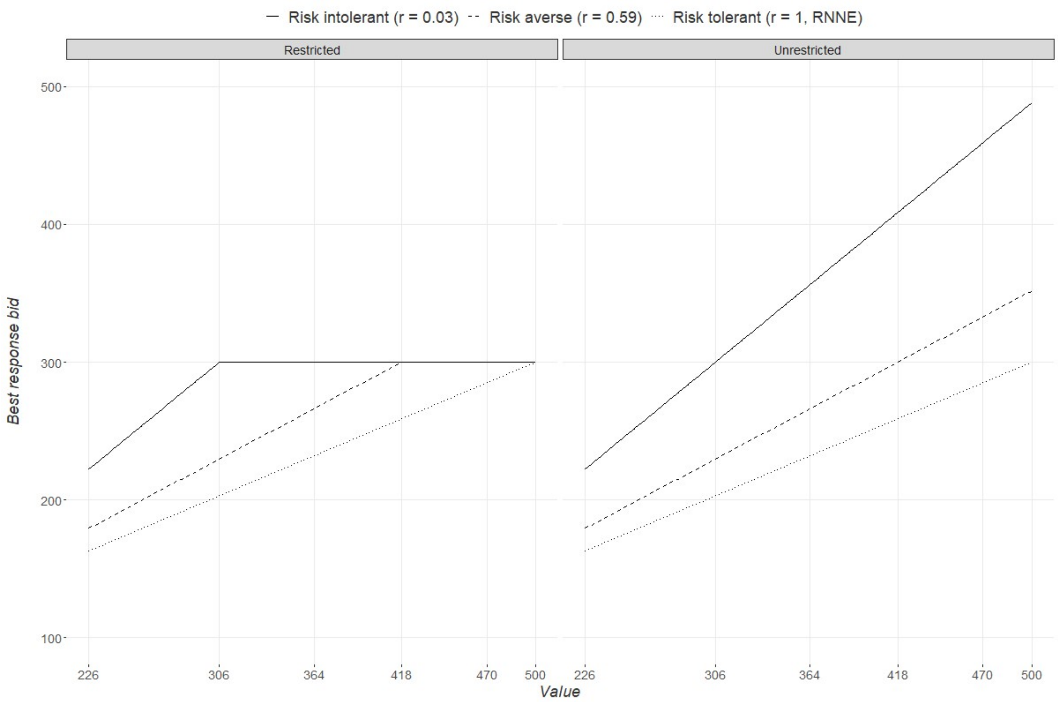
Example best response bid functions derived from maximization of (2) are presented in Figure 1. The best response for risk tolerant subjects, captured here by the RNNE prediction, coincides in the two auction tasks. For risk averse and risk intolerant subjects, there is a kink in the CRRA best response function in the *Restricted* task at some interior value.

[5] For any bid below 300, there is a constant probability of winning $(b_{ij} - 100)/(300 - 100)$.

Table 1 – Theoretical correspondence between the risk and auction tasks.

Number of safe choices in Holt-Laury task	Range of relative risk aversion for $U(x) = x^{r_i}$	Risk preference classification	Auction value support for CRRA bid in *Restricted*
Less than 4	$r_i > 1.15$	Risk tolerant	≤ 500
4	$0.85 < r_i < 1.15$		≤ 470
5	$0.59 < r_i < 0.85$	Risk averse	≤ 418
6	$0.32 < r_i < 0.59$		≤ 364
7	$0.03 < r_i < 0.32$	Risk intolerant	≤ 306
More than 7	$r_i < 0.03$		226

Figure 1. Example best response bid functions in the auction tasks.



We obtain the following testable hypotheses, based on the premise of risk aversion in the population.

Hypothesis 1. Bids are lower on average in the *Restricted* auction task than in the *Unrestricted* auction task.

Hypothesis 2. The adjustment in bids between the *Restricted* and *Unrestricted* auction tasks is increasing in the level of risk aversion, with risk tolerant subjects making smaller bid adjustments over a larger range of the value support.

Part three of the experiment is a questionnaire to collect information on subject demographics and prior experience of financial and auction situations in the field. The field experience questions ask how often subjects trade financial products (such as stocks), and how often they bid in online auctions (such as eBay). Subjects can choose one of the following options: “Never”, “Less than once a year”, “1-10 times a year”, “11-50 times a year”, “51-100 times a year” or “More”. By asking both questions, we can explore the behavioural effects of experience from different real-world domains.

Prior evidence from *second-price* auctions suggests that field experience is at least partially transferable to bidding behaviour in the laboratory. Garratt et al. (2012) conduct controlled experiments using highly experienced eBay buyers and sellers to test the persistence of a behavioural tendency towards overly aggressive bidding. While experienced and inexperienced subjects consistently fail to bid their value as the theory would predict, only inexperienced subjects tend to bid overly aggressively.

To our knowledge, there is little empirical evidence on this question in first-price auctions, in which it is no longer a dominant strategy to bid one’s value.[6] Our design permits us to assess whether bidders can transfer some of their related field experience to an abstract auction setting and control for the potentially confounding effects of risk preferences. We formalize this conjecture in a third hypothesis:

Hypothesis 3. Related experience in the field mitigates overbidding in the auction task.

Experiment Procedure

The experiment was programmed using Qualtrics software (Qualtrics, Provo, UT). The data was collected using the web-based labour platform Amazon Mechanical Turk (https://www.mturk.com), henceforth MTurk. The experiment was posted on MTurk as Human Intelligence Tasks (HITs). Subjects were recruited using the third-party research platform TurkPrime (Litman et al. 2017), which integrates the MTurk platform. No subject could take the experiment more than once and for comparability the location of subjects was restricted to the USA. To improve data quality, subjects were screened based on their number of approved HITs (100+) and approval rating (40%+). To attain greater variation for our field experience questions, we also screened potential subjects for financial experience.

[6] Katuščák et al. (2015) find no systematic relationship between self-reported field experience and reactions to different types of feedback while investigating laboratory bidding behaviour in one-shot first-price auctions with known costs. Other studies consider the relationship between experience and bidding behaviour in the field itself (see for example Bajari and Hortaçsu, 2003; Malmendier and Lee, 2011; Pownall and Wolk, 2013) or the role of within-session experience and learning in experiments (see for example Kagel and Levin, 1986; Güth et al., 2003).

Specifically, we only made the experiment available to those who previously answered "Yes" to the following question: "Do you personally invest in the stock market?".[7]

After accepting the HIT, subjects had to choose the undominated choice in the Holt-Laury task, answer three comprehension questions correctly and pass an attention check for their response to be recorded. Any subject who exhibited straight-lining behaviour in the experiment was excluded (straight-lining is defined as choosing the same option for every row of a given task). Parts one and two of the experiment were incentivized: immediately after completion, one decision from the Holt-Laury task and one decision from each of the two auction tasks was randomly selected for payment. Earnings from the experiment were converted to US dollars at an exchange rate of 100 points to 10 US cents and paid to subjects as a bonus in addition to a participation fee of thirty cents. The median completion time was five minutes and median payment was sixty-six cents (an hourly rate of eight US dollars).

Results

We collected experiment data from 101 subjects. The results in this section are qualitatively unchanged if we use the full sample or exclude subjects who displayed inconsistent behaviour.[8] For completeness, we elect to include all subjects in the analysis. A full summary of demographic characteristics for our sample can be found in the Appendix Table A 1.

In Figure 2, we present the proportion of safe choices (lottery A) for each decision of the Holt-Laury task. Risk neutrality implies a probability of one for the first four decisions, followed by a probability of zero for the remaining six decisions. As expected from prior experiments, there is a tendency toward risk aversion in our sample, with the observed series lying to the right of the RNNE after decision four. This supports the premise of risk aversion underlying our hypotheses.

Further in line with previous experiments, we find that overbidding is common in the auction task when the opponent's bid interval is unrestricted: of the 606 bids observed in this task, 55% are above the RNNE. This tendency, however, disappears when the opponent's bid interval is restricted by the price ceiling: in the *Restricted* task, only 35% of bids are above the RNNE prediction. The difference in bids between tasks is highly significant (p-value < 0.001, two-tailed Wilcoxon signed rank test). This

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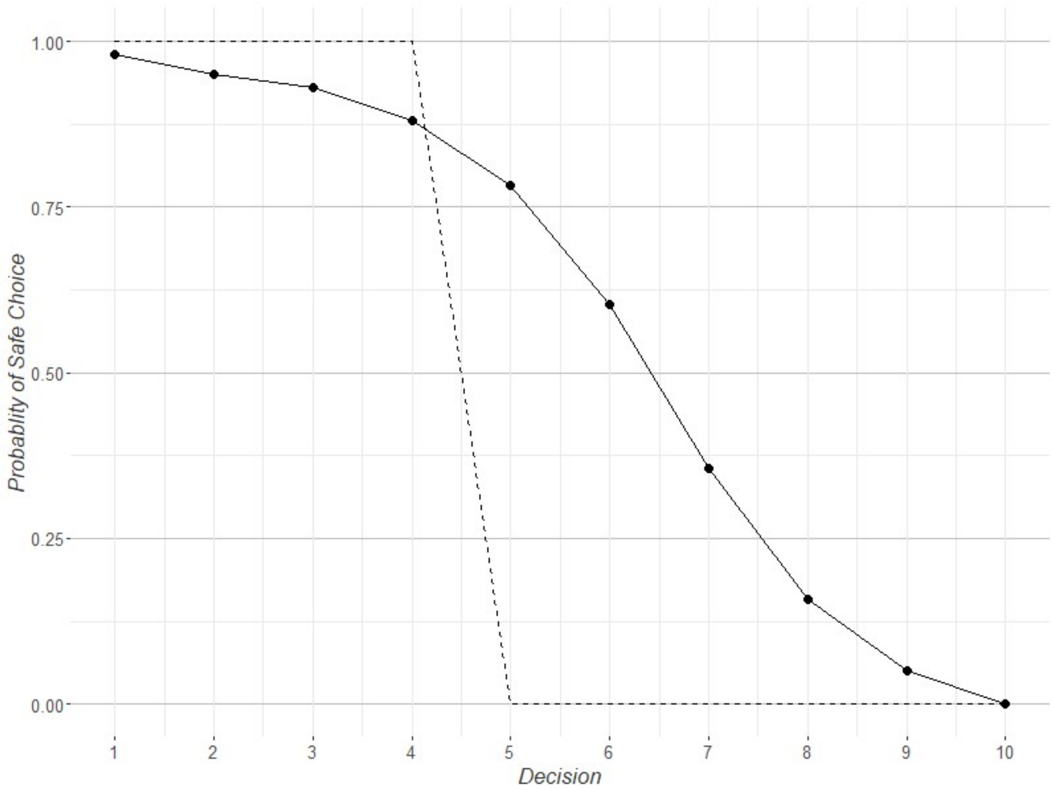
[7] The TurkPrime demographic screening question is asked only periodically and so does not preclude that, in Part three of our experiment, subjects report never trading financial products (for details, see https://go.cloudresearch.com/knowledge/how-does-turkprime-know-panel-demographic-data). We find that this is the case for nine subjects in our sample.

[8] Twenty nine subjects displayed inconsistent behaviour, switching more than once in the Holt-Laury task or choosing bids that are not weakly increasing in the auction value. For subjects who switched more than once in the Holt-Laury task, we use the risk preference implied by their first switching point.

finding is consistent with Hypothesis 1. It is observed independently of risk preferences (see Table 2) and across the value interval (see Figure 3).

Figure 2. Proportion of safe choices in each decision of the Holt-Laury task.



Notes: Data averages for the Holt-Laury task (solid line) and RNNE (dashed line).

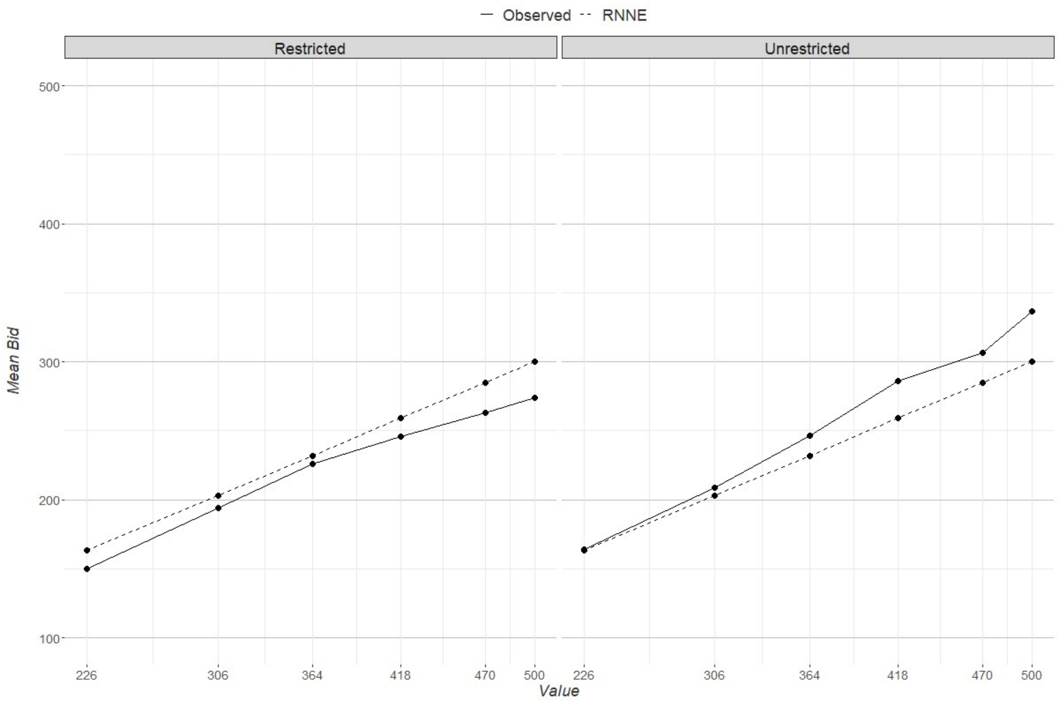
To investigate the intensity of bidding deviation from the risk-neutral prediction, we construct a measure of *relative bid deviation*. This measure is the difference between a subject's bid and the RNNE bid function and captures the degree of bidding aggression. A positive relative deviation indicates bidding higher and more aggressively than the theory predicts. On average, bids are 6% below the RNNE in the *Restricted* task and 7% above the RNNE in the *Unrestricted* task. Again, the difference is highly significant (p-value < 0.001, two-tailed Wilcoxon signed rank test). The mean degree of underbidding in the *Restricted* task ranges from 12% among risk tolerant subjects to just 1% among risk intolerant subjects. The differences among risk preference categories are statistically significant (Kruskal-Wallis rank sum test, p-value = 0.034). In the *Unrestricted* task, whereas risk tolerant subjects still do not tend to overbid, risk averse and risk intolerant subjects overbid the RNNE by 7% and 11% respectively, although the equivalent differences are not significant at conventional levels (Kruskal-Wallis rank sum test, p-value = 0.217).

Table 2 – Risk preferences and bidding behaviour.

Risk preference classification	N	*Bid*		*Relative bid deviation*[a]	
		Restricted	*Unrestricted*	*Restricted*	*Unrestricted*
Risk tolerant	22	212.43	238.45***	-0.12	-0.02*
		(34.36)	(48.42)	(0.14)	(0.20)
Risk averse	43	222.16	257.89**	-0.07	0.07***
		(43.84)	(65.15)	(0.18)	(0.27)
Risk intolerant	36	237.46	270.27***	-0.01	0.11**
		(45.14)	(65.72)	(0.19)	(0.28)
Total	101	225.49	258.07***	-0.06	0.07***
		(43.16)	(62.65)	(0.18)	(0.26)

Notes: *** $p < 0.001$, ** $p < 0.01$, * $p < 0.05$. Mean (SD) values reported in body of the table. Statistical comparison tests of *Unrestricted* versus *Restricted* auction tasks are based on two-tailed Wilcoxon signed rank tests. Risk preference classification is based on number of safe choices in the Holt-Laury task (see Table 1).
[a] *Relative bid deviation* = $(b_i - 1)/b_{RNNE}$.

Figure 3. Average bid as a function of value in the auction task.



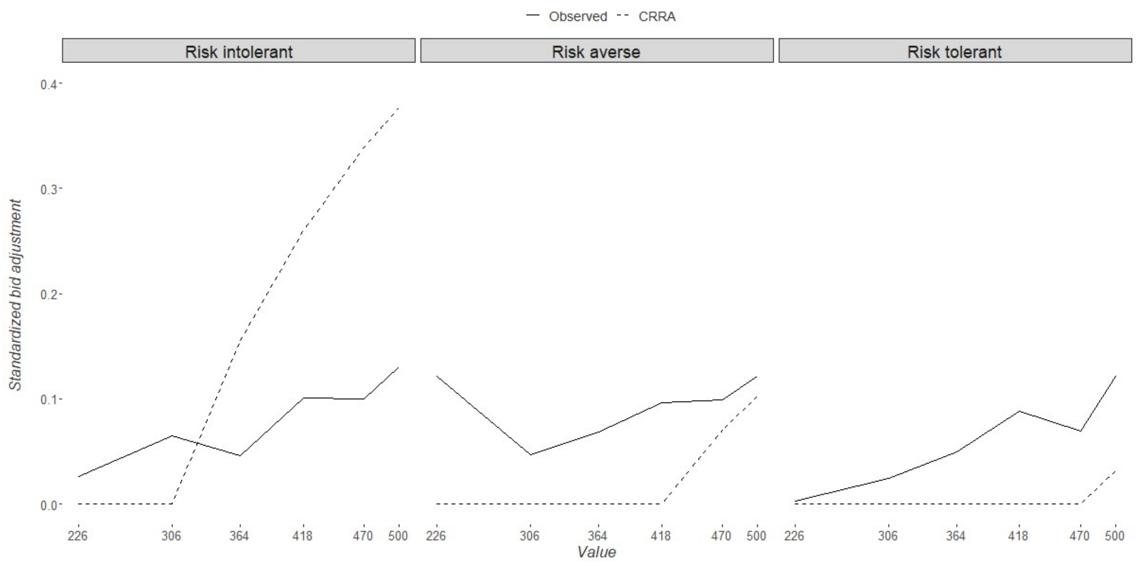
Notes: Data averages for the respective auction tasks (solid line) and RNNE (dashed line).

Result 1. *We find strong support for Hypothesis 1. Given a revealed preference towards risk aversion, bids are lower when the opponent's bid range is known to be restricted by a price ceiling; the effect is large enough to induce underbidding by all but the most risk-averse subjects.*

In Table 2, there is also evidence to suggest that the difference in bids between auction tasks is smallest for risk tolerant subjects. This would be consistent with the conjecture in Hypothesis 2 that the bid adjustment between the *Restricted* and *Unrestricted* auction tasks is increasing in the level of risk aversion. The aggregate data does not, however, inform about differences across the distribution of values, which is important for our identifying restriction.

To gain insight into how behaviour corresponds within-subjects and across the value distribution, we compare observed bid adjustments between the auction tasks to those predicted by the CRRA theory, separately for each value and risk preference classification (see Figure 4). All bid adjustments are standardized by the respective value. In support of Hypothesis 2, we observe that bid adjustments are smallest for risk tolerant subjects at low values. Note that the anomalous large bid adjustment for risk averse subjects at the lowest value (middle panel of Figure 4) disappears if we restrict attention to consistent subjects – see Appendix Figure A 1. At intermediate values, the slope is steepest for risk intolerant subjects. At high values, bid adjustments are similar across risk preference classifications.

Figure 4. Empirical correspondence between the risk and auction tasks.



Notes: Data averages for the respective auction tasks (solid line) and associated CRRA best response (dashed line). *Standardized bid adjustment* is the difference in bids between the auction tasks, as a proportion of the auction value.

We further estimate random effects panel regressions of bidding behaviour in the auction task, for individual i and value j (see Table 3). In model [1], the dependent variable is the relative bid deviation from the RNNE. In model [2], the dependent variable is the absolute difference in bid adjustments between the data and theory. Both regression models include indicators for subjects' risk preference classification. The omitted category is risk tolerant subjects. We control for subject's financial experience, gender, age and occupation, as elicited in the Part three questionnaire. To account for repeated observations, we cluster robust standard errors at the subject level.

The regression estimates in model [1] reinforce our Result 1. The coefficient estimate on the dummy variable for the *Restricted* auction task is negative and highly significant (p-value < 0.001). The positive and significant coefficient estimates on the risk averse indicator (p-value = 0.022) and the risk intolerant indicator (p-value = 0.001) support the consistency of individual behaviour between the Holt-Laury and first-price auction institutions. The degree of overbidding is largest for the most risk-averse subjects.

Regression model [2] enables us to conduct a more formal test of Hypothesis 2. In addition to the risk preference classification variables, we include indicator variables for whether the absolute difference in bid adjustments applies to one of the two intermediate auction values (364 and 418) or high values (470 and 500). The low values (226 and 306) serve as a benchmark. The empirical correspondence between risk and auction tasks is closest for risk tolerant and risk averse subjects at low auction values. This is captured by the constant term and the risk averse indicator, neither of which is significantly different from zero (p-values = 0.240 and 0.570, respectively). The theory does less well at explaining bid adjustments for risk intolerant subjects and at intermediate and high auction values, where differences in bid adjustments are significantly larger than the theory would predict.

Result 2. *We find partial support for Hypothesis 2. The adjustment in bids between the Restricted and Unrestricted auction tasks is smaller for risk tolerant and risk averse subjects than for risk intolerant subjects; there is correspondence with the predicted bid adjustments at low auction values.*

In regression model [1] of Table 3, we included self-reported financial experience as an explanatory variable.[9] This serves as an empirical test of Hypothesis 3. Independently of risk preferences, some level of financial experience reduces *relative bid deviation* in the auction task and this is increasing in the amount of experience. While the bids of those subjects who report trading financial products less than once a year are not significantly different from those who never trade financial products (p-value

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[9] Since just three subjects report trading financial products more than 100 times a year, we pool the two highest experience categories in the regression analysis. There is no systematic relationship between self-reported auction experience and bidding behaviour. Thus, we do not discuss this measure further. The sample variation in auction experience is much lower than for financial experience. Unlike for financial experience, we were not able to screen for auction experience during recruitment.

= 0.102), they are significantly lower among those subjects who trade 1-10 times a year (p-value = 0.039), 11-50 times a year (p-value = 0.054) or more (p-value = 0.027), respectively. The average effect size is large enough to offset the risk-aversion induced increase in bids.

Table 3 – Random effects panel regressions of bidding behaviour.

Dependent variable Model	*Relative bid deviation*[a] [1]	*DiA*[b] [2]
Restricted	-0.127***	
	(0.022)	
Risk preference		
Risk averse	0.100*	0.012
	(0.043)	(0.020)
Risk intolerant	0.132**	0.070**
	(0.041)	(0.023)
Financial experience		
Less than once a year	-0.103	0.040
	(0.063)	(0.047)
1-10 times a year	-0.121*	0.035
	(0.059)	(0.046)
11-50 times a year	-0.134+	-0.002
	(0.070)	(0.047)
More	-0.134*	0.015
	(0.061)	(0.053)
Value		
Intermediate		0.038**
		(0.014)
High		0.063***
		(0.019)
Constant	-0.011	0.081
	(0.105)	(0.069)
Control variables	Yes	Yes
Random effects	Yes	Yes
Observations	1212	606
N	101	101
Wald χ^2	148.20***	42.36**

Notes: *** p < 0.001, ** p < 0.01, * p < 0.05, + p < 0.1. Robust standard errors in parentheses, clustered at the subject level using the Huber/White sandwich estimator of variance (101 clusters). The reference category for *Risk preference* is "Risk tolerant". The reference category for *Financial experience* is "Never". The reference category for *Value* is "Low" All models include control variables for gender, age and occupation. Random effects are included at the subject level.

[a] *Relative Bid Deviation* = $b_{ij}/b_{RNNE} - 1$.

[b] *DiA* is the difference in standardized bid adjustment between the data and CRRA prediction.

At first sight, these regression results lend some support to Hypothesis 3. Nevertheless, while financial experience reduces bidding aggression, it may not necessarily mitigate overbidding. If bids are below the RNNE, as we observed in the *Restricted* task, it will instead accentuate underbidding. To test this conjecture formally, we re-estimate model [1] with the *absolute* (rather than *relative*) bid deviation as the dependent variable (see the Appendix Table A 2). There is no statistical evidence to suggest that financial experience reduces absolute deviations in bids from the RNNE.

Result 3. *We reject Hypothesis 3. While financial experience reduces bidding aggression independently of risk preferences, it does not mitigate overbidding due to risk aversion.*

Conclusions

Identifying individual risk preferences is one of the most elusive goals in experimental economics research. One reason is that there is no way to directly observe risk preferences—they can only be inferred from choices that deviate from theoretical predictions of risk neutral best response, and these deviations can arise for any number of reasons not directly related to risk preferences (Kirchkamp and Reiß 2011). Second, there is no one perfect test to measure individual risk aversion. The Holt-Laury method we employ here as a robustness check remains the most popular and widely used, but it has many disadvantages and is not particularly robust (see overview by Bosch-Domènech and Silvestre 2013). Third, individual behavior can be related to individual characteristics, which are not trivial to link to experimental tasks intended to elicit risk preferences (Hartog et al. 2002, Harrison et al. 2007).

In this work, we zero in on measuring risk aversion in first-price auctions. All the issues raised above are magnified in first-price auctions when it comes to risk aversion. In first-price auctions, this identification becomes even more elusive because the computation of best response, especially in the presence of risk aversion, is far from trivial and the incentive function can be especially flat (Cox et al. 1992, Harrison, 1989, Kagel and Roth 1992). The debate over identification of bidders' utility functions and risk preferences in first-price auctions has been referred to as "the loudest debate yet heard among experimental economists" (Friedman, 1992, p. 1374).

The goal here was to come up with an identifying restriction that could cleanly separate out risk preferences. We proposed and tested a new method of identifying the role of individual risk preferences in first-price auctions. We study individuals' bidding behaviour depending on whether they face a computerised opponent programmed to submit bids at random from the full value support, or from the narrower risk-neutral Nash equilibrium bid support (capped at the upper bound of the RNNE support). The risk neutral bidder always bids weakly below the upper bound of the RNNE support (cf. Figure 1). Thus, the unrestricted and restricted tasks should show no cross-task difference in the auction behaviour of this bidder. However, the risk averse bidder would bid above the RNNE upper bound in the unrestricted task at high valuations and at the RNNE upper bound in the restricted task. Bids above that restricted upper bound in the restricted task are clearly computation errors and not indicative of risk aversion. While we call it an identifying restriction, it serves also as an "attribution" restriction because it allows us to attribute equilibrium deviations to computation errors or aggression rather than risk aversion, when appropriate.

This setup also permitted us to assess whether risk aversion predicts overbidding and, since the risk neutral best response is independent, whether overbidding remains after controlling for beliefs.

The first result we obtain from our experiment is that the imposition of a price ceiling on the opponent’s bid function eliminates overbidding. The effect is strong enough to result in underbidding near-uniformly across subjects and values. We also find that individual risk preferences, as elicited in a multiple price list task, have some predictive power in explaining bid adjustments between the auction environments. This contrasts to some previous literature suggesting that risk preferences are not consistent across institutions (Isaac and James 2000). Finally, we observe that financial experience attenuates bidding aggression, but does not mitigate overbidding. Since our measure of financial experience is self-reported, further work would be desirable to establish a consensus on the relationship between bidding and experience in first-price auctions, where risk preferences are a confounding factor.

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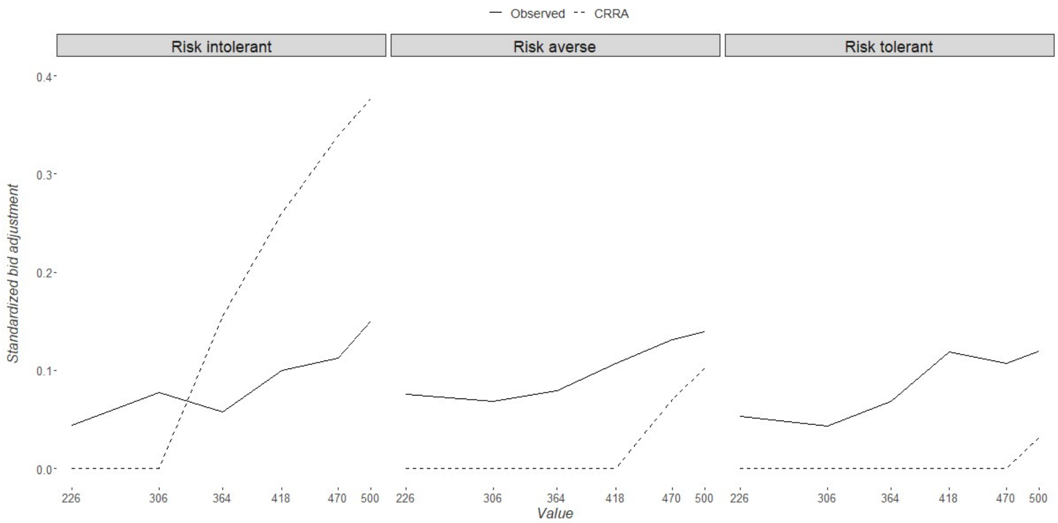
Appendix A: Additional figures and tables.

Figure A 1. Empirical correspondence between the risk and auction tasks for consistent subjects only.



Notes: Data averages for the respective auction tasks (solid line) and associated CRRA best response (dashed line). *Standardized bid adjustment* is the difference in bids between the auction tasks, as a proportion of the auction value.

Table A 1 – Demographic characteristics of the experiment sample.

	Number of subjects (N = 101)
Gender	
Female	30
Male	71
Age	
18-25	8
26-30	17
31-35	29
36-40	19
41-50	18
51-60	8
61-70	2
Employment status	
Full-time employed	81
Part-time employed	3
Retired	4
Self-employed	6
Unemployed	6
Other	1
Occupation	
Construction, extraction, and maintenance	4
Government	8
Management, professional, and related	47
Production, transportation, and material moving	3
Sales and office	17
Services	10
Not applicable	12
Financial experience:	
How often do you trade financial products (such as stocks)?	
Never	9
Less than once a year	26
1-10 times a year	42
11-50 times a year	17
51-100 times a year	4
More	3
Auction experience:	
How often do you bid in online auctions (such as eBay)?	
Never	23
Less than once a year	26
1-10 times a year	48
11-50 times a year	3
51-100 times a year	1

Table A 2 – Random effects panel regression of absolute bid deviation.

Dependent variable Model	*Absolute bid deviation*[a] [1]
Restricted	-0.062***
	(0.016)
Risk preference	
Risk averse	0.010
	(0.022)
Risk intolerant	0.008
	(0.022)
Financial experience	
Less than once a year	0.056^{+}
	(0.032)
1-10 times a year	0.058^{+}
	(0.031)
11-50 times a year	0.051
	(0.036)
More	-0.007
	(0.041)
Constant	0.216**
	(0.067)
Control variables	Yes
Random effects	Yes
Observations	1212
N	101
Wald χ^2	65.13***

Notes: *** p < 0.001, ** p < 0.01, * p < 0.05, $^{+}$ p < 0.1. Robust standard errors in parentheses, clustered at the subject level using the Huber/White sandwich estimator of variance (101 clusters). The reference category for *Risk preference* is "Risk tolerant". The reference category for *Financial experience* is "Never". All models include control variables for gender, age and occupation. Random effects are included at the subject level.
[a] *Absolute Bid Deviation* = $|b_{ij}/b_{RNNE} - 1|$.

Appendix B: Experimental instructions and task protocol.

After accepting the Human Intelligence Task on Amazon Mechanical Turk, subjects were redirected to a three-part online survey. First, they were presented with the following welcome information (investigator and ethical approval details anonymised for review purposes).

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.

<u>Consent Information</u>

The study is being conducted by xxxx, 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 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.

On giving their consent to participate in the study, subjects were then asked to complete the first part of the survey (the Risk task). This 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) was subsequently removed from the study and subjects were informed of this.

A screenshot of the Risk task is displayed underneath:

In the first part of the survey you will 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.

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.

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 = 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

Subjects then received information about the second part of the survey (the two Auction tasks), as follows:

In the second part of the survey, you will bid against a random number. This random number is drawn from a specified interval. 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 with this part of the survey, subjects had to answer a set of three comprehension questions correctly (on the first attempt).

Comprehension question

Please note: if you fail to answer the following questions correctly, the survey will end without payment.

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 the two auction tasks in this part of the survey, sequentially (see screenshots on the next two pages). These tasks correspond to the Unrestricted and Restricted auction task variants. The order in which the two task variants were presented to subjects in the experiment was randomized.

Unrestricted auction task:

You will now bid against a random number drawn from between **100 and 500**. 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*	

Restricted auction task:

You will now bid against a random number drawn from between **100 and 300**. 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*	

After completing the auction tasks, 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. Any subject who failed the attention check was subsequently excluded from the sample for analysis.

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 (full details of these questions and the response data can be found in Table A 1).