Does Risk Aversion cause Overbidding? 
New Experimental Evidence from First Price Sealed Bid Auctions

Sascha Füllbrunn, Dirk-Jan Janssen and Utz Weitzel
Does Risk Aversion cause Overbidding? New Experimental Evidence from First Price Sealed Bid Auctions

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Abstract

Bidding above the risk-neutral Nash Equilibrium in first price sealed bid auctions has traditionally been ascribed to risk aversion. Recent studies, however, offer other explanations and argue that risk aversion plays no or only a minor role. So far, no study has shown a causal relationship between risk aversion and overbidding. We implement a new experimental design which directly tests this relationship by controlling for the distribution of risk attitudes in auction markets. We find a causal relationship between our measure of risk aversion and overbidding. This result is robust to learning effects and the inclusion of feedback.

Keywords: Auction, Overbidding, Risk aversion, Experimental economics

JEL: D44, C91,

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1 Introduction

Since the early eighties, laboratory experiments repeatedly provided evidence that subjects tend to bid above the risk neutral Nash equilibrium (RNNE) in first price sealed bid (FPSB) auctions (for an overview see Kagel and Levin, 2002, 2011). This overbidding behavior has initially been rationalized with risk aversion Cox et al. (1982a). Assuming constant relative risk aversion in a expected utility framework, the bidding function depends directly on a risk aversion parameter thereby explicitly modeling the relationship between risk aversion and overbidding (henceforth CRRAM for constant relative risk aversion model). In an independent private value auction framework with \(N\) bidders with CRRA utility function \(u_i(x) = x^{r_i}\), where \(r_i\) is the risk aversion parameter, each subject \(i\) maximizes expected utility \(U_i(b_i)\) by submitting the equilibrium bid \(b^*_i\), given uniformly distributed private values \(v \in (0, \bar{v})\) and the subjective probability \(F_i(b_i)\) that s/he can win the auction by bidding bid \(b_i\):

\[
U_i(b_i) = F_i(b_i)u_i(v_i - b_i), \quad b^*_i(v) = \frac{N - 1}{N - 1 + r_i}v.
\]

In general, subjects face the trade off that a higher bid increases the probability of winning the auction, \(dF_i(b_i)/db_i > 0\), while at the same time profit decreases in bids \(du_i(v_i - b_i)/db_i < 0\). For a risk neutral agent with \(r_i = 1\) the RNNE bid equals \(b^*_i(v) = b_{RN}(v) = (N-1)v/N\). For risk averse subjects with \(0 < r_i < 1\) the equilibrium bid \(b_{RA}(v)\) is greater than \(b_{RN}(v)\). Hence, higher risk aversion \((r_i \downarrow)\) increases the equilibrium bid and thus overbidding, i.e. \(b_{RA}(v) - b_{RN}(v) > 0\).

To the best of our knowledge, experimental evidence in support of a positive relationship between risk aversion and overbidding is restricted to fitting models, like the CRRAM, to auction data (Cox et al. 1982a, 1982b, 1983a, 1983b, 1984, 1985, 1988). Using experimentally observed auction prices and bids, the authors estimated the implied value of \(r_i\) and find that bidders tend to be risk averse, which, assuming CRRAM, could explain overbidding. However, these early results have been obtained ex post by implication and not by administering a treatment effect from which the influence of risk preferences on overbidding could have been tested directly and, importantly, with causal inference. In fact, despite a rich literature and long debate about the role of risk preferences in auction markets (see, e.g., Svorončík (2015) chapter six for a discussion) no study has been able to show a direct causal relationship between risk aversion and overbidding in FPSB auctions.

The missing experimental evidence is not because of a lack of trying. Three recent
studies analyze the risk-overbidding relationship in different settings. Using a within-subjects design, Isaac and James (2000) and Berg et al. (2005) elicit individual risk preferences with the Becker-DeGroot-Marschak procedure (BDM, Becker and DeGroot, 1974) and with FPSB auctions. Assuming CRRAM, the authors compare the inferred risk aversion parameter \( r_i \) across institutions at the individual level. Neither of the two studies finds significant evidence for a positive relationship between the inferred risk aversion parameters of BDM and FPSB. In a third study, Engelbrecht-Wiggans and Katok (2009) apply a treatment effect by varying the risk that bidders face in auctions against computer agents. The authors compare a condition, in which each bidding decision affects a single auction, with a condition in which each bidding decision affects ten independent auctions simultaneously. If CRRAM applies, risk averse bidders should display less overbidding in the latter condition, because of a lower variance of a subject’s payoff (risk). Although the authors find some risk effects, overall the difference between the two conditions is not significant and Engelbrecht-Wiggans and Katok (2009) conclude that there is “virtually no support for the risk aversion model” (p. 83). Possible reasons why these studies find no relationship between risk aversion and overbidding will be discussed in Section 4.

Given the limited experimental evidence in support of risk aversion as explanation for overbidding in FPSB auctions, a number of studies offered alternative explanations, which effectively claim that risk aversion plays no or only a minor role. Harrison (1989) claimed that overbidding is rather due to the low cost of increasing the winning probability than due to risk aversion (the so-called ‘flat maximum critique’). Kagel and Roth (1992) argued that risk aversion cannot be solely held responsible for overbidding, because the latter has also been observed in second price sealed bid auctions, where risk preferences should have no effect on bids. Goeree et al. (2002) fitted a non-expected utility model to their auction data and showed that a convex probability weighting function “fits the data as well as the risk aversion model”. Armantier and Treich (2009a) and Armantier and Treich (2009c) fitted a non-expected utility model and concluded that overbidding can be fully rationalized with non-linear probability weighting functions. Ockenfels and Selten (2005) report that overbidding can be due to dynamic bidding behavior in line with learning direction theory (Selten and Buchta, 1994). Neugebauer and Selten (2006) reported that learning direction theory fits their bidding data better than both CRRAM and RNNE bid functions. Engelbrecht-Wiggans (1989) introduce regret theory as a reason for overbidding: ‘Winner regret’ occurs when the winner realizes that her bid

\[1\] Bidders decrease their bids after being outbid and increase their bids after having won an auction. This behavior strongly depends on feedback about prices and bids. As learning direction theory presumes a direct relationship between feedback and bids, it is inconsistent with the CRRAM.
could have been lowered while still having won the auction (money left on the table).

‘Loser regret’ occurs when a loser realizes that her bid could have been increased above the
winning bid without surpassing her private value. When both forms of regret are weighed
equally, the bidder’s utility maximizing bidding strategy is the RNNE bid, but when loser
regret is weighed more heavily, the optimal bid increases. Engelbrecht-Wiggans and
Katok (2008) reported that loser regret is indeed stronger than winner regret, which can
explain overbidding in repeated FPSB auctions if bidders receive the relevant feedback.\footnote{Filiz-Ozbay and Ozbay (2007) go one step further and experimentally test ‘anticipated regret’. Here, bidders anticipate winner and loser regret and, ex ante, adjust their bids accordingly. They conclude that bidding behavior in one-shot auctions is consistent with both forms of regret (although bidding in their winner regret treatment does not differ statistically from bidding in a corresponding treatment without feedback). In a replication study with additional robustness checks, Katušcák et al. (2013) find no evidence for anticipated regret. This is in line with results from other studies, which do not report a treatment effect of winner and or loser regret in the first round of repeated auctions with feedback (see, e.g., Isaac and Walker (1985); Ockenfels and Selten (2005); Neugebauer and Selten (2006)).}

The reported evidence against the exclusive validity of the CRRAM clearly suggests
that a number of factors play a role in the bidding process. The same evidence, however,
cannot exclude the possibility of a fundamental relationship between risk aversion and
overbidding. In this paper, we therefore directly test for this relationship by manipulating
the level of risk aversion in markets. We use the Bomb Risk Elicitation Task (BRET), in-
troduced by Crosetto and Filippin (2013), to elicit risk preferences. The BRET requires
only one simple choice, yet allows for a fine-grained measurement of risk preferences,
which is robust to loss aversion and violations of the Reduction Axiom. We then com-
pose auction markets with different levels of risk aversion (unknown to subjects). By
comparing bidding behavior across markets, we find a robust, causal and positive effect
of the level of bidders’ risk aversion, measured by BRET, on overbidding. By design, all
alternative explanations mentioned above cannot account for this result, because they
explicitly focus on factors that are not related to risk aversion, while in our design the
only change across markets is the level of risk aversion. We find that our result applies
to all stages in a repeated auction setting and are robust to the inclusion of feedback and
hence to possible regret effects.

2 Experimental design and hypotheses

2.1 Design

The idea behind our experimental manipulation is straightforward. If risk aversion leads
to overbidding in FPSB auctions, we expect to observe higher bids – and thus higher
auction prices—in a market composed of only risk averse subjects than in a market composed of only risk seeking subjects. More generally, we expect a positive relationship between the level of bidders’ risk aversion in a market and bids/prices. To be able to test our conjecture, we first categorize subjects by their risk attitudes and then organize auction markets with four subjects whose risk attitudes are similar within markets but sufficiently heterogeneous between markets. In comparison to studies that elicit risk aversion for model-fitting or within-subject comparisons, this design has the advantage that it experimentally manipulates the variable of interest: the average level of risk aversion in a market serves as the treatment variable while leaving everything else constant. Hence, if we find that bids and prices are higher in markets with a higher level of risk aversion we can infer with high internal validity that risk aversion causes overbidding.\footnote{Earlier studies use similar techniques to manipulate the distribution of particular subject characteristics in markets. For example, in recent double auction experiments subjects have been separated by gender \cite{Eckel2015} or the propensity to speculate \cite{Janssen2015}. In an earlier study, \cite{Ang1985} elicited risk aversion, and assigned risk averse subjects to one asset market and risk seeking participants to another. In auction experiments, \cite{Goertz2012} assigned and compared experienced vs. inexperienced markets in common value auctions.}

To measure risk aversion we made use of the dynamic BRET introduced by \cite{Crosetto2013}. We chose this relatively new task, because of several advantages: it is based on an intuitive, single choice, requires minimal numeracy skills, allows for a virtually continuous distribution of estimates of risk preferences and avoids truncation of the data.\footnote{A recent neuro-scientific study supports the elicitation design by providing evidence that the baseline cortical activity in the right prefrontal cortex predicts individual risk-taking behavior in a task that is closely related to the BRET \cite{Gianotti2009}.} Because of the unique choice, the BRET avoids violations of the Reduction Axiom. Moreover, risk preference measurements are not affected by loss aversion, because the BRET does not provide endogenous reference points against which some outcomes could be perceived as losses. For us it is crucial that we can clearly categorize bidders.\footnote{For example, multiple price list risk elicitation tasks \cite[e.g.,][]{Holt2002} can lead to inconsistent or dominated choices making it impossible to assign some of the observations to a category.}

The BRET works as follows. A subject collects a number of boxes, $0 \leq k \leq 100$, from 100 boxes available. For each collected box, the subject earns 0.1 Euro. However, the computer has randomly assigned a hidden bomb to one of the 100 boxes with equal probability. If at the end of the task, after subjects have collected their desired number of boxes, the bomb is among the collected boxes, it 'explodes' and the payoff for the task is zero. Otherwise the payoff equals $k \times 0.1$ Euro. In our experiment, subjects only learned whether or not the bomb was collected – and thus their earnings in the BRET task – at the very end of the experiment. In the dynamic version used in our experiment, 100 boxes
are shown on the computer screen and per second one box automatically disappears (is collected) until the subject clicks on a stop button and confirms the number of collected boxes. Given that the random position of the time bomb is uniformly distributed, collecting exactly 50 boxes can be interpreted as risk neutral behavior, while collecting less (more) boxes can be categorized as risk averse (risk seeking) behavior.

We make no strict assumptions on the utility function of our subjects as we are primarily interested in the ordinal ranking of subjects in terms of risk aversion to analyze the relationship between degrees of risk aversion and overbidding. In order to do so, we categorize the auction markets and the individual subjects in these markets in three distinct risk categories, which are based on the average market BRET score: ‘LRA’ (low risk aversion), ‘MRA’ (moderate risk aversion), and ‘HRA’ (high risk aversion). So, HRA markets contain HRA subjects with a relatively low k who are willing to take less risk than the LRA subjects with a relatively high k in LRA markets.

Specifically, the above mentioned categorization is executed as follows: In each session with M subjects, we first elicited the BRET score (k_i) for each subject i. Then, we ranked the subjects according to their BRET score such that k_{[1]} < k_{[2]} < ... < k_{[M]}.

After that we composed auction markets such that the subjects with k_{[1]}, k_{[2]}, k_{[3]}, and k_{[4]} are in auction market one, subjects with k_{[5]}, k_{[6]}, k_{[7]}, and k_{[8]} are in auction market two, ..., and subjects with k_{[M−3]}, k_{[M−2]}, k_{[M−1]}, and k_{[M]} are in auction market M/4. We randomly allocated ties. Having six sessions with M = 24 and two sessions with M = 20, this procedure resulted in a total of 46 auction markets with average BRET scores K_{[1]} ≤ K_{[2]}, ..., ≤ K_{[46]}. We classify nine auction markets with K > 50 as LRA markets; the mean BRET score is K_{LRA} = 58.33 (sd = 4.37). We take the same number of markets on the other side of the distribution, i.e., we classify the nine markets with the lowest BRET scores as HRA markets (K_{HRA} = 28.86, sd = 3.11). We classify the remaining 28 markets as MRA markets (K_{MRA} = 42.93, sd = 5.15). We then categorize subjects in HRA (n_{HRA} = 36), MRA (n_{MRA} = 112), and LRA subjects (n_{LRA} = 36) in line with their market affiliation. Note that the three market categories differ significantly in terms of BRET scores showing that our sample is sufficiently heterogeneous in terms of risk attitudes.

\[ \text{In comparison to the static BRET, the dynamic version is less demanding at a cognitive level, better suited to facilitate subjects' comprehension, and is characterized by a richer set of parameters that can be manipulated. For these and other reasons, } \text{Crosetto and Filippin (2013) conclude that "the visual version in continuous time is our preferred choice."} \]

\[ \text{We find distributions of K to be significantly different comparing the three categories with each other using a Mann Whitney U test } (p < 0.001). \text{ We can also reject the Null hypothesis that } K_{HRA} ≥ K_{MRA} ≥ K_{LRA}\text{ in favor of the alternative that } K_{HRA} < K_{MRA} < K_{LRA} \text{ using a Cuzick trend test } (p < 0.001). \]
After the markets had been composed subjects submitted sealed bids in 50 subsequent FPSB auctions. Auction markets consisted of four subjects submitting one bid per period. The bidder with the highest bid earns the difference between her private value and her bid, while the other bidders’ payoff equals zero. The private values for each subject were pre-drawn from a uniform distribution over the integer set \([0, 10000]\). In this setting, a RNNE bidder would submit a bid that equals \(3/4\) of his private value while bidders in the CRRA model submit higher bids when being risk averse. Our treatment variable is the risk attitude - the average BRET score \(K[j]\) - of the auction market. We kept all parameters equal in each auction market. Private values have been the same in each auction market. Additionally, we ranked the bidders in each market according to their BRET score \(k\) and assigned the same private value to the same rank. Hence, we made sure that we have the same condition in each market and only vary the level of risk aversion.

While in the first 25 auctions, feedback included only whether or not the subject submitted the highest bid (‘No Regret’ phase), in the last 25 period they additionally learned the winning bid and the value of their ‘missed opportunity’ (‘Regret’ phase). The missed opportunity is the difference between a subject’s value and the winning bid given the subject had a higher value than the winning bid, and zero otherwise. Subjects received new instructions between the No Regret phase (Periods 1-25) and the Regret phase (Periods 26-50). We implemented the different feedback regimes as a robustness check. Our aim is to show that even if feedback plays a role in bidding behavior (as a level effect), the relationship between risk aversion and overbidding still holds. Finally, the total earnings of all auctions have been accumulated and divided by 1500 to calculate the auction payoff in Euro.

A total of eight session were run with 24 subjects in six sessions and 20 subjects in two sessions (due to no-shows) with 184 subjects in total. Instructions were read out aloud by the experimenter separately for each part of the experiment. Comprehension questions have been administered and discussed. Subject earned about twelve euro including a 2.50 euro show-up fee. The experiments lasted roughly one hour. Payments were made in cash and in private at the very end of the experiment. The experiment was computerized using

\footnote{For instructions and a screenshot see the online supplement.}

\footnote{For example, in groups 21 and 26 the subjects’ elicited BRET scores have been 59, 60, 61, and 70, and 25, 27, 30, and 31 respectively. In period 14, the computer assigned \(v = 6403\) to the subjects with scores 59 and 25, \(v = 2124\) to the subjects with scores 60 and 27, \(v = 1210\) to the subjects with scores 61 and 30, and \(v = 7086\) to the subjects with scores 70 and 31.}

\footnote{We are aware of the fact that experience itself might change bidding behavior over time. The 100 private values in the No Regret Phase and in the Regret Phase do not significantly differ using an ordinary t-test (\(p = 0.556\)).}
z-Tree [Fischbacher, 2007]. Subjects were recruited using ORSEE [Greiner, 2004]. The sessions were conducted in the period from April to June of 2015 at the NSM Decision Lab at the Radboud University, The Netherlands.

2.2 Measurements and hypotheses

We formulate and test our hypotheses at two different levels: the market level and the individual level. The former is relevant to show the effect of the distribution of risk aversion on market performance, i.e. on pricing. The individual level is relevant to show how risk aversion influences the individual bid function.

At the market level, we consider ‘overpricing’, the percentage deviation of the observed auction price from the RNNE price \( (\text{OP}_{jt} = 100 \times (p_{jt}/p_{RNNE,t} - 1)) \), as the relevant unit of observation. When risk aversion has no effect on overbidding, overpricing should be the same across auction markets. Hence, our Null hypotheses is that overpricing is not significantly different across the three risk categories: \( H_{1\text{NULL}} : \text{OP}_{HRA} = \text{OP}_{MRA} = \text{OP}_{LRA} \). In line with CRRAM, however, the alternative hypothesis predicts that overpricing is increasing in the level of risk aversion: \( H_{1} : \text{OP}_{HRA} > \text{OP}_{MRA} > \text{OP}_{LRA} \).

At the individual level, we consider ‘overbidding’, the percentage deviation of the observed bid from the RNNE bid \( (\text{OB}_{ijt} = 100 \times (b_{ijt}/b_{RNNE,it} - 1)) \), as the relevant unit of observation. The hypotheses on overbidding are analogue to overpricing at the market level \( (H_{2\text{NULL}} : \text{OB}_{LRA} = \text{OP}_{MRA} = \text{OB}_{HRA}, H_{2} : \text{OB}_{HRA} > \text{OB}_{MRA} > \text{OB}_{LRA}) \).

In all statistical tests, unless stated otherwise, we make use of the Wilcoxon signed rank test (for paired replicates), the Mann-Whitney U test for independent samples, and the Cuzick test to perform trend tests using a significance level of 5%.

3 Results

3.1 Overpricing

Figure 1 shows average overpricing for the HRA, MRA and LRA markets divided into the No Regret phase (Period 1-25) and the Regret phase (Period 26-50).

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\(^{12}\)Note that the RNNE price is determined by the highest value. But the bidder with the highest value not necessarily determines the price.

\(^{13}\)However, running permutation tests instead yield similar results.
**Figure 1:** Average Overpricing

![Figure 1: Average Overpricing](image)

**Notes:** Bars show mean overpricing for the categories HRA (n=9), MRA (n=28), and LRA (n=9) in the No Regret phase (round 1-25) and in the Regret phase (round 26-50) together with error bars, e.g. for HRA in the No Regret phase $\overline{OP} = \frac{1}{7} \sum_{j=1}^{7} \left( \frac{1}{25} \sum_{t=1}^{25} 100 \times \left( \frac{p_{jt}}{p_{RNNE,t}} - 1 \right) \right)$. The average BRET score in each category is $K$.

As a lower $K$ is associated with higher risk aversion, the figure clearly shows a positive relationship between risk aversion in a market and overpricing. Average OP is about 710 basis points higher in the HRA markets than in the LRA markets in the No Regret phase. In the Regret phase, average OP is about 923 basis points higher in the HRA markets than in the LRA markets. We find a significant difference comparing the HRA with LRA markets in both phases ($p_{NR} = 0.009$, $p_{R} = 0.001$). Further, we find the trend to be significant in both phases ($p_{NR} = 0.003$, $p_{R} < 0.001$). Hence, at this level of aggregation we can clearly reject the Null hypothesis $H1_{NULL}$ of equal overpricing levels across all three risk categories in favor of the alternative hypothesis $H1$ that overpricing increases with a higher average risk aversion in the market.

To strengthen this result, we conducted random effects panel regressions with $OP_{jt}$, overpricing in market $j$ in round $t$, as the dependent variable which amounts to $46 \times 50 = 2300$ observations at market level. With random effects at market level, we additionally correct for possible intra-session correlation by adjusting all standard errors with the Huber and White sandwich estimator of variance at session level (eight clusters). Table II reports the results.

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14The $p$-values for comparing HRA to MRA are $p_{NR} = 0.018$ and $p_{R} = 0.002$, and the $p$-values for comparing MRA to LRA are $p_{NR} = 0.103$ and $p_{R} = 0.034$. 

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Table 1: Random effects panel regressions at market level: overpricing

<table>
<thead>
<tr>
<th></th>
<th>Model 1</th>
<th>Model 2</th>
<th>Model 3</th>
<th>Model 4</th>
<th>Model 5</th>
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<tr>
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<td>-0.23***</td>
<td>-0.23***</td>
<td>-0.22***</td>
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<td>2.51**</td>
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<td>(0.50)</td>
<td>(0.77)</td>
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<td>Round</td>
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<td>(0.038)</td>
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<td>0.000</td>
<td>0.000</td>
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</tr>
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</table>

Notes: The dependent variable is overpricing (OP) in each round for each group. The RHS consists of K, the auction groups’ average BRET score, the Regret Dummy, equal to one in the Regret phase (Period 26-50) and zero otherwise (No Regret: Period 1-25), Round, which captures the number of auctions played and, finally, round NR and Round R, including the number of auctions played in the No Regret or the Regret phase, respectively. We use random effects at market level and correct for intra-session correlation by adjusting all standard errors with the Huber and White sandwich estimator of variance at session level (eight clusters). Models (1) and (2) include all 50 rounds, while model (3) and (4) include rounds 1-25 and 26-50 respectively. Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1.
The main variable of interest on the RHS is the auction markets’ average BRET score $K$. Recall that a higher $K$ stands for lower risk aversion. Hence, a negative coefficient indicates that an increase in average risk aversion (decrease in $K$) leads to an increase in overpricing. And indeed in all specifications we find the coefficient to be significantly negative, strongly supporting $H1$. The positive and significant coefficient of the regret dummy (equal to one in the Regret phase) in Model (1) indicates that overbidding is not driven by risk aversion alone. As shown in Model (2) the regret effect also survives if we control for possible experience effects by including the variable Round, which records the number of rounds played and is statistically significant and positive, too. When analyzing the No Regret phase and the Regret phase separately in Model (3), Model (4) and Model (5), the experience effect turns out not to be very strong. This suggests that the coefficient of the count variable Round picks up some of the regret effect in Model (2), rather than the other way around.

To consider the economic effect of overpricing we look at the seller’s revenues. Conditional on the private values drawn, the seller’s actual revenue – assuming prices equal RNNE prices – is 193.90 Euro in each auction market.\textsuperscript{15} The actual average gain in the experiment is 43.64 Euro in HRA markets, 33.67 Euro in MRA markets, and 27.08 Euro in LRA markets. Hence, the seller’s gain is about 61 per cent higher in the HRA markets than in the LRA markets. Statistically, we can reject the hypothesis of equal revenues in HRA and LRA markets ($p = 0.002$).\textsuperscript{16}

To sum up, we show that the distribution of risk aversion in an auction market has a significant impact on overpricing in general and on the seller’s revenue in particular. The higher the level of risk aversion in a market, the higher overpricing and the higher the revenues for the seller.

### 3.2 Overbidding

The predicted bid-value ratio $b/v$ is determined by the number of bidders in the RNNE ($b/v = (N - 1)/N$) and, in the CRRAM, by the number of bidders and the risk aversion parameter ($b/v = (N - 1)/(N - 1 + r)$). In both models the bid-value ratio is constant across private values, i.e. independent of the magnitude of the private value. Prior studies suggest, however, that the bid-value ratio is not constant across values (see e.g., Cox et al. 1985; Füllbrunn and Neugebauer 2013) and that OB differs depending on the private

\textsuperscript{15}As the RNNE price is $p_{RNNE}(v_{[1]}) = (4 - 1) \times v_{[1]}/4$, we compute the revenue for the seller by summing up the highest private value from each of the 50 rounds, multiplying it by $3/4$ to get the RNNE price and by the exchange rate 1/1500 for Euro amounts.

\textsuperscript{16}The p-value for comparing HRA to MRA is $p = 0.008$, and the p-value for comparing MRA to LRA are $p = 0.061$. The Cuzick trend test yields $p < 0.001$. 

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value. If this is true, the relationship between risk aversion and overbidding might depend on the private value. To account for this, we segment the value range into quartiles, and analyze overbidding not only in aggregate but also for each of the following four value segments: \{1, \ldots, 2500\}, \{2501, \ldots, 5000\}, \{5001, \ldots, 7500\}, and \{7501, \ldots, 10000\}.

Figure 2 visualizes mean overbidding in blocks of five periods, for each value segment and risk aversion category. We see that overbidding in HRA exceeds LRA consistently from the first to the last block, with MRA mostly in between. A Cuzick trend test confirms this ranking for each block: we find p-values at or far below 0.021 in every block (across value segments) when neglecting outliers. Including outliers the block with \( p = 0.021 \) is the only one where the trend is insignificant (with \( p = 0.207 \)). It is remarkable how stable the relationship between market levels of risk aversion and overbidding is over time. In fact, visually there is no indication for a regret effect, because there is no clear shift in the level of overbidding after block five (red vertical line).

**Figure 2:** Mean overbidding over time

![Figure 2: Mean overbidding over time](image)

**Notes:** Mean overbidding for the categories HRA (n=9), MRA (n=28), and LRA (n=9) in blocks of five periods separated by value segments.

Table 2 shows average overbidding separated by risk category (HRA, MRA, LRA), subdivided over four value segments for both the No Regret and the Regret phase, along with p-values from Mann Whitney U tests, testing the Null Hypothesis that overbidding

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17 We take five periods blocks to allow for sufficient observations in each value segment plot.

18 See further below in this section for the definition of outliers.
in HRA and LRA are not significantly different, and with p-values from a Cuzick trend test testing the Null Hypothesis of no trend across HRA, MRA, and LRA. Pooling all values, we find overbidding to be significantly higher for the HRA than the LRA subjects in both phases.\(^{19}\) Further, the Cuzick trend test rejects the Null Hypothesis in favor of the alternative hypothesis \(OB_{HRA} > OB_{MRA} > OB_{LRA}\).

Table 2: Average overbidding

<table>
<thead>
<tr>
<th>Private value</th>
<th>(0-10000)</th>
<th>(0-2500)</th>
<th>(2500-5000)</th>
<th>(5000-7500)</th>
<th>(7500-10000)</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>No Regret</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>HRA (n=36)</td>
<td>18 (12)</td>
<td>14 (20)</td>
<td>21 (13)</td>
<td>20 (10)</td>
<td>19 (8)</td>
</tr>
<tr>
<td>MRA (n=112)</td>
<td>16 (8)</td>
<td>12 (17)</td>
<td>19 (10)</td>
<td>18 (7)</td>
<td>14 (9)</td>
</tr>
<tr>
<td>LRA (n=36)</td>
<td>13 (10)</td>
<td>9 (19)</td>
<td>18 (8)</td>
<td>17 (8)</td>
<td>10 (9)</td>
</tr>
<tr>
<td>p-value HRA=LRA</td>
<td>0.001</td>
<td>0.077</td>
<td>0.015</td>
<td>0.006</td>
<td>&lt;0.001</td>
</tr>
<tr>
<td>p-value Cuzick</td>
<td>0.001</td>
<td>-0.001</td>
<td>&lt;0.001</td>
<td>&lt;0.001</td>
<td>&lt;0.001</td>
</tr>
<tr>
<td><strong>Regret</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>HRA (n=36)</td>
<td>21 (11)</td>
<td>13 (24)</td>
<td>24 (10)</td>
<td>25 (6)</td>
<td>22 (6)</td>
</tr>
<tr>
<td>MRA (n=112)</td>
<td>16 (11)</td>
<td>10 (24)</td>
<td>20 (8)</td>
<td>20 (7)</td>
<td>17 (7)</td>
</tr>
<tr>
<td>LRA (n=36)</td>
<td>12 (13)</td>
<td>3 (34)</td>
<td>17 (10)</td>
<td>17 (8)</td>
<td>12 (7)</td>
</tr>
<tr>
<td>p-value HRA=LRA</td>
<td>0.001</td>
<td>0.053</td>
<td>0.001</td>
<td>&lt;0.001</td>
<td>&lt;0.001</td>
</tr>
<tr>
<td>p-value Cuzick</td>
<td>&lt;0.001</td>
<td>-0.001</td>
<td>&lt;0.001</td>
<td>&lt;0.001</td>
<td>&lt;0.001</td>
</tr>
</tbody>
</table>

Notes: First we calculated the average overbidding of each subject in the respective category, then we averaged over all subjects in that category. For example, 18 is the average of 36 subjects’ average overbidding for the first 25 periods independent of the redemption value. The remaining rows show the p-values for the Mann Whitney U test comparing overbidding between HRA and LRA, and the p-values for a Cuzick trend test.

To analyze the four value segments individually, we calculate the average overbidding for each subject in each value segment and then test whether whether differences in average overbidding between value segments are zero (Wilcoxon Sign Rank test). Independent whether we look at all subjects \((n = 184)\) or at risk categories \((n_HRA = n_LRA = 36, n_MRA = 112)\), we find significant lower overbidding in value segment \(\{1, \ldots, 2500\}\) than in value segment \(\{2501, \ldots, 5000\}\) \((p < 0.001, p_{HRA} = 0.004 p_{MRA} < 0.001 p_{LRA} = 0.003)\). In line with Cox et al. (1985, p. 161) we believe that subjects in the low value segment do not submit serious bids: "This ‘throw away’ bid phenomenon [in the low value segment] can be interpreted as the result of payoffs being so low that it is not worth the trouble of a ‘serious’ bid." We can support this claim as almost 90 percent of the outlier bids – defined as bids that are either above valuation \((OB > 33.33)\) or below half of the valuation \((OB < -33.33)\) – fall in the lowest value segment.\(^{20}\) Overbidding in

\(^{19}\)The p-values for comparing HRA to MRA are \(p_{NR} = 0.047\) and \(p = 0.007\), and the p-values for comparing MRA to LRA are \(p_{NR} = 0.245\) and \(p = 0.251\) with \(n_{HRA} = n_{LRA} = 28\) and \(n_{MRA} = 84\).

\(^{20}\)In total, we identify 308 outlier bids (of 9,200 bids). And 268 bids are submitted in the lowest values
the next two segments is not significantly different from each other \( (p = 0.385, p_{HRA} = 0.271, p_{MRA} < 0.249, p_{LRA} = 0.354) \), but overbidding is significantly lower in segment \{7501, ..., 10000\} than in segment \{5001, ..., 7500\} \( (p < 0.001, p_{HRA} = 0.004, p_{MRA} < 0.001, p_{LRA} < 0.003) \). In the second and third value segment, subjects might believe that although not having the highest value they still can win the auction with a sufficient profit when they overbid. In the highest value segment, however, subjects might believe that they have the highest value anyway, making overbidding less relevant. The focus of this paper is not to explain why overbidding differs between value segments, but to show that the positive relationship between risk aversion and overbidding persists across value segments. We find a significant difference in overbidding comparing HRA and LRA individuals in all value segments (see Table 2, weakly significant in the lowest value segment). The Cuzick test shows a significant trend in all segments \( (p \leq 0.001) \) and overall. Hence, the relationship between risk aversion and overbidding holds for each value segment considered.

To further strengthen our results, we apply a random effects regressions with three levels of dependencies (in line with Chapter 4.7 in Moffatt, 2015) with \( OB_{ijt} \) — overbidding of subject \( i \) in group \( j \) in round \( t \) — as the dependent variable which amounts to \( 4 \times 46 \times 50 = 9,200 \) observations. We correct for intra-session correlation by estimating the variance at individual and auction group level. In all models we control for age, gender and economics major. We also added the number of rounds (Rounds) to cope for experience and a dummy for being an outlier as explained above (Outlier Dummy). The main variable of interest on the RHS is the subjects BRET score \( k \). A negative coefficient indicates that an increase in average risk aversion leads to a decrease in overpricing. Table 3 reports the results.

The first two models (1) and (2) consider all observations. Here we control for the regret phase using the Regret Dummy. The variable is not significant, which might be due to the fact that the Round variable interacts with the Regret phase. Further, we added dummies for the value segments with the lowest value segment as the reference. The coefficients reflect the discussion above, i.e. overbidding is higher in the second and third value segment but lower in the highest value segment. Model (3) considers only
Table 3: Three-level model regression: overbidding

<table>
<thead>
<tr>
<th></th>
<th>Model 1</th>
<th>Model 2</th>
<th>Model 3</th>
<th>Model 4</th>
</tr>
</thead>
<tbody>
<tr>
<td>k</td>
<td>-0.12**</td>
<td>-0.12**</td>
<td>-0.12</td>
<td>-0.13**</td>
</tr>
<tr>
<td></td>
<td>(0.047)</td>
<td>(0.047)</td>
<td>(0.045)</td>
<td>(0.045)</td>
</tr>
<tr>
<td>Regret Dummy</td>
<td>0.34</td>
<td>-0.28</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>(0.57)</td>
<td>(0.56)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>2501-5000</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>2501-5000</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>5001-7500</td>
<td>2.40***</td>
<td>3.27***</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>(0.30)</td>
<td>(0.48)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>7501-10000</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>7501-10000</td>
<td>-3.23***</td>
<td>-3.48***</td>
<td>-5.68***</td>
<td></td>
</tr>
<tr>
<td></td>
<td>(0.42)</td>
<td>(0.48)</td>
<td>(0.26)</td>
<td></td>
</tr>
<tr>
<td>Round</td>
<td>0.035</td>
<td>0.054**</td>
<td>0.19***</td>
<td>0.047***</td>
</tr>
<tr>
<td></td>
<td>(0.020)</td>
<td>(0.020)</td>
<td>(0.023)</td>
<td>(0.0074)</td>
</tr>
<tr>
<td>Outlier Dummy</td>
<td>-86.3***</td>
<td>-86.1***</td>
<td>-87.2***</td>
<td>-85.4***</td>
</tr>
<tr>
<td></td>
<td>(0.83)</td>
<td>(0.84)</td>
<td>(1.09)</td>
<td>(1.39)</td>
</tr>
<tr>
<td>Constant</td>
<td>20.4***</td>
<td>19.8***</td>
<td>18.6***</td>
<td>23.1***</td>
</tr>
<tr>
<td></td>
<td>(4.70)</td>
<td>(4.69)</td>
<td>(4.53)</td>
<td>(4.07)</td>
</tr>
<tr>
<td>No. Observations</td>
<td>9200</td>
<td>9200</td>
<td>4600</td>
<td>6532</td>
</tr>
<tr>
<td>No. Auction Groups</td>
<td>46</td>
<td>46</td>
<td>46</td>
<td>46</td>
</tr>
<tr>
<td>No. Subjects</td>
<td>184</td>
<td>184</td>
<td>184</td>
<td>184</td>
</tr>
<tr>
<td>Wald $\chi^2$</td>
<td>10892</td>
<td>11330</td>
<td>6859</td>
<td>4295</td>
</tr>
<tr>
<td>Prob $&lt; \chi^2$</td>
<td>0.000</td>
<td>0.000</td>
<td>0.000</td>
<td>0.000</td>
</tr>
<tr>
<td>$\sigma_v$</td>
<td>0.000</td>
<td>0.000</td>
<td>0.001</td>
<td>1.847</td>
</tr>
<tr>
<td>$\sigma_u$</td>
<td>6.374</td>
<td>6.360</td>
<td>5.996</td>
<td>5.256</td>
</tr>
<tr>
<td>$\sigma_\epsilon$</td>
<td>13.614</td>
<td>13.466</td>
<td>11.262</td>
<td>8.377</td>
</tr>
<tr>
<td>Controls</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
</tr>
</tbody>
</table>

Notes: The dependent variable is overbidding (OB) in each round for each subject. The RHS consists of $k$, the subject's BRET score, the Regret Dummy, which equals one when considering auction showing the missed opportunity feedback and zero otherwise, and Round, the number of auctions played, a dummy for each value segment (2501-5000, 5001-7500, 7500-10000) with the lowest value segment being the reference, the number of rounds (Rounds), and an outlier dummy being one if overbidding is higher than 33 or lower than -33. Controls not shown are Age, a dummy for being an economics student, and a dummy for being male. We correct for intra-session correlation by estimating the variance at individual and auction group level. Note that the distribution of private values is the same in each auction group. Models (1) and (2) consider all 50 rounds, model (3) only considers the No Regret phase, and model (4) we only consider values above 2500. Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1.
the No Regret phase. In model (4) we drop the lowest value segment to account for the fact that bidding is not serious in the lowest values segment (see discussion above). The coefficient of interest related to the subjects BRET score $k$ is significantly negative in each of the four specifications. Hence, the higher the BRET score – i.e. the lower the level of risk aversion – the lower is the level of overbidding.

Overbidding can be measured in several ways (analogue for overpricing) and we ran robustness checks with different measures. [Füllbrunn and Neugebauer (2013) use the difference between the bid-value ratio and the RNNE bid-value ratio which is actually exactly 0.75 of our measure. Further we can look at the log deviation $\ln(b/b_{RNNE})$ to consider symmetric deviations from the RNNE-bid. We also tested for absolute deviations from the RNNE bid $(b - 0.75v)$. The level of the private values introduces a lot of noise, which is the reason why the former measures standardize the deviation from the RNNE-bid. Robustness checks with these alternative measures for overbidding yield qualitatively the same results, i.e. auction markets with higher levels of risk aversion display more overbidding.

Finally, we look at the economic effect by analyzing foregone profits, i.e. profits that could have been earned when submitting a RNNE bid. We compute the cumulative profits (in Euro) for each subject assuming that the subject submitted a RNNE bid while the other submitted their actual bid. Then we compare this profit to the actual profits earned in the experiment. The average HRA-subject would earn about 3.24 Euro more when playing the RNNE bids which is an increase in profits of about 65% (mean profit observed = 4.98 Euro, mean profit from unilateral deviation to RNNE = 8.22). The average LRA-subjects would earn about 1.75 Euro more when playing the RNNE bid which is an increase in profits of about 20% (mean profit observed = 8.38 Euro, mean profit from unilateral deviation to RNNE = 10.38). If all subjects would play the RNNE strategy earnings would be at 16.16 Euro. Using a Cuzick trend test and comparing the three categories, we find that risk aversion significantly increases the foregone profits ($p = 0.037$).

To sum up, we show that risk aversion as measured by the BRET has a significant impact on overbidding in general and on the bidders’ profit in particular. The higher the risk aversion – measured by $k$ – the higher overbidding and the lower the earnings for the bidder. This leads us to conclude that $H_2^{\text{null}} : OB_{LRA} = OB_{MRA} = OB_{HRA}$ is rejected in favor of $H_2 : OB_{HRA} > OB_{MRA} > OB_{LRA}$. 


4 Discussion

To study bidding behavior in FPSB auctions, earlier studies randomly assigned subjects to auction groups. In this study, we do not measure bidding behavior in heterogeneous markets, but attempt to compose rather homogeneous markets in which subjects have almost similar levels of risk aversion as measured by their BRET score. We hypothesized that overpricing – the deviation from the RNNE price – is higher in markets with a high average level of risk aversion in comparison to markets with a low average level of risk aversion. And indeed, our experimental results support this hypothesis. As the level of risk aversion is the only difference across markets, our results strongly suggest that the observed differences in overpricing are due to differences in risk aversion as measured by the BRET. The question remains, however, whether our results can also be explained by other theories on overbidding.

Harrison (1989) started a debate on overbidding costs, i.e. the amount of profits to sacrifice in order to increase the probability of winning the auction. The argument is that subjects tend to overbid, because overbidding costs are negligible and it is more important to increase the winning probability. In our experiment, we keep the overbidding costs constant in all auction groups. Although this argument might explain a level effect in all markets it does not explain the differences across markets.

Regret theory serves as a further explanation for overbidding (Engelbrecht-Wiggans, 1989). As risk aversion is not related to regret theory, it cannot explain the treatment effect. But it might explain a shift in overbidding when we report the missed opportunity in the Regret phase. Although we find some indication for a regret effect – in particular in overpricing – it does not significantly affect the risk-overbidding relationship across HRA, MRA and LRA.

Armantier and Treich (2009c) test in an experiment whether a star shaped probability weighting function explains overbidding. By fitting a model to the data they show – assuming a star shaped probability weighting function – that probability weighting explains overbidding better than risk aversion. However, as the probability weighting function is not assumed to be correlated with risk aversion we have no reason to believe that probability weighting is different across treatments. Hence, the probability weighting might have an equal effect on overbidding but does not explain the treatment effect.

Further reasons for overbidding are related to joy of winning (e.g. Cox et al., 1983b; Goeree et al., 2002) or the ex-post relative standing of bidders (Turocy and Watson).

Hence, the discussion about using the payoff space or the message space as discussed by several articles in the American Economic Review in the early 90s has no influence on the comparison across treatments. See Svoenêck (2013) for a survey of the debate on overbidding in FPSB auctions.
Aggressive bidding might be observed due to the extra utility a bidder gains when winning the auction. To some extent this is in line with ex-post relative standing of the bidders. The argument here is that bidders try to outperform others in terms of profits, i.e., they want to gain more relative to others. As in the standard FPSB auction only the winner earns a profit and even a small profit is higher than the profit for all others, overbidding is in line with ex-post relative standing. Turocy and Watson (2012) compare the standard FPSB profit frame in which only the winner earns a profit with a surplus frame with outside options. In the latter the equilibrium prediction is perfectly in line with the standard FPSB auction. However, the winner earns the lowest profits among all bidders. The authors report that subjects bid more aggressive in the profit frame than in the surplus frame. They conclude that ex-post relative standing plays an important role. As long as joy of winning and relative standing are not related to risk aversion these determinants might serve as a reason for a particular level effect in all markets but not for our observed treatment effect. Further interpersonal explanations for overbidding are collusion (Isaac and Walker, 1985) and spite (Morgan et al., 2003). They require post round interaction and knowledge on the profit of the winner, respectively. Neither is provided in our auction design. Hence, these potential causes of overbidding should not confound our results.

Recent studies that focused directly on the risk-overbidding relationship did not find supporting evidence for the CRRAM. Engelbrecht-Wiggans and Katok (2009) look at bidding behavior in a FPSB auction against computer agents. They compare a ‘k = 1’ condition in which each bidding decision affects one single auction, and a ‘k = 10’ condition in which each bidding decision affects ten independent auctions simultaneously and earnings equal the average payments from all ten auctions. Hence, if CRRAM plays a role and bidders are risk averse, then bids should be lower in the k = 10 condition than in the k = 1 condition, because the variance of payoffs is lower in the k = 10 condition. The authors find a risk effect in the No Regret condition, but not in the two Regret conditions when feedback allows for loser regret and/or winner regret.23 The design of Engelbrecht-Wiggans and Katok (2009) is very different from ours, which makes it difficult to compare the results. We can only speculate why the evidence in favor of the risk aversion model is not as strong as in our setting. First, it is possible that the regret effect in Engelbrecht-Wiggans and Katok (2009) is stronger than risk aversion, allowing for a effect of risk on overbidding in the No Regret condition but not

23The authors consider three additional conditions: the loser regret condition in which feedback includes the missed opportunity when not being the winner, the winner regret condition in which feedback includes the money left on the table, and a condition with loser regret and winner regret.
in the Regret conditions. Second, the relevant unit of observation in the data analysis of Engelbrecht-Wiggans and Katok (2009) is the average bid. Non-serious bidding in some value segments may have added some noise to the aggregate data, reducing the chance for a rejection of the null hypothesis. Finally, subjects played against computerized agents without knowing their predefined strategy (see instructions in Appendix B in Engelbrecht-Wiggans and Katok (2009)). The overbidding effect might therefore be weaker than in our setting, because bidding against computer agents has been found to reduce overbidding (Teubner et al. 2015).

Two related studies derive the risk coefficient from bidding behavior in FPSB auctions assuming CRRA (which is inversely related to overbidding) and test whether these risk coefficients are in line with risk coefficients derived from a BDM procedure. Assuming CRRA, Isaac and James (2000) infer risk coefficients of 28 subjects from bidding behavior in a FPSB auction against a the computer (40 periods) and from the last two bids of four repetitions of the BDM procedure. Surprisingly, correlations between the two risk aversion coefficients are rather negative. However, applying our analysis from above on their data we find no significant relationship. Applying their method to our data, i.e. using individual linear censored regressions to derive a risk coefficient, we indeed find a significant positive relationship with the risk coefficient derived from the BRET score. Berg et al. (2005) criticize Isaac and James (2000) due to their restricted form of using the BDM and assuming a special form of a utility function. They used a modified design but also found no significant relationship between inferred risk coefficients from FPSB auctions (n=48, 20 periods) and from the BDM procedure (20 periods). One reason why positive correlations between bidding behavior and overbidding are insignificant might be that subjects bid against computerized bidders (in Isaac and James, 2000), which has been found to reduce overbidding (Teubner et al. 2015). Further, these studies make use of the BDM procedure; and recently the reliability of the procedure has been called into question (Cason and Plott, 2014). The procedure might produce too much noise such that a significant relationship with a low number of participants cannot be found. Berg et al. (2005) for example find that only 45% percent of all subjects exhibited risk-averse or risk-neutral behavior in BDM which is quite low in comparison to other risk elicitation methods (see Crosetto and Filippin, 2013, table 4). Find recent comparisons

\[ OB = 100 \times \left( \frac{Nv}{(N-1)\beta} - 1 \right) \]

and

\[ b = \frac{N-1}{N-1+r} \]

we get

\[ 1 + OB/100 = \frac{N}{N-1+r}. \]

The authors excluded all bids in the high and low value segments, and excluded all bidders for which the bidding regression \( bid_i = \alpha_i + \beta_i value_i + error \) yields a significant \( \alpha \) which is not inline with theory.

We thank Mark Isaac for providing the data.

Estimations and test results are available upon request.
of risk elicitation tasks in Charness et al. (2013) or Crosetto and Filippin (2015).

Finally, a remaining question is how risk aversion affects overbidding in our setting. On the one hand bidders might adjust their bidding function according to risk aversion in the sense that they increase the probability to win by sacrificing profits independent of the behavior in the market. On the other hand bidders might best reply to potential or perceived overbidding behavior. If the latter is true, we should observe a stronger increase on overbidding in HRA than in LRA. In order to test this, we run a random effects regression (unreported) on OB with HRA and LRA data in the No Regret Phase only with a HRA dummy variable, the number of rounds, and an interaction between the two as independent variables (with and without controls). While the HRA dummy and the number of rounds are significant drivers of OB, the interaction coefficient is insignificant, also in different specifications. Hence, adjustment of bidding over time is not different between HRA and LRA. Eyeballing figure 2 we also find no indication for differences between HRA and LRA with respect to changes in overbidding over time. All this indicates that it is indeed our individual measurement of risk aversion, rather than learning about the level of risk aversion in the market, which drives our results.

Although the theoretical link between risk preferences and overbidding has been questioned in recent studies, this paper suggests that it is to early to discard risk preferences as an explanation for overbidding in FPSB auctions. Rather than claiming that these risk preferences are the only explanation for overbidding we contend that they might play an important role besides some of the more recent suggestions such as regret aversion, probability weighting functions, and learning direction theory.

References


Appendix

A BRET task

A.1 Instructions

General instructions

You are about to participate in an economic experiment. Please read carefully the following instructions. They are identical for all participants. Please do not communicate with the other participants, stay quiet, and turn off your mobile phone during the experiment. If you have questions, please raise your hand. An instructor will come and answer. If you follow the instructions and make good decisions, you might earn a considerable amount of money, which will be paid to you in cash at the end of the experiment. The experiment will consist of two parts and in addition to your earnings in both parts, you will be paid a 2.5€ show-up fee.

Instructions (Part 1)

On your screen you find a field composed of 100 boxes. You can see that every second one of those boxes is deleted, starting from the top-left corner. We say that every time a box is removed you “collect” a box. By clicking stop at some point in time, you collect the number of boxes that have been removed up to that point in time. Thus the later you click stop, the more boxes you will have collected. You can now try to press the stop button to collect the indicated number of boxes. You earn 10 euro cents for every box that is collected. Once collected, the box disappears from the screen and your earnings are updated accordingly. At any moment you can see the amount earned in euros (denoted with “virtual earnings”) up to that point. However, such earnings are only potential (hence called “virtual”) because in one of the boxes a bomb is hidden. When you collect this bomb-box all your earnings collected so far will be destroyed. When collecting boxes, you do not know which box contains the bomb. You only know that the bomb can be in any of the 100 boxes with equal probability. Which box contains the bomb will be randomly determined by the computer AFTER you have collected your desired number of boxes. The computer will do so by randomly picking one of the 100 boxes (all are equally likely). The chosen box will then be the one that contains the bomb. The more boxes you collect, the higher the probability of also collecting the bomb.

THUS: Your task is to choose how many boxes you want to collect. If you happen to have collected the box that contains the bomb you will earn zero. If the bomb is located in a box that you did not collect you will earn 10 euro cents for each collected box. Are there any questions? We will now continue with some test questions that you will find on your screen.
A.2 Comprehension questions (shown on screen and discussed afterwards)

1. Suppose that the bomb is located in the 25th box.
   (a) If you collect the first 21 boxes, how much will you earn in euros? (2.1)
   (b) If you collect the first 38 boxes, how much will you earn in euros? (0)
   (c) If you collect the first 62 boxes, how much will you earn in euros? (0)
   (d) If you collect the first 79 boxes, how much will you earn in euros? (0)

2. Suppose that the bomb is located in the 75th box.
   (a) If you collect the first 21 boxes, how much will you earn in euros? (2.1)
   (b) If you collect the first 38 boxes, how much will you earn in euros? (3.8)
   (c) If you collect the first 62 boxes, how much will you earn in euros? (6.2)
   (d) If you collect the first 79 boxes, how much will you earn in euros? (0)

3. Do you agree with the following: The location of the bomb depends on how many boxes you decide to collect. (No)
B Auction markets

B.1 Instructions (on paper)

Instructions (part 2)

This part of the experiment will consist of a sequence of 50 auctions. Money in this experiment is expressed in tokens (Examples are not representative for the values in the experiment).

General procedure - In each auction one fictive object is auctioned off. You and three other participants submit integer bids to buy the object. This object has a private value to each bidder called the “private value”. The private value of the object is the number of tokens the experimenter pays you in case you buy it. The bidder with the highest bid buys the object (ties are broken randomly) and pays her/his own bid. Hence, your payoff is equal to your personal private value minus your bid when you buy, or zero, otherwise. Example: Suppose your private value is 8000 and your bid is 7000. If 7000 is the highest bid amongst all four bidders you earn 8000 - 7000 = 1000 tokens, otherwise you earn zero.

Private value - Before each auction, a new individual private value between zero and 10,000 is randomly picked by the computer for each bidder. Each number within this interval is equally probable. Private values thus differ for all participants and across all auction rounds!

Auction payoff – Your payoff equals “private value-bid” when you have submitted the highest bid, and zero, otherwise. (Note: bids above your private value lead to negative earnings!) Your total payoff in Euros is the sum of all earnings from the 50 auctions expressed in tokens divided by 1500 (thus the exchange rate is 1500 tokens = 1 Euro).

Other bidders - The three other bidders are selected from the bidders in this room. Neither you nor they know the identity of the other bidders.

Feedback – Information about the result of the auction will be provided after each auction. Besides knowing your own bid and your own private value, you will learn whether you won the auction (and thus whether you buy the object or not) as well as your earnings in this round and your total earnings over all rounds.

Are there any questions? Before we start with the 50 auction rounds, we will first go through test questions
B.2 Comprehension questions (shown on screen and discussed afterwards)

Stage 1: Generate an example

Please enter five different numbers (between 0 and 10,000) in decreasing order! We use them to provide an example.

- Enter the highest number: (recorded as private value of winner)
- Enter the second highest number: (recorded a bid 2=winning bid)
- Enter the third highest number: (recorded as bid 3)
- Enter the fourth highest number: (recorded as bid 4)
- Enter the lowest number: (recorded as bid 5)

Stage 2: Entered numbers under step 1 are used in the following questions (corrects answers in brackets)

Four bidders submit the following bids:

Bidder 1: (bid 3)
Bidder 2: (bid 2)
Bidder 3: (bid 5)
Bidder 4: (bid 4)

Who buys the object? (Bidder 2)

What is the price (in tokens) s/he has to pay? (bid 2)

Suppose the private value of the highest bidder equals (bid 2). What is the buyer’s payoff in tokens? (private value of winner - bid 2)

What is the payoff of all other bidders in tokens? (0)

Stage 3: Subject is shown the correct answers on screen. The instructor explains the correct answers and asks if there are any further questions.
B.3  Additional information loser regret treatment after period 25 (shown on screen and read out)

In the remaining auctions, the winning bid (= highest bid) will be made public to all bidders. Moreover, you will also learn your "missed opportunity" value. This value is always 0 when you DO win the auction or when your private value is below the winning bid amount, and otherwise it is your private value minus the winning bid amount. The "missed opportunity" value tells you the maximum amount of tokens you could have made by bidding higher than you did. This of course only makes sense when your private value is higher than the winning bid, meaning that you could have actually won the auction without bidding higher than your private value! For example: when your private value is 2000 and your bid is 1500 but the winning bid is 1750, your missed opportunity is equal to: 2000-1750=250. This is what you could have earned by bidding slightly over the winning bid of 1750. Again, when your private value is lower than the winning bid or you won the auction, there would have been no room for improvement and your missed opportunity value thus equals 0.
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