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RISK AVERSION AND OVERBIDDING IN FIRST PRICE SEALED BID AUCTIONS: NEW EXPERIMENTAL EVIDENCE

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Bidding above the risk-neutral Nash equilibrium in first price sealed bid auctions has traditionally been ascribed to risk aversion. Later studies, however, offer other explanations and even argue that risk aversion plays no or a minor role. In a novel experimental design, we directly test the relationship between risk aversion and overbidding by systematically varying the distribution of risk attitudes in auction markets. We find a significant relationship between our measure of risk aversion and overbidding. (*JEL* D44, C91)

I. INTRODUCTION

Since the early eighties, laboratory experiments repeatedly have 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, 2016). This overbidding (OB) behavior has initially been rationalized with risk aversion (Cox, Roberson, and Smith 1982a). As the buy price equals the buyers own bid in FPSB auctions, the optimal bid is necessarily below the buyer's valuation of the object. Bidders face a trade-off between the probability of winning the object—higher bids increase this probability—and the profit conditional on winning the auction—higher bids decrease this profit. As a higher degree of risk aversion translates into a preference for a safer lottery, risk averse bidders sacrifice potential profit with a higher probability of winning and submit bids above RNNE.

Experimental evidence in support of a *positive* relationship between risk aversion and OB is restricted to fitting models—like the constant relative risk aversion model (CRRAM)—ex post to auction data (Cox, Smith, and Walker 1982b, 1983a, 1983b, 1984, 1985, 1988). These studies postulate utility functions to estimate risk aversion parameters from experimentally observed bids. For example, some use the power utility function $u(x) = x^r$ with r being the risk coefficient to be estimated, with $r = 1$ indicating risk neutrality. As r is frequently estimated to be below one, these studies conclude that risk aversion leads to OB. However, these results have been obtained ex post by implication and not by administering a treatment effect. In fact, despite a rich literature and long debate about the role of risk preferences in auction markets (see Svorenčík 2015, Ch. 6 for a discussion) no study has been able to show a direct relationship between a bidder's risk attitudes and OB behavior in FPSB auctions.

We aim to test for this relationship by manipulating the level of risk aversion across auction groups of four bidders using a partner matching.

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ABBREVIATIONS

BDM: Becker–DeGroot–Marschak method
BRET: Bomb Risk Elicitation Task
CRRAM: Constant Relative Risk Aversion Model
FPSB: First Price Sealed Bid
HRA: High Elicited Risk Aversion
LRA: Low Elicited Risk Aversion
MRA: Moderate Elicited Risk Aversion
OB: Overbidding
OP: Overpricing
RNNE: Risk Neutral Nash Equilibrium

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In a first step, we elicit the subjects' level of risk aversion by using the *Bomb Risk Elicitation Task* (Crosetto and Filippin 2013). In a second step, we compose auction markets such that the bidders in a group are almost homogeneous with respect to elicited risk aversion. With this novel design element, we can test whether the group level of elicited risk aversion has an effect on price levels. In real markets, the distribution of risk attitudes can also be biased due to self-selection of bidders into markets with very risky (or particularly low risk) asset classes or business opportunities. Our design allows us to study such price effects. Furthermore, subjects do not bid against standardized computer agents. Hence, outlier bidding behavior, for example, induced by extreme risk attitudes, by very few subjects might influence the bidding behavior of all others in a group.[1] To keep the impact of such outliers as small as possible we opt for homogeneity in terms of risk attitudes. Other studies that use elicited risk attitudes to compose groups consider bargaining games (Murnighan, Roth, and Shoumaker 1987), rent seeking games (Millner and Pratt 1991), or trading in asset market experiments (Ang and Schwarz 1985). We are not aware of any auction experiment which is using this technique. In line with those studies, we keep elicited risk attitudes almost similar within markets but sufficiently heterogeneous between markets. At the same time, we can study individual bidding behavior as subjects were not aware of the fact that they were grouped according to elicited risk aversion.

On market level, we hypothesize that "risk averse" markets have significantly higher prices due to OB, and on subject level, we hypothesize that elicited risk aversion positively correlates with bids. Our experimental results clearly support our hypotheses as overpricing (OP)—the percentage difference to the RNNE price—is significantly higher in markets with higher average elicited risk aversion, and OB—the percentage difference to the RNNE bid—is significantly higher for bidders with higher elicited risk aversion. Hence, we provide further evidence that OB behavior is—at least to a substantial extent—a result of risk attitudes.

Our paper contributes to a rich literature on explaining OB in FPSB auctions. A number of studies offer alternative explanations for OB, (implicitly) claiming that risk aversion plays no or only a minor role. Harrison (1989) argued that the payoff saliency in early experiments is not sufficient to show the risk-OB effect (the so-called flat maximum critique). Kagel and Roth (1992) argued that risk aversion cannot be solely held responsible for OB, as OB has also been observed in second price sealed bid auctions, in which risk preferences should have no effect on bidding.[2] Fitting nonexpected utility models to their auction data, Armantier and Treich (2009a, 2009b) concluded that OB can be fully rationalized with nonlinear probability weighting functions, while Goeree, Holt, and Palfrey (2002) concluded that a convex probability weighting function "*fits the data as well as the risk aversion model*." Ockenfels and Selten (2005) reported that OB can be due to dynamic bidding behavior in line with learning direction theory (Selten and Buchta 1999).[3] Neugebauer and Selten (2006) reported that learning direction theory fits their bidding data better than CRRAM and RNNE bid functions. Engelbrecht-Wiggans (1989) introduced regret theory as a reason for OB. "Winner regret" occurs when the winner realizes that a lower bid would have reduced the price while "loser regret" occurs when a loser realizes that a higher bid would have earned a profit. Eventually, loser regret is more strongly weighted than winner regret which leads to an asymmetric adjustment leading to OB (see Engelbrecht-Wiggans and Katok 2008 for experimental evidence).[4] The reported evidence clearly suggests that a number of factors may moderate OB. The same evidence, however, cannot exclude the possibility of a fundamental relationship between risk aversion and OB. Our design allows us to isolate the effect of elicited risk aversion levels on OB from the alternative explanations mentioned above, as these explanations rely on factors that are theoretically not related to risk aversion.

Some correlational studies tested for the relationship between elicited risk aversion

1. Assume the risk-OB relationship to hold and that an extreme risk-averse subject bids his value but is in an otherwise extremely risk-seeking group. Then quickly the risk seekers might increase their bids to be able to make at least some profit.

2. More recently, Georganas, Levin, and McGee (2017) considered overbidding behavior in second price sealed bid auctions related to optimistic irrationality.

3. 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.

4. Filiz-Ozbay and Ozbay (2007) go one step further and provide experimental evidence for "anticipated regret." In this model, bidders anticipate winner and loser regret and, ex ante, adjust their bids accordingly. Katušcák, Michelucci, and Zajícek (2015) find no evidence for anticipated regret though.

and individual bidding behavior in FPSB auctions. Isaac and James (2000) and Berg, Dickhaut, and McCabe (2005) concentrated on the Becker–DeGroot–Marschak (BDM) method procedure (Becker and DeGroot 1964). Neither of the two studies found evidence for a positive relationship between the inferred risk aversion parameters and OB. Engel (2011) elicited risk coefficient using the Holt-Laury Risk Aversion task and find that rankings of risk coefficients derived from the risk elicitation task and from the FPSB auction are consistent. Engelbrecht-Wiggans and Katok (2009) tested whether the CRRA model applies by using a special treatment which varies the risk of bidding (see Section IV for more details). They concluded that there is "*virtually no support for the risk aversion model*" (p. 83).

In the next section, we discuss the experimental design and hypothesis. Then we consider our experimental results. Finally, we discuss our results in the light of the literature and limits.

II. EXPERIMENTAL DESIGN AND HYPOTHESES

A. Design

Our experimental design consists of three parts. In part one, we elicit risk attitudes. In part two, subjects participate in 50 FPSB auctions. In part three, subjects answer a questionnaire. To elicit risk attitudes, we want subjects to be clearly categorized by a scale which allows for sufficient heterogeneity in elicited risk aversion levels. Further on, the task should not be too complex to reduce the bias in measurement due to confusion (e.g., Dave et al. 2010). We therefore administered the "Bomb Risk Elicitation Task" (BRET) introduced by Crosetto and Filippin (2013) which is based on a single choice, requires minimal numeracy skills, allows for a virtually continuous distribution of risk aversion levels, avoids truncation of the data, and allows for sufficient heterogeneity of observed risk attitudes in the sample (Crosetto and Filippin 2015).[5]

In the BRET, a subject collects a number of boxes (k) from 100 boxes available. The computer randomly assigns a hidden bomb to one of the 100 boxes with equal probability. If the bomb is among the boxes collected, it "explodes" and destroys all boxes collected leaving the subject with zero payoff. Otherwise, the payoff equals $k \times 0.1$ euro. We used the dynamic BRET version in which 100 boxes are shown on the screen and each second one box automatically disappears (is collected) until the subject clicks on a stop button to confirm the number of collected boxes.[6]

We then use k as a measure of risk aversion. We must not assume an underlying model to categorize subjects by their level of risk aversion. It is sufficient to separate subjects via their relative risk posture based on k (see also Engel 2011; Murnighan, Roth, and Shoumaker 1987). In line with Millner and Pratt (1991), we think that the ability to distinguish between more and less risk averse subjects (low and high k respectively) is greater than the ability to induce successfully an (arbitrary) expected utility function.[7]

We then organize the auction groups as follows. We ranked the M subjects in a session by k_i such that $k_{[1]} < k_{[2]} < ... < k_{[M]}$. Subjects with $k_{[1]}$, $k_{[2]}$, $k_{[3]}$, and $k_{[4]}$ are in group one, subjects with $k_{[5]}$, $k_{[6]}$, $k_{[7]}$, and $k_{[8]}$ are in group two,..., and subjects with $k_{[M-3]}$, $k_{[M-2]}$, $k_{[M-1]}$, and $k_{[M]}$ are in group $M/4$. We randomly allocated ties.

Given the ordinal ranking based on the average elicited risk aversion levels $K_j = \sum_i k_{ji}/4$, $K_{[1]} \leq K_{[2]}, ..., \leq K_{[46]}$, we categorized auction groups and bidders in three distinct risk categories. We classified the nine groups with $\underline{K} > 50$ as *LRA* (low elicited risk aversion, mean $\overline{K}_{LRA} = 58.33$, $SD = 4.37$) and the nine groups with the lowest K as *HRA* (high elicited risk aversion, $\overline{K}_{HRA} = 29.97$, $SD = 3.11$). The remaining 28 markets became *MRA* (moderate elicited risk aversion, $\overline{K}_{MRA} = 43.01$, $SD = 5.34$).[8] We then categorize subjects in HRA ($n_{HRA} = 36$), MRA ($n_{MRA} = 112$), and LRA subjects ($n_{LRA} = 36$) in line with their group affiliation. We admit that any ex post categorization is arbitrary. However,

5. Even a recent neuro-scientific evidence corroborates 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 (Gianotti et al. 2009).

6. 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. Crosetto and Filippin (2013) conclude that "*the visual version in continuous time [is] our preferred choice*."

7. However, we could "convert" k into a risk coefficient using the CRRA model. Crosetto and Filippin (2013) provide a table of risk coefficients assuming CRRA in Appendix A; choosing $k = 50$ converts to $r = 1$ which would categorize such a subject as risk neutral, subjects with $k < 50$ would be categorized as risk averse ($r < 1$), and subjects with $k > 50$ would be risk seeking ($r > 1$).

8. The three categories are significantly different in mutual comparisons using a Mann-Whitney U test (all $p < .001$) and also using a Cuzick trend test ($p < .001$).

we are interested in having a sufficiently high difference in levels of elicited risk aversion between categories to allow for a significant effect on OB.[9]

Afterward, subjects participated in 50 subsequent FPSB auctions in a partner matching.[10] Receiving a new private value in each period, subjects submitted one bid in each period. The bidder with the highest bid earned the difference between her private value and her bid, while the other bidders' payoff equaled zero. The private values for each subject were predrawn from a uniform distribution over the integer set [0, 10,000], analogue to earlier auction experiments (Füllbrunn and Neugebauer 2013).[11] In this setting, a RNNE bidder would submit a bid that equals 3/4 of his private value while bidders in line with the CRRAM 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 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_i and assigned the same randomly drawn private value to the same rank.[12] Hence, we made sure that we have the same condition in each market and only vary the level of risk aversion measured via K.

In the first 25 auctions, feedback included only whether or not the subject submitted the highest bid ("No Regret" phase). In the last 25 periods, bidders 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 and the Regret phase. We implemented the different feedback regimes as a robustness check. Our aim was to show that even if feedback plays a role in bidding behavior (as a level effect), the relationship between risk aversion and OB still holds. We are aware of the fact that experience itself might change bidding behavior over time.[13] Finally, the total earnings of all auctions have been accumulated and divided by 1,500 to calculate the auction payoff in euro.

We ran 6 sessions with 24 subjects and 2 sessions with 20 subjects (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. Subjects earned about 12 euro including a 2.50 euro show-up fee. The experiments lasted roughly 1 hour. Payments were made in cash and in private at the end of the experiment. The experiment was computerized using z-Tree (Fischbacher 2007). Subjects were recruited using ORSEE (Greiner 2015). The sessions were conducted in the period from April to June of 2015 at the IMR Experimental Laboratory, Nijmegen School of Management, Radboud University, the Netherlands.

B. Measurements and Hypotheses

We formulate and test our hypotheses at two different levels. At the market level, we want to show the effect of market level risk aversion on pricing. At the subject level, we want to show how elicited risk aversion influences the individual bid function. The benchmark for defining OB is the RNNE bid which equals $b_{RNNE} = (N-1)/N \times v$ (Vickrey 1961).

At the market level, we consider "*overpricing*" (OP) in market j and period t as the relevant unit of observation, defined as the percentage deviation of the observed auction price from the RNNE price (the RNNE bid of the highest value), that is, $OP_{jt} = 100 \times (p_{jt}/p_{RNNE,\,t} - 1)$. Note, the highest private value determines the RNNE price but every bidder can determine the auction price. The alternative hypothesis predicts that OP is increasing in our risk categories: $H1$: $OP_{HRA} > OP_{MRA} > OP_{LRA}$, while the Null hypotheses are that OP is not different across the three risk categories or even decreasing: $H1_{NULL}$: $OP_{HRA} \leq OP_{MRA} \leq OP_{LRA}$.

At the individual level, we consider "*OB*" (OB) of subject i in market j and period t as the relevant unit of observation and we define OB as the percentage deviation of the observed bid from

9. Our findings do not change when we simply split into three equally sized categories.

10. Instructions can be found in Appendix A.

11. We consider the independent private value environment in line with earlier experiments on first price auctions with common value elements (e.g., Aycinena, Baltaduonis, and Rentschler 2014).

12. 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 $v = 6{,}403$ to the subjects with scores 59 and 25, $v = 2{,}124$ to the subjects with scores 60 and 27, $v = 1{,}210$ to the subjects with scores 61 and 30, and $v = 7{,}086$ to the subjects with scores 70 and 31.

13. Note that the private values in the No Regret phase and in the Regret phase do not significantly differ using an ordinary t-test ($p = .556$) such that effects due to differences in private values cannot be expected.

the RNNE bid ($OB_{ijt} = 100 \times [b_{ijt}/b_{RNNE,\,it} - 1]$). The hypotheses for OB are defined analogously to OP ($H2_{NULL}$: $OB_{LRA} \leq OP_{MRA} \leq OB_{HRA}$, $H2$: $OB_{HRA} > OB_{MRA} > OB_{LRA}$).

If we reject the Null hypotheses, we can infer with a relatively high internal validity that a negative relationship between elicited risk aversion $k(K)$, and OB (OP) in FPSB auctions exists. In all statistical tests, unless stated otherwise, we make use of the Wilcoxon signed rank test (for paired replicates), the two-sided Mann-Whitney U test for independent samples, and the Cuzick test to perform trend tests using a significance level of 5%.[14]

III. RESULTS

A. *Overpricing*

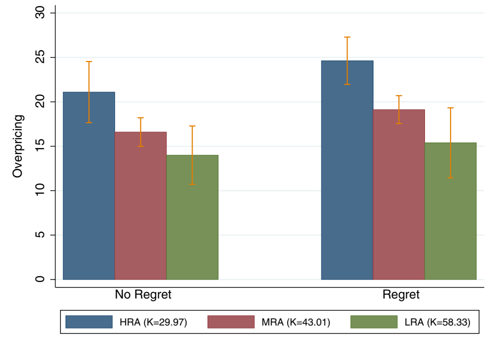
Figure 1 shows average OP for the HRA, MRA, and LRA markets divided into the No Regret phase (Round 1–25) and the Regret phase (Round 26–50).

As a lower K is associated with higher risk aversion, the figure clearly shows a positive relationship between elicited risk aversion in a market and OP. Average OP is about 710 (923) basis points higher in the HRA markets than in the LRA markets in the No Regret (Regret) phase. We find a significant difference comparing the nine HRA with the nine LRA markets in both phases ($p_{NR} = .009$, $p_R = .001$)[15] and also a significant trend ($p_{NR} = .003$, $p_R < .001$).

To complement this result, we conducted random effects panel regressions with OP_{jt}, OP in market j in round t, as the dependent variables. With random effects at market level, we additionally correct for possible intrasession correlation by adjusting all standard errors with the Huber and White sandwich estimator of variance at session level (eight clusters). Table 1 reports the results.

A negative coefficient for K indicates a positive relationship between elicited market risk aversion and OP. Indeed, we find the coefficient to be significantly negative in all specifications. We should also note that the positive and significant coefficient of the regret dummy (equal to one in the Regret phase) indicates that OP is not driven by elicited risk aversion alone and also survives if we control for possible experience effects by including the variable *Round* (Model 2), which records the number of rounds played. When analyzing the No Regret phase and the Regret phase separately in Models (3), (4), and (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.

FIGURE 1
Average Overpricing



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, for example for HRA in the No Regret phase $\overline{OP} = (1/9)\sum_{j=1}^{9}(1/25)\sum_{t=1}^{25} 100 \times \left(p_{jt}/p_{RNNE,t} - 1\right)$. The average BRET score in each category is K.

To consider economic effects of OP, we look at the seller's revenues. Using RNNE pricing as a benchmark—total revenue would be 193.90 euro in each market given the private values—the observed average mark-up due to OP would be 43.64 euro in HRA markets, 33.67 euro in MRA markets, and 27.08 euro in LRA markets. Hence, the seller's mark-up is significantly higher in HRA markets than in LRA markets ($p = .002$).

Hence, we can clearly reject the $H1_{NULL}$ in favor of the alternative hypothesis $H1$ that OP increases with a higher level of elicited risk aversion in the market.

B. *Overbidding*

Even though the bid-value ratio (b/v) should be constant over private values (e.g., assuming CRRAM), prior studies show that bid-value ratio vary across private values segments (e.g., Cox, Smith, and Walker 1985; Füllbrunn and Neugebauer 2013). We need to take this effect into account when analyzing our data. Therefore, we analyze OB on one hand using the entire value range and on the other hand using four separate

14. Permutation tests yield similar results.

15. The p values for comparing HRA to MRA are $p_{NR} = .018$ and $p_R = .002$, and the p values for comparing MRA to LRA are $p_{NR} = .103$ and $p_R = .034$.

TABLE 1
Random Effects Panel Regressions at Market Level: Overpricing

	Model 1	Model 2	Model 3	Model 4	Model 5
K	−0.23***	−0.23***	−0.23***	−0.22***	−0.25***
	(0.042)	(0.042)	(0.042)	(0.042)	(0.050)
Regret Dummy	2.50***	1.20*	2.51**		
	(0.47)	(0.50)	(0.77)		
Round		0.052*			
		(0.026)			
Round NR (1–25)			0.052	0.052	
			(0.038)	(0.038)	
Round R (1–25)			0.051		0.051
			(0.028)		(0.028)
Constant	27.1***	26.5***	26.5***	25.7***	29.7***
	(2.03)	(1.98)	(1.82)	(1.89)	(2.40)
Number of observations	2,300	2,300	2,300	1,150	1,150
Number of auction groups	46	46	46	46	46
Number of clusters	8	8	8	8	8
Wald χ^2	75.089	100.537	160.601	27.481	29.561
Prob < χ^2	.000	.000	.000	.000	.000

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 phase: 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 phase 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 Models (3) and (4) include rounds 1–25 and 26–50, respectively. Robust standard errors in parentheses.

$^{*}p < .05$; $^{**}p < .01$; $^{***}p < .001$.

value segments: {1, ..., 2,500}, {2,501, ..., 5,000}, {5,001, ..., 7,500}, and {7,501, ..., 10,000}.[16]

Figure 2 visualizes mean OB in blocks of five periods, for each value segment and risk category.[17] OB in HRA exceeds LRA consistently from the first to the last block in each value segment, with MRA mostly in between. A Cuzick trend test confirms this ranking for each block; we find *p* values at or far below .021 in every block (across value segments) when neglecting outliers.[18] It is remarkable how stable the relationship between risk categories and OB is over time. However, visually there is no indication for a regret effect because there is no clear upward shift in the level of OB after block five (red vertical line).

Table 2 shows average OB separated by risk category, subdivided over four-value segments for the No Regret phase and the Regret phase, along with *p* values from Mann-Whitney *U* tests, testing the Null hypothesis that OB 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 OB 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 $OB_{HRA} > OB_{MRA} > OB_{LRA}$.

To analyze the four-value segments individually, we calculate the average OB for each subject in each value segment to compare the three groups within each segment. We find a significant difference in OB comparing subjects from the HRA and the LRA groups in all value segments (see details in Table 2, weakly significant in the lowest value segment though). Also, the Cuzick test shows a significant trend in all segments ($p \leq .001$) and overall. Hence, the relationship between elicited risk aversion and OB holds for each value segment under consideration.

To further strengthen our results, we apply a random effects regressions with three levels of dependencies (in line with Chapter 4.7 in

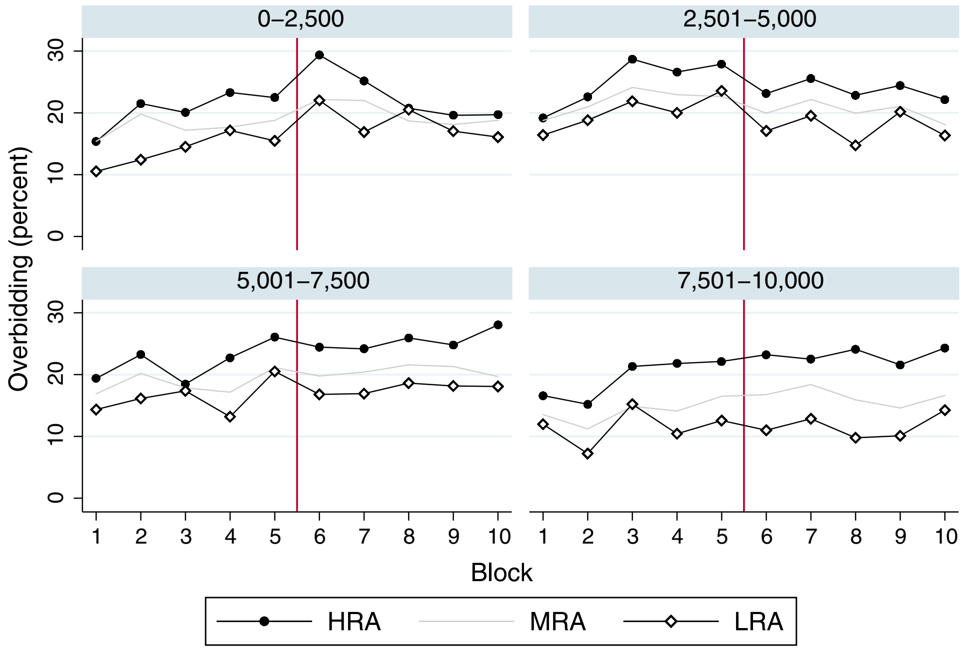
16. Indeed, we find signficant differences between value segments. In Appendix C, we consider experimental evidence on the differences between segments.

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

18. See further below in this section for the definition of outliers. Including outliers the block with $p = .021$ is the only one where the trend is insignificant (with $p = .207$).

19. The *p* values for comparing HRA to MRA are $p_{NR} = .047$ and $p_R = .007$, and the *p* values for comparing MRA to LRA are $p_{NR} = .245$ and $p_R = .251$ with $n_{HRA} = n_{LRA} = 28$ and $n_{MRA} = 84$.

FIGURE 2
Mean Overbidding over Time



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

Moffatt 2015) with OB_{ijt} (OB 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 intrasession correlation by estimating the variance at individual and auction group level.[20] 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 OP. 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. Model (3) considers only 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 in Appendix C). The coefficient of interest related to the subjects' BRET score k is significantly negative in each of the four specifications. Hence, the higher k—the lower the level of risk aversion—the lower is the level of OB. For example, for $k = 30$ the predicted OB is 17.15% (Model 1, round 10) while for $k = 31$ the predicted OB decreases by 12 basis points to 17.03%.

OB can be measured in several ways (analogue for OP) and we ran robustness checks with different measures. Füllbrunn and Neugebauer

20. The specification of the regression model is $OB_{ijt} = \alpha + \beta_1 \; k_i + \beta_2 \; D_{\text{Regret}} + \beta_3 \; D_{\text{Outlier}} + \beta_4 \; t + \gamma' D_{\text{Value Segment}} + \delta' z_i + u_i + v_j + \varepsilon_{ijt}$ with variances $Var\left(u_i\right) = \sigma_u^2$, $Var\left(v_j\right) = \sigma_v^2$, and $Var\left(\varepsilon_i t\right) = \sigma_\varepsilon^2$. The three levels are $t = 1, \ldots 50$ (Rounds), $i = 1, \ldots 148$ (Subjects), and $j = 1, \ldots 46$ (Auction Groups). Independent variables are the level of risk aversion (k_i), a regret dummy (D_{Regret}) which is one for periods 26–50, an outlier dummy (D_{Outlier}) which is one if the bid is higher than the private value or lower than 50% of the private value, a dummy for the three upper value segments ($D_{2{,}501-5{,}000}$,$D_{5{,}001-7{,}500}$,$D_{7{,}501-10{,}000}$), and controls (z_i) including a gender dummy, age, and a dummy equal to one for being an econ student.

TABLE 2
Average Overbidding

		Private Value				
		(0–10,000)	**(0–2,500]**	**(2,500–5,000]**	**(5,000–7,500]**	**(7,500–10,000]**
No Regret	HRA ($n=36$)	18 (12)	14 (20)	21 (13)	20 (10)	19 (8)
	MRA ($n=112$)	16 (8)	12 (17)	19 (10)	18 (7)	14 (9)
	LRA ($n=36$)	13 (10)	9 (19)	18 (8)	17 (8)	10 (9)
	p value HRA = LRA	.001	.077	.015	.006	<.001
	p value Cuzick	.001	<.001	<.001	<.001	<.001
Regret	HRA ($n=36$)	21 (11)	13 (24)	24 (10)	25 (6)	22 (6)
	MRA ($n=112$)	16 (11)	10 (24	20 (8)	20 (7)	17 (7)
	LRA ($n=36$)	12 (13)	3 (34)	17 (10)	17 (8)	12 (7)
	p value HRA = LRA	.001	.053	.001	<.001	<.001
	p value Cuzick	<.001	<.001	<.001	<.001	<.001

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 private 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.

(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 OB yield qualitatively the same results.[21]

To visualize the effect in a more traditional bid-value figure, we provide a linear fit suppressing the constant term for HRA and LRA during the No Regret phase and the Regret phase in Figure 3. We can clearly see that the HRA line is above the LRA line, that is, bids are indeed higher in HRA. Even though we do not find a clear regret effect in the regressions, we can see that the Regret phase lines are somewhat higher than their No Regret phase pendants. However, this effect nearly disappears if we drop the first ten rounds to adjust for some inexperiences.

To measure the economic effect of OB we analyze foregone profits, that is, profits that could have been earned when submitting a RNNE bid. We compute the cumulative profits (in euro) for each subject assuming that this subject submitted RNNE bids while the others submitted their actual bid. Then we compare this profit to the actual profits earned. The average HRA-subject would earn about 3.24 euro more when submitting 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-subject would earn about 1.75 euro more when playing the RNNE bid which is an increase in profits of about 20% (8.83 euro, 10.38 euro).[22] Using a Cuzick trend test on the three categories, we find that elicited risk aversion significantly increases foregone profits ($p=.037$).

Hence, we can clearly reject the $H2_{NULL}$ in favor of the alternative hypothesis $H2$ that OB increases with a higher level of elicited risk aversion.

A remaining question is how elicited risk aversion affects OB 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 OB behavior. If the latter is true, we should observe a stronger increase on OB in HRA than in LRA. In order to test this, we run a random effects regression (see Appendix D) 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, we find

21. Find respective regression tables in Appendix D.

22. If all subjects would play the RNNE strategy earnings would be at 16.16 Euro.

TABLE 3
Three-Level Model Regression: Overbidding

	Model 1	Model 2	Model 3	Model 4
k	−0.12**	−0.12**	−0.12*	−0.13**
	(0.047)	(0.047)	(0.045)	(0.045)
Regret Dummy	0.34	−0.28		
	(0.57)	(0.56)		
2,501–5,000		2.40***	3.27***	
		(0.39)	(0.48)	
5,001–7,500		1.39***	0.81	−1.00***
		(0.40)	(0.49)	(0.25)
7,501–10,000		−3.23***	−3.48***	−5.68***
		(0.42)	(0.48)	(0.26)
Round	0.035	0.054**	0.19***	0.047***
	(0.020)	(0.020)	(0.023)	(0.0074)
Outlier Dummy	−86.3***	−86.1***	−87.2***	−85.4***
	(0.83)	(0.84)	(1.09)	(1.39)
Constant	20.4***	19.8***	18.6***	23.1***
	(4.70)	(4.69)	(4.53)	(4.07)
Number of observations	9,200	9,200	4,600	6,532
Number of auction groups	46	46	46	46
Number of subjects	184	184	184	184
Wald χ^2	10,892	11,330	6,859	4,295
Prob < χ^2	.000	.000	.000	.000
σ_v	0.000	0.000	0.001	1.847
σ_u	6.374	6.360	5.996	5.256
σ_ε	13.614	13.466	11.262	8.377
Controls	Yes	Yes	Yes	Yes

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 an auction showing the missed opportunity feedback and zero otherwise, and *Round*, the number of auctions played, a dummy for each value segment (2,501–5,000, 5,001–7,500, and 7,500–10,000) 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 intrasession 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) only considers values above 2,500. Robust standard errors in parentheses.
$^{*}p < .05$; $^{**}p < .01$; $^{***}p < .001$.

no evidence that adjustment of bidding over time is different between HRA and LRA. Eyeballing Figure 2, we also find no indication for differences between HRA and LRA with respect to changes in OB over time. All these indicate that rather the elicited risk aversion drives the results than learning about the market level of risk aversion (in line with Kirchkamp and Reiss 2011).

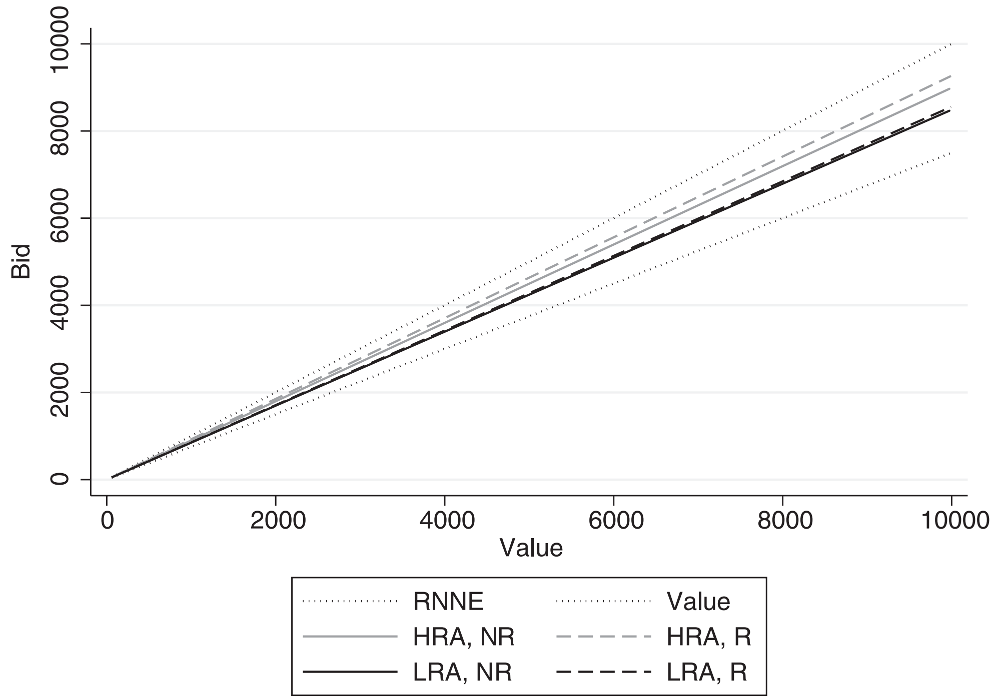
IV. DISCUSSION

In this study, we attempt to compose homogeneous markets in which subjects have similar levels of risk aversion as measured by the BRET. We hypothesized that OP—the percentage 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 K is the only difference across markets, our results strongly suggest that the observed differences in OP are due to differences in elicited risk aversion as measured by the BRET. The question remains, however, whether our results can also be explained by other theories on OB or experimental design issues. If so, these explanations need to be correlated with our treatment variable K.

Harrison (1989) started a debate on payoff saliency in FPSB auctions claiming that the Nash equilibrium payoff functions did not provide sufficient payoff saliency so as to be able to distinguish risk-averse from risk-neutral bidders. We keep the OB costs constant in all auction groups; hence, this argument might explain a shift in the level of bids in all markets but it does not explain the differences across markets.[23]

23. 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 1990s has no influence on the comparison across treatments. See Svorenčík (2015) for a survey of the debate on overbidding in FPSB auctions.

FIGURE 3
Bid-Value Diagram



Notes: Linear fit of $b = \beta v$ for HRA and LRA separated by No Regret phase and Regret phase. The dotted lines indicate $b = v$ (upper) and $b = :75v$, that is, the RNNE bid.

As regret theory is not related to the concept of risk aversion, it cannot explain the observed risk-OB relationship. However, the BRET measure itself might be sensitive to regret as subjects would select fewer boxes to prevent regret. Hence, the HRA subjects would feel regret stronger than the LRA subjects. If so, we would expect the increase in OB when switching from the No Regret phase to the Regret phase to be stronger for HRA subjects than for LRA subjects. We tested this relationship but find no significant difference comparing HRA and LRA subjects.[24] However, probably no risk elicitation task is free from this concern.

24. We tested whether the change in average overbidding between periods 11–25 (dropping the inexperienced phase) and periods 26–40 ($DIFF_i = \overline{OB}_{26-40,i} - \overline{OB}_{11-25,i}$) is significantly different comparing the HRA-subjects ($n = 36$) group to the LRA-subjects group ($n = 36$) using a Mann-Whitney U test. We cannot reject the Null hypothesis for the entire value range ($p = .4064$) or for each of the four value segments separately ($p = .7366$, .5657, .0956, and .1839).

Nonetheless, we expected an increase in OB when subjects enter the Regret phase. We found some indication for higher OP in the Regret phase but barely an indication for higher OB, in contrast to the literature mentioned above. One reason might be that subjects already achieved a relatively high OB level. But it might also be that regret in auction experiments is not as strong as it has been found in earlier experiments. For example, Ratan and Wen (2016) and also Katušcák, Michelucci, and Zajícek (2015) find no effect of regret treatments concluding that "*loser feedback does not appear to be a good explanation of OB relative to the risk-neutral Nash equilibrium*" (p. 26). It is, however, difficult to pinpoint why this difference in results exists as our experimental setting differs from that of the aforementioned papers in multiple ways (computerized vs. human bidders, number of auction rounds, timing of feedback, etc.).

Armantier and Treich (2009b) tested whether particular probability weighting functions explain OB. By ex post fitting different models to the bidding data they conclude that probability weighting explains OB better than risk aversion. Instead, Goeree, Holt, and Palfrey (2002) concluded that a convex probability weighting function "*fits the data as well as the risk aversion model*." However, the probability weighting function is theoretically not assumed to be correlated with risk aversion. Hence, probability weighting might have an effect on general OB levels, but is unlikely to explain effects between markets.

Further reasons for OB are related to the joy of winning (e.g., Cox, Smith, and Walker 1983b; Goeree, Holt, and Palfrey 2002) or the ex post relative standing of bidders (Turocy and Watson 2012). 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, that is, 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, OB is in line with ex post relative standing. Turocy and Watson (2012) compared 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 reported that subjects bid more aggressively in the profit frame than in the surplus frame. They concluded 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 OB are collusion (Isaac and Walker 1985) and spite (Morgan, Steiglitz, and Reis 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 OB should not confound our results.

When looking at experimental studies of the risk-OB relationship, two correlational studies derive the risk coefficient from bidding behavior in FPSB auctions assuming CRRA and test whether these risk coefficients are in line with risk coefficients derived from a BDM procedure.[25] Isaac and James (2000) use individual linear censored regressions to infer risk coefficients of 28 subjects from bidding behavior in a FPSB auction against the computer (40 periods).[26] They then relate these coefficients to risk aversion measures from the last two bids of four repetitions of the BDM procedure and find a negative relationship rather than a positive. As a robustness check for our results, we apply their method to our data. That is, we use individual linear censored regressions to derive risk coefficients from our FPSB auction data. When we compare these coefficients with the risk coefficient derived from the BRET, we still find a significant positive relationship.[27] In a related study, Berg, Dickhaut, and McCabe (2005) administered a modified design and found no significant relationship between inferred risk coefficients from FPSB auctions ($N = 48$, 20 periods) and from the BDM procedure (20 periods). Both studies find no indications for a positive relationship between OB and risk aversion. One possible reason is that subjects bid against computerized bidders (in Isaac and James 2000), an environment which has been shown to reduce OB (Teubner, Adam, and Riordan 2015). Another reason could be that both studies use the BDM procedure, the reliability of which has recently been called into question (Cason and Plott 2014). As the noise level differs between risk elicitation tasks (Crosetto and Filippin 2015), the individual risk aversion parameters from the BDM procedure might be too noisy to enable a significant relationship with a relatively low number of observations. In particular, Berg, Dickhaut, and McCabe (2005) find that only 45% of all subjects exhibited risk-averse or risk-neutral behavior in BDM which is quite low in comparison to all other risk elicitation methods (see Crosetto and Filippin 2013, Table 4). Harrison and Rutström (2008), however, showed that OB in 10 two-subject auctions can partly be explained by the choice in the Holt and

25. Note that the risk coefficient inferred from FPSB auctions is inversely related to overbidding: with $OB = 100 \times ([Nb/((N-1)v)] - 1)$ and $b = [(N-1)/(N-1+r)]v$.

26. The authors excluded all bids in the high- and low-value segments, and excluded all bidders for which the bidding regression $bid_i = \alpha_i + \beta_i value_i + error_i$ yields a significant α, because the latter is not in line with theory.

27. We also applied the analysis in this paper to the data from Isaac and James (2000) and did not find a significant relationship. All estimations and test results are available upon request. We sincerely thank Mark Isaac for providing the data.

Laury (2002) design (among other individual characteristics) which is in line with our results. For a detailed discussion on elicitation of risk preferences see, for example, Charness, Gneezy, and Imas (2013) or Crosetto and Filippin (2015).

Rather than using a correlational study, Engelbrecht-Wiggans and Katok (2009) compare two FPSB conditions in which students bid 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 10 independent auctions simultaneously and earnings equal the average payments from all 10 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.[28] 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 effect 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 an effect of risk on OB in the No Regret condition but not in the Regret conditions. Second, the relevant unit of observation in the data analysis of Engelbrecht-Wiggans and Katok (2009) is the average bid. Nonserious bidding in some value segments might therefore have reduced 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 OB effect might therefore be weaker than in our setting, because bidding against computer agents has been found to reduce OB (Teubner, Adam, and Riordan 2015).

We think that our experiment quite clearly shows the negative relationship between k and OP/OB. However, if we apply the CRRA model a k greater than 50 implies risk seekingness (Crosetto and Filippin 2013, Appendix A) which means that LRA markets are consistent with risk seekingness as well. Yet we observe positive OP and OB in LRA markets. Unfortunately, we are not able to find out whether our implementation of the BRET underreports risk aversion or whether our implementation of the FPSB auction overreports risk aversion.

Although the link between risk preferences and OB has been questioned in the auction literature, our experimental implementation shows that it is too early to completely discard risk aversion as an explanation for OB in FPSB auctions. We do not claim that risk aversion is the only explanation for OB. Rather, we contend that it plays an important and possibly underestimated role alongside other factors such as regret aversion or probability weighting functions.

Of course, our study also includes some limitations. We find the BRET score k to have a significant relationship with OB. As long as BRET indeed measures risk aversion, we can say that risk aversion leads to OB. However, the main problem of any correlational study is that risk aversion might simply be a correlate of some other individual characteristic that drives bidding behavior. Hence, although findings can barely be taken to imply causality, we hope that our study brings us closer to a causal interpretation.

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[euro] 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

28. The 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*.

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 afterward) .

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)

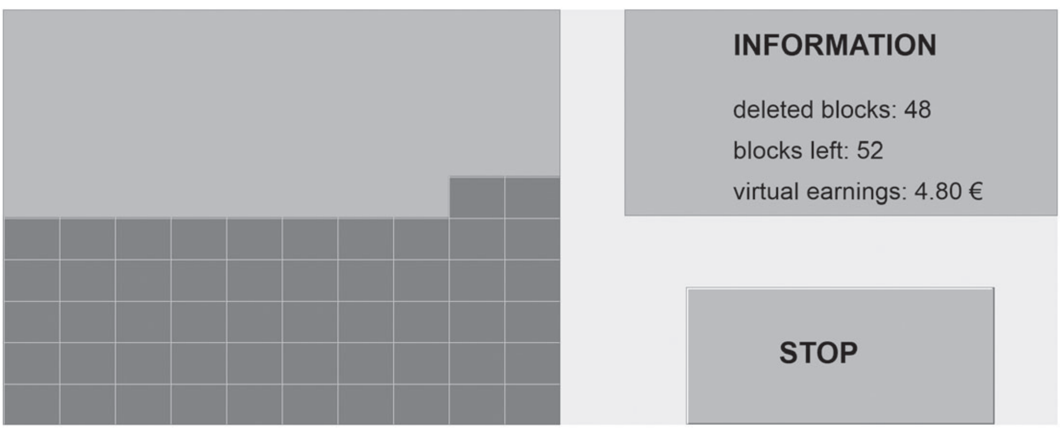
2. **Suppose that the bomb is located in the 75th box.**

   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)

FIGURE A1

Screenshot of the BRET Task



APPENDIX 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 8,000 and your bid is 7,000. If 7,000 is the highest bid among all four bidders you earn 8,000 – 7,000 = 1,000 tokens, otherwise you earn zero.

Private value – Before each auction, a new individual private value between 0 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 can lead to negative earnings!) Your total payoff in euros is the sum of all earnings from the 50 auctions expressed in tokens divided by 1,500 (thus the exchange rate is 1,500 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 afterward)

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 as 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 2,000 and your bid is 1,500 but the winning bid is 1,750, your missed opportunity is equal to: 2,000 − 1,750 = 250. This is what you could have earned by bidding slightly over the winning bid of 1,750. 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.

APPENDIX C. A COMPARISON OF VALUE SEGMENTS

We also test whether OB is dependent on the value segment. We take the average OB for each bidder in each value segment and then test whether differences in average OB between value segments are zero (Wilcoxon signed-rank test). Independent of whether we look at all subjects ($n = 184$) or within risk categories ($n_{HRA} = n_{LRA} = 36$, $n_{MRA} = 112$), we find significant lower OB in value segment {1, ..., 2,500} than in value segment {2,501, ..., 5,000} ($p < .001$; $p_{HRA} = .004$, $p_{MRA} < .001$, $p_{LRA} = .003$). In line with Cox et al. (1985, 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*." Also Teubner, Adam, and Riordan (2015) find lower emotional arousal in lower value segments than in higher segments in auction experiments. We can support this claim as almost 90% 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.[29] OB in the next two segments is not significantly different from each other ($p = 0.385$; $p_{HRA} = .271$, $p_{MRA} < .249$, $p_{LRA} = .354$), but

29. In total, we identify 308 outlier bids (out of 9,200 bids) of which 268 bids are submitted in the lowest value segment (2,668 bids were made in this segment).

OB is significantly lower in segment {7,501, ..., 10,000} than in segment {5,001, ..., 7,500} ($p < .001$; $p_{HRA} = .004$, $p_{MRA} < .001$, $p_{LRA} < .003$). 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 and thus costs for OB might be too high to justify an increase in the probability of winning which makes OB less attractive. The focus of this paper is not to explain why OB differs between value segments, but to show that the positive relationship between risk aversion and OB persists in each value segment.

APPENDIX D. ADDITIONAL REGRESSIONS

D.1. OP REGRESSIONS WITH OVERPRICING MEASURES

The regression below is in line with Model 1 in Table 1 in the paper. Actually, Model 1 in the table below is the same as in Table 1 in the paper. The three other models contain three further ways to measure overpricing. Model 2 considers the log deviation $op = 100 * ln(price_{observed}/price_{rnne})$, Model 3 looks at overpricing as the fraction of potential overpricing $op = 100 * (price_{observed} - price_{rnne})/(v_{max} - price_{rnne})$, and Model 4 looks simply at the difference $op = price_{observed} - price_{rnne}$. In all models, K is significantly negative.

TABLE D1
The Dependent Variable Is Overpricing (OP) in Each Round for Each Group

	Model 1	Model 2	Model 3	Model 4
K	−0.23***	−0.20***	−0.70***	−14.4***
	(0.042)	(0.035)	(0.13)	(2.63)
Regret Dummy	2.50***	2.26***	7.49***	62.4*
	(0.47)	(0.42)	(1.42)	(27.9)
Constant	27.1***	24.1***	81.4***	1,623.0***
	(2.03)	(1.72)	(6.09)	(128.2)
Number of observations	2,300	2,300	2,300	2,300
Number of auction groups	46	46	46	46
Number of clusters	8	8	8	8
Wald χ^2	75.089	90.197	75.089	46.315
Prob < χ^2	.000	.000	.000	.000

Notes: Definitions of OP are as discussed above. The RHS consists of *K*, the auction groups' average BRET score and the *Regret Dummy*, equal to one in the Regret phase (Period 26–50) and zero otherwise (No Regret: Period 1–25). 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). Robust standard errors in parentheses.

$^{*}p < .05$; $^{**}p < .01$; $^{***}p < .001$.

D.2. OB REGRESSIONS WITH OVERPRICING MEASURES

The regression below is similar to the regression "Model 1" in Table 3 in the article. Actually, Model 1 in the table below is the same as in Table 3 in the paper. The three other models contain three further ways to measure overbidding. Model 2 considers the log deviation $100 * ln(b_{observed}/b_{rnne})$, Model 3 looks at overpricing as the fraction of potential overpricing $100 * (b_{observed} - b_{rnne})/(v - b_{rnne})$, and Model 4 looks simply at the difference $b_{observed} - b_{rnne}$. In all models, apart from Model 2, k is significantly negative. Apparently, the outliers have a huge impact on Model 2. When we drop the outliers in Model 2′, we again find k to be significant.

TABLE D2
The Dependent Variable Is Overbidding (OB) in Each Round for Each Group

	Model 1	Model 2	Model 2′	Model 4	Model 5
k	−0.12**	−0.092	−0.12**	−0.37**	−4.73**
	(0.047)	(0.085)	(0.039)	(0.14)	(1.63)
Regret Dummy	0.34	1.68	−0.22	1.02	−33.3
	(0.57)	(1.64)	(0.40)	(1.70)	(22.5)
Round	0.035	−0.068	0.051***	0.11	2.99***
	(0.020)	(0.057)	(0.014)	(0.059)	(0.78)
Outlier Dummy	−86.3***	−271.6***		−258.8***	−1,264.7***
	(0.83)	(2.56)		(2.48)	(32.7)
Constant	20.4***	26.3**	15.8***	61.2***	763.1***
	(4.70)	(8.53)	(3.85)	(14.1)	(148.1)
Number of observations	9,200	9,150	8,892	9,200	9,200
Number of auction groups	46	46	46	46	46
Number of subjects	184	184	184	184	184
Wald χ^2	10,892	11,293	58	10,892	1,528
Prob < χ^2	.000	.000	.000	.000	.000
σ_v	0.000	0.000	0.735	0.000	67.082
σ_u	6.374	10.680	5.227	19.122	182.382
σ_ε	13.614	39.142	9.352	40.842	538.769
Controls	Yes	Yes	Yes	Yes	Yes

Notes: Definitions of OB are as discussed above. 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, 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 intrasession correlation by estimating the variance at individual and auction group level. In Model 2′ we dropped the outliers. Robust standard errors in parentheses.

$^{*}p < .05$; $^{**}p < .01$; $^{***}p < .001$.

D.3. SECTION III.B—RESPONSE BIDDING

The random effects regression below confirms the claim made at the end of Section III.B. While the the coefficients of the HRA Dummy and Round are significant, the interaction between the two is not.

TABLE D3
The Dependent Variable Is Overbidding (OB) in Each Round for Each Subject

	Model 1	**Model 2**
HRA Dummy	4.58*	4.26*
	(1.91)	(2.06)
Round	0.21***	0.21***
	(0.048)	(0.048)
HRA Dummy × Round	0.13	0.13
	(0.069)	(0.069)
Age		0.42
		(0.32)
Male Dummy		−1.32
		(1.86)
Economics		0.82
		(1.79)
Constant	12.7***	4.46
	(1.35)	(7.14)
Number of observations	1,740	1,740
Number of auction groups	72	72
Wald χ^2	82	85
Prob < χ^2	.000	.000

Notes: Data consists of HRA and LRA only, the No Regret phase and only valid bids (no outliers). The RHS consists of a HRA dummy, Round (1–25) and the interaction between the two. Further on, controls were added: age, a male dummy, and a dummy for studying economics. Robust standard errors in parentheses.

$^{*}p < .05$; $^{**}p < .01$; $^{***}p < .001$.

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