

Llorente-Saguer, Aniol; Sheremeta, Roman; Szech, Nora

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Designing Contests Between Heterogeneous Contestants: An Experimental Study of Tie-Breaks and Bid-Caps in All-Pay Auctions

Aniol Llorente-Saguer ^{a,b}
Roman M. Sheremeta ^{c,d}
Nora Szech ^{e,f,g}

^a School of Economics and Finance, Queen Mary University of London, UK

^b Centre for Economic Policy Research (CEPR), London, UK

^c Weatherhead School of Management, Case Western Reserve University, OH, USA

^d Economic Science Institute, Chapman University, CA, USA

^e Institute of Economics, Karlsruhe Institute of Technology, Germany

^f WZB, Berlin, Germany

^g CESifo Institute, Munich, Germany

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Abstract

Contests are well-established mechanisms for political lobbying, innovation, rent-seeking, incentivizing workers, and advancing R&D. A well-known theoretical result in the contest literature is that greater heterogeneity decreases investments of contestants because of the “discouragement effect.” Leveling the playing field by favoring weaker contestants through strict bid-caps and favorable tie-breaking rules can reduce discouragement and increase the designer’s revenue. We test these predictions in a laboratory experiment. Our data confirm that placing bid-caps and using favorable tie-breaking rules significantly diminishes discouragement in weaker contestants. The impact on revenue is more intricate. In contrast to theory, a strict bid-cap does not increase revenue, but a mild bid-cap can increase revenue even when not predicted by theory. Our data also show that tie-breaking rules seem to have little impact on the designer’s revenue: the encouragement of weaker contestants is offset by stronger contestants competing less aggressively. We discuss deviations from the Nash predictions in light of different behavioral approaches.

JEL Classifications: C72, C91, D72

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All authors have contributed equally and share first coauthorship. Corresponding authors: Aniol Llorente-Saguer, a.llorente-saguer@qmul.ac.uk, Roman Sheremeta, rms246@case.edu, and Nora Szech, nora.szech@kit.edu. We want to thank the Editor of this journal and two anonymous referees for their helpful comments and suggestions. Also, for valuable suggestions, we want to thank Tim Cason, Mikhail Drugov, Andrea Mattozzi, Navin Kartik, Dan Kovenock, Henrik Orzen, Ronald Peeters, Nikolaus Schweizer, and seminar participants at Chapman University, as well as participants at the Contests and Innovation Conference in Anchorage and the North American Economic Science Association Conference in Tucson. Additionally, we thank Frederik Franz, Nicolas Meier and Paul Nobis for research assistance. Sibille Hackel provided excellent administrative support. Any remaining errors are ours.

1. Introduction

Contests are fundamental in political lobbying and campaign spending (Che and Gale, 1998), innovation races (Terwiesch and Xu, 2008), incentivizing workers (Lazear and Rosen, 1981), and advancing R&D (Harris and Vickers, 1985, 1987). A long-standing question within the literature and practice is how to design contests in a way that results in the highest level of performance by contestants (Moldovanu and Sela, 2001; Che and Gale, 2003; for a survey, see Konrad, 2009).

One of the main challenges in contest design is that most contests are between heterogeneous contestants (Baye et al., 1993; Che and Gale, 1998). A well-known theoretical result in the contest literature is that greater heterogeneity decreases performance of contestants (Konrad, 2009).¹ The reason for this is the so-called “discouragement effect”: weaker contestants, with either higher marginal costs or a lower value of winning, cut back expenditures when facing a stronger contestant. Such a discouragement effect has been shown to hold in the field (Brown, 2011), and it is supported by a large body of experimental research (Dechenaux et al., 2015).²

One solution suggested by theoretical analysis is to level the playing field by imposing strict caps on expenditures (Che and Gale, 1998; Gaviious et al., 2002, Hart, 2016). Via such bid-caps, weaker contestants are encouraged to compete more intensively, which also increases overall competition. Szech (2015) extends this analysis by showing that a combination of tie-breaking rules favoring the disadvantaged contestants together with appropriately chosen, mild bid-caps can

¹ However, Ryvkin (2013) shows that higher heterogeneity can increase revenues under certain conditions. See also Drugov and Ryvkin (2017).

² Experimental studies found support for the discouragement effect in all-pay auctions (Davis and Reilly, 1998; Müller and Schotter, 2010; Deck and Sheremeta, 2012; Fehr and Schmidt, 2018), lottery contests (Fonseca, 2009; Kimbrough et al., 2014), rank-order tournaments (Weigelt et al., 1989; Schotter and Weigelt, 1992), and real-effort tournaments (Cason et al., 2010; Gill and Prowse, 2012).

foster competition even more.³ Both of these policies aim to reduce heterogeneity among contestants, to encourage weaker contestants, and to strengthen overall competition. This also translates into higher revenue for the designer of the contest.

Despite a well-established theoretical literature, little empirical research has been done to evaluate how bid-caps and tie-breaking rules impact individual behavior and revenue in contests between heterogeneous contestants. To address this gap, we conduct a laboratory experiment in which heterogeneous contestants compete in an all-pay auction. Our data confirm that when there is no bid-cap and the tie-breaking rule is symmetric, a significant discouragement effect causes the weaker contestant to bid less than the stronger contestant. Consistent with theory, strengthening the weaker contestant using bid-caps and favorable tie-breaking rules increases the average bid of the weaker contestant. Thus, our data show that, consistent with theory, tie-breaks and bid-caps can significantly diminish discouragement. The impact on revenue, however, is more intricate. Contrary to theory, a strict bid-cap combined with symmetric tie-breaking does not increase revenue. Theoretically, a mild bid-cap, combined with a favorable tie-breaking rule for the weaker contestant, can increase revenue even more. Indeed, the data show that a mild bid-cap can increase revenue by almost 30%, compared to the unrestricted all-pay auction. In the data, however, this effect is independent of tie-breaking. An encouragement of the weaker contestant via favorable tie-breaking goes hand in hand with the stronger contestant bidding less aggressively. Thus, contrary to theory, stronger contestants often react with discouragement, by placing a significant

³ Kaplan and Wettstein (2006) argue that if caps are not rigid, the existence of a cap will not result in increased spending. Cotton (2009) shows that under certain circumstances, a tax on spending is strictly preferred to a spending limit. Fang (2002) demonstrates that introducing a cap does not increase total revenues in lottery contests. Finally, Szech (2015) shows that the counterintuitive result that caps increase total revenue no longer holds when ties are always broken in favor of the stronger contestant.

mass at 0. We discuss these deviations from Nash equilibrium in light of different behavioral approaches.

There is a growing experimental literature examining behavior in all-pay auctions; for an overview, see Dechenaux et al. (2015). The studies most closely related to ours are done by Rapoport and Amaldoss (2000, 2004) and Amaldoss and Jain (2002).⁴ All of these studies examine behavior in all-pay auctions with “coarse” strategy space and a budget constraint (a form of a bid-cap). However, none of the studies treat a bid-cap as a design tool for eliminating the discouragement effect and increasing revenue. Moreover, with a coarse strategy, pronounced probabilities for ties at various bid levels may arise, making it difficult to examine the interaction between bid-caps and tie-breaks. Finally, all-pay auctions with a discrete strategy space have asymmetric equilibria (Dechenaux et al., 2006), complicating the interpretation of the actual behavior of participants. Our paper attenuates this issue by having a fine grid rather than a coarse bidding space.⁵ There are other details of our study that make it different from the existing studies, but most importantly, our study is the first to examine how bid-caps and tie-breaks impact individual behavior and revenue in contests between heterogeneous contestants.

Our study also contributes to a large literature on rent-seeking. Since the seminal papers of Tullock (1967) and Krueger (1974), rent-seeking has inspired a vast literature. In contrast to innovation contests, however, expenditures are often considered to be socially wasteful. Using a

⁴ Two other studies by Cohen et al. (2012) and Gelder et al. (2015) investigate the impact of a tie-breaking rule on behavior of symmetric contestants. In both studies, a tie represents a “status quo” and unless one contest outperforms the other by some critical threshold, the status quo does not change.

⁵ The fine grid is assumed to approximate the situation of continuous bidding, without making the bidding task too complex for participants. From a theoretical point of view, Szech (2015) demonstrates that for the parameters studied here, under continuous bidding, the equilibrium is unique. The only potential places for atoms on bids are at zero and/or at the cap. At all other potential bids, if they were played with positive probability, at least one bidder would prefer to deviate. With a sufficiently fine grid, this logic should carry through in the sense that bidders should not play larger atoms on bids different from zero and/or the cap. Yet, multiplicity of equilibrium cannot be ruled out in the discrete case.

theoretical model, Che and Gale (1998) show that a strict bid-cap may actually increase aggregate expenditures. However, they caution the reader against generalizing their results without a proper empirical investigation. Our experimental examination shows that such caution is indeed warranted – although the unwanted effects on aggregate spending may emerge only if caps are mild.

We review the theoretical findings on all-pay auctions with bid-caps and tie-breaks in Section 2. Section 3 outlines the experimental design, procedures and hypotheses. Section 4 presents our main results, along with sub-sections focusing on different parts of the data. We discuss implications of our results in Section 5.

2. Theory

Consider an all-pay auction with two risk-neutral contestants. Contestant H values the prize at v_H and contestant L at v_L , where $v_H > v_L$. These values are common knowledge. Contestants simultaneously submit their bids b_H and b_L , which are capped at m . The prize is awarded to the highest bidder, but both contestants need to pay their bids. In the case of a tie, the tie-breaking rule α , where $0 \leq \alpha \leq 1$, assigns the prize to contestant H with probability α and to contestant L with probability $1 - \alpha$. The designer's revenue is $R = b_H + b_L$. If $m > v_L$, equilibrium behavior is as in a standard all-pay auction without a cap (Baye et al., 1996). In the mixed strategy Nash equilibrium, the two contestants submit bids according to cumulative distribution functions $F_H(b) = b/v_L$ and $F_L(b) = 1 - v_L/v_H + b/v_H$ on an interval $[0, v_L]$. Therefore, the stronger contestant H , who has higher valuation for winning, randomly chooses a bid from the interval $[0, v_L]$. The weaker contestant L , who has lower valuation for winning, chooses to bid 0 with probability $1 - v_L/v_H$, and with the remaining probability randomly chooses a bid from the interval $[0, v_L]$. The expected equilibrium

bids of contestants H and L are $E(b_H) = v_L/2$ and $E(b_L) = v_L^2/(2v_H)$. This results in an expected total revenue of $R = (v_H + v_L)v_L/(2v_H)$ for the designer. The weaker contestant L earns an expected payoff of 0, while the stronger contestant H earns the difference between the valuations $v_H - v_L$ (in expected terms).

Che and Gale (1998) show in their game-theoretic analysis that competition can be enhanced by using a rather strict bid-cap. They focus on the case of symmetric tie-breaking (i.e., the probability that the stronger contestant wins the tie is $\alpha = 1/2$). Through the use of strict bid-caps, the weaker contestant can be encouraged to bid at the cap in equilibrium. Che and Gale (1998) show that if $m < v_L/2$, the equilibrium bid of both contestants is the bid-cap m , and thus the total revenue for the designer is $2m$. Within this class, revenue is maximized for $m^* = v_L/2$.⁶ This leads to a total revenue of $R^* = 2m^* = v_L$ for the designer, which is an improvement over the revenue $R = (v_H + v_L)v_L/(2v_H)$ from the unrestricted auction of Baye et al. (1996). However, although m^* increases the organizer's revenue, it reduces the efficiency of the all-pay auction, since it reduces the probability of winning for the high-valuation contestant.

The basic idea of strengthening competition by leveling the playing field is further elaborated in Szech (2015), who shows that combining a moderate bid-cap with an asymmetric tie-breaking rule in favor of the weaker contestant can further increase competition and revenue. The revenue-maximizing combination is the bid-cap $m^{**} = (1 - \alpha^{**})v_L$ and the tie-breaking rule $\alpha^{**} = v_L/(v_H + v_L)$. In equilibrium, both contestants bid m^{**} , and both earn zero in expectation. The total revenue for the designer is $R^{**} = 2m^{**} = 2v_Hv_L/(v_H + v_L)$, which is a further improvement over the revenue $R^* = 2m^* = v_L$ from the capped auction of Che and Gale (1998).

⁶ At $m^* = v_L/2$ there is a multiplicity of equilibria, which can be eliminated by reducing the cap by a small ϵ .

3. Experimental Design, Procedures and Hypotheses

3.1. Experimental Design

To study the effects of bid-caps and tie-breaks on behavior in all-pay auctions, we employ five treatments as shown in Table 1. In all treatments, two contestants compete against each other. The stronger contestant's valuation for winning, v_H , is 180 Talers (experimental currency), and the weaker contestant's valuation for winning, v_L , is 60 Talers. The treatments differ along two dimensions: the bid-cap m and the tie-breaking rule α . We denote treatments using the notation m_α .

Treatment 200_{1/2} is our baseline treatment. Given the valuations of the contestants, the cap of 200 should not be binding, as in Nash equilibrium, contestants should bid up to 60, following mixed strategies. Theoretically, tie breaking should be of low importance in this treatment, as ties should practically never occur. For this treatment, we chose the symmetric tie-breaking rule of $\alpha = 1/2$. According to the theoretical predictions, revenue in treatment 200_{1/2} should be 40, with the stronger contestant bidding 30 and the weaker contestant bidding 10 in expectation.

Treatment 29_{1/2} approximates the policy suggested by Che and Gale (1998). Contestants are restricted to bid up to $m^* = 29$ ($\epsilon = 1$ is chosen to avoid a multiplicity of equilibria), and tie-breaking is symmetric, i.e., $\alpha = 1/2$. According to the Nash equilibrium prediction, the designer's revenue in this treatment should increase to 58, with both contestants bidding the cap of 29.

Szech (2015) suggests combining a tie-breaking rule in favor of the weaker contestant with a mild bid-cap in order to further encourage the weaker contestant, to intensify overall competition, and thus, to increase the designer's revenue. To approximate the globally optimal combination of a bid-cap m^{**} and tie-breaking rule α^{**} , we implement treatment 53_{1/6}. In the case of a tie, the stronger contestant wins with a probability of $\alpha^{**} = 1/6$ while the weaker contestant wins with a

probability of $5/6$.⁷ Theoretically, treatment 53_1/6 should lead to the expected revenue of 80.3, with an expected bid of 47 by the weaker contestant and 33.3 by the stronger contestant.

It may be difficult for participants to understand a tie-breaking rule that works differently from simple winning probabilities such as 0, $1/2$ (i.e., the toss of a fair coin), or 1. A way to eliminate this problem is to approximate the theoretically optimal solution with a tie-breaking rule that is easy to understand. As a simplification of treatment 53_1/6, we also run treatment 53_0, in which the tie-breaking rule $\alpha = 0$ is always in favor of the weaker contestant. Theoretically, treatment 53_0 should lead to the revenue of 68, an expected bid of 45.2 by the weaker contestant and 23.4 by the stronger contestant. Thus, this treatment should still lead to a higher revenue than the unrestricted all-pay auction, and it should still outperform the policy of Che and Gale (1998).

Finally, to complete our understanding of the impact of tie-breaks, we also run treatment 53_1/2 with a symmetric tie-breaking rule of $\alpha = 1/2$. This treatment facilitates comparisons with treatments 53_1/6 and 53_0 as well as with treatment 29_1/2. Theoretically, treatment 53_1/2 should generate a revenue of 40. The stronger contestant is expected to bid 30, and the weaker contestant is expected to bid 10.

To summarize, our treatments can be separated into two sets. The first set of treatments looks at the effects of introducing bid-caps under symmetric tie-breaking in order to study the predictions of Che and Gale (1998). We thus compare treatments 29_1/2, 53_1/2, and 200_1/2. The second set studies the predictions of Szech (2015). We thus focus on treatment 53_1/6 as the global optimum, and compare it to treatments 200_1/2 and 29_1/2. Moreover, in order to understand the effect of tie-breaks under a mild bid-cap, we compare treatments 53_1/6 to treatments 53_0 and 53_1/2.

⁷ Using the winning probability of $1/6$ has the advantage that participants may recall this probability from playing board games involving dice throws.

3.2. Experimental Procedures

We conducted the experiment at the University of Bonn. 240 participants were recruited via ORSEE (Greiner, 2015) from the participant pool consisting mainly of undergraduate students. We ran 10 experimental sessions (2 per treatment) with 24 participants in each session (between-subject design). Participants interacted via visually isolated computer terminals, and the experiment was programmed and conducted with the experiment software z-Tree (Fischbacher, 2007). At the beginning of the experiment, each participant received a copy of the instructions (available in the Appendix), which an experimenter read out loud. Participants were informed about their initial endowment of 15 Euros (which we describe as a participation fee). They were also introduced to the in-game currency “Talers” and informed about the conversion rate of 60 Talers to 1 Euro.

Each session consisted of 40 periods of an all-pay auction. The design of the auction was kept identical across all 40 periods. In the first period, participants were assigned to the specific role of either contestant H (framed as player 1) or contestant L (framed as player 2). Participants remained in their roles for the first 20 periods of the experiment. For the last 20 periods, participants switched their roles, so all contestants H became contestants L and vice versa.⁸ In each session, 24 subjects were divided into 3 matching groups, each of which had an equal number of participants with role H and L . Participants were randomly matched in pairs in each period within each matching group, and there were no interactions with participants belonging to different matching groups throughout the experiment. Therefore, we treat each matching group as an

⁸ The process of role switching after period 20 was used to mitigate any concerns about fairness and inequality among participants in the experiment.

independent observation. This gives a total of 6 independent observations per treatment (2 sessions per treatment \times 3 matching groups per session).

In the baseline treatment, participants could bid any amount between 0 and 200 Talers, up to one decimal point. In the other treatments, participants could bid any amount between 0 and the bid-cap, up to one decimal point. At the end of each period, the computer displayed individual bids as well as individual payoffs. To reinforce the one-shot incentives of the game, 4 of the 40 periods were selected for payment. Participants' total earnings from these 4 periods were added to their initial endowment of 15 Euros.⁹ At the end of the experiment, participants answered a series of demographic and socioeconomic questions. The experimental sessions lasted about 90 minutes each.

3.3. Hypotheses

Our experiment consists of five treatments (summarized in Table 1) designed to test the theoretical predictions of Che and Gale (1998) and Szech (2015). Our first set of hypotheses, based on treatments 200_1/2, 53_1/2 and 29_1/2, are designed to test the predictions of Che and Gale (1998) that leveling the playing field through bid-caps under a symmetric tie-breaking rule can significantly reduce discouragement of the weaker contestant L and increase revenue in all-pay auctions. We begin by pointing out that placing a strict bid-cap of $m = 29$ as in treatment 29_1/2 should significantly increase the average bid of the weaker contestant, compared to treatments 53_1/2 and 200_1/2.

⁹ If the total payoff of the 4 selected periods was negative, the absolute value of this amount was subtracted from the initial endowment.

Hypothesis 1. Under symmetric tie-breaking, a strict bid-cap (i.e., $m = 29$) increases the average bid of the weaker contestant, with the predicted ordering of treatments: $200_{1/2} = 53_{1/2} < 29_{1/2}$.

At the same time, the bid-cap should not have much of an impact on the behavior of the stronger contestant. Indeed, the expected bid of the stronger contestant in treatments $53_{1/2}$ and $200_{1/2}$ is 30. The expected bid in treatment $29_{1/2}$ is slightly lower (i.e., it is 29) because the cap is marginally below 30.¹⁰

Hypothesis 2. Under symmetric tie-breaking, a bid-cap should not significantly impact the average bid of the stronger contestant, with the predicted ordering of treatments: $29_{1/2} \leq 53_{1/2} = 200_{1/2}$.

Given that the strict bid-cap significantly increases the average bid of the weaker contestant (from 10 to 29, see Table 1) and leaves the average bid of the stronger contestant almost unchanged (from 30 to 29), the average revenue should increase with the bid-cap. This main theoretical prediction of Che and Gale (1998) is our next hypothesis.

Hypothesis 3. Under symmetric tie-breaking, a strict bid-cap (i.e., $m = 29$) increases the average revenue compared to an unrestricted all-pay auction and an all-pay auction with a mild bid-cap (i.e., $m = 53$), with the predicted ordering of treatments: $200_{1/2} = 53_{1/2} < 29_{1/2}$.

According to Szech (2015), combining a milder bid-cap than in Che and Gale (1998) with a tie-breaking rule in favor of the weaker contestant can further increase revenue and reduce discouragement in the weaker contestant. We approximate the theoretical optimum via treatment $53_{1/6}$ in which the stronger contestant only wins in one out of six cases if he ends up in a tie with the weaker contestant. Theoretically, this should be enough tie-winning probability to keep the

¹⁰ As explained before, this was done to avoid multiplicity of equilibria.

stronger contestant motivated to bid at the cap, while the weaker contestant should be encouraged enough to bid at the cap as well. Also, treatment 53_1/6 should outperform treatments 53_1/2 and 53_0.

Hypothesis 4. A mild bid-cap (i.e., $m = 53$) combined with a tie-breaking in favor of the weaker contestant (i.e., $\alpha = 1/6$) generates higher average revenue than a strict bid-cap (53_1/6 > 29_1/2), an unrestricted all-pay auction (53_1/6 > 200_1/2), and other treatments with the same bid-cap but different tie-breaking (53_1/6 > 53_1/2 and 53_1/6 > 53_0).

Next, we describe how tie-breaks impact the individual behavior of contestants. Table 1 shows that among the treatments with the mild bid-cap of 53, treatment 53_1/6 generates the highest average bid from the weaker contestant. Nash equilibrium predicts an average bid of 47.0 for the weaker contestant. In this treatment, the advantage in tie-breaking for the weaker contestant should encourage high bids from both contestants. This is closely followed by treatment 53_0 in which the weaker contestant should invest 45.2. The mild decline in bid despite the even more advantageous tie-breaking is because competition with the stronger contestant softens, since the stronger contestant gets discouraged by the zero tie-winning probability. In contrast, in treatment 53_1/2, the weaker contestant should invest only 10.0 as the chance to win a tie is low.

Hypothesis 5. An advantage in tie-breaking for the weaker contestant (i.e., $\alpha < 1/2$) increases the average bid of the weaker contestant compared to symmetric tie-breaking: 53_1/2 < 53_1/6 and 53_1/2 < 53_0.

The impact of tie-breaking on the stronger contestant is more nuanced. According to theory, an advantage in tie-breaking for the weaker contestant should have a non-monotonic effect on the behavior of the stronger contestant, with treatment 53_1/6 generating the highest average bid, followed by treatments 53_1/2 and 53_0.

Hypothesis 6. Tie-breaking has a non-monotonic effect on the average bid of the stronger contestant, with the predicted ordering of treatments: $53_0 < 53_{1/2} < 53_{1/6}$.

4. Results

In the following analysis, we focus on the data from all 40 periods. Furthermore, in order to account for differential dynamics across treatments, we indicate whether the results are robust to considering only the second half of each part (periods 11-20 and 31-40). When performing the non-parametric tests, we use the average within a single re-matching group of 8 participants over all periods of the experiment as one independent observation (6 independent observations per treatment). When performing regression analyses, we control for individual participant effects and correlation within a matching group.

4.1. Optimal Bid-Caps under Symmetric Tie-Breaking

Table 2 displays average bids, payoffs, and revenue by treatment. The top part of the table presents the data for all 40 periods. The bottom part presents the data from periods 11-20 and 31-40 as a robustness check. We begin by focusing on treatments $200_{1/2}$, $53_{1/2}$ and $29_{1/2}$ in order to test the predictions of Che and Gale (1998) about optimal bid-caps under symmetric tie-breaking. According to theory, in treatment $200_{1/2}$, the weaker contestant should be discouraged and bid only 10, while the stronger contestant should bid 30. Indeed, we see that the weaker contestant bids three times less than the stronger contestant (11.7 versus 35.2; Wilcoxon rank-sum test, p -value < 0.01).¹¹ When comparing to the theoretical predictions, the average bid of the weaker contestant is not significantly different from prediction (11.7 versus 10.0; Wilcoxon

¹¹ This result also holds when examining the data from the second half of each part of the experiment (12.4 versus 33.3; Wilcoxon rank-sum test, p -value < 0.01).

signed-rank test, p -value = 0.34), while the stronger contestant bids significantly more than predicted (35.2 versus 30.0; Wilcoxon signed-rank test, p -value = 0.02). For visual representation of these results, see Figure 1 showing the average bid by treatment and type.

The prediction of Che and Gale (1998) is that strengthening the weaker contestant L , by placing a strict bid-cap on both contestants while keeping the tie-breaking rule symmetric, should enhance competition, reduce the discouragement effect and increase L 's average bid. In line with these predictions, treatment 29_1/2 significantly increases the average bid by the weaker contestant compared to the baseline treatment 200_1/2 (20.2 versus 11.7; Wilcoxon rank-sum test, p -value < 0.01), supporting Hypothesis 1 and indicating that the strict cap of $m = 29$ significantly diminishes discouragement.¹² However, compared to the theoretical prediction, the average bid is significantly lower from prediction (20.2 versus 29.0; Wilcoxon signed-rank test, p -value = 0.02). We also find that, contrary to Hypothesis 1, a mild bid-cap of $m = 53$ is as effective as the strict cap. Specifically, we find that the average bid by the weaker contestant in treatment 53_1/2 is significantly higher than in treatment 200_1/2 (20.5 versus 11.7; Wilcoxon rank-sum test, p -value = 0.01), and it is not different from treatment 29_1/2 (20.5 versus 20.2; Wilcoxon rank-sum test, p -value = 0.87).¹³

To further check the robustness of our non-parametric tests, we estimate a random effects GLS regression of the bid on dummies indicating the interaction between a treatment and a bidder type (with bids of low types in the 200_1/2 treatment as the reference group) and a constant.¹⁴ The estimation results are reported in Table 3. Based on these estimation results, we provide pairwise

¹² This result is robust when examining the data from the second half of each part of the experiment (12.4 versus 20.2; Wilcoxon rank-sum test, p -value = 0.01).

¹³ The difference between 53_1/2 and 200_1/2 becomes insignificant if we restrict the analysis to the second half of each part (Wilcoxon rank-sum test, p -value = 0.15). Also, the difference between 53_1/2 and 29_1/2 remains insignificant when examining only the second half (Wilcoxon rank-sum test, p -value = 0.33).

¹⁴ We ran this regression to ease the interpretation of the coefficients. Adding controls for the number of periods and the number of the part played, did not change any of the results presented. In order to account for differential learning across treatments, we indicate robustness of the results when considering only the later bidding periods in the respective roles, i.e., periods 11-20 and 31-40.

comparisons of the weaker contestant's bids across treatments, reported in Table 4. Consistent with the non-parametric tests, the introduction of either a strict or a mild bid-cap motivates the weaker contestant and reduces the discouragement effect.

Result 1. Consistent with Hypothesis 1, a strict bid-cap significantly increases the average bid by the weaker contestant. However, contrary to Hypothesis 1, a mild bid-cap has a similar impact on the average bid as the strict bid-cap.

Result 1 suggests that optimal bid-caps may not have to be as small as the analysis in Che and Gale (1998) suggests. We now turn to the bidding behavior of the stronger contestant. In line with the Nash equilibrium prediction and consistent with Hypothesis 2, we find no significant difference in average bidding behavior between treatments 53_1/2 and 200_1/2 (38.6 versus 35.2; Wilcoxon rank-sum test, p-value = 0.14). Yet in both treatments, bids are significantly higher than the predicted level of 30.0 (both p-values are 0.02). Theoretical analysis further predicts only a marginal decrease when the cap is $m = 29$, with the contestant bidding at the cap. Our data reveal a more substantial and significant decrease to an average bid of 25.3 (p-value = 0.02). The average bid of the stronger contestant in treatment 29_1/2 is significantly lower than in treatments 53_1/2 and 200_1/2 (both p-values < 0.01). These results are robust to focusing on the second half of bidding periods, indicating that a strict bid-cap decreases the average bid of the stronger contestant.

To further check the robustness of our non-parametric tests, we provide pairwise comparisons of the stronger contestant's bids across treatments in Table 5. These comparisons are based on the regression estimation results presented in Table 3. Consistent with the non-parametric tests, the stronger contestant bids less when there is a strict bid-cap.

Result 2. A strict bid-cap significantly reduces the average bid by the stronger contestant. This is in contrast to Hypothesis 2.

Finally, we examine the impact of bid-caps on the average revenue. According to Results 1 and 2, a strict bid-cap increases the bid of the weaker contestant and decreases the bid of the stronger contestant. Therefore, given that revenue equals the sum of bids exerted by the stronger and weaker contestants, the total impact hinges on which effect is stronger.

Figure 2 shows the average revenue by treatment. The theoretical prediction of Che and Gale (1998) is that placing a strict bid-cap of $m = 29$ should raise revenue relatively to an unrestricted all-pay auction. Our data show that, contrary to this prediction and Hypothesis 3, revenue in treatment 29_1/2 is not significantly different from revenue in the baseline treatment 200_1/2 (45.5 versus 46.9; Wilcoxon rank-sum test, p-value = 0.87).¹⁵ Theory also predicts that a mild bid-cap of $m = 53$ should have no impact on revenue compared to the unrestricted auction. Again, contrary to this prediction and Hypothesis 3, revenue in treatment 53_1/2 is significantly higher than in treatment 200_1/2 (59.1 versus 46.9; Wilcoxon rank-sum test, p-value = 0.05). It is also higher than in treatment 29_1/2 (59.1 versus 45.5; Wilcoxon rank-sum test, p-value = 0.01).

To further check the robustness of our non-parametric tests, we provide pairwise comparisons of revenue across treatments in Table 6. These comparisons are based on the regression estimation results presented in Table 3. Consistent with the non-parametric tests, we find that a strict bid-cap has no impact on the designer's revenue, while a mild bid-cap increases revenue.

Result 3. Contrary to Hypothesis 3, a strict bid-cap does not significantly increase the average revenue, while a mild bid-cap does.

The reason for this departure from theory is twofold. First, revenue in treatment 200_1/2 is significantly higher than predicted (46.9 versus 40.0; Wilcoxon signed-rank test, p-value = 0.02),

¹⁵ This conclusion stands when examining the data from the second half of the experiment.

as well as revenue in treatment 53_1/2 (59.1 versus 40.0; Wilcoxon signed-rank test, p-value = 0.01). Such overbidding is common in all-pay auction experiments (Davis and Reilly, 1998; Gneezy and Smorodinsky, 2006; Lugovskyy et al., 2010; Chen et al., 2015).¹⁶ Second, revenue in treatment 29_1/2 is significantly lower than predicted (45.5 versus 58.0; Wilcoxon signed-rank test, p-value = 0.02). For this treatment, the Nash equilibrium is at the upper boundary of the bidding space (i.e., both bidders should bid at the cap), so any deviation from equilibrium implies a lower-than-predicted revenue (Laury and Holt, 2008; Kimbrough et al., 2014).¹⁷ But as we will see in Section 4.3, the main reason that revenue in treatment 29_1/2 is significantly lower than predicted is because contestants place a significant mass point around 0.

4.2. Optimal Combination of Bid-Caps and Tie-Breaking Rules

Che and Gale (1998) optimize the bid-cap assuming that tie-breaking is symmetric. Szech (2015) studies Nash equilibrium for all possible combinations of bid-cap and tie-breaking rule. Theoretically, a mild bid-cap combined with a tie-breaking rule under which the weaker contestant wins more often than the stronger contestant, is optimal. The global optimum in revenue is approximated by treatment 53_1/6. In line with Hypothesis 4, treatment 53_1/6 outperforms the strict bid-cap of Che and Gale (1998) under symmetric tie-breaking, i.e., treatment 29_1/2, (57.2 versus 45.5; Wilcoxon rank-sum test, p-value = 0.01) and the unrestricted auction, i.e., treatment 200_1/2, (57.2 versus 46.9; Wilcoxon rank-sum test, p-value = 0.03). However, compared to the theoretical prediction, the average revenue in treatment 53_1/6 is significantly lower from

¹⁶ Explanations for overbidding include bounded rationality (Sheremeta, 2011; Chowdhury et al., 2014; Lim et al., 2014), the utility of winning (Sheremeta, 2010; Cason et al., 2012, 2017), relative payoff maximization (Sheremeta, 2013, 2015; Mago et al., 2016), and limited cognitive ability (Sheremeta, 2016).

¹⁷ This problem of equilibrium predictions at the boundary has been well recognized in linear public good experiments, where the dominant strategy is to contribute nothing. For a review, see Laury and Holt (2008).

prediction (57.2 versus 80.26; Wilcoxon signed-rank test, p-value = 0.02). Also, contrary to Hypothesis 4, we find no significant differences between treatments 53_1/6, 53_0, and 53_1/2 (Wilcoxon rank-sum test, p-values = 0.42, 0.74, and 0.63).¹⁸ Similarly, pairwise comparisons of revenue in Table 6, based on the regression analysis presented in Table 3, show no significant difference between these treatments.¹⁹

Result 4. Consistent with Hypothesis 4, a mild bid-cap combined with a tie-breaking in favor of the weaker contestant generates higher average revenue than a strict bid-cap ($53_{1/6} > 29_{1/2}$) and an unrestricted all-pay auction ($53_{1/6} > 200_{1/2}$). However, contrary to Hypothesis 4, under the mild bid-cap, average revenue does not change significantly as tie-breaking changes ($53_{1/6} = 53_{1/2} = 53_0$).

To further understand the impact of tie-breaks we examine individual behavior of contestants in treatments 53_1/2, 53_1/6 and 53_0. The theoretical prediction of Szech (2015) is that strengthening the weaker contestant L , by a tie-breaking rule that lets the stronger bidder win only in 1 out of 6 cases, should enhance competition. It should also reduce the discouragement effect and increase L 's average bid. In line with the latter prediction, treatment 53_1/6 significantly increases the average bid by the weaker contestant compared to treatment 53_1/2 (27.9 versus 20.5; Wilcoxon rank-sum test, p-value = 0.03), supporting Hypothesis 5 and indicating that the tie-breaking rule of $\alpha = 1/6$ significantly diminishes discouragement. However, the impact is weaker than predicted. While theory predicts a very large increase from 10 to 47, we find an increase from 20.5 to 27.9 in the data. Theory also predicts that a further favoring of the weaker

¹⁸ The comparison between 53_1/6 and 53_1/2 becomes marginally significant when we only consider the second half of each part (Wilcoxon rank-sum test, p-value = 0.08).

¹⁹ However, all three treatments – 53_1/6, 53_0, and 53_1/2 – generate significantly higher revenues than the unrestricted baseline treatment 200_1/2 (Wilcoxon rank-sum test, p-values = 0.03, 0.01, and 0.05) and treatment 29_1/2 (Wilcoxon rank-sum test, p-values = 0.01, 0.01, and 0.01). Revenue increases substantially, amounting to almost 30% higher than that of the unrestricted all-pay auction.

contestant, so that the stronger contestant never wins the tie, leaves the high bid of the weaker contestant virtually unchanged (47 versus 45.2). The data show that indeed, the average bid of the weaker contestant in treatment 53_0 is not significantly different from treatment 53_1/6 (32.3 and 27.9; Wilcoxon rank-sum test, p-value = 0.20). These results hold when examining the second half of bidding periods or using the regression analysis, see Table 4.

Result 5. Consistent with Hypothesis 5, a tie-breaking rule favoring the weaker contestant significantly increases the average bid of the weaker contestant compared to a symmetric tie-breaking rule.

When examining the behavior of the stronger contestant, theory predicts that his average bid should be the highest in treatment 53_1/6 where competition is the toughest. He should bid 33.3 in expectation. This is followed by treatment 53_1/2 where he should bid 30. In treatment 53_0, he should bid 23, which is the lowest among these three treatments. Contrary to this prediction, we find that the average bid of the stronger contestant is the highest in treatment 53_1/2. It is different from treatments 53_1/6 and 53_0 at the 0.01 significance level. When comparing treatments 53_1/6 and 53_0, we find no significant difference in bidding behavior (29.3 versus 27.0; Wilcoxon rank-sum test, p-value = 0.26). Thus, the stronger contestant becomes more easily discouraged by a non-favorable tie-breaking rule than theory predicts. These results are robust when performing pairwise comparisons of the average bid in Table 5, based on the regression analysis presented in Table 3.

Result 6. Contrary to Hypothesis 6, a tie-breaking rule favoring the weaker contestant significantly decreases the average bid of the stronger contestant.

In summary, while we find support that the weaker contestant increases his bid when the tie-breaking rule is in his favor, the stronger contestant responds in a way not predicted by theory.

Specifically, we find that the stronger contestant decreases his bid in reaction to a disadvantage in tie-breaking. As a result, across the three treatments with a bid-cap of 53, revenue is not significantly different. The overall level of revenue, however, is high: all treatments with a mild bid-cap outperform the unrestricted auction treatment as well as the treatment with the strict bid-cap. Next, we provide additional analysis to understand departures from theoretical predictions.

4.3. Distribution of Bids

In order to better understand departures of our data from the Nash equilibrium, we examine the distribution of bids across types and treatments. Figure 3 displays the realized and the predictive cumulative distributions of bids for each treatment and type. Overall, we see that the observed data is fairly consistent with the theoretical predictions, with some deviations that we will discuss.

In the unrestricted treatment 200_1/2, as predicted by standard theory, most bids by both types are between 0 and 60.0. Only 2.5% of bids are strictly above 61.0, and only 1.1% are strictly above 65.0. Also, as we have previously documented, the bidding behavior of the stronger contestant is significantly higher than predicted. From Figure 3 we can see that this overbidding comes primarily from participants placing a significant mass point around 60 (which is not predicted by theory).

In treatment 29_1/2, theory predicts that all bids should be concentrated at the bid-cap of $m = 29$. Indeed, we find that the stronger contestant follows this strategy 82.6% of the time. Although the average bid is significantly lower than predicted (25.3 versus 29.0; Wilcoxon signed-rank test, p -value = 0.02), the weaker contestant concentrates his bids around the bid-cap, as predicted. Yet there is also a mass point around 0 that is not predicted by theory, and it is even

more pronounced than that of the stronger contestant (the frequency of bidding 0 is significantly higher; Wilcoxon signed-rank test, p-value = 0.03).

The only difference across the three treatments with a mild bid-cap of $m = 53$ is the tie-breaking rule α . We see that effects of tie-breaking on bidding behavior are substantial. The weaker contestant shifts mass from 0 to the cap as the tie-breaking rule becomes more favorable. At the same time, the stronger contestant displays the reverse bidding behavior by shifting mass from the cap to 0 as the tie-breaking rule becomes less favorable for him. Focusing on treatments 53_0 and 53_1/2 in which the tie-breaking rule is relatively easy to understand, the shifts in the mass points are in line with the Nash equilibrium prediction. This is not the case for treatment 53_1/6. Here, we observe again substantial mass at 0, which is not predicted by theory.

Result 7. In most treatments, there is a mass point at 0, part of which is not predicted by theory.

One may think that an explanation for excessive bidding at 0 could be that participants are best responding to observed behavior. We examine this option in the following Section 4.4 and demonstrate that it is not a suitable explanation. The reason is that usually, a small bid different from 0 leads to a higher payoff than bidding at 0.

Finally, in order to establish whether the distribution of bids is independent across rounds, we analyze contestants' behavior in response to previously observed behavior. Table 7 displays panel regressions by treatment and type, demonstrating the impact of different lag variables in period $t-1$ on bid in period t . Theory predicts that participants should randomly and independently choose their bids according to the mixed strategy Nash equilibrium. Instead, we find two important deviations from this prediction. First, the significant *bid-lag* variable in all specifications shows that participants' bids are serially correlated. Second, the significant *otherbid-lag* variable shows

that participants respond to the opponents' behavior in the past period. Both of these observations point out that, instead of using mixed strategies, contestants are influenced by the salience of their experiences. These results are in line with previous results that show the difficulty of participants to play mixed strategies (see, for instance, Brown and Rosenthal, 1990; Ochs, 1995; Foster and Young, 2003; Chowdhury et al., 2013).

4.4. Best Response to Observed Behavior

In this section, we analyze the expected payoffs of each bid for both types of contestants in each treatment. According to the theoretical predictions, contestants should be indifferent between bids that are played with positive probabilities. In the data, this may be different because (i) even if contestants play according to the theoretical predictions, the distribution of realized bids might not perfectly reflect the theoretical distribution, and (ii) as we saw previously, there are significant departures from theoretical predictions.

Echoing the analysis in Section 4.3, we begin with the unrestricted treatment 200_1/2. The best response to empirical frequencies observed in the experiment for the stronger contestant is to bid 42.1, which yields an expected payoff of 124.7. But, as Figure 4 shows, the expected payoff function is relatively flat: any bid between 10.1 and 68.8 gives a payoff of at least 110.²⁰ The best response for the weaker contestant is to bid 2.2, which yields an expected payoff of 5.1. The expected payoff function is also relatively flat around the maximum, but overall, the expected payoff tends to decrease with the bid, and any bid higher than 18.6 yields a negative payoff (with the exception of bids between 20.2 and 20.5).

²⁰ Any bid between 1.3 and 79.2 gives an expected payoff of 100.

The best response to empirical frequencies in treatment 29_1/2, see Figure 4, is in line with the theoretical predictions – to bid at the cap. The stronger contestant has an incentive to bid at the cap: expected payoff of bidding the cap is 91.8 while the expected payoff of other bids is, at most, 46.7. But unlike the theoretical prediction, due to the high frequency of weaker contestants bidding 0, the expected payoff of any bid is strictly positive and no less than 19.3.²¹ The incentive to bid at the cap by the weaker contestant is of course lower: the expected payoff of bidding at the cap is 6.2 while the expected payoff of other bids is at most 3.0.

Figure 5 summarizes the expected payoff of different bids for both contestants for the treatments with a cap of 53. The three treatments display similar patterns. The weaker contestant receives a positive expected payoff for low bids, but this payoff decreases with the bid, except for bids exactly at the cap. When examining the expected payoff of the stronger contestant, we see that in treatment 53_0, the expected payoff is flat (between 46.29 and 51.90) for bids between 30.1 and the cap. In the other two treatments, there is a clear best response to observed behavior: bidding at the cap. In treatment 53_1/6, bidding the cap delivers an expected payoff of 72.3, while the expected payoff of other bids is at most 62.4. In treatment 53_1/2, bidding at the cap brings a payoff of 98.7, but other bids yield as much as 92.6. In particular any bids between 5.1 and 9.3 and between 10.0 and 22.6 yield at least 88.0.

An important conclusion from this analysis is that bidding 0 by the stronger contestant is a strictly dominated strategy in all treatments.

Result 8. Bidding 0 by the stronger contestant is a strictly dominated strategy in all treatments.

²¹ The minimum expected payoff of a stronger contestant from making any strictly positive bid is 32.3.

Therefore, a substantial mass at 0 by the stronger contestant which we have documented in Section 4.3, see Figure 3, is not only inconsistent with the theoretical predictions, but it is not a best response to observed behavior either. To explain this apparent inconsistency we revert to behavioral explanations.

4.5. Behavioral Explanations

A potential candidate to explain a substantial mass point at 0 is loss aversion (Kahneman and Tversky, 1979). It is well-documented both, by the theoretical and experimental literature on all-pay auctions, that loss and risk aversion impacts bidding behavior (Müller and Schotter, 2010; Sheremeta and Zhang, 2010; Baye et al., 2012; Mago et al., 2013; Shupp et al., 2013; Dechenaux et al., 2015).²² However, it is easy to demonstrate that neither risk nor loss aversion can explain excessive bidding at 0. To show this, assume that bidders are loss averse so that a negative payoff receives higher weight. Under this assumption, some standard characteristics of equilibrium still apply. Specifically, it cannot happen in equilibrium that both bidders place mass on zero. If both bidders played zero with positive probability, one bidder could profitably deviate to a slightly higher bid (see Szech, 2015). The data from treatments 53_1/6 and 29_1/2 violate this, since in these treatments both bidders simultaneously place significant mass on 0.

Other potential candidates are the models of bounded rationality such as quantal response equilibrium (McKelvey and Palfrey, 1995) or cursed equilibrium (Eyster and Rabin, 2005). Goeree et al. (2002) show that quantal response equilibrium can indeed account for some of the departures observed in private value first price auctions. In our setup, however, quantal response equilibrium

²² Looking at our data on self-reported willingness to take risks (where 0 denotes “completely unwilling to take risks” and 10 denotes “completely prepared to take risks”), we find that participants who indicate that they are unwilling to take risks avoid bidding at the cap of 29. A random effects GLS regression of the probability of bidding zero on our risk measure shows a significant relationship (p-value < 0.01).

cannot account for the pronounced peaks observed at zero and the cap. Also, since our game is a game of complete information, cursed equilibrium coincides with the Nash prediction.

Finally, we examine whether deviations from Nash equilibrium in our experiment can be explained by the level- k model of reasoning (Stahl and Wilson, 1994, 1995; Nagel, 1995). This model assumes that the population is partitioned into types that differ in their depth of reasoning. A level-0 type is nonstrategic and follows a simple decision rule. The level-1 type behaves as if best-responding to the belief that the other is a level-0 type. Similar logic applies to other types. People typically exhibit reasoning on lower levels; it is very uncommon to observe level-4 reasoning or higher (Arad and Rubinstein, 2012; Crawford et al., 2013).²³

Table 8 displays bidding behaviors according to level- k for the stronger contestant H and the weaker contestant L . The three panels (Panel A, B and C) show the predictions based on how we model a level-0 type. Panel A assumes that level-0 randomly chooses a bid between 0 and the bid-cap (60 in the baseline treatment). Panel B assumes that level-0 bids 0. Panel C assumes that level-0 bids the minimum of v_L and m .

Recall that the most puzzling behavior that we observe in our experiment is the excessive bidding at 0 by the stronger contestant (see Section 4.3), despite the fact that it is a strictly dominated strategy for the stronger contest in all treatments (see Section 4.4). While this type of behavior is inconsistent with the theoretical predictions and a best response to observed behavior, it can be explained by the level- k model of reasoning. From Table 8, we see that despite how we model a level-0 type, bidding 0 (or near 0) is a strategy employed by at least one of the levels of reasoning.

²³ Level- k reasoning has been used to explain the behavior in auctions (Crawford and Iriberri, 2007), beauty contests (Nagel, 1995), guessing games (Stahl and Wilson, 1994, 1995), coordination games (Crawford et al., 2008), and centipede games (Kawagoe and Takizawa, 2012).

The level-k model also captures well the comparative statics with respect to the tie-breaking rule. The bid distribution for the stronger contestant displays mass points at the cap of comparable sizes when the tie-breaking rule is $\alpha = 0$ and $\alpha = 1/6$ (see Panels A and C), and a much more pronounced mass point at the cap when the rule is $\alpha = 1/2$. The bid distributions for the weaker contestant, on the other hand, show a reverse pattern: the frequency of bidding 0 increases when the tie-breaking rule becomes less favorable.

Result 9. Deviations from the standard game-theoretic predictions are in line with level-k reasoning.

5. Conclusion

It has been well recognized that the discouragement effect can decrease the performance of contestants.²⁴ One theoretical solution that has been proposed is to impose a rather strict cap on expenditures (Che and Gale, 1998). Theoretically, even better effects are attainable when implementing a mild bid-cap combined with a tie-breaking rule favoring the weaker contestant (Szech, 2015). In this paper we provide empirical evidence that these policies are indeed powerful. Compared to the unrestricted baseline auction, our data show that the average bid of the weaker contestant is more than 70% higher when the strict bid-cap suggested by Che and Gale (1998) is in place. An appropriate combination of a mild bid-cap and a favorable tie-breaking rule can further increase the average bid of the weaker contestant, such that he bids more than 170% higher compared to the unrestricted contest. Moreover, revenue increases if a mild bid-cap is chosen. The mild bid-cap outperforms the strict bid-cap and the unrestricted all-pay auction with regard to revenue. In our data, this finding holds independently of the tie-breaking rule. The reason is that,

²⁴ See, for example, Brown (2011) for evidence in the field or Dechenaux et al. (2015) for evidence in the lab.

the encouragement of the weaker contestant goes together with some discouragement on the side of the stronger contestant.

Our study contributes to a growing literature on innovation contests (Terwiesch and Xu, 2008, Boudreau et al., 2011). Our empirical findings may explain why in practice, contest designers sometimes place relatively small restrictions on contestants and often stick to symmetric tie-breaking when focusing on overall revenues (Jeppesen and Lakhani, 2010; Boudreau et al., 2011).²⁵ In other cases, objectives may include encouraging weaker contestants, as for example in sports competitions (to level the playing field and create more of a thrill for viewers) or labor markets (to increase diversity); here, tie-breaking rules in favor of the weaker contestants are frequently used, and may successfully apply. Anti-discrimination policies that solve ties in favor of specific subgroups of a population may benefit from these effects. Our data illustrates that policies designed to diminish the discouragement effect do not harm revenue, instead, they can increase it compared to unrestricted contests.

²⁵ Innovation contests provide a good example in which tie-breaking rules are typically symmetric.

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Table 1: Overview of treatments and theoretical predictions

Treatment	Type	200 1/2	29 1/2	53 1/2	53 1/6	53 0
Cap m		–	29	53	53	53
Tie-breaking rule α		1/2	1/2	1/2	1/6	0
Expected bid $E(b)$	H	30.0	29.0	30.0	33.3	23.4
	L	10.0	29.0	10.0	47.0	45.2
Expected revenue R		40.0	58.0	40.0	80.3	68.6
	H	Uniform mixing on [0,60]	Atom of 1 at 29	Atom of 0.23 at 53, uniform mixing on [0,46] with remaining probability	Atom of 0.51 at 53 and atom of 0.03 at 0, uniform mixing on [0, 28] with remaining probability	Atom of 0.11 at 0, mixing on [0,53] with remaining probability
Bidding strategy according to Nash equilibrium	L	Atom of 0.67 at 0, uniform mixing on [0,60] with remaining probability	Atom of 1 at 29	Atom of 0.67 at 0 and atom of 0.08 at 53, uniform mixing on [0,46] with remaining probability	Atom of 0.85 at 53, uniform mixing on [0, 28] with remaining probability	Atom of 0.71 at 53, uniform mixing on [0,53] with remaining probability

Table 2: Average bid, payoff and revenue by treatment

Treatment	Type	200 1/2	29 1/2	53 1/2	53 1/6	53 0
All 40 periods						
Average bid	H	35.2 (26.5)	25.3 (8.7)	38.6 (21.1)	29.3 (22.8)	27.0 (22.9)
	L	11.7 (19.3)	20.2 (12.8)	20.5 (23.9)	27.9 (23.5)	32.3 (21.8)
Average payoff	H	111.0 (66.6)	88.0 (84.8)	94.3 (76.1)	56.7 (83.9)	31.7 (77.3)
	L	-0.4 (20.2)	1.9 (25.5)	-4.8 (24.3)	3.3 (23.7)	8.0 (21.7)
Average revenue		46.9 (33.9)	45.5 (16.0)	59.1 (34.6)	57.2 (33.9)	59.4 (31.8)
Periods 11-20 and 31-40						
Average bid	H	33.3 (22.7)	25.2 (9.1)	35.2 (22.4)	25.7 (23.2)	27.0 (22.5)
	L	12.4 (19.8)	20.2 (13.0)	17.5 (22.9)	26.1 (23.9)	31.2 (22.2)
Average payoff	H	106.9 (69.4)	91.0 (84.1)	99.7 (74.9)	57.0 (84.3)	32.5 (78.1)
	L	0.8 (20.6)	1.0 (25.6)	-2.5 (23.5)	6.2 (24.0)	8.9 (20.3)
Average revenue		45.7 (30.5)	45.4 (16.6)	52.8 (34.6)	51.9 (34.9)	58.2 (31.4)

Standard deviation in parenthesis.

Table 3: Random effects GLS regression of the bid

Variable	Coef.	St. Err.	Z	P > z	95% Conf. Int.
200_1/2 × H	23.5	0.99	23.61	0.000	[21.54, 25.44]
29_1/2 × H	13.6	1.39	9.80	0.000	[10.91, 16.37]
53_1/2 × H	26.9	2.15	12.50	0.000	[22.66, 31.09]
53_1/6 × H	17.6	1.83	9.57	0.000	[13.98, 21.18]
53_0 × H	15.3	1.60	9.56	0.000	[12.20, 18.48]
29_1/2 × L	8.5	1.89	4.47	0.000	[4.76, 12.20]
53_1/2 × L	8.8	2.74	3.22	0.001	[3.44, 14.19]
53_1/6 × L	16.2	2.69	6.01	0.000	[10.92, 21.48]
53_0 × L	20.6	2.12	9.72	0.000	[16.46, 24.78]
Constant	11.7	1.25	9.32	0.000	[9.26, 14.20]
Observations	9600				
Subjects	240				

Random effects GLS regression of the bid on dummies indicating the interaction between a treatment and a bidder type and a constant.

200_1/2 × L is the reference type.

Table 4: Pairwise comparisons of the weaker contestant's bids across treatments

	29_1/2	53_0	53_1/6	53_1/2
200_1/2	<	<	<	<
	p = 0.00	p = 0.00	p = 0.00	p = 0.00
29_1/2		<	<	=
		p = 0.00	p = 0.01	p = 0.91
53_0			=	>
			p = 0.13	p = 0.00
53_1/6				>
				p = 0.03

The statistics in this table are based on the estimation results of the random effects GLS regression presented in Table 3. All results are robust to considering only the second half of each part.

Table 5: Pairwise comparisons of the stronger contestant's bids across treatments

	29_1/2	53_0	53_1/6	53_1/2
200_1/2	>	>	>	=
	p = 0.00	p = 0.00	p = 0.01	p = 0.16
29_1/2		=	<	<
		p = 0.14	p = 0.01	p = 0.00
53_0			=	<
			p = 0.18	p = 0.00
53_1/6				<
				p = 0.00

The statistics in this table are based on the estimation results of the random effects GLS regression presented in Table 3.

Table 6: Pairwise comparisons of the revenue across treatments

	29 1/2	53 0	53 1/6	53 1/2
200_1/2	=	<	<	<
	p = 0.69	p = 0.00	p = 0.02	p = 0.01
29_1/2		<	<	<
		p = 0.00	p = 0.00	p = 0.00
53_0			=	=
			p = 0.59	p = 0.95
53_1/6				=
				p = 0.71

The statistics in this table are based on the estimation results of the random effects GLS regression presented in Table 3.

Table 7: Random effects regression of the bid on lag variables

Dependent variable, <i>bid</i>	Treatment				
	200_1/2	29_1/2	53_1/2	53_1/6	53_0
	Type <i>H</i>				
<i>bid-lag</i>	0.48***	0.44***	0.66***	0.65***	0.62***
[own bid in <i>t-1</i>]	(0.15)	(0.05)	(0.04)	(0.05)	(0.05)
<i>otherbid-lag</i>	0.31***	0.09***	0.09***	0.03	-0.15***
[other bid in <i>t-1</i>]	(0.08)	(0.03)	(0.03)	(0.02)	(0.03)
<i>win_lag</i>	-2.55	-0.36	-3.14	0.26	-5.33***
[dummy for win in <i>t-1</i>]	(4.96)	(0.56)	(2.07)	(1.64)	(1.45)
<i>period</i>	0.12	0.00	-0.06	-0.20***	-0.02
[linear period trend]	(0.15)	(0.03)	(0.12)	(0.04)	(0.10)
<i>switch</i>	1.17	1.29**	-1.80	-1.76	-1.70
[dummy for role switching]	(2.83)	(0.65)	(1.11)	(1.14)	(1.36)
<i>constant</i>	13.36***	11.99***	14.88***	11.85***	17.71***
	(4.10)	(1.32)	(2.45)	(2.04)	(2.87)
	Type <i>L</i>				
<i>bid-lag</i>	0.34***	0.66***	0.65***	0.70***	0.56***
[own bid in <i>t-1</i>]	(0.13)	(0.05)	(0.06)	(0.04)	(0.05)
<i>otherbid-lag</i>	0.00	0.04	0.02	0.09***	0.22***
[other bid in <i>t-1</i>]	(0.05)	(0.04)	(0.03)	(0.03)	(0.04)
<i>win_lag</i>	1.76	-1.10	1.06	-4.70***	-2.08
[dummy for win in <i>t-1</i>]	(1.92)	(0.84)	(1.80)	(1.32)	(2.10)
<i>period</i>	0.08	0.04	-0.21**	-0.04	-0.04
[linear period trend]	(0.10)	(0.04)	(0.10)	(0.09)	(0.10)
<i>switch</i>	1.43	-0.80	-2.13	0.04	0.00
[dummy for role switching]	(1.60)	(1.22)	(2.32)	(1.60)	(1.59)
<i>constant</i>	5.77***	6.41***	9.28***	8.57***	9.97***
	(2.20)	(1.63)	(2.89)	(1.84)	(1.61)

* significant at 10%, ** significant at 5%, *** significant at 1%. The standard errors in parentheses are clustered at the group level. All models include a random effects error structure, with the individual subject as the random effect, to account for the multiple decisions made by individual subjects.

Table 8: Level-k bids by contestant type and by treatment

Treatment	200_1/2		29_1/2		53_1/2		53_1/6		53_0	
	<i>H</i>	<i>L</i>	<i>H</i>	<i>L</i>	<i>H</i>	<i>L</i>	<i>H</i>	<i>L</i>	<i>H</i>	<i>L</i>
Panel A: Level-0 is uniformly distributed										
Level-0	U[0,60]	U[0,60]	U[0,29]	U[0,29]	U[0,53]	U[0,53]	U[0,53]	U[0,53]	U[0,53]	U[0,53]
Level-1	60	Nash	29	29	53	53	53	53	53	53
Level-2	U[0,60]	0	29	29	53	0	0	0	0	53
Level-3	“0.1”	Nash	29	29	“0.1”	0	“0.1”	“0.1”	0	“0.1”
Panel B: Level-0 is 0										
Level-0	0	0	0	0	0	0	0	0	0	0
Level-1	“0.1”	“0.1”	“0.1”	“0.1”	“0.1”	“0.1”	“0.1”	“0.1”	“0.1”	0
Level-2	“0.2”	“0.2”	“0.2”	“0.2”	“0.2”	“0.2”	“0.2”	“0.2”	“0.1”	“0.1”
Level-3	“0.3”	“0.3”	“0.3”	“0.3”	“0.3”	“0.3”	“0.3”	“0.3”	“0.2”	“0.1”
Panel C: Level-0 is the minimum of v_L and m										
Level-0	60	60	29	29	53	53	53	53	53	53
Level-1	“60.1”	0	29	29	53	0	0	0	0	53
Level-2	“0.1”	0	29	29	“0.1”	0	“0.1”	“0.1”	0	“0.1”
Level-3	“0.1”	“0.2”	29	29	“0.1”	“0.2”	“0.2”	“0.2”	“0.2”	0

Panel A: U[A,B] denotes a uniform distribution with boundaries A and B. “0.1” approximates the theoretical solution of ε as subjects could adjust their bid to a tenth of the in-game currency. Panel B: “0.1”, “0.2”, and “0.3” approximate the theoretical solutions of ε , 2ε , and 3ε , respectively, as subjects could adjust their bid to a tenth of the in-game currency. Panel C: “0.1”, “0.2”, and “60.1” approximate the theoretical solutions of ε , 2ε , and $60+\varepsilon$ as subjects could adjust their bid to a tenth of the in-game currency.

Figure 1: Average bid by treatment and type

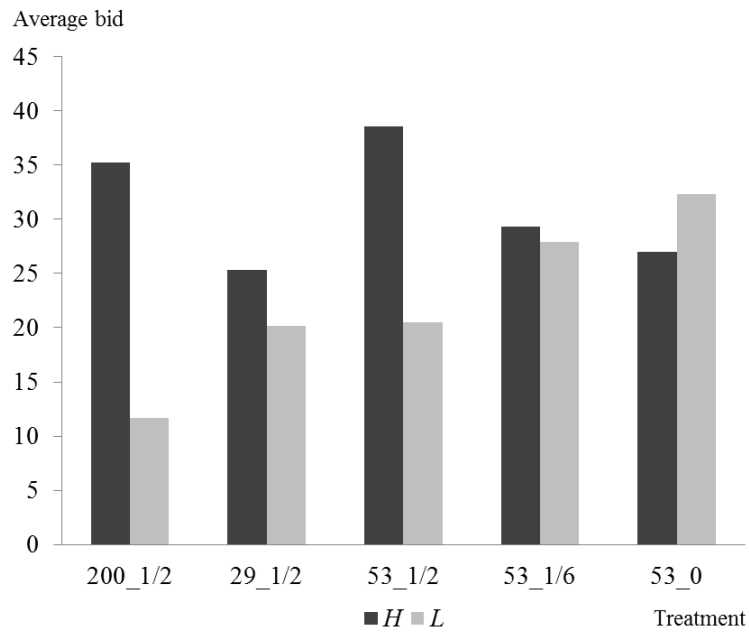


Figure 2: Average Revenue by treatment

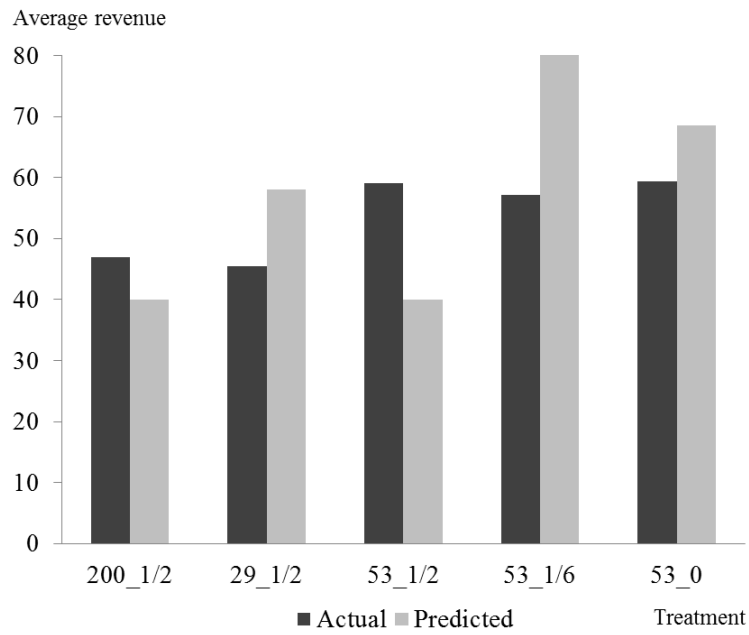
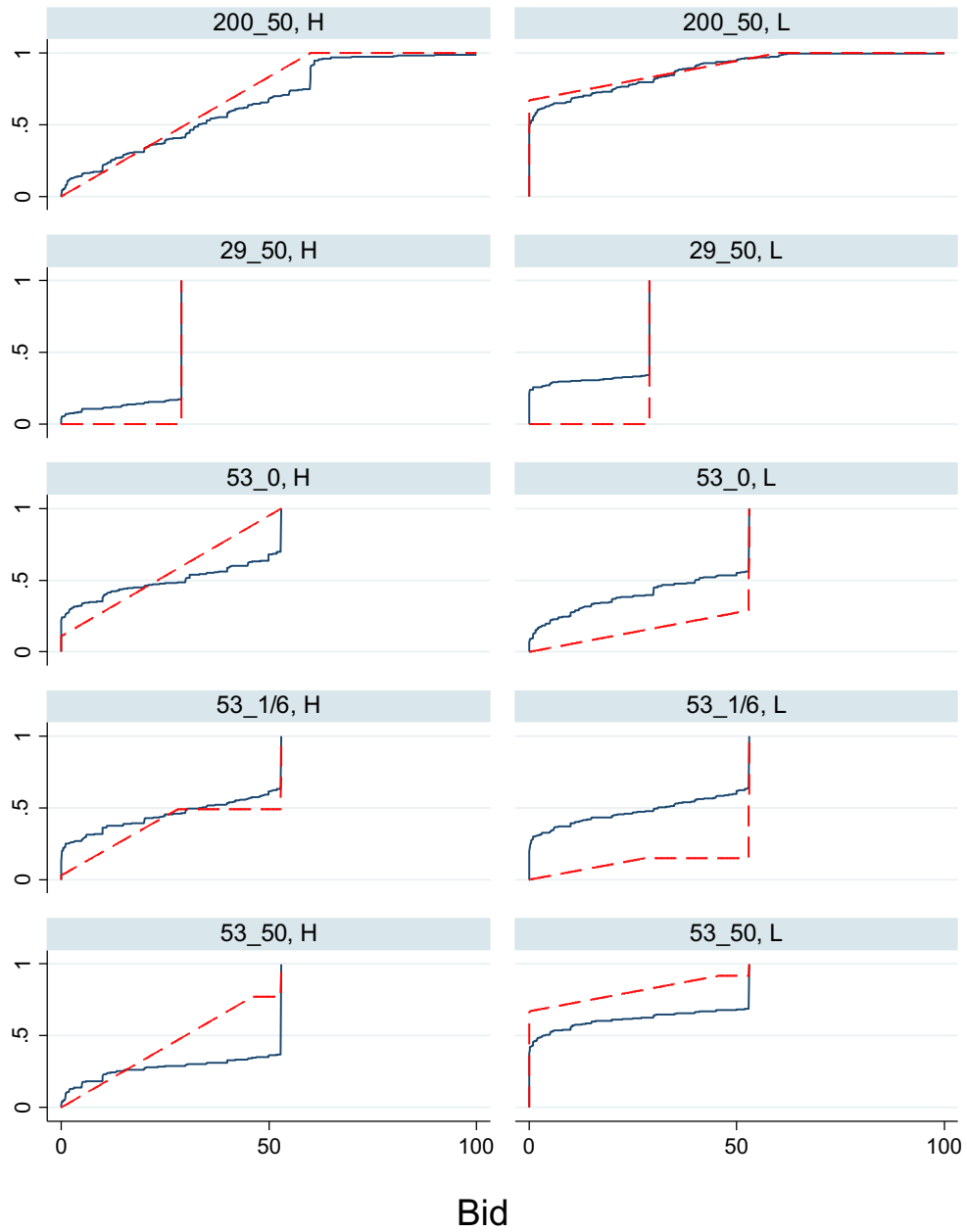
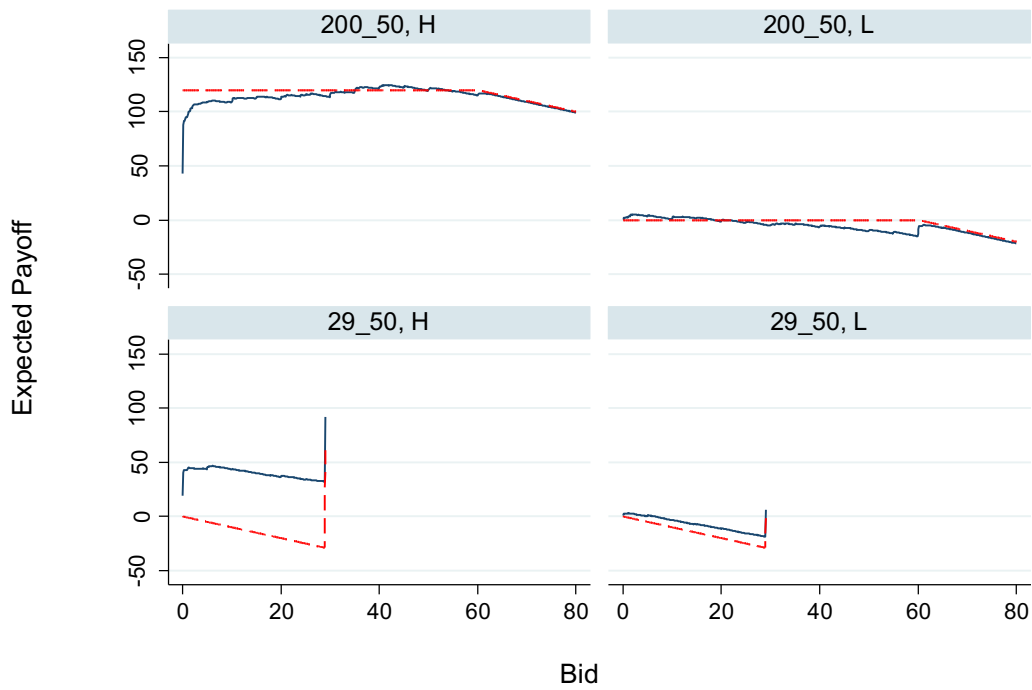


Figure 3: Cumulative distribution of bids by treatment and type



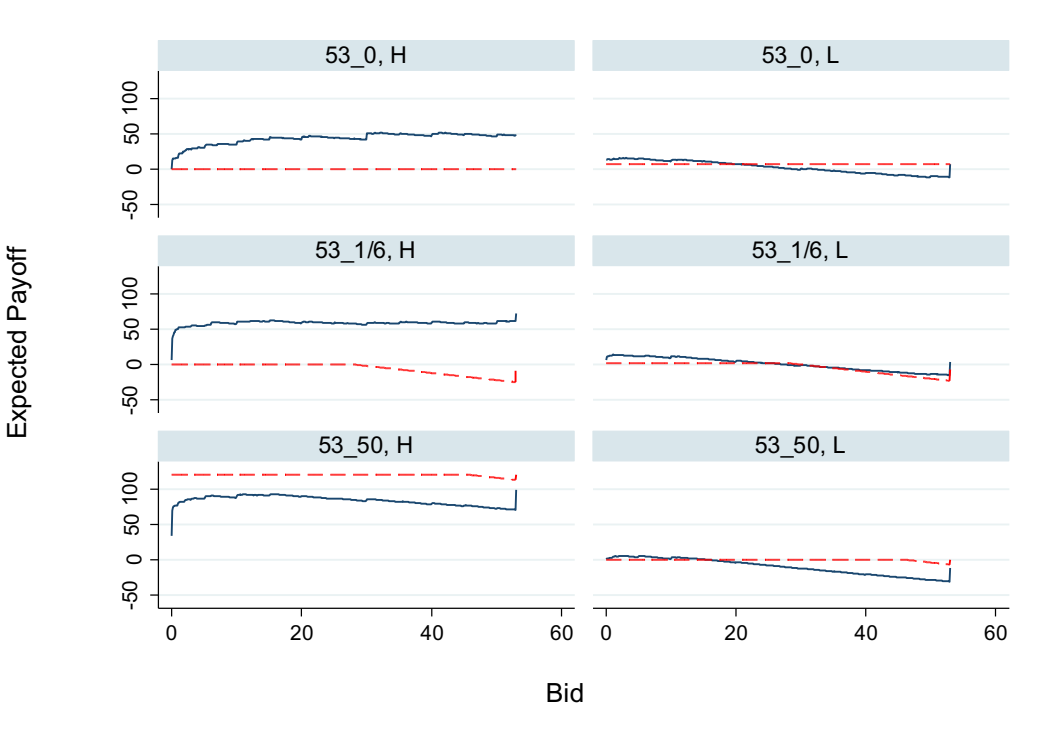
The Nash predicted distribution is the dashed red line and the observed distribution is the solid blue line.

Figure 4: Expected payoff conditional on bids in treatments 200_1/2 and 29_1/2 by type



The expected payoff is calculated based on the observed frequencies of bids in the experiment. The theoretically predicted payoff is the dashed red line and the observed expected payoff is the solid blue line.

Figure 5: Expected payoff conditional on bids in treatments 53_0, 53_1/6 and 53_50 by type



The expected payoff is calculated based on the observed frequencies of bids in the experiment. The theoretically predicted payoff is the dashed red line and the observed expected payoff is the solid blue line.

Appendix (For Online Publication) – Instructions for the 53_1/6 Treatment

GENERAL INSTRUCTIONS

Thank you for participating in this experiment. Please read these instructions carefully. If you have any questions, or need assistance of any kind, raise your hand and an experimenter will come to you and answer your questions privately. Please do not ask anything aloud. It is very important that you remain silent and do not look at other people's work. If you talk, laugh, exclaim out loud, etc., you will be asked to leave and you will not be paid. We expect and appreciate your cooperation.

During this experiment you can earn a substantial amount of money. The currency used in the experiment is Talers. Talers will be converted to euros at a rate of 60 Talers to 1 euro. The earnings from all parts will be added to a participation fee of **15** euros. At the end of today's experiment, you will be paid in private and in cash.

There are **24** participants in today's experiment. At this time we proceed to Part 1 of the experiment.

INSTRUCTIONS FOR PART 1

YOUR DECISION

The first part of the experiment consists of **40 decision-making periods**. At the beginning of the first period, you will be randomly assigned either as **participant 1** or as **participant 2**. You will stay in the same role assignment for the **first 20 periods** and then change your role assignment for the **last 20 periods** of the experiment. Each period you will be randomly re-paired with another participant of opposite assignment to form a **two-person group**. So, if you are participant 1, each period you will be randomly re-paired with another participant 2. If you are participant 2, each period you will be randomly re-paired with another participant 1. You will not know the identity of the person you are matched with, and vice versa.

Each period, you may bid for a reward. The reward is worth **180 Talers** to participant 1 and **60 Talers** to participant 2. You may bid any number **between 0 and 53 Talers** (including 0.1 decimal points).

YOUR EARNINGS

After both participants make their bids, **the computer will assign the reward to a participant who makes the highest bid**. So, for example, if participant 1 bids 30 Talers while participant 2 bids 30.1 Talers then the computer will assign the reward to participant 2. **In case of tie**, the computer will assign the reward either to participant 1 or participant 2. The chance that the computer will assign the reward to participant 1 is **1 out of 6** (16.7% chance), while the chance that the computer will assign the reward to participant 2 is **5 out of 6** (83.3% chance). Therefore, in case of a tie, participant 2 is five times more likely to receive the reward than participant 1.

Remember, the reward is worth 180 Talers to participant 1 and 60 Talers to participant 2. Regardless of who receives the reward, both participants will have to **pay their bids**. Thus, the period earnings will be calculated in the following way:

If participant 1 receives the reward:

Participant 1's earnings = **180** – Participant 1's Bid

Participant 2's earnings = **0** – Participant 2's Bid

If participant 2 receives the reward:

Participant 1's earnings = **0** – Participant 1's Bid

Participant 2's earnings = **60** – Participant 2's Bid

Remember you have already received a **15.00** euro participation fee (equivalent to **600 Talers**). Depending on the outcome in a given period, you may receive either positive or negative earnings. At the end of the experiment we will randomly select 2 out of the first 20 periods and 2 out of the last 20 periods of the experiment for actual payment. You will sum the total earnings for these two periods and convert them to a U.S. dollar payment. If the earnings are negative, we will subtract them from your participation fee. If the earnings are positive, we will add them to your participation fee.

At the end of each period, your bid, the other participant's bid, whether you received the reward or not, and your earnings for the period are reported on the outcome screen. Once the outcome screen is displayed you should record your results for the period on your **Personal Record Sheet** under the appropriate heading.

IMPORTANT NOTES

At the beginning of the first period, you will be randomly assigned either as **participant 1** or as **participant 2**. You will stay in the same role assignment for the **first 20 periods** and then change your role assignment for the **last 20 periods** of the experiment. Each period you will be randomly re-paired with another participant of opposite

assignment to form a two-person group. So, if you are participant 1, each period you will be randomly re-paired with another participant 2. If you are participant 2, each period you will be randomly re-paired with another participant 1.

Both participants will bid for a reward. The reward is worth **180 Talers** to participant 1 and **60 Talers** to participant 2. The computer will assign the reward to a participant who makes the highest bid. In case of tie, participant 2 is five times more likely to receive the reward than participant 1. Regardless of who receives the reward, both participants will have to **pay their bids**. At the end of the experiment we will randomly select 2 out of the first 20 periods and 2 out of the last 20 periods for actual payment using a bingo cage. You will sum the total earnings for these two periods and convert them to a U.S. dollar payment.

Are there any questions?

INSTRUCTIONS FOR PART 2

YOUR DECISION

In this part of the experiment we ask you to fill out a questionnaire. Although you will not be paid for this task, we ask you to pay careful attention to each question and answer each question honestly. The answers to these questions are completely anonymous and will be used only to analyze the data.

Are there any questions?