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Designing contests between heterogeneous contestants: An experimental study of tie-breaks and bid-caps in all-pay auctions

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A B S T R A C T

A well-known theoretical result in the contest literature is that greater heterogeneity decreases investments of contestants because of the “discouragement effect.” Levelling the playing field by favouring weaker contestants through strict bid-caps and favourable 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 favourable tie-breaking rules significantly diminishes discouragement of weaker contestants. However, its impact on revenues is muted by the fact that the encouragement of weaker contestants is offset by stronger contestants competing less aggressively, even when not predicted by theory. We discuss deviations from the Nash predictions in light of different behavioural approaches.

1. Introduction

Contests are fundamental in 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 to motivate 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

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[1] The typical finding in the literature is that greater heterogeneity is associated with lower total effort. However, Ryvkin (2013) shows that this result is not universal. That is, there are instances in which greater heterogeneity implies higher total effort. See also Drugov and Ryvkin (2017).

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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; Gavious et al., 2002; Hart, 2016).[3] 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 favouring the disadvantaged contestants together with appropriately chosen, mild bid-caps can enhance competition even more.[4] 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 behaviour 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 favourable 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. Differences in revenues, however, are much smaller than predicted. This is due to the fact that the encouragement of the weaker contestant via favourable tie-breaking goes hand in hand with the stronger contestant bidding less aggressively, even when not predicted by theory.

One systematic departure from theoretical predictions is that players of both types abandon the competition by placing a significant mass of bids at 0. In the last section of the paper we discuss how this and other deviations can be accommodated by different behavioural approaches. We conclude that level-k is a useful theory to organize the behavioural data from our experiment.

Our paper contributes to the growing experimental literature examining behaviour in all-pay auctions.[5] The studies most closely related to ours are done by Rapoport and Amaldoss (2000, 2004) and Amaldoss and Jain (2002).[6] All of these studies examine behaviour 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. Finally, all-pay auctions with a discrete strategy space have asymmetric equilibria (Dechenaux et al., 2006), complicating the interpretation of the actual behaviour of participants. Our paper attenuates this issue by having a fine grid rather than a coarse bidding space.[7] 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 behaviour and revenue in contests between heterogeneous contestants.

Our study also contributes to the vast literature on rent-seeking that followed the seminal papers of Tullock (1967) and Krueger (1974). In contrast to innovation contests, however, expenditures in rent-seeking contests are often considered to be socially wasteful. Using a 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 $0 \le \alpha \le 1$,

[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).

[3] The literature has proposed several policies to level the playing field. For example, sequential bidding gives an advantage to the second bidder (Fischer et al., 2021). In some settings, this can be used to favor the weaker bidder (Cohensius and Segev, 2018).

[4] 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.

[5] For an overview, see Dechenaux et al. (2015).

[6] Two other studies by Cohen et al. (2012) and Gelder et al. (2015) investigate the impact of a tie-breaking rule on behaviour 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.

[7] The fine grid is assumed to approximate the situation of continuous bidding. 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. This provides an additional motivation to run the experiment.

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		200	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
Bidding strategy according to Nash equilibrium	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
	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

assigns the prize to contestant H with probability α and to contestant L with probability 1 - α. The designer's revenue is $R = b_H + b_L$. If $m > v_L$, equilibrium behaviour 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 2 m. Within this class, revenue is maximized for $m^* = v_L / 2$.[8] 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 levelling the playing field is further elaborated in Szech (2015), who shows that combining a moderate bid-cap with an asymmetric tie-breaking rule in favour 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).

3. The experiment

3.1. Experimental design

To study the effects of bid-caps and tie-breaks on behaviour 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 by $m\_ \alpha$.

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 $m^* = 29$, and tie-breaking is symmetric, i.e., $\alpha = 1/2$.[9] 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 favour 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

[8] At $m^* = v_L/2$ there is a multiplicity of equilibria, which can be eliminated by reducing the cap by a small ε.
[9] We choose 29 instead of 30 to avoid the multiplicity of equilibria, see footnote 8.

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.[10] 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 favour 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.

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.

Each session consisted of two parts of 20 periods each. The design of the auction was kept identical across all 40 periods. At the beginning of the first part, participants were assigned to the specific role of either contestant H (framed as player 1) or contestant L (framed as player 2), and participants kept their roles throughout the part. In the second part, participants switched their roles, so all contestants H became contestants L and vice versa.[11] In each session, 24 subjects were divided into 3 matching groups, each of which had an equal number or 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 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 (the experimental currency), 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 converted at the rate of 60 Talers to 1 euro, and added to their initial endowment of 15 Euros.[12] Subjects earned an average of 17.58€, with minimum and maximum payoffs of 12.30€ and 21.62€ respectively. At the end of the experiment, participants answered a series of demographic and socioeconomic questions. The experimental sessions lasted about 90 min 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 hypotheses are the following:

Hypothesis 1. **(H1).** 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:

$$b^L_{200\_1/2} = b^L_{53\_1/2} < b^L_{29\_1/2}.$$

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

[11] The process of role switching after period 20 was used to mitigate any concerns about fairness and inequality among participants in the experiment. One concern about the change of role is that it might trigger participants to think of 'meta strategies'. However, most results are robust to using only the data of the second part.

[12] If the total payoff of the 4 selected periods was negative, the absolute value of this amount was subtracted from the initial endowment. This was the case for 15% of the subjects.

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
	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)
	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)

Standard deviation in parenthesis.

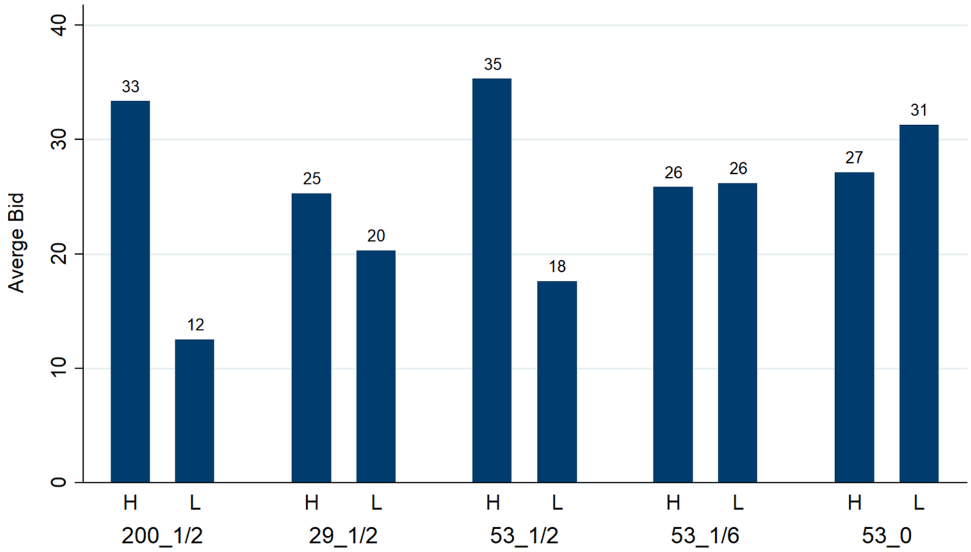

Fig. 1. Average bid by treatment and type.

Hypothesis 2. **(H2).** Under symmetric tie-breaking, a bid-cap should not significantly impact the average bid of the stronger contestant, with $b^H_{29\_1/2} + 1 = b^H_{53\_1/2} = b^H_{200\_1/2}$.

Hypothesis 3. **(H3).** 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: $R_{200\_1/2} = R_{53\_1/2} < R_{29\_1/2}$.

Hypothesis 4. **(H4).** A mild bid-cap (i.e., $m = 53$) combined with a tie-breaking in favour of the weaker contestant (i.e., $\alpha = 1/6$) generates higher average revenue than a strict bid-cap ($R_{53\_1/6} > R_{29\_1/2}$), an unrestricted all-pay auction ($R_{53\_1/6} > R_{200\_1/2}$), and other treatments with the same bid-cap but different tie-breaking ($R_{53\_1/6} > R_{53\_1/2}$ and $R_{53\_1/6} > R_{53\_0}$).

Hypothesis 5. **(H5).** 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: $b^L_{53\_1/2} < b^L_{53\_1/6}$ and $b^L_{53\_1/2} < b^L_{53\_0}$.

Hypothesis 6. **(H6).** Tie-breaking has a non-monotonic effect on the average bid of the stronger contestant, with the predicted ordering of treatments: $b^H_{53\_0} < b^H_{53\_1/2} < b^H_{53\_1/6}$.

Our first set of hypotheses (H1, H2 and H3), based on treatments 200_1/2, 53_1/2 and 29_1/2, is designed to test the predictions of Che and Gale (1998) that levelling 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. H1 compares average revenues across treatments,

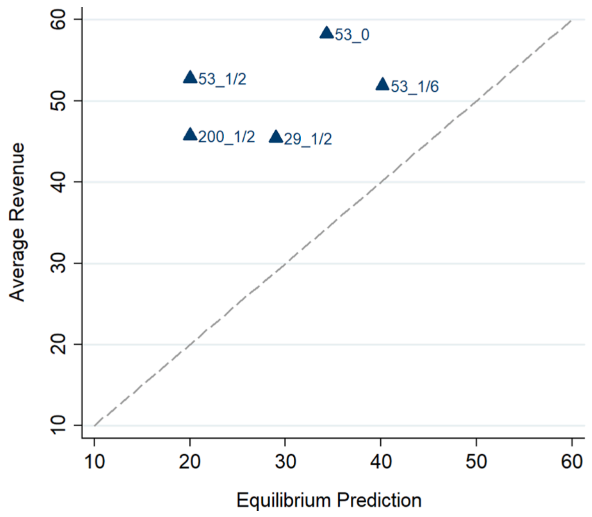

Fig. 2. Average revenue by treatment.

while H2 and H3 compares the bidding behaviour of low and high types respectively.

Our second set of hypotheses (H4, H5 and H6) relates to the predictions on having a mild cap. According to Szech (2015), combining a milder bid-cap than in Che and Gale (1998) with a tie-breaking rule in favour 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. H4 compares aggregate revenues, H5 compares the bidding behaviour of low types across treatments and H6 does the same for high types.

4. Results

In the following analysis, we focus on the second half of each part (periods 11–20 and 31–40) to allow for learning in the initial periods. We test our hypotheses with the non-parametric Fisher-Pitman permutation test. In order to test predicted null effects, we complement this with Bayesian analysis based on linear regressions. When performing these tests, we use the average within a single re-matching group of 8 participants as one independent observation.

Average bids, payoffs, and revenue in all treatments are summarized in Table 2. Fig. 1 shows the average bid by treatment and type, and Fig. 2 displays the revenues.

4.1. Bid-caps under symmetric tie-breaking

We begin by focusing on treatments with a symmetric tie-breaking rule. In treatment 200_1/2, consistent with the theoretical predictions, the weaker contestant bids approximately three times less than the stronger contestant (12.4 versus 33.3; p-value $<$ 0.01).[13]

The prediction of Che and Gale (1998) is that placing a strict bid-cap 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 12.4; p-value $<$ 0.01), supporting H1 and indicating that the strict cap of $m = 29$ significantly diminishes discouragement.[14] In treatment 53_1/2, the average bid by the weaker contestant lies between the other two symmetric treatments, and but none of these differences are statistically significant from zero (p-value = 0.145 and 0.446 for 200_1/2 and 29_1/2, respectively).

Result 1. Consistent with Hypothesis 1, a strict bid-cap significantly increases the average bid by the weaker contestant. However, contrary to Hypothesis 1, we find no significant differences between the mild and the strict bid-cap.

We now turn to the bidding behaviour of the stronger contestant. In line with the Nash equilibrium prediction and consistent with

[13] When comparing to the theoretical predictions, the average bid of the stronger contestant is not significantly different from the theoretical prediction (33.3 versus 30.0; p-value = 0.125), while the weaker contestant bids significantly more than predicted (12.4 versus 10.0; p-value = 0.063). Non-parametric tests comparing average bids of the weaker contestant, bids of the stronger contestant and revenues across all treatments as well as tests against the theoretical predictions can be found in Appendix A.

[14] The average bid of the weaker contestant is significantly lower than the theoretical prediction (20.2 versus 29.0; p-value = 0.02).

Table 3
Random effects regression of the bid on lag variables.

Dependent variable, *bid*	Treatment 200_1/2	29_1/2	53_1/2	53_1/6	53_0
	Type *H*				
bid-lag	0.48***	0.44***	0.66***	0.65***	0.62***
[own bid in *t*-1]	(0.15)	(0.04)	(0.04)	(0.07)	(0.07)
otherbid-lag	0.31***	0.09***	0.09***	0.03	−0.15***
[other bid in *t*-1]	(0.04)	(0.02)	(0.02)	(0.02)	(0.03)
win_lag	−2.55	−0.36	−3.14**	0.26	−5.33***
[dummy for win in *t*-1]	(3.61)	(0.72)	(1.52)	(2.12)	(1.43)
Period	0.12	−0.00	−0.06	−0.20***	−0.02
[linear period trend]	(0.17)	(0.01)	(0.14)	(0.04)	(0.10)
Switch	−1.19	1.34*	−0.63	2.19**	−1.36
[dummy for role switching]	(5.17)	(0.71)	(3.78)	(1.07)	(2.05)
Constant	13.36***	11.99***	14.88***	11.85***	17.71***
	(4.95)	(1.44)	(2.25)	(2.34)	(3.12)
	Type *L*				
bid-lag	0.34***	0.66***	0.65***	0.70***	0.56***
[own bid in *t*-1]	(0.13)	(0.05)	(0.07)	(0.04)	(0.06)
otherbid-lag	0.00	0.04	0.02	0.09***	0.22***
[other bid in *t*-1]	(0.03)	(0.06)	(0.02)	(0.03)	(0.03)
win_lag	1.76	−1.10	1.06	−4.70***	−2.08
[dummy for win in *t*-1]	(1.99)	(0.89)	(1.74)	(1.47)	(2.78)
Period	0.08	0.04	−0.21**	−0.04	−0.04
[linear period trend]	(0.10)	(0.04)	(0.10)	(0.08)	(0.07)
Switch	−0.07	−1.50	2.09	0.87	0.79
[dummy for role switching]	(1.60)	(1.56)	(2.60)	(1.47)	(2.11)
Constant	5.77**	6.41***	9.28**	8.57***	9.97***
	(2.29)	(1.54)	(3.64)	(2.03)	(1.69)

*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.

H2, we find no significant difference in average bidding behaviour between treatments 53_1/2 and 200_1/2 (35.2 versus 33.3; p-value $= 0.487$).[15] 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 25.2 (p-value $= 0.031$), which is significantly lower than in treatments 53_1/2 and 200_1/2 (p-value < 0.01 in both cases).

Result 2. Contrary to Hypothesis 2, a strict bid-cap significantly reduces the average bid by the stronger contestant.

Finally, we examine the impact of bid-caps on the average revenue. Contrary to the theoretical predictions, the average revenue in treatment 29_1/2 is lower than in treatments 200_1/2 and 53_1/2. While the difference with 200_1/2 is virtually null (45.4 vs 45.7), the difference with 53_1/2 is more substantial (45.4 vs 52.8). However, find that revenue is not statistically significantly different across any of the pairwise comparisons (see Table 3).[16] Therefore, we reject H3.

Result 3. Contrary to Hypothesis 3, a strict bid-cap does not significantly increase the average revenue with respect to the treatments with a mild cap or no cap.

The reason for this departure from theory is twofold. First, revenue in treatments 200_1/2 and 53_1/2 is significantly higher than predicted (45.7 vs 40.0 and 52.8 vs 40.0; p-values $= 0.094$ and 0.063).[17] Second, revenue in treatment 29_1/2 is significantly lower than predicted (45.4 vs 58.0; p-value $= 0.031$). Recall that in this treatment the Nash equilibrium strategy of both players 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.[18]

4.2. Optimal combination of bid-caps and tie-breaking rules

As indicated by Szech (2015), combining an asymmetric tie-breaking rule that favours the weak contestant with the right cap can further increase revenues. With our experimental parameters, the global optimum in revenue is approximated by treatment 53_1/6.

[15] Average bids are higher than the predicted level of 30.0 in both cases, but these differences are not significantly different from zero (both p-values are 0.125). The Bayesian posterior of an effect of no more than 5 is 83.11%. See the supplementary material for details.

[16] The difference in revenues between treatments 200_1/2 and 53_1/2 is 7.05. The Bayesian posterior that the (absolute) difference is no more than 10 is 71.07%.

[17] Such overbidding is common in all-pay auction experiments (Davis and Reilly, 1998; Gneezy and Smorodinsky, 2006; Lugovskyy et al., 2010).

[18] 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).

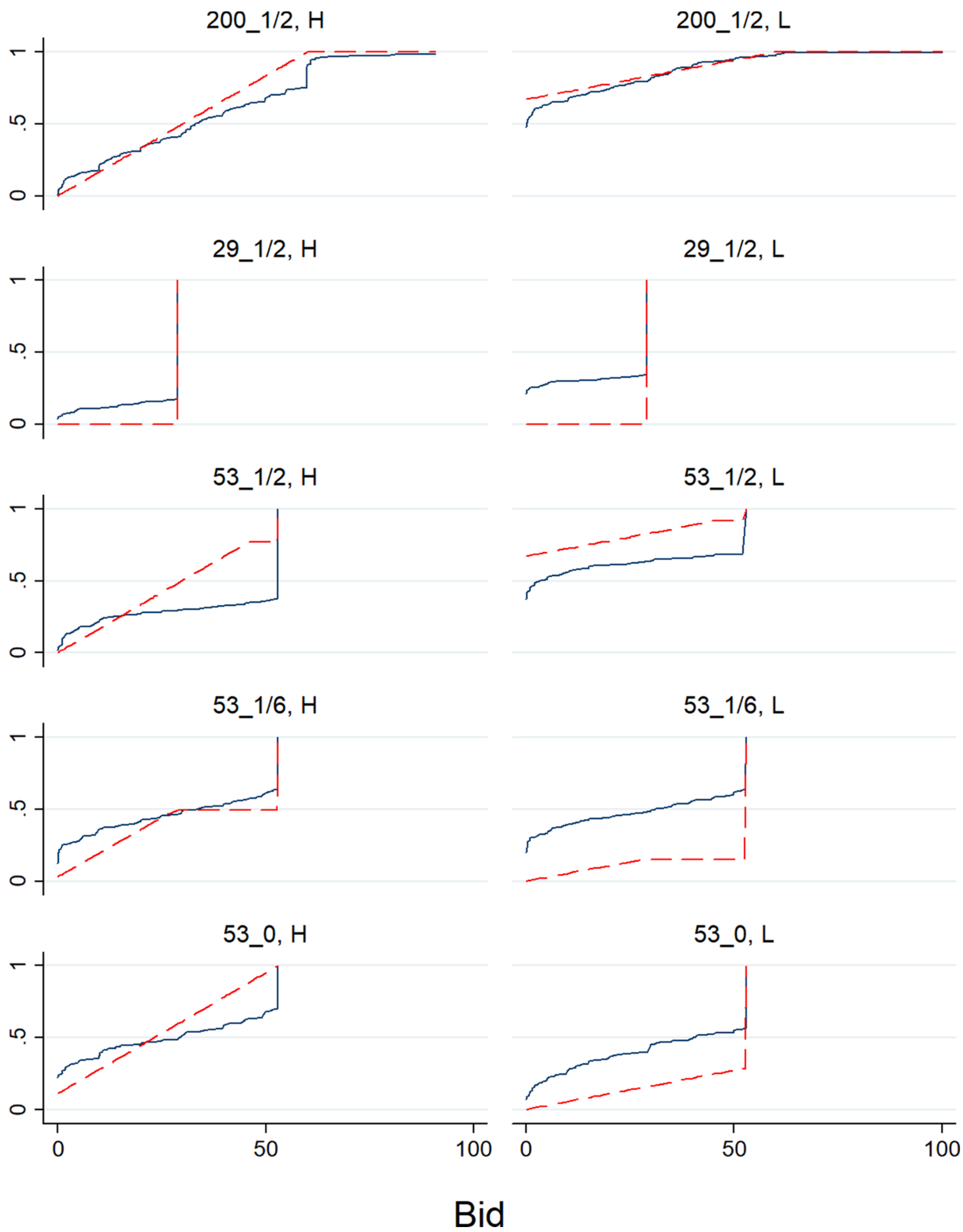

Fig. 3. Cumulative distribution of bids by treatment and type. The Nash predicted distribution is the dashed red line and the observed distribution is the solid blue line.

Although the average revenues in this treatment are higher than the ones observed in treatments 29_1/2 and 200_1/2 (51.9 vs 45.7 and 45.4 respectively), none of these differences are statistically significant from zero (p-values = 0.284, and 0.225).[19] Also, contrary to H4, we find no significant differences between treatments 53_1/6, 53_0, and 53_1/2 (p-values > 0.221 in all cases).[20]

Result 4. . Contrary to Hypothesis 4, we find that a mild bid-cap combined with a tie-breaking in favour of the weaker contestant does not generate higher average revenue than a strict bid-cap and an unrestricted all-pay auction. Moreover, under the mild bid-cap, average revenue does not change significantly with the tie-breaking rule.

To further understand the impact of tie-breaks, we examine contestants' behaviour in treatments with a mild bid-cap. Consistent with H5, treatment 53_1/6 significantly increases the average bid by the weaker contestant compared to treatment 53_1/2 (26.1 versus

[19] The average revenue in treatment 53_1/6 is significantly lower from the theoretical prediction (57.2 versus 80.26; p-value = 0.031).

[20] In fact, unlike predicted, the average revenues are higher in treatments 53_0 and 53_1/2 than in treatment 53_1/6.

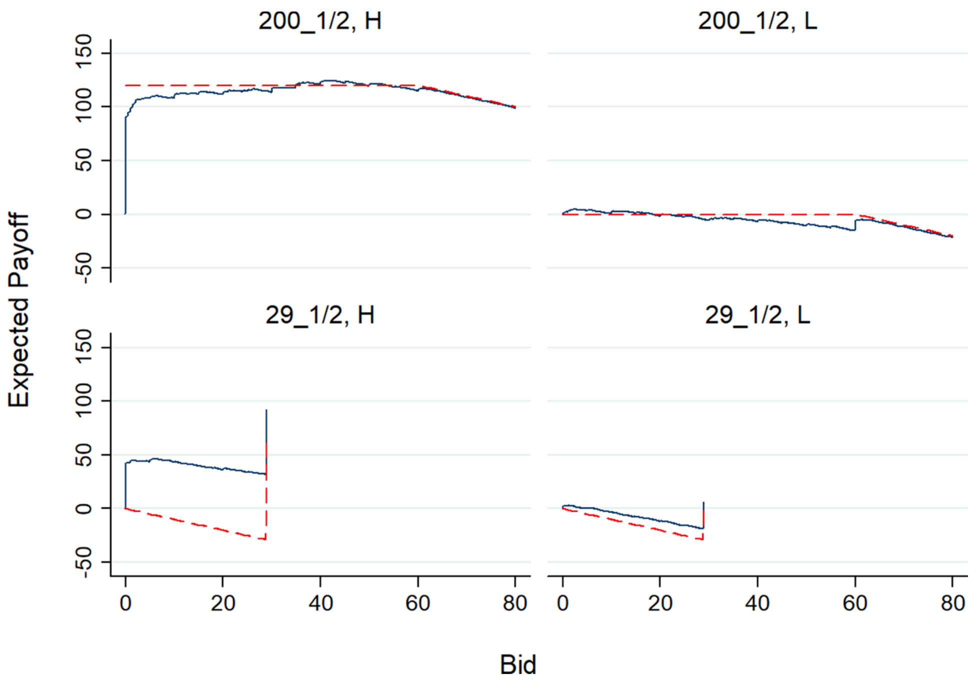

Fig. 4. Expected payoff conditional on bids in treatments 200_1/2 and 29_1/2 by type. The expected payoff is calculated based on the observed frequencies of bids in the experiment. The theoretically predicted payoff is the dashed red line and the observed expected payoff is the solid blue line.

17.5; p-value = 0.058). However, the magnitude of the effect is more than four times smaller than predicted (8.6 instead of 37). Theory also predicts that a further favouring of the weaker 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 (31.2 and 26.1; p-value = 0.154).

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

When examining the behaviour of the stronger contestant, theory predicts that his average bid should be the highest in treatment 53_1/6 where competition is the toughest, followed by treatment 53_1/2 and treatment 53_0. Contrary to this prediction, we find that the average bid of the stronger contestant in treatment 53_1/2 is significantly higher than in treatments 53_1/6 and 53_0 (p-values = 0.011 and 0.013 respectively). When comparing treatments 53_1/6 and 53_0, we find no significant difference in bidding behaviour (25.7 versus 27.0; p-value = 0.595). Thus, the stronger contestant becomes more easily discouraged by a non-favourable tie-breaking rule than theory predicts.

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

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. Fig. 3 displays the realized and the predictive cumulative distributions of bids for each treatment and type.[21] Overall, we see that the observed data is fairly consistent with the theoretical predictions, with some systematic 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.[22] The cumulative distribution of bids of the weak contestants is remarkably close to the predicted one. The stronger ones, however, and unlike predicted by theory, place a significant mass point around 60 (which explains the overbidding by these types).

In treatment 29_1/2, theory predicts that all bids should be concentrated at the bid-cap of $m = 29$. We find that the stronger contestant follows this strategy 84.4% of the time, while weak contestants do it 67.9%. The most remarkable departure from theory is a

[21] In order to have more data and smoother distribution functions, this section considers data from *all* periods. The qualitative results, however, are very similar to the ones restricting the analysis to the data from the second half of each block. The same applies to section 4.4 on observed behaviour.

[22] Only 2.5% of bids are strictly above 61.0, and only 1.1% are strictly above 65.0.

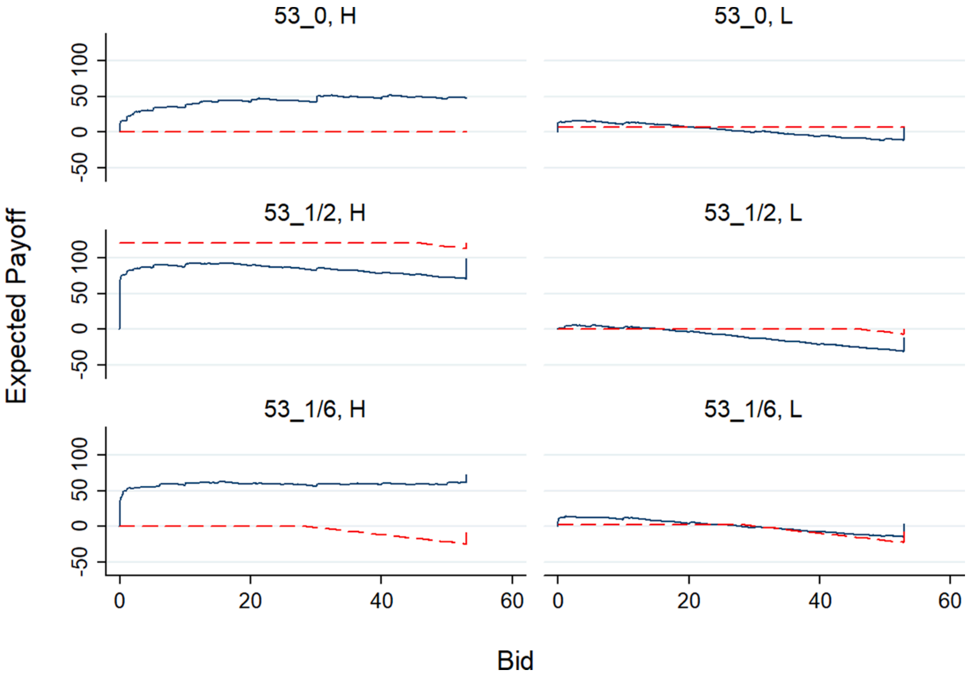

Fig. 5. Expected payoff conditional on bids in treatments with a mild cap, by type. The expected payoff is calculated based on the observed frequencies of bids in the experiment. The theoretically predicted payoff is the dashed red line and the observed expected payoff is the solid blue line.

mass point around 0 in the bid distribution of weak types: 21.9% of the bids are exactly zero.

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 behaviour are substantial. The weaker contestant shifts mass from 0 to the cap as the tie-breaking rule becomes more favourable. At the same time, the stronger contestant displays the reverse bidding behaviour by shifting mass from the cap to 0 as the tie-breaking rule becomes less favourable 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 contrast to theory, the empirical distribution of bids displays a mass point at 0 in most treatments.

Finally, in order to establish whether the distribution of bids is independent across rounds, we analyse contestants' behaviour in response to previously observed behaviour. Table 3 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' behaviour 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).

4.4. *Best response to observed behaviour*

In this section, we analyse 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 probability. However, when computing the expected payoffs playing against the distribution of bids observed in the experiment, this might not be the case for two reasons. First, even if contestants play according to the theoretical predictions, the distribution of realized bids might not perfectly reflect the theoretical distribution. And second, as we saw previously, there are significant departures from theoretical predictions.

In 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 Fig. 4 shows, the expected payoff function is relatively flat: any bid between 10.1 and 68.8 gives a payoff of at least 110.[23] 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

[23] Any bid between 1.3 and 79.2 gives an expected payoff of at least 100.

Table 4
Level-k bids by contestant type and by treatment.

Treatment	200_1/2		29_1/2		53_1/2		53_1/6		53_0	
	H	*L*	*H*	*L*	*H*	*L*	*H*	*L*	*H*	*L*
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+ε as subjects could adjust their bid to a tenth of the in-game currency.

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).

The best response to empirical frequencies in treatment 29_1/2 is in line with the theoretical predictions – to bid at the cap. The expected payoff for the stronger contestant bidding at 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.[24] 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.

Fig. 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 behaviour: 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 leads to significantly lower expected payoff than the one obtained by any other bid below min{60,cap}. The reason is that usually, a small bid different from 0 leads to a higher payoff than bidding at 0.

Result 8. Bidding 0 by the stronger contestant leads to lower expected payoff than bidding any other amount below min{60,cap}.

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

4.5. Behavioural 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 behaviour (Müller and Schotter, 2010; Baye et al., 2012; Mago et al., 2013; Dechenaux et al., 2015).[25] 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,

[24] If we exclude bidding zero, the minimum expected payoff of a stronger contestant is 32.3.

[25] 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).

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 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).[26]

Table 4 displays bidding behaviours 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 behaviour that we observe in our experiment is the excessive bidding at 0 by the stronger contestant.[27] While this type of behaviour is inconsistent with best responding to both theoretical predictions and observed behaviour, it can be explained by the level-k model of reasoning. From Table 4, 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.

The level-k model also captures the comparative statics with respect to the tie-breaking rule well. 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 favourable.

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.[28] One 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 favouring 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 favourable tie-breaking rule can further increase the average bid of the weaker contestant, whose bids are over 150% higher compared to the unrestricted contest. However, these policies seem less effective at raising total revenues. While treatments with a mild bid-cap generate higher revenues than the strict bid-cap and the unrestricted all-pay auctions, these differences are not statistically significant.

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).[29] 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 labour markets (to increase diversity); here, tie-breaking rules in favour of the weaker contestants are frequently used, and may successfully apply. Anti-discrimination policies that solve ties in favour 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.

Acknowledgments

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[26] Level-k reasoning has been used to explain the behaviour 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).

[27] Another departure from theory reported in section 4.4 is that subjects react to passed own and rivals' bids. None of these models can explain such departure given their static nature. While this is out of the scope of this paper, it might be interesting to extend the analysis to dynamic models that can explain both features.

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

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

Supplementary materials

Supplementary material associated with this article can be found, in the online version, at doi:10.1016/j.euroecorev.2022.104327.

Appendix

Appendix A: non-parametric tests

Table A1, A2, A3, A4, A5

Table A1
Pairwise comparisons of the weaker contestant's bids across treatments.

	29_1/2	53_0	53_1/6	53_1/2
200_1/2	< $p = 0.009$	< $p = 0.002$	< $p = 0.004$	= $p = 0.145$
29_1/2		< $p = 0.004$	< $p = 0.078$	= $p = 0.446$
53_0			= $p = 0.154$	> $p = 0.009$
53_1/6				> $p = 0.058$

Two-sided Fisher-Pitman permutation tests. > (<) indicates that the column (row) is signifficantly higher. = indicates that there is no signifficant difference at 10% level. P-values are indicated below this sign.

Table A2
Pairwise comparisons of the stronger contestant's bids across treatments.

	29_1/2	53_0	53_1/6	53_1/2
200_1/2	> $p = 0.006$	> $p = 0.026$	> $p = 0.024$	= $p = 0.487$
29_1/2		= $p = 0.314$	= $p = 0.810$	< $p = 0.002$
53_0			= $p = 0.595$	< $p = 0.013$
53_1/6				< $p = 0.011$

Two-sided Fisher-Pitman permutation tests. > (<) indicates that the column (row) is signifficantly higher. = indicates that there is no signifficant difference at 10% level. P-values are indicated below this sign.

Table A3
Pairwise comparisons of the revenue across treatments.

	29_1/2	53_0	53_1/6	53_1/2
200_1/2	= $p = 0.952$	< $p = 0.006$	= $p = 0.284$	= $p = 0.223$
29_1/2		< $p = 0.006$	= $p = 0.225$	= $p = 0.175$
53_0			= $p = 0.221$	= $p = 0.305$
53_1/6				= $p = 0.877$

Two-sided Fisher-Pitman permutation tests. > (<) indicates that the column (row) is signifficantly higher. = indicates that there is no signifficant difference at 10% level. P-values are indicated below this sign.

Table A4
Comparisons with theoretical predictions.

	200_1/2	29_1/2	53_1/2	53_1/6	53_0
Bids Weaker Player	0.063	0.031	0.031	0.063	0.031
Bids Stronger Player	0.125	0.031	0.063	0.125	0.031
Revenues	0.094	0.031	0.031	0.063	0.031

Two-sided Fisher-Pitman permutation tests.

Table A5
Stronger vs weaker contestant bids.

200_1/2	29_1/2	53_1/2	53_1/6	53_0
0.031	0.031	0.813	0.031	0.250

Two-sided Fisher-Pitman permutation tests.

Appendix B: instructions for treatment 53_1/6

Instructions for other treatments were identical except for the value of the cap and the probability of winning in case of a tie.

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?

References

Amaldoss, W., Jain, S., 2002. David vs. Goliath: an analysis of asymmetric mixed-strategy games and experimental evidence. Manag. Sci. 48, 972–991.
Arad, A., Rubinstein, A., 2012. The 11–20 money request game: a level-k reasoning study. Am. Econ. Rev. 102, 3561–3573.
Baye, M.R., Kovenock, D., de Vries, C.G., 1993. Rigging the lobbying process: an application of the all-pay auction. Am. Econ. Rev. 83, 289–294.
Baye, M.R., Kovenock, D., de Vries, C.G., 1996. The all-pay auction with complete information. Econ. Theory 8, 291–305.
Baye, M.R., Kovenock, D., de Vries, C.G., 2012. Contests with rank-order spillovers. Econ. Theory 51, 315–350.
Boudreau, K.J., Lacetera, N., Lakhani, K.R., 2011. Incentives and problem uncertainty in innovation contests: an empirical analysis. Manag. Sci. 57, 843–863.
Brown, J., 2011. Quitters never win: the (adverse) incentive effects of competing with superstars. J. Polit. Econ. 119, 982–1013.
Brown, J., Rosenthal, R., 1990. Testing the minimax hypothesis: a reexamination of O'Neill's game experiment. Econometrica 58, 1065–1081.
Cason, T.N., Masters, W.A., Sheremeta, R.M., 2010. Entry into winner-take-all and proportional-prize contests: an experimental study. J. Public Econ. 94, 604–611.
Che, Y.K., Gale, I.L., 1998. Caps on political lobbying. Am. Econ. Rev. 88, 643–651.
Che, Y.K., Gale, I.L., 2003. Optimal design of research tournaments. Am. Econ. Rev. 93, 646–671.
Cohen, C., Shavit, T., Rosenboim, M., 2012. The over-weighting of unfair tie in all-pay contest: an experimental study. Int. J. Econ. Theory 8, 301–311.
Cohensius, G., Segev, E., 2018. Sequential bidding in asymmetric first price auctions. BE J. Theor. Econ. 18 (1).
Cotton, C., 2009. Should we tax or cap political contributions? A lobbying model with policy favours and access. J. Public Econ. 93, 831–842.
Crawford, V.P., Costa-Gomes, M.A., Iriberri, N., 2013. Structural models of nonequilibrium strategic thinking: theory, evidence, and applications. J. Econ. Lit. 51, 5–62.
Crawford, V.P., Iriberri, N., 2007. Level-k auctions: can a non-equilibrium model of strategic thinking explain the winner's curse and overbidding in private-value auctions? Econometrica 75, 1721–1770.
Crawford, V.P., Gneezy, U., Rottenstreich, Y., 2008. The power of focal points is limited: even minute payoff asymmetry may yield large coordination failures. Am. Econ. Rev. 98, 1443–1458.
Davis, D., Reilly, R., 1998. Do many cooks always spoil the stew? An experimental analysis of rent seeking and the role of a strategic buyer. Public Choice 95, 89–115.
Dechenaux, E., Kovenock, D., Lugovskyy, V., 2006. Caps on bidding in all-pay auctions: comments on the experiments of A. Rapoport and W. Amaldoss. J. Econ. Behav. Organ. 61, 276–283.
Dechenaux, E., Kovenock, D., Sheremeta, R.M., 2015. A survey of experimental research on contests, all-pay auctions and tournaments. Exp. Econ. 18, 609–669.
Deck, C., Sheremeta, R.M., 2012. Fight or flight? Defending against sequential attacks in the game of siege. J. Confl. Resol. 56, 1069–1088.
Drugov, M., Ryvkin, D., 2017. Biased contests for symmetric players. Games Econ. Behav. 103, 116–144.
Eyster, E., Rabin, M., 2005. Cursed equilibrium. Econometrica 73, 1623–1672.
Fang, H., 2002. Lottery versus all-pay auction models of lobbying. Public Choice 112, 351–371.
Fehr, D., Schmid, J., 2018. Exclusion in all-pay auctions: an experimental investigation. J. Econ. Manag. Strategy 27 (2), 326–339.
Fischbacher, U., 2007. z-Tree: zurich toolbox for ready-made economic experiments. Exp. Econ. 10, 171–178.
Fischer, S., Güth, W., Kaplan, T.R., Zultan, R.I., 2021. Auctions with leaks about early bids: analysis and experimental behavior. Econ. Inq. 59 (2), 722–739.
Fonseca, M.A., 2009. An experimental investigation of asymmetric contests. Int. J. Ind. Organ. 27, 582–591.
Foster, D.P., Young, H.P., 2003. Learning, hypothesis testing, and Nash equilibrium. Games Econ. Behav. 45, 73–96.
Gavious, A., Moldovanu, B., Sela, A., 2002. Bid costs and endogenous bid caps. RAND J. Econ. 33, 709–722.
Gelder, A., Kovenock, D., & Sheremeta, R. (2015). Behaviour in all-pay auctions with ties. Working Paper.
Gill, D., Prowse, V., 2012. A structural analysis of disappointment aversion in a real effort competition. Am. Econ. Rev. 102, 469–503.
Gneezy, U., Smorodinsky, R., 2006. All-pay auctions – an experimental study. J. Econ. Behav. Organ. 61, 255–275.
Goeree, J.K., Holt, C.A., Palfrey, T.R., 2002. Quantal response equilibrium and overbidding in private-value auctions. J. Econ. Theory 104, 247–272.
Greiner, B., 2015. Subject pool recruitment procedures: organizing experiments with ORSEE. J. Econ. Sci. Assoc. 1, 114–125.
Harris, C., Vickers, J., 1985. Perfect equilibrium in a model of a race. Rev. Econ. Stud. 52, 193–209.
Harris, C., Vickers, J., 1987. Racing with uncertainty. Rev. Econ. Stud. 54, 1–21.
Hart, S., 2016. Allocation games with caps: from Captain Lotto to all-pay auctions. Int. J. Game Theory 45, 37–61.
Jeppesen, L.B., Lakhani, K.R., 2010. Marginality and problem-solving effectiveness in broadcast search. Organ. Sci. 21, 1016–1033.
Kahneman, D., Tversky, A., 1979. Prospect theory: an analysis of decision under risk. Econometrica 47, 263–291.
Kaplan, T.R., Wettstein, D., 2006. Caps on political lobbying: comment. Am. Econ. Rev. 96, 1351–1354.
Kawagoe, T., Takizawa, H., 2012. Level-k analysis of experimental centipede games. J. Econ. Behav. Organ. 82, 548–566.
Kimbrough, E.O., Sheremeta, R.M., Shields, T.W., 2014. When parity promotes peace: resolving conflict between asymmetric agents. J. Econ. Behav. Organ. 99, 96–108.
Konrad, K.A., 2009. Strategy and Dynamics in Contests. Oxford University Press.
Krueger, A.O., 1974. The political economy of the rent-seeking society. Am. Econ. Rev. 64, 291–303.
Laury, S.K., & Holt, C.A. (2008). Voluntary provision of public goods: experimental results with interior Nash Equilibria. In C. R. Plott & V. L. Smith (Eds.), Handbook of Experimental Economics Results. (Vol. 1) 792–801. New York: Elsevier.
Lazear, E.P., Rosen, S., 1981. Rank-order tournaments as optimum labor contracts. J. Polit. Econ. 89, 841–864.
Lugovskyy, V., Puzzello, D., Tucker, S., 2010. An experimental investigation of overdissipation in the all pay auction. Eur. Econ. Rev. 54, 974–997.
Mago, S.D., Sheremeta, R.M., Yates, A., 2013. Best-of-three contest experiments: strategic versus psychological momentum. Int. J. Ind. Organ. 31, 287–296.
McKelvey, R.D., Palfrey, T.R., 1995. Quantal response equilibrium for normal form games. Games Econ. Behav. 10, 6–38.
Moldovanu, B., Sela, A., 2001. The optimal allocation of prizes in contests. Am. Econ. Rev. 91, 542–558.
Müller, W., Schotter, A., 2010. Workaholics and dropouts in organizations. J. Eur. Econ. Assoc. 8, 717–743.
Nagel, R., 1995. Unraveling in guessing games: an experimental study. Am. Econ. Rev. 85, 1313–1326.
Ochs, J., 1995. Games with unique, mixed strategy equilibria: an experimental study. Games Econ. Behav. 10, 202–217.
Rapoport, A., Amaldoss, W., 2000. Mixed strategies and iterative elimination of strongly dominated strategies: an experimental investigation of states of knowledge. J. Econ. Behav. Organ. 42, 483–521.
Rapoport, A., Amaldoss, W., 2004. Mixed-strategy play in single-stage first-price all-pay auctions with symmetric players. J. Econ. Behav. Organ. 54, 585–607.
Ryvkin, D., 2013. Heterogeneity of players and aggregate effort in contests. J. Econ. Manag. Strategy 22, 728–743.
Schotter, A., Weigelt, K., 1992. Asymmetric tournaments, equal opportunity laws, and affirmative action: some experimental results. Q. J. Econ. 107, 511–539.
Stahl, D.O., Wilson, P.W., 1994. Experimental evidence on players' models of other players. J. Econ. Behav. Organ. 25, 309–327.
Stahl, D.O., Wilson, P.W., 1995. On players' models of other players: theory and experimental evidence. Games Econ. Behav. 10, 218–254.
Szech, N., 2015. Tie-breaks and bid-caps in all-pay auctions. Games Econ. Behav. 92, 138–149.

Terwiesch, C., Xu, Y., 2008. Innovation contests, open innovation, and multiagent problem solving. Manag. Sci. 54, 1529–1543.
Tullock, G., 1967. The welfare costs of tariffs, monopolies, and theft. Western Econ. J. 5, 224–232.
Weigelt, K., Dukerich, J., Schotter, A., 1989. Reactions to discrimination in an incentive pay compensation scheme: a game-theoretic approach. Organ. Behav. Hum. Decis. Process. 44, 26–44.