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Entry decisions and bidding behavior in sequential first-price procurement auctions: An experimental study

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Abstract

Though many real life auctions are run independently of each other, from the bidders' point of view they often form sequences of auctions. We investigate how behavior responds to the additional incentives that are present in such auction sequences. Comparing subjects' decisions in single first-price procurement auctions with their decisions in a game consisting of two subsequent first-price procurement auctions, we find that, in line with the theoretical prediction, entry and bidding behavior is crucially affected by the opportunity cost of early bid submission. Though, entry decisions and average bids in the auction sequence systematically deviate from the perfect Bayesian equilibrium prediction. While the nature of the opponent (human being or computer) has no significant effect on these findings, giving subjects additional feedback on winners and prices seems to reduce the deviations from the equilibrium prediction.

JEL classification: D44; C91; C72

Keywords: Experimental economics; Sequential auctions; First-price procurement auction

1. Introduction

Originating in Coppinger et al. (1980) and Cox et al. (1982) there is extensive experimental research on subjects' behavior in independent private value auctions (for an overview, see Kagel, 1995). While this research provides fundamental insights into the allocation of objects in a single auction environment, it abstracts away from the fact that auctions, which are run independently

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of each other, might form a sequence of auctions from the bidders' point of view. This feature is particularly relevant if bidders are constrained in their demand, since in this case bidders have to consider their opportunity cost of early bid submission. That demand constraints might influence entry and bidding behavior in consecutive auctions is demonstrated in recent empirical studies on procurement auctions. In this context, demand constraints correspond to supply constraints that might result from a limited production capacity. For example, in two studies on procurement auctions run by the California Department of Transportation between 1994 and 2000, Jofre-Bonet and Pesendorfer (2000, 2003) found that firms that did not win a highway paving contract earlier in a sequence of auctions were more likely to enter a subsequent auction than firms that already won contracts. In a similar study on auctions held by the Oklahoma Department of Transportation between 1998 and 2000, De Silva et al. (2002) reported that firms that lost in morning auctions bid more aggressively in the afternoon than those that won in the morning. This evidence suggests that firms are aware of their opportunity costs of early bid submission and respond accordingly. However, bidding patterns in reality might be influenced by a variety of factors other than the opportunity cost of bidding created by employed capacity. Therefore, it is not clear to what extent this opportunity cost is the driving factor of the reported results.

In this paper we use laboratory experiments to investigate the impact of opportunity costs on entry and bidding behavior in an auction sequence. Motivated by the empirical research, we particularly focus on a sequence of two first-price sealed-bid procurement auctions with stochastically equivalent projects in which bidders were faced with a capacity constraint. Since there exists no study that experimentally investigates bidding behavior in single first-price sealed-bid procurement auctions that would allow us to compare subjects' decisions in both environments, we additionally employ this investigation in our experiment.

For our analyses of behavior in an auction sequence, we considered four treatments varying the nature of the opponent (human or computerized) and the information feedback (no feedback or feedback). The computerized opponent treatment was implemented to find out how subjects respond to the richer auction environment excluding additional features that might be triggered by the human component like uncertainty about the opponents' bidding strategy and other-regarding concerns. Since learning effects might be an important determinant of bidding behavior (see, e.g., Isaac and Walker, 1985; Selten and Buchta, 1999; Güth et al., 2003), we analyzed how feedback on winners and prices changes subjects' behavior.

The next section presents the single procurement auction game and the sequential procurement auction game that were used in our experiment as well as the theoretical predictions. Section 3 describes our experimental design. The results on entry decisions and bidding behavior are provided in Section 4. Section 5 briefly concludes.

2. Games and theoretical predictions

2.1. *The single procurement auction game*

The single procurement auction game considered here is the competitive bidding analog to the standard symmetric independent private values auction model without reserve price (for surveys of the SIPV model, see McAfee and McMillan, 1987; Krishna, 2002; Wolfstetter, 1995; on competitive bidding with private costs, see Holt, 1980, and Cohen and Loeb, 1990). In our context, there are two bidders competing for a single project contract that is allocated by a first-price sealed-bid auction. Each bidder specifies a price at which he is willing to execute the project. The one submitting the lowest bid is assigned execution of the project in exchange for a payment

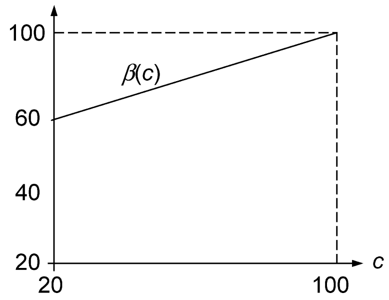

Fig. 1. Equilibrium bidding in the single procurement auction game.

that equals his bid. Before bid submission, bidders are informed about their own project completion cost, that their competitor's completion cost is randomly and independently drawn from a uniform distribution with support [20, 100], and that bids exceeding 100 are not accepted (the maximum bid might be interpreted as the procurers outside option). For this game, the symmetric risk-neutral Nash equilibrium bidding function depending on cost realization c is given by

$$\beta^{\text{single}}(c) = 50 + c/2.$$

Figure 1 depicts the equilibrium bidding function. Obviously, the bidder with the lowest cost level, say c_l, submits the lowest bid and receives the profit $\beta^{\text{single}}(c_l) - c_l$ from winning and completing the project. The losing bidder makes a zero-profit.

2.2. *The sequential procurement auction game*

The sequential procurement auction game used in our experiment augments the single auction game by a second single auction game where another independent project contract is offered after the outcome of the first one is observed. There are two bidders in this auction sequence, each with capacity to undertake a single project at most. The first auction auctions off project A. The second auction auctions off project B. In each of the two auctions, bidders can submit a bid at which they are willing to execute the project. The bidder submitting the lowest bid is assigned execution of the project in exchange for a payment equal to her bid. Before the two bidders have to decide simultaneously whether to enter the first auction and to submit a bid for project A, they are informed about their individual pair of completion costs for the projects A and B. Bidders know that nobody will receive any information about their competitor's exact costs for the two projects. They are only informed that the competitor's project costs are randomly and independently drawn from a uniform distribution with support [20, 100] and that bids exceeding 100 are not accepted.

Although this game is highly stylized, it captures basic incentives that are present in auction sequences. The next three subsections present the theoretical predictions for bids and entry decisions in the sequential auction game.

Theoretical prediction for bidders' participation in auction A

Let $(a, b) \in [20, 100]^2$ denote the representative bidder's cost pair where the first (second) entry refers to his cost of completing the first (second) project auctioned off (for a more general model, see Reiß and Schöndube, 2002; for a related model with second-price auctions and a non-procurement frame, see Gale and Hausch, 1994). If $a < b$ then the bidder is said to have a cost advantage for project A and if $a > b$ she has one for project B. The opportunity cost of winning the first auction equals $100 - b$ since losing it implies (due to the competitor's capacity constraint) that the bidder is the only one in the second auction. For a bidder with a cost advantage for project B, it follows that his opportunity cost of winning auction A strictly exceeds his largest possible profit realization from winning A since $100 - b > 100 - a$. Hence, any bidder that faces a higher cost for project A prefers to lose the first auction provided that he submits a bid in this auction. In case the bidder does, he clearly bids the largest amount that is accepted by the procurer. This minimizes her chance of ending up with project A and maximizes her profit if so. However, a bidder with a cost advantage for project B might decide to skip bidding in the first auction if his opportunity cost of starting to bid in this auction exceeds his benefit. As an extreme, consider a bidder with $a = 100$ and $b < 100$. Clearly he cannot make any positive profit in the first procurement auction and only earns a positive expected profit if he bids in the second auction. Since there is a positive probability that he may end up with project A even if he bids 100 in the first auction and is thus prevented from making money, he decides to skip bidding for the first project. In contrast, bidders with a cost advantage for project A always participate in the first auction since, in auction A, they can earn more than the largest possible payoff obtainable in auction B, $100 - b$, by submitting a bid, β^A, that fully includes both the completion cost for project A and its opportunity cost from winning this project, i.e. $\beta^A > a + 100 - b$. In general, if both bidders are risk-neutral, a bidder submits a bid for the first project if

$$E\left[\Pi^{A+B}(a,b)\right] \geqslant E\left[\Pi^{B}(b)\right] \tag{1}$$

where $E[\Pi^{A+B}(a,b)]$ denotes her expected equilibrium profit if bidding for the first and possibly for the second project and $E[\Pi^{B}(b)]$ is her expected equilibrium profit if she skips bidding for project A. In general, $E[\Pi^{A+B}(a,b)]$ is decreasing in the completion cost for project A, a, and $E[\Pi^{B}(b)]$ is independent of a. If (1) holds with equality, the bidder is indifferent between entering and skipping auction A and the entry indifference curve $a^{\text{crit}} = g(b)$ is implicitly defined by

$$E\left[\Pi^{A+B}\left(a^{\text{crit}},b\right)\right] = E\left[\Pi^{B}(b)\right].$$

In the symmetric perfect Bayesian equilibrium of this game, the entry decision rule is

$$\epsilon(a,b) = \begin{cases} \text{Enter auction } A & \text{if } a \leqslant g(b), \\ \text{Skip auction } A & \text{if } a > g(b), \end{cases}$$

where the entry indifference curve $g(b)$ is approximately given by

$$g(b) = 100 + 8.938\left[e^{\frac{b-100}{48.332}} - e^{\frac{100-b}{48.332}}\right].$$

The equilibrium entry behavior of any bidder with cost pair (a,b) is illustrated in Fig. 2.

For any $b \in [20, 100]$, the entry indifference curve $g(b)$ lies above the 45-degree line where the completion costs for both projects coincide. Intuitively, a bidder with $a \leqslant b$ who enters the first auction can secure himself a profit $100 - b$ with certainty. If, instead, this bidder skips the first auction, he may have to compete with the other bidder in the second auction leading to a winning bid less than 100. As a result, entry indifference only occurs if a bidder has a cost advantage for the second project. Moreover, the entry indifference curve $g(b)$ is strictly monotonic increasing in b. To see this, note that as b increases the expected equilibrium profit that results from entering the first auction, $E[\Pi^{A+B}(a,b)]$, falls less sharply than the expected equilibrium profit that results from skipping this auction, $E[\Pi^{B}(b)]$. That is, as b increases entry indifference requires a relatively lower profit resulting from entering the first auction which is accomplished by an increase in the completion cost for the first project, a.

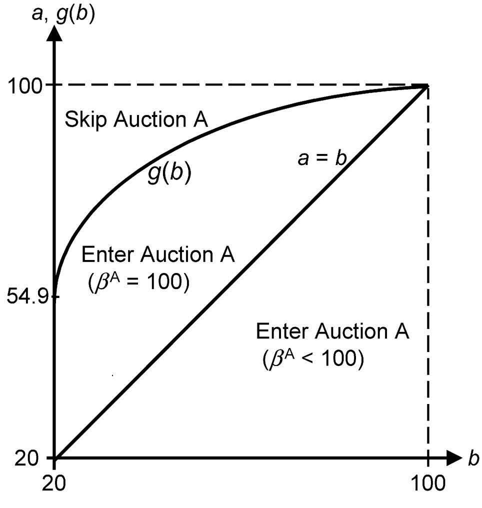

Fig. 2. Equilibrium entry behavior.

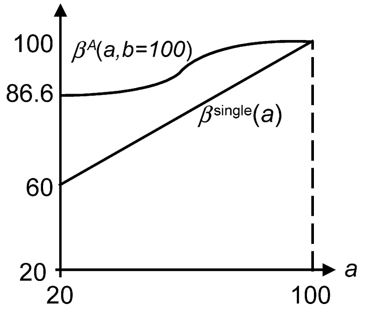

Fig. 3. Equilibrium bidding function for project A.

Equilibrium bidding for project A

Let λ denote the total cost of completing project A that includes both, the actual cost of executing project A and its opportunity cost created by employed capacity, i.e.

$$\lambda = a + 100 - b, \quad \lambda \in [20, 180].$$

Using total completion cost for project A, the equilibrium bidding function may be written as

$$\beta^A(\lambda) = \begin{cases} 100 & \text{if } \lambda > 100 \Leftrightarrow a > b, \\ \frac{2}{3}\frac{\lambda^3 - 30\lambda^2 - 1{,}660{,}000}{\lambda^2 - 40\lambda - 12{,}400} & \text{otherwise.} \end{cases}$$

Since $\partial\beta^A/\partial b < 0$ for $a < b$, bids for project A decrease in b and the equilibrium bidding function shifts downwards as the opportunity cost of winning project A falls. Hence, $\beta^A(\lambda, b = 100) = \beta^A(\lambda = a)$ is the lower bound of equilibrium bidding functions. As Fig. 3 illustrates, it does not coincide with the standard bidding function in a single procurement auction, $\beta^{\text{single}}(a) = 50 + a/2$, since the bidder's competitor does not always participate in the first auction and submits higher bids than in the standard case if he participated. As a result, the lowest equilibrium bidding function $\beta^A(\lambda, b = 100)$ lies above the bidding function in the standard procurement auction model.

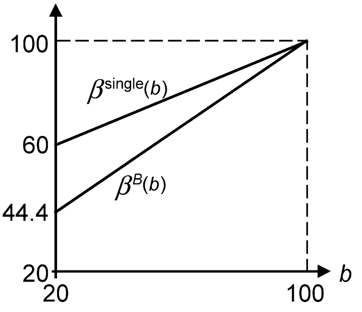

Fig. 4. Equilibrium bidding function for project B with competition.

Equilibrium bidding for project B

If a bidder has already won project A which is known before bid submission for project B, there is only a single bidder in auction B who obviously bids the largest feasible amount. Thus, bidding competition in the second auction implies that both bidders skipped the first one. The equilibrium bidding function is given by

$$\beta^A(b) = \begin{cases} 100 & \text{if she is the only bidder,} \\ b + \frac{0.5839(b-100)+14.11[e^{(100-b)/48.332}-e^{(b-100)/48.332}]}{0.292[e^{(100-b)/48.332}+e^{(b-100)/48.332}]-0.5839} & \text{otherwise.} \end{cases}$$

The difference to a standard procurement auction lies in the fact that both bidders have the additional information that neither of them has a pair of completion costs that leads him to bid for project A. Inspection of Fig. 2 illustrates that types with low completion costs for project B more often skip auction A than types with large costs. It follows that a competitor's completion cost for project B conditional on the fact that he skipped the first auction is not uniformly distributed but rather characterized by a probability density function that decreases in b. Therefore, equilibrium bidding for project B is more aggressive than in the standard model as depicted in Fig. 4.

3. Experimental design

In our study, we used a 2×2 matrix design with the treatment variables information feedback (no feedback, feedback) and nature of the opponent (human, computerized). In all four treatments, subjects first participated in a single auction part, which was the same for all treatments, and then they played a sequential auction part. The within subject design allowed us to compare the subjects' decisions in single auction games with their entry and bidding behavior in sequential auction games. In order to test whether the employment of a single auction part influenced the subjects' behavior in the sequential auction part, we additionally run a treatment, in which subjects only participated in the sequential auction part.

In the single auction part, each subject played 14 single auction games against a computerized bidder. Subjects were informed that the computerized bidder was programmed to maximize his expected payoff, to be risk-neutral, and to act on the assumption that the opponent behaves in the same way as he does. It was known that nobody will receive any feedback on the opponents' behavior either in the course of or after the completion of the single auction part.

In the sequential auction part, subjects played 28 sequential auction games, each of the sort described in the last section. The two feedback treatments only differed with respect to the on-screen information displayed after each sequential auction game. While in the feedback treatment, subjects were informed about winners and prices, in the no feedback treatment subjects

Table 1
Experimental treatments

Opponent	Feedback	Single auctions	Other characteristics	Treatment label	# of subjects
Computerized	No feedback	no		CnF_seq	24
		yes		CnF	12
			modified instructions	CnF_mi	12
			other cost pair series	CnF_os	12
	Feedback	yes		CF	12
Human	No feedback	yes		HnF	12 (+12)[a]
	Feedback	yes		HF	24 (+24)[a]

[a] The number in brackets indicates the number of subjects faced with a different series of completion cost pairs in the sequential auction part. All data are available from the authors upon request.

received no such information. In the human opponent treatment, subjects played the 28 sequential auctions with different opponents. These opponents were randomly selected from a group of five participants with the restriction that subjects could not be matched with the same partner in two consecutive games. In the computerized opponent treatment, subjects received the same information about the computerized bidder's behavior as in the single auction part. In order to be more precise about the consequences of this behavior in the sequential auction game, in all treatments, subjects were informed that if the opponent maximizes his expected payoff, is risk-neutral and acts on the assumption that his opponent behaves in the same way as he does, he would skip the first auction with a probability of 25 percent. Since the latter might influence subjects' behavior we ran an additional computerized opponent treatment without this information.

Before the first session, we independently drew two series of completion costs for the 14 single auction games and the 28 sequential auction games from a uniform distribution ranging from 20 to 100 (as was explained in the instructions).[1] One series was assigned to subjects and the other series was assigned to their computerized and human opponents. To facilitate statistical analyses and to make the data straightforwardly comparable across treatments, the same series of completion costs were used in all sessions and treatments except for one.[2]

The experiments were run with a total of 144 students at the Magdeburg Laboratory for Experimental Economics (MaXLab) using Fischbacher's (1999) *z*-tree software tool. No subject participated in more than one experiment. Average payoffs were about €15.39, with a minimum of €9.83 and a maximum of €18.88. No experiment lasted longer than 90 minutes. Table 1 summarizes the treatments and sample sizes.

4. Results

The next subsections present our results on subjects' behavior in the single auction part and in the sequential auction part. The investigation of the sequential auction part particularly focused on subjects' entry decisions and their bidding behavior in the sequential auction game.

[1] All instructions are included in Appendix A.

[2] To test a hypothesis regarding subjects' behavior it was necessary to run a session with a different series of cost pairs (see Section 4.2).

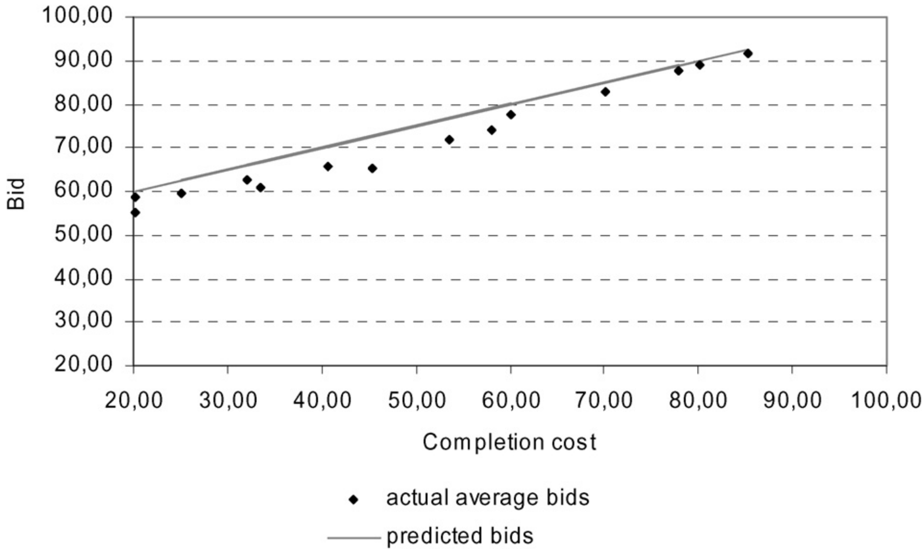

Fig. 5. Average bids in the single auction part.

4.1. *Single auction part*

In the single auction part, we observed that out of a total of 1680 observed bids, 71.3 percent were below the RNNE-prediction.[3] In order to test if there is a tendency for underbidding in the data, we adopted the null hypothesis that underbidding is as likely as overbidding where the 13 observations of RNNE-bidding were counted as overbidding favoring the null. Using one-tailed Binomial tests with data pooled over treatments, we could reject the null at significance levels below 1.2 percent for every game confirming underbidding as the dominant pattern.[4] This finding also emerged when applying one-tailed t tests: In 13 of the 14 first-price auctions subjects' average bids significantly fell short off the risk-neutral Nash-equilibrium prediction $\beta^{\text{single}}(\cdot)$ ($p < 0.026$). Since in our procurement auction context it is the lowest bid that wins the auction (and not the highest bid as in the standard auction context), underbidding in single procurement auctions nicely translates to the overbidding phenomenon observed in standard first-price auction experiments (see Kagel, 1995). Figure 5 shows the average bids submitted by subjects in the single auction part sorted by the subjects' completion cost in the 14 auction games.

4.2. *Sequential auction part*

Effect of playing the single auction part

A comparison of behavior in the CnF treatment without a preceding single auction part and the CnF treatment with a preceding single auction part (CnF_seq) revealed no significant differences

[3] In Appendix B, Table B.2 provides more detailed bidding data.

[4] Note that a pairwise comparison of subjects' average bids between our six treatments revealed no significant differences ($p > 0.335$, exact two-tailed Mann–Whitney U test). We obtained similar results when comparing subjects' average bids for each auction game separately. Only three of the 210 comparisons were (weakly) significant ($p = 0.034$ for one comparison and $0.060 < p < 0.077$ for two comparisons, exact two-tailed Mann–Whitney U test).

either with regard to the average number of correct entries ($p = 0.848$, exact two-tailed Mann–Whitney U test) or with regard to the subjects' average bids for project A (for each of the 28 auction games: $p > 0.050$, exact two-tailed Mann–Whitney U test) or with regard to the subjects' average bids for project B (for each of the 28 auction games: $p > 0.050$, exact two-tailed Mann–Whitney U test). These results suggest that our observations in the 28 sequential auction games are not affected by the implementation of a preceding single auction part.

Entry decisions

The analysis of subjects' 28 entry decisions revealed that, in all treatments, more than 70 percent of these decisions were "correct" in the sense that they were in line with the equilibrium prediction of the sequential auction model, see Table 2.

In particular, the frequency of correct entries per subject as a share of the total number of all sequential auction games (28) significantly exceeded 57 percent (which is the expected relative frequency of correct entries under the entry rule "enter always auction A" since equilibrium entry behavior predicts subjects to enter auction A in 16 out of 28 auction games), but was significantly lower than 100 percent (in all treatments: $p < 0.005$, one-tailed t test).[5,6] This result implies that the observed share of correct entry decisions also significantly exceeded the expected relative frequency of correct entries generated by any arbitrary random entry rule where the chances of entry and non-entry are given by q and $(1 - q)$, since "enter always auction A" (i.e., $q = 1$) is the most successful rule in this class of entry rules.[7] Another class of decision rules that might have been applied by our subjects is characterized by "enter if $a < \mu$" where μ is some exogenous threshold.[8] These rules ignore the level of completion cost for project B and would lead subjects to enter the first auction as long as their completion cost for project A is smaller than the threshold μ. The best random entry rule for the series of realized completion cost pairs ("enter

Table 2
Frequencies of correct entries

Sample statistics of the relative frequency of correct entries per subject (%)	CnF	CF	HnF	HF	Pool
Mean	70.8	84.2	72.6	81.6	78.2
Median	69.6	82.1	75.0	83.9	78.6
Minimum	46.4	71.4	50.0	35.7	35.7
Maximum	96.4	100	92.9	96.4	100
Std. Dev.	14.7	9.6	12.7	13.5	13.7

[5] Binomial tests reject the hypotheses that the share of correct entries observed in any of the treatments is lower than or equal to 60% or that it is larger than or equal to 90% at significance levels below 0.0007.

[6] Note that if subjects interpreted the information that "if the opponent maximizes his expected payoff, is risk-neutral and acts on the assumption that his opponent behaves in the same way as he does, he would skip the first auction with a probability of 25 percent" in a way that lead them to skip the first auction in 25 percent of our 28 sequential auction games, their average frequency of correct entry decisions should be 53.6 percent. This was not the case, however. In addition, we tested whether giving this information had any effect on entry decisions revealing that in 27 out of 28 auction games there was no significant effect (CnF vs. CnF_mi: $p > 0.213$, 1 game: $p = 0.037$, two-tailed Fisher test). Similar results are obtained for bidding behavior for projects A and B.

[7] To see this, note that the expected relative frequency of correct entries for any of these random entry rules over our 28 sequential auction games is: E[correct entry share for random entry] $= q \cdot$ Pr.[entry is correct] $+ (1 - q) \cdot$ Pr.[non-entry is correct] $= (3 + q)/7$, where the probability of a correct entry is 16/28.

[8] We are grateful to a referee for suggesting this class of decision rules.

Table 3
Share of observed entry decisions that coincide with predictions of a particular entry rule

Entry rule	Share of explained entry decisions
(1) enter always auction A	60.89 percent
(2) enter auction A if $a < 70$	71.96 percent
(3) enter if $a < g(b)$ (theory)	78.16 percent

always auction A") is a special case of this class with $\mu = 100$ resulting in a correct entry share of 57.1 percent as discussed. A decrease of threshold $\mu = 100$ leads to an increase in the resulting share of correct entries. The largest correct entry share that this class of rules can achieve is 85.7 percent with any $\mu \in (64.84, 85.23)$. In the two no feedback treatments (CnF, HnF), the observed correct entry share was significantly lower than 85.7 percent ($p < 0.005$, two-tailed t test), and in the two feedback treatments (CF, HF), it did not significantly differ from 85.7 percent ($p > 0.1316$, two-tailed t test).[9] However, this class of rules is inconsistent with the observed entry behavior since probit estimations that relate the observed entry decisions to the completion costs for the two projects yield a significantly positive coefficient on completion cost b that is disregarded by this rule (for all treatments, $p < 0.001$). This effect biases downward the share of explained entry predictions as compared to the explanatory power of the theoretical benchmark. For each of the best simple entry rules and theory, Table 3 briefly summarizes the share of observed entry decisions that are in line with the entry prediction under the corresponding rule.[10]

Looking at the average frequency of correct entry decisions per sequential auction game as a share of the total number of entry decisions in a given auction game (see Fig. 6) we observed that this frequency strongly varied over the 28 auctions. In some auction games, the relative frequency of correct entries is particularly low, e.g. 45 percent in game 14, in others it is close to 100 percent such as in games 18 and 19 where it equals 98.3 percent. Since auction games differ only in project cost pairs, it is natural to relate the frequency of correct entries in a given auction game to the associated project cost pair. Figure 7 displays pooled entry data on all 28 auction games in the project cost space where treatment-specific figures are similar. Every marking corresponds to a single cost pair and its size indicates the observed average frequency of correct entries in that game basing on 60 individual entry decisions. Marking sizes come in the four categories 85–100 percent, 70–85 percent, 55–70 percent, and 40–55 percent and classify the observed average frequency of correct entries. E.g. the cost pair (a, b) in game 28 was (45.27, 40.57) and its marking size indicates that 70–85 percent of all entry decisions in this game were in line with the theoretical prediction (in game 28 the precise number was 81.3 percent.)

From Fig. 7 it is evident that the share of correct entries increases as the cost pair's vertical distance to the entry indifference curve $g(b)$, i.e. $|a - g(b)|$, increases. Since both entry decisions (enter A/skip A) for cost pairs that lie on $g(b)$ lead to the same expected equilibrium profit by definition, the opportunity cost of an incorrect entry decision increases in the cost pair's distance to the entry indifference curve. Thus, Fig. 7 suggests that the variation of correct entry decisions across auction games might be explained by the subjects' expected cost of an incorrect entry

[9] This result indicates that giving feedback on winners and prices increased the share of correct entries, see our more detailed discussion below.
[10] Treatment-specific figures are similar.

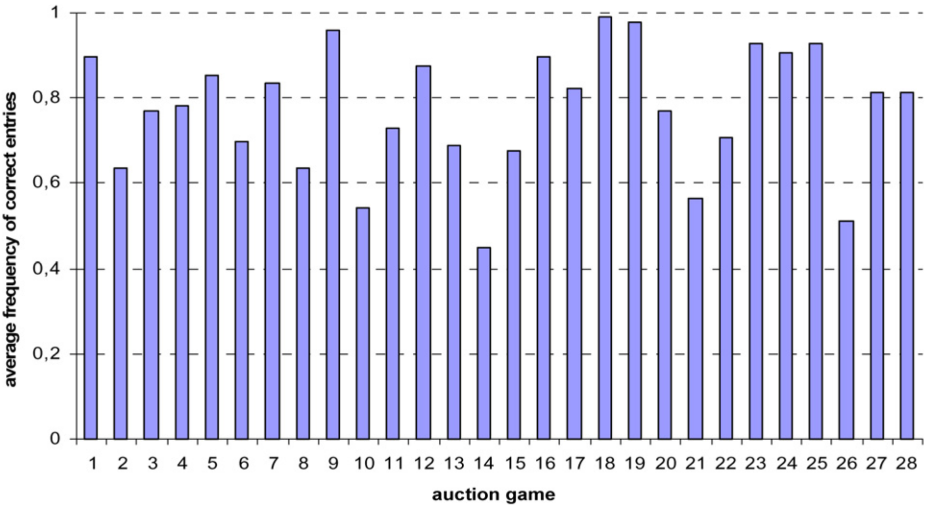

Fig. 6. Relative frequency of correct entries per auction game.

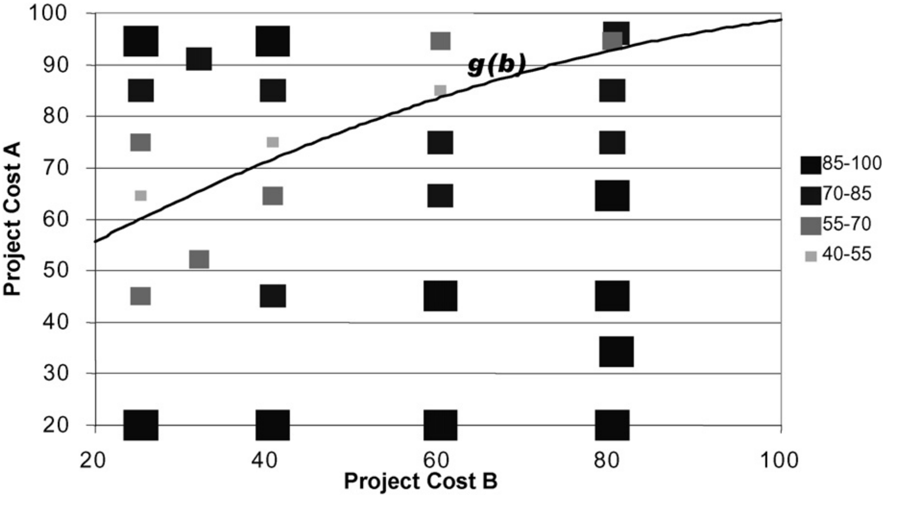

Fig. 7. Relative frequencies of correct entries in cost space.

decision. In particular, we hypothesize that the higher the subjects' expected cost of an incorrect entry is, the more subjects are aware of this cost and, consequently, the higher is their average frequency of correct entry decisions. Analyzing this hypothesis yields a significantly positive correlation between the subjects' expected cost of an incorrect entry and the average frequency of correct entry decisions in all four treatments (Spearman's $\rho > 0.6213$, $p < 0.001$, see Fig. 8).[11]

Further investigations of treatment effects demonstrated that feedback information seems to increase the frequency of correct entries as illustrated by Fig. 9. This is not only true for the

[11] The reported analyses do not include the subjects faced with a different completion cost pair series in the human opponent treatments. Including these subjects does not change the results, however.

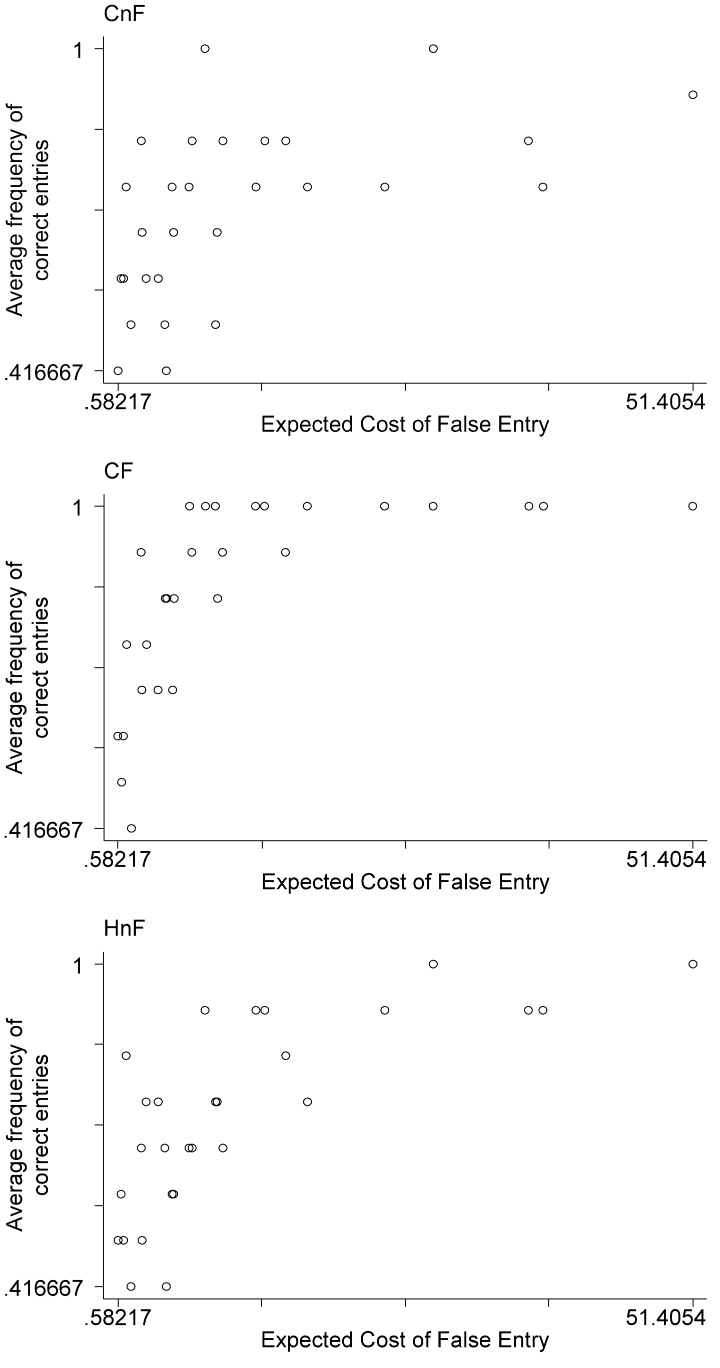

Fig. 8. Relative frequency of correct entries per game and expected cost of incorrect entry.

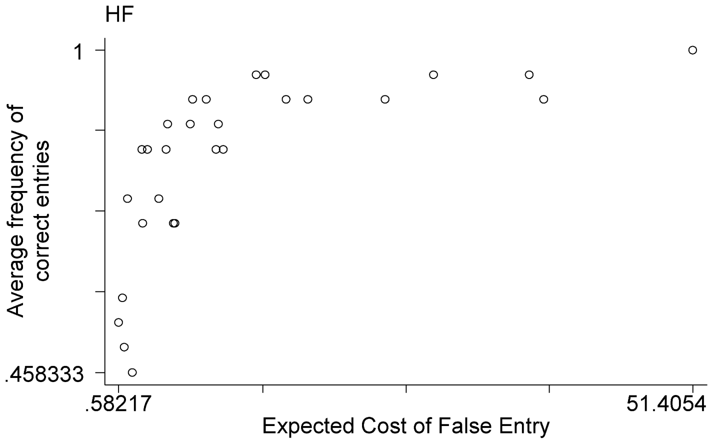

Fig. 8. (*continued*)

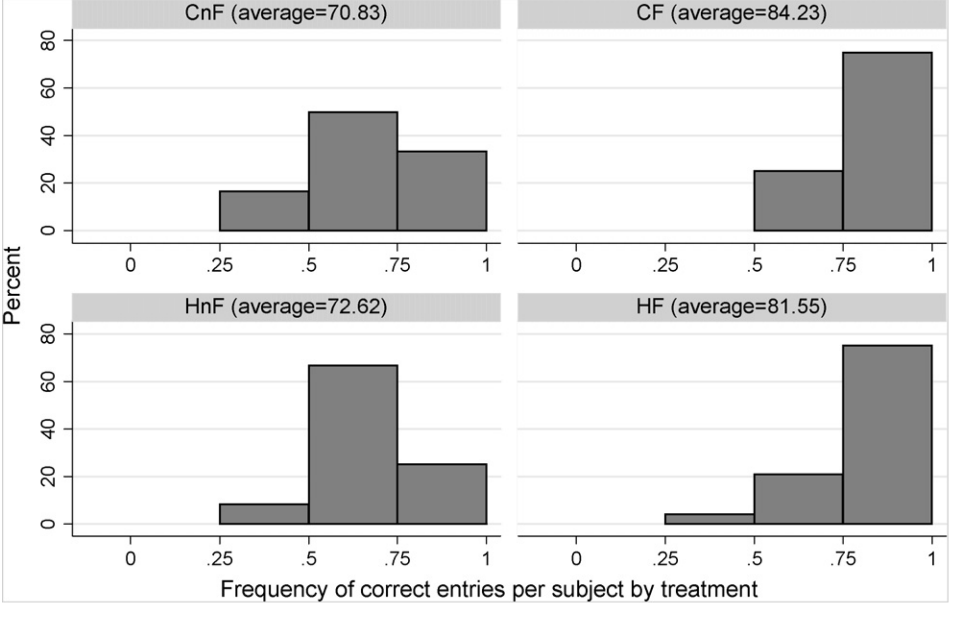

Fig. 9. Empirical distributions of subjects' (relative) correct entry frequencies.

human opponent treatment, but also true for the computerized opponent treatment ($p < 0.054$, exact two-tailed Mann–Whitney U test).

Interestingly, subjects' entry behavior was not significantly influenced by the nature of the opponent ($p > 0.678$, exact two-tailed Mann–Whitney U test). This finding is in line with previous results in a standard first-price auction experiment conducted by Walker et al. (1987). Our finding suggests that subjects' behavior in the sequential auction game is neither driven by some kind of other-regarding concerns (see, e.g., Fehr and Schmidt, 1999; Bolton and Ockenfels, 2000; Charness and Rabin, 2002; Dufwenberg and Kirchsteiger, 2004) nor by strategic uncertainty.

Bidding for project A

As predicted by the sequential auction model, average bids for project A are considerably higher than those observed in the single auction games (see Fig. 10) suggesting that subjects responded to the opportunity cost of early bid submission.

This impression is further confirmed by comparing average bids for project A to the RNNE-predictions for *single* auction games. From Fig. 10 and the data included in Table 4 it is evident that there is an extreme pattern of overbidding in the first stages of the 28 sequential auction games relative to β^{single}. Applying one-tailed t tests per round and per treatment, in 91 of the 105 total comparisons we found that subjects submitted significantly higher bids than predicted by $\beta^{\text{single}}(c)$ ($p < 0.025$).[12]

Another test for the impact of the subjects' opportunity costs on their observed bidding behavior is to compare the distribution of bids when subjects were faced with a cost advantage for project B to the distribution of bids when they were faced with a cost advantage for project A. Whenever there is a cost advantage for project B, theory predicts a bid equal to the maximum amount 100 and it predicts a bid less than 100, if there is a cost advantage for project A.[13] Figure 11 provides the observed bid distributions by treatment. It is evident that the bid distribution

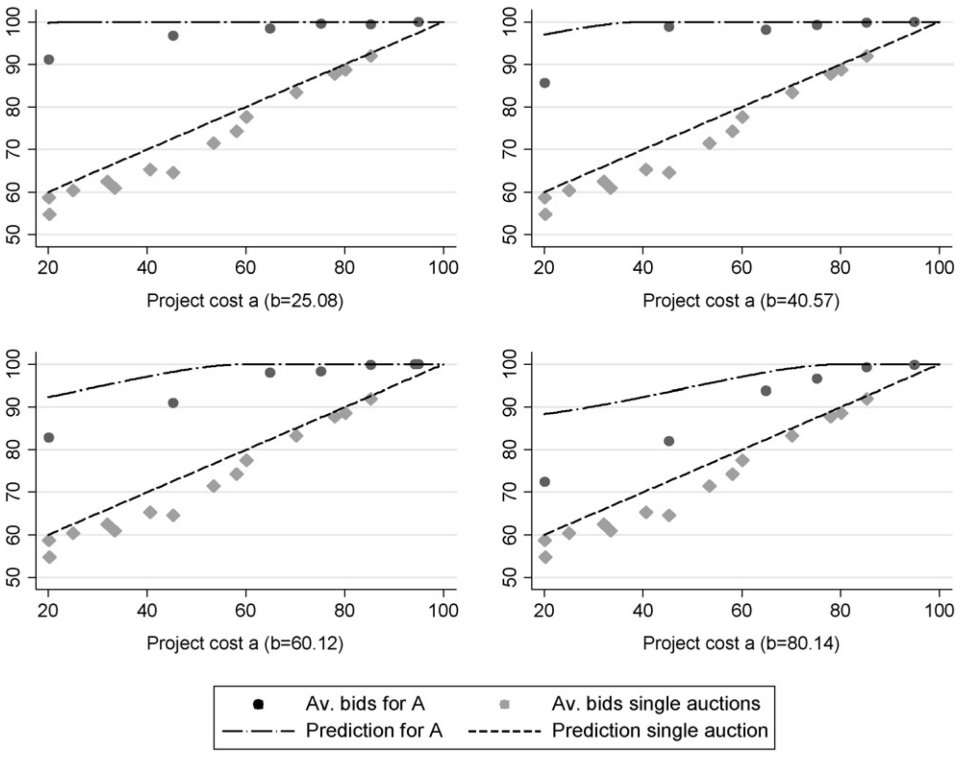

Fig. 10. Bidding data for project A vs. bidding data from single auction games.

[12] Binomial tests by treatments and by rounds with at least five observations allow to reject the hypothesis that observed bids are as likely below as above $\beta^{\text{single}}(c)$ in 63 of 86 comparisons at the 5% level.

[13] We are grateful to a referee for suggesting this test.

Table 4
Bidding in auction A in comparison to the single auction bidding prediction

Treatment	#Underbids (A-bids vs. β^{single})	#Overbids (A-bids vs. β^{single})	Total
CF	8 (4.8%)	203 (95.2%)	211
CnF	32 (15.8%)	1702 (84.2%)	202
HF	41 (9.8%)	3771 (90.2%)	418
HnF	44 (22.9%)	1484 (77.1%)	192
Pool	125 (12.2%)	8985 (87.8%)	1023

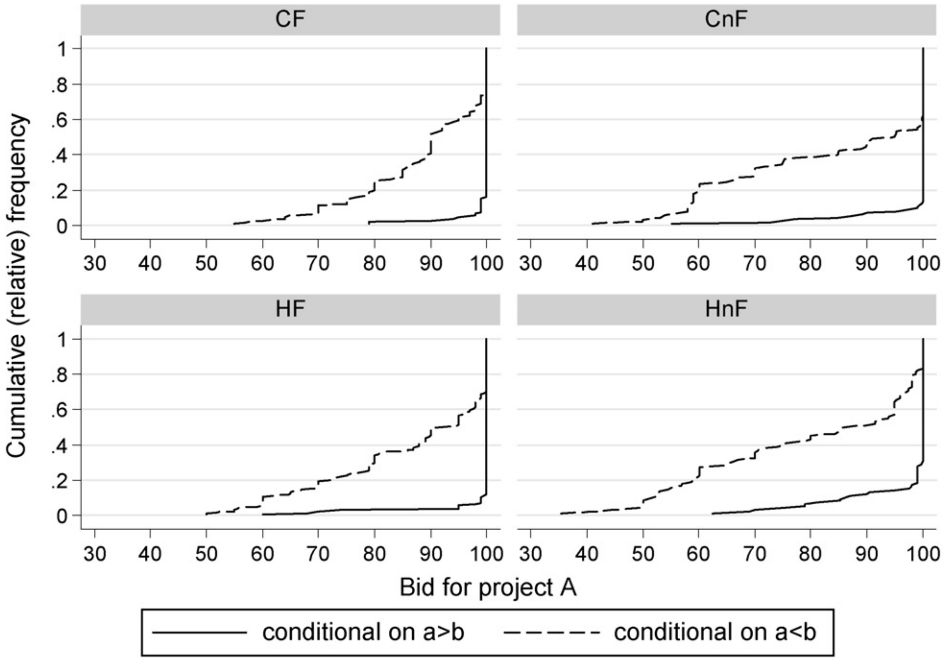

Fig. 11. Empirical distributions of subjects' bids for project A conditional on qualitative cost advantages and treatments.

conditional on $a > b$ first-order stochastically dominates the distribution conditional on $a < b$ in each treatment. Although, the theoretical benchmark for bids with $a > b$ predicts that all observations cluster at 100, we observed minor deviations: For the treatment pool, 77.9 percent of observed bids under $a > b$ were exactly equal to 100 and further 12.6 percent of observed bids fell into the interval [99,100) suggesting that opportunity costs were broadly understood.[14]

Moreover, the theoretical prediction that a higher cost for project B leads to more aggressive bidding for project A is also supported by subjects' bidding behavior, see Fig. 12.

However, Fig. 10 illustrates that subjects' average bids per round and per treatment were somewhat lower than theoretically predicted by the sequential auction model. Similar to bidding

[14] If we further restrict our observations to satisfy $g(b) > a > b$, i.e. the cost pairs that underlie the observed bids belong to the "middle region" in Fig. 2, then for the treatment pool, 74.2 percent of observed bids were exactly equal to 100 and 13.4 percent of observed bids fell into the interval [99,100).

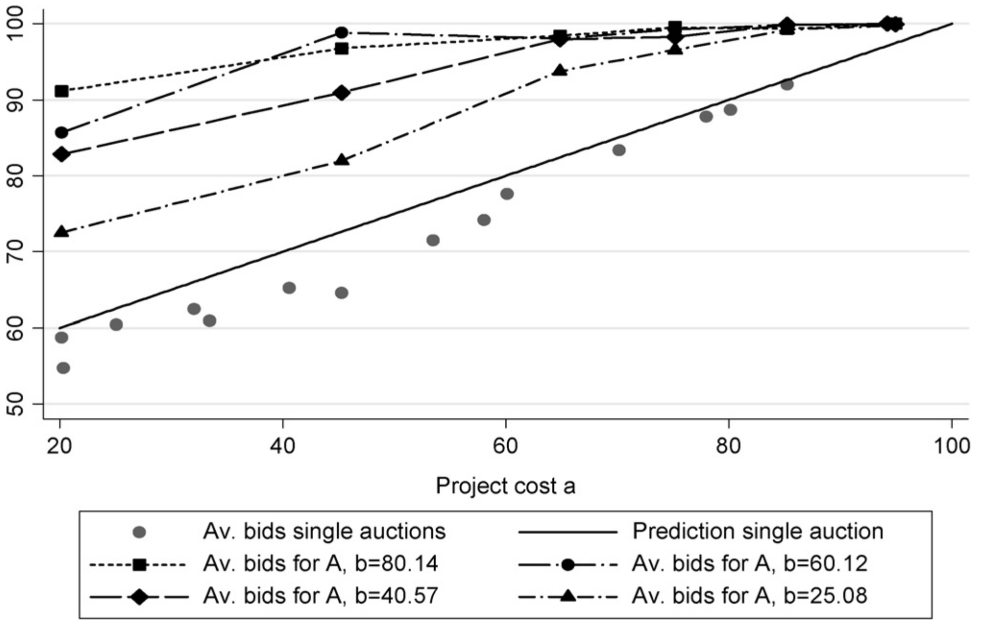

Fig. 12. Bidding data for project A given cost for project B.

behavior in single auction games, these observations translate to the overbidding phenomenon observed in standard first-price auction experiments. Though, in only 22 of the 105 total comparisons[15] these differences were significant at the 5-percent level (two-tailed t test). That is, in over 70 percent of all cases behavior was fairly in line with the theoretical prediction $\beta^A(a,b)$.

Testing for treatment effects, we observed in only 2 out of 102 comparisons between the four treatments significant differences at the 5-percent level (exact two-tailed Mann–Whitney U test; see Fig. 13). Neither the feedback on winners and prices nor the nature of the opponent seem to have a strong effect on subjects' bids for project A. The latter result confirms our supposition that other-regarding concerns or strategic uncertainty are not the driving factors for subjects' behavior in the sequential auction game.

Bidding for project B

Our analysis of subjects' bidding behavior in the second auction is restricted to the case of two bidders competing for project B.[16] Looking at Fig. 14 reveals that the subjects' average bids do not depend on the completion cost for project A as predicted by the sequential auction model. This is also formally verified by regressing individual bids for project B under competition on

[15] The total number of observations resulted from the number of treatments, 4, multiplied by the number of auctions, 28, minus the number of auctions without entries or with only one entry, 7. Given that in 48 games (over all treatments) subjects are predicted to skip the first auction, the number of games in which we observe no or only one entry might appear very low. Note, however, that out of the 720 entry decisions that could be made in these 48 games 505 were correct in the sense that subjects chose to "skip the first auction".

[16] If there is no bidding competition, subjects are predicted to bid 100, which is the largest accepted bid. In the experiment, subjects were informed that their bids were automatically set to 100, if they were the only bidder in the second auction.

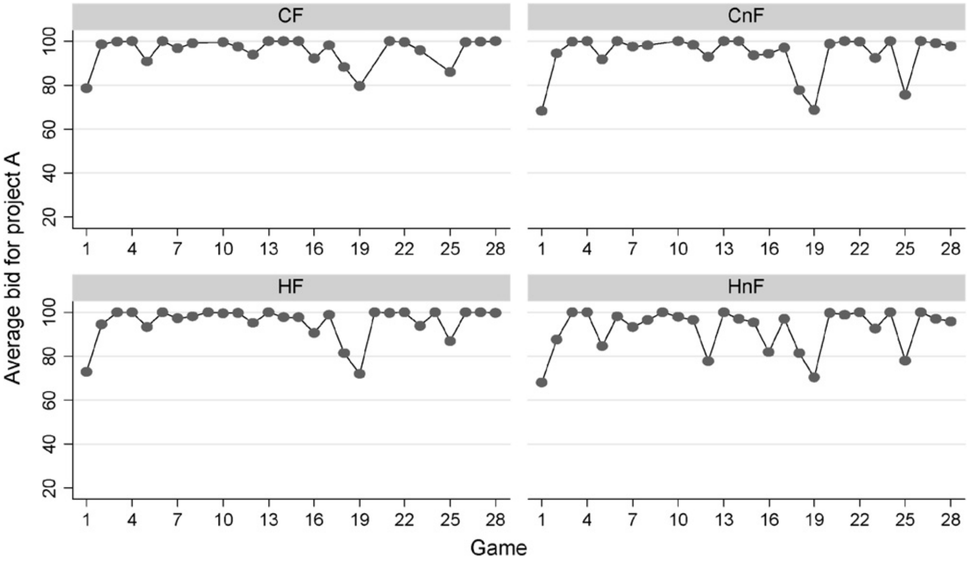

Fig. 13. Bidding data for project A by treatment.

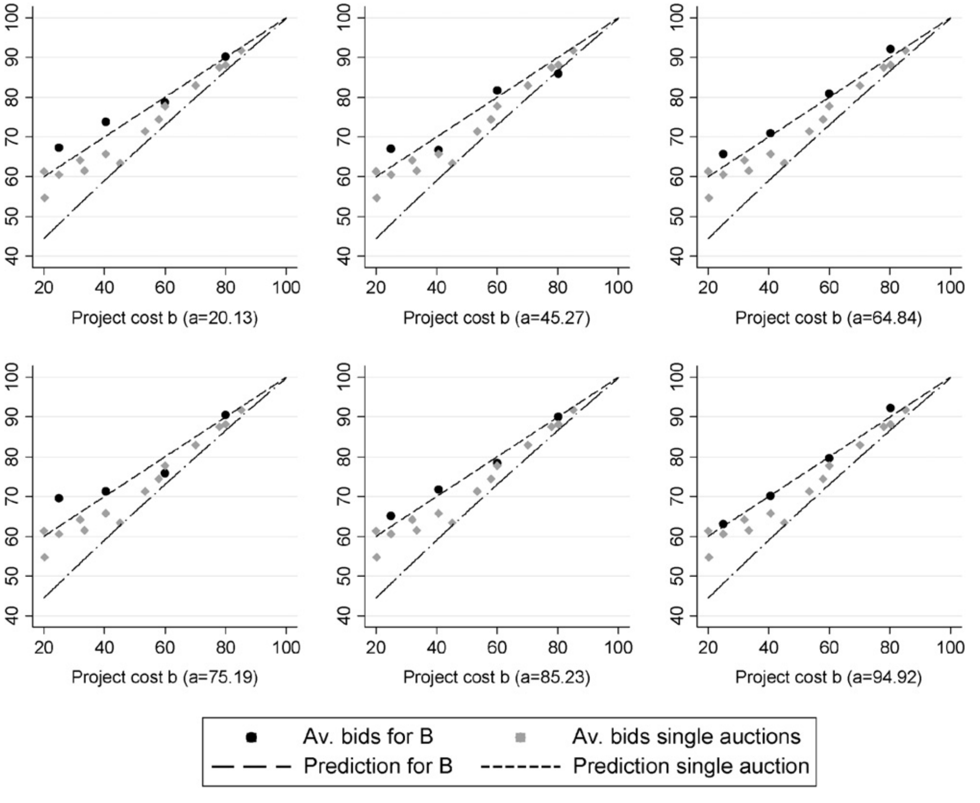

Fig. 14. Bidding data for project B vs. bidding data from single auction games.

completion costs a and b (for a: $p > 0.373$, for b: $p < 0.002$; detailed results are provided in Appendix B, Table B.1).

However, average bids per round and per treatment were higher than predicted. In 36 out of 88 comparisons these differences were significant at the 5-percent level (two-tailed t test). That is, in more than 40 percent of all cases actual average bids significantly deviated from those predicted by theory. In contrast, testing whether there was a significant difference between actual average bids and theoretically predicted bids for *single* auction games, we found that in 83 of the 88 total comparisons the differences were not significant at the 5-percent level (two-tailed t test). These observations suggest that subjects' bids for project B are more in line with the theoretical prediction for single auction games than with the theoretical prediction of the sequential auction model. Possibly, this effect is attributable to subjects' ignorance of the endogenous bidder selection effect. According to this effect, bidders are predicted to update their beliefs according to Bayes rule and, consequently, to bid more aggressively for project B than in the single auction game, since bidders with a lower cost for project B are more likely to skip the first auction and subjects' bids only refer to the case of two bidders.

Since subjects appear to act as if they do not update their beliefs about their competitor's cost for project B, it is a priori not obvious if our results on entry, that depend on Bayesian updating through the theoretical entry prediction, continue to hold once the behavioral assumption of non-updating is accounted for by the solution of our auction model.[17] If equilibrium predictions are modified as a consequence of the assumption that bidding behavior for project B under competition coincides with that in a single auction game, the resulting entry indifference curve rotates

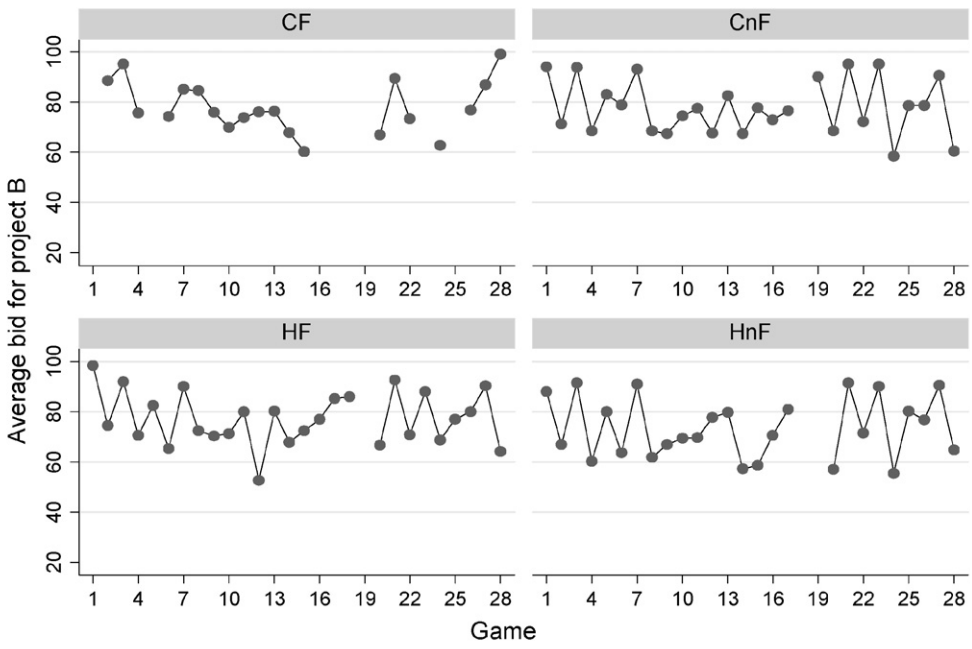

Fig. 15. Bidding data for project B by treatment.

[17] Notice that predicted bidding behavior in the first auction does not depend on the entry indifference curve.

in the point (100, 100) somewhat downward. Given that this new entry indifference curve leads to identical entry predictions as the original equilibrium entry indifference curve for our series of cost pairs, we conducted an additional treatment with an alternative cost pair series (CnF_os) that allows to differentiate between the two types of entry predictions. The data obtained in this treatment reveal that the original entry indifference curve is in line with 78.6 percent of the subjects' entry decisions while the new entry indifference curve is in line with 72.9 percent of subjects' entries. The difference between the relative frequencies of 'correct' entries per subject is not significant ($p = 0.228$, two-tailed exact Wilcoxon test for matched pairs), however. It appears that subjects' entry behavior is consistent with both entry indifference curves to the same extent.

Comparing the four treatments for each auction game separately revealed in only 3 of the 76 total comparisons differences that were significant on the 5-percent level (exact two-tailed Mann–Whitney U test). That is, similar to our observations for subjects' behavior in auction A, their average bids for project B were not strongly influenced by feedback on winners and prices and by the nature of the opponent.

5. Conclusions

This paper experimentally investigated behavior in first-price sealed-bid procurement auctions. The results on the 14 single auction games demonstrated that subjects' bids were significantly lower than those predicted by theory. Since underbidding in first-price procurement auctions corresponds to overbidding in standard first-price auctions, this observation suggests that the deviation pattern is quite robust with regard to the auction frame.

Analyzing the 28 sequential auction games revealed that, in line with the theoretical prediction, both, subjects' auction entries and their bidding behavior for project A, were significantly influenced by the opportunity cost of early bid submission. Though, similar to our findings in the single auction games, subjects' bids for project A were somewhat lower than those predicted by the sequential auction model.

Our result that bidding behavior for project B is more in line with the theoretical prediction for the single auction games than with the sequential auction model indicates that subjects, who are informed that their competitor did not submit a bid for project A, do not update their beliefs accordingly, i.e. they do not consider that skipping is a payoff maximizing behavioral pattern only for those subjects whose completion cost for project B is relatively low.

The reported findings for the sequential auction games were similar across all treatments. The investigations of treatment effects demonstrated that the nature of the opponent had no significant effect on behavior, whereas giving subjects feedback on winners and prices significantly reduced the deviations from the theoretical prediction for entry decisions. Given our findings on the sequential auction games, opportunity costs seem to be a crucial determinant of real-life entry and bidding behavior in auctions and have to be taken into account when investigating auction mechanisms. Further research is required to find out how robust these results are when there are more than two bidders who compete for project contracts.

Acknowledgments

We thank Werner Güth, Jens Robert Schöndube, Reinhard Selten, Joachim Weimann, and two anonymous referees for very helpful comments and stimulating discussions. We are especially indebted to Jens Robert Schöndube for his help in conducting the experiments. Financial support by the Magdeburg Laboratory of Experimental Economics (MaxLab) is gratefully acknowledged.

Appendix A. Instructions (Translation from German)

Preliminary Remark

You are participating in an experimental analysis of individual decision-making. During the experiment, you and the other subjects are asked to make decisions. In doing so, you can earn money. The exact amount of money will depend on your decisions. At the end of the experiment, your total earnings will be converted into Euros at the rate 90 LD : 1 EURO and will be paid off in cash together with a show-up fee of 3 EURO.

The experiment lasts approximately 90 minutes and consists of two different parts. At the beginning of each part, you will receive a detailed set of instructions. All subjects in the experiment will receive an identical set of instructions and briefings. Please notice that neither your decisions in the first part of the experiment nor your decisions in the second part of the experiment will affect the respective other part of the experiment.

None of the participants will receive information about the identity of the other participants in the course of the experiment.

Part 1

Please read this set of instructions. About five minutes after you've received these instructions we will come to you for answering open questions. If you have questions during the experiment, please raise your hand. We will come to you.

During the first part of the experiment, you will participate in 14 auction rounds.

Description of the auction rounds

In each of the 14 auction rounds, one project is auctioned off. The winning bidder is the one who submits the lowest bid. In each auction round, there are precisely two bidders, you and another bidder.

Information: For both bidders, we have independently drawn the cost of completing the project from the interval 20 LD to 100 LD for each auction round. Each of the two bidders will be informed only about his own completion cost. The only available information on the cost of the other bidder is that it is randomly and independently drawn from the above-mentioned interval, whereby each amount within this range is selected with equal probability.

Course: At the beginning of each auction round, each of the two bidders can decide on the bid, he wants to submit for the project.

- If your bid for project A is *lower* than the bid of the other bidder, then you win the auction and your profit in this round is the difference between your bid and your completion cost for that project.
- If your bid for project A is *higher* than the bid of the other bidder, then you lose the auction and your profit in this round is equal to zero.
- If your bid for project A is *equal to* the bid of the other bidder, then you win the auction with 50 percent probability.

The other bidder: In each of the 14 auction rounds, the other bidder is a computer. The computer is programmed to maximize its expected payoff in each auction round. More specifically, it bids according to the (symmetric) Nash-equilibrium strategy under risk-neutrality. In doing so, it acts on the assumption that you behave in the same way as the computer does. It expects that your completion cost is randomly and independently drawn from the interval 20 LD to 100 LD, whereby each amount within this range is selected with equal probability.

Payment: Upon completion of the 14 auction rounds, the sum of your profits per auction round will be converted into Euros at the rate 90 LD : 1 EURO. This amount will be paid off at the end of the entire experiment.

Notice that none of the bidders will receive information about his profits in the course of the first part of the experiment.

In the course of the entire experiment, none of the participants will receive information about any other subject's bidding behavior and profits in part 1 of the experiment.

Part 2

Please read this set of instructions. About five minutes after you've received this instructions we will come to you for answering open questions. If you have questions during the experiment, please raise your hand. We will come to you.

During the second part of the experiment, you will participate in 28 auction rounds.

Description of the auction rounds

In each of the 28 auction rounds you participate in, two projects will be auctioned off one after the other. In the first stage of each round, project A will be auctioned off and in the second stage of each round, project B will be auctioned off. In each stage, the bidder who submits the lowest bid wins the auction.

In each auction round, there are precisely two bidders, you and another bidder. Each of the two bidders can win one project *at most* in each auction round.

Information: For both bidders, we have independently drawn the completion cost for both projects from the interval 20 LD to 100 LD for each auction round. Each of the two bidders will be informed only about his own completion costs. The only available information on the costs of the other bidder is that it is randomly and independently drawn from the above-mentioned interval, whereby each amount within this range is selected with equal probability.

This implies that with a probability of almost 50 percent the other bidder's completion cost of project A is smaller than his completion cost for project B and that with a probability of almost 50 percent the completion cost of project B is smaller than the completion cost for project A (with a residual probability smaller than 0.1 percent the other bidder has the same completion cost for both projects).

[*This sentence was only included in the feedback treatments CF and HF*: Upon completion of each auction round, you will be informed about the winner in each auction and about the prices resulting from the two auctions]

Course: At the beginning of each auction round, each of the two bidders can decide whether he submits a bid in the first auction (project A) of this auction round.

If you submit a *bid in the first auction* (*project A*), then there are two possibilities:

(a) The other bidder submits a bid for project A, too.
- If your bid for project A is *lower* than the bid of the other bidder, then you win project A and your profit for this auction round is the difference between your bid and your completion cost for project A.
- If your bid is *higher* than the bid of the other bidder, then you lose the first auction and you will be the only remaining bidder in the second auction (project B). In that case, your bid in the second auction will automatically be set to 100 LD (this is equal to the largest possible amount of completion cost for project B). Your profit for the auction round is then the difference between 100 LD and your completion cost for project B.
- If your bid is *equal to* the bid of the other bidder, then you win the first auction with 50 percent probability.

(b) The other bidder does not submit a bid for project A.
You win the first auction and your profit for the auction round is the difference between your bid and your completion cost for project A.

If you *do not submit a bid in the first auction* (*project A*), again, there are two possibilities:

(c) The other bidder submits a bid for project A.
- The other bidder wins the first auction and you are the only remaining bidder in the second auction (project B). Your bid in the second auction will automatically be set to 100 LD (this is equal to the largest possible amount of completion cost for project B). Your profit in the auction round is then the difference between 100 LD and your completion cost for project B.

(d) The other bidder does not submit a bid for project A, too. That is, in this case both bidders will submit a bid in the second auction (project B).
- If your bid for project B is *lower* than the bid of the other bidder, then you win the second auction and your profit in this auction round is the difference between your bid and your completion cost for project B.
- If your bid is *higher* than the bid of the other bidder, then you lose the second auction. In this case, your profit in this auction round is zero.
- If your bid for project B *is equal* to the bid of the other bidder, then you win the second auction with 50 percent probability.

[*In the computerized bidder treatments, CF and CnF, the following paragraph was included*:
The other bidder:

In each of the 28 auction rounds, the other bidder is a computer. The computer is programmed to maximize its expected payoff in each auction round. More specifically, it bids according to the (symmetric) Nash-equilibrium strategy under risk-neutrality. In doing so, the computer acts on the assumption that you behave in the same way as it does. The computer expects that your completion costs are randomly and independently drawn from the interval 20 LD to 100 LD, whereby each amount within this range is selected with equal probability.

This information implies that the computer does not submit a bid in the first auction with the probability of almost 25 percent.] [The last sentence was eliminated in treatment *CnF_mi*.]

[*In the human bidder treatments, HF and HnF, the following paragraph was included*:

The other bidder: In the second part of the experiment, you and five other participants form a group of bidders. In each of the 28 auction rounds, you are randomly assigned a bidder from your group of bidders. It is ensured that you will not be assigned to the same bidder in two consecutive rounds.

If the respective other bidder in each auction round maximizes his expected payoff, i.e. he bids according to the (symmetric) Nash-equilibrium strategy under risk-neutrality, and acts on the assumption that you behave in the same way as he does, and expects that your completion costs are randomly and independently drawn from the interval 20 LD to 100 LD, whereby each amount within this range is selected with equal probability, then *the other bidder does not submit a bid in the first auction with the probability of almost 25%.*]

Payment: Upon completion of the 28 auction rounds, the sum of your profits per auction round will be converted into Euros at the rate 90 LD : 1 EURO and paid off to you in cash together with your profit from the first part of the experiment and the show-up fee.

Notice that, in the course of the second part of the experiment, none of the bidders will receive information about [*These words were only included in the no feedback treatments CnF and HnF*: his profits and] the bidding behavior and profits of the other bidders.

Appendix B

Table B.1
Estimation of bids for project *B* under competition (Note that the estimation procedure takes into account that bids of any given subject may be correlated, that there may be dependencies within matching groups, and that observations between matching groups are independent, see Rogers, 1993); non-robust OLS-estimated standard errors for the same models lead to the same conclusion, for all treatments: $p > 0.279$).

Treatment	Expl. variable	Coefficient	Robust SE	t	$P > \|t\|$
	constant	57.33279	10.01783	5.72	0.000
CnF	a	−0.0371006	0.0918525	−0.40	0.694
	b	0.4587084	0.0929365	4.94	0.000
	constant	65.89897	9.358437	7.04	0.000
CF	a	−0.0953477	0.1137251	−0.84	0.420
	b	0.4048851	0.0913286	4.43	0.001
	constant	48.41588	7.123198	6.80	0.000
HnF	a	−0.0598807	0.064294	−0.93	0.374
	b	0.588068	0.0560378	10.49	0.000
	constant	54.58808	4.46719	12.22	0.000
HF	a	0.0075551	0.0355698	0.21	0.838
	b	0.4372036	0.0471857	9.27	0.000
	constant	55.32419	4.052724	13.65	0.000
Pool	a	−0.0236282	0.037447	−0.63	0.531
	b	0.4620281	0.0323729	14.27	0.000

Table B.2
Analysis of bidding data for the single procurement auction game

Treatment\Round		1	2	3	4	5	6	7	8	9	10	11	12	13	14	Pool
Project cost		80.14	20.30	45.27	70.18	25.08	33.41	85.23	58.06	40.57	77.99	20.13	53.48	60.12	32.01	–
RNNE-prediction		90.07	60.15	72.64	85.09	62.54	66.71	92.62	79.03	70.29	89.00	60.07	76.74	80.06	66.01	–
CF	#Underbids	11	9	9	9	5	8	7	8	8	5	7	9	8	7	110
($n = 12$)	#Overbids	1	3	3	3	7	4	5	4	4	7	5	3	4	5	58
	Average bid	87.72	57.97	64.20	81.73	66.37	62.70	91.78	75.46	67.96	89.08	63.17	72.61	77.08	66.58	73.17
	Median bid	87.50	58.88	62.34	79.00	65.50	65.00	90.00	75.50	65.00	90.50	60.00	73.24	79.00	65.00	74.45
	Std. dev.	3.52	9.25	9.83	7.43	11.06	8.72	4.85	10.17	9.56	7.35	11.19	10.43	8.94	12.59	13.76
CnF	#Underbids	10	10	11	8	10	10	8	10	11	9	10	12	10	11	140
($n = 12$)	#Overbids	2	2	1	4	2	2	4	2	1	3	2	0	2	1	28
	Average bid	89.17	51.65	64.00	82.97	55.71	60.39	91.55	72.29	64.32	87.89	54.44	70.27	77.54	60.43	70.17
	Median bid	89.50	59.00	65.14	84.50	59.00	61.00	92.08	70.78	65.50	85.99	59.00	71.74	79.56	61.01	70.00
	Std. dev.	5.49	14.83	7.32	7.78	11.27	12.13	3.02	5.79	8.06	6.29	11.81	5.55	6.54	5.64	15.52
HF	#Underbids	37	36	34	28	32	36	30	35	36	28	32	37	34	35	470
($n = 48$)	#Overbids	11	12	13	19	15	11	17	12	11	17	16	10	14	13	191
	Average bid	89.09	56.60	64.49	83.34	59.81	60.27	92.10	73.40	64.24	87.63	58.52	71.46	77.31	64.79	71.43
	Median bid	89.54	57.50	60.00	81.18	59.50	60.00	90.00	70.00	60.00	85.66	57.45	70.00	75.00	60.00	70.00
	Std. dev.	5.73	18.11	12.67	8.59	17.25	13.42	4.54	10.19	11.84	6.51	16.48	11.05	10.66	14.53	17.07
HnF	#Underbids	18	18	19	15	15	17	16	14	16	15	15	17	16	15	226
($n = 24$)	#Overbids	6	6	5	9	8	7	8	10	8	8	9	7	8	9	108
	Average bid	87.98	50.94	65.29	84.27	60.96	61.64	92.15	76.17	66.44	87.54	59.06	71.64	78.36	62.72	71.80
	Median bid	87.50	49.65	60.00	84.00	59.99	60.00	90.00	71.78	63.64	86.50	60.00	70.00	79.00	63.02	70.42
	Std. dev.	5.25	18.65	11.93	9.08	16.62	14.45	4.76	12.05	12.44	6.84	16.24	12.76	11.39	13.85	17.40

Table B.2 (*continued*)

Treatment\Round		1	2	3	4	5	6	7	8	9	10	11	12	13	14	Pool
CnF_mi	#Underbids	9	6	9	9	8	9	9	9	7	8	8	10	9	7	117
($n = 12$)	#Overbids	3	6	3	3	4	3	3	3	5	4	4	2	3	5	51
	Average bid	89.73	60.03	68.44	82.68	58.92	62.03	91.02	73.09	69.30	87.75	58.93	72.42	79.33	67.42	72.93
	Median bid	90.00	60.15	67.00	80.00	59.50	60.00	90.00	70.00	67.50	86.50	87.00	70.00	80.00	65.00	70.07
	Std. dev.	4.53	14.94	9.31	6.59	12.65	11.56	3.04	7.82	10.73	4.71	10.06	9.27	8.22	15.22	14.57
CnF_os	#Underbids	8	10	10	11	11	11	9	11	10	8	9	8	10	9	135
($n = 12$)	#Overbids	4	2	2	1	1	1	3	1	2	4	3	4	2	3	33
	Average bid	90.84	53.17	66.20	81.50	55.64	59.34	91.34	71.95	63.92	86.66	58.80	72.25	75.32	60.42	70.52
	Median bid	90.00	50.00	63.75	80.00	54.11	59.50	90.00	70.00	30.00	88.00	58.94	72.26	78.00	59.01	70.00
	Std. dev.	4.45	13.82	10.81	5.57	13.86	12.27	2.43	7.71	10.55	5.03	13.54	9.86	9.71	13.04	15.39
Pool	#Underbids	93	89	92	80	81	91	79	87	88	73	81	93	87	84	1198
($n = 120$)	#Overbids	27	31	27	39	37	28	40	32	31	43	39	26	33	36	469
	Average bid	88.98	55.11	65.14	83.08	59.78	60.88	91.84	73.87	65.54	87.67	58.76	71.67	77.52	62.74	71.61
	Median bid	89.53	56.05	60.00	80.45	59.99	60.00	90.00	70.00	61.64	87.00	59.00	70.00	78.00	60.00	70.00
	Std. dev.	5.17	16.51	11.19	7.96	15.32	12.63	4.14	9.74	11.13	6.25	14.59	10.48	9.86	13.43	16.33

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