Discussion Paper No. 747

AUCTIONS WITH ENDOGENOUS PRICE CEILING: THEORETICAL AND EXPERIMENTAL RESULTS

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July 2009

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Auctions with endogenous price ceiling: Theoretical and experimental results*

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July 6, 2009

Abstract

This paper analyzes an auction mechanism that excludes overoptimistic bidders inspired by the rules of the procurement auctions adopted by several Japanese local governments. Our theoretical and experimental results suggest that the endogenous exclusion rule reduces the probability of suffering a monetary loss induced by winning the auction, and also mitigates the problem of the winner's curse in the laboratory. However, this protection comes at the price of a lower revenue for the seller.

Keywords: common-value auctions, experiments, winner's curse

JEL Classification Numbers: C91, D44, D82

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*Veszteg gratefully acknowledges the financial support from project SEJ2006-10087 of the Spanish Ministry of Education and Sciences, and from the Plan de Investigación de la Universidad de Navarra (PIUNA).

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1 Introduction

Several Japanese local governments have adopted a special auction format for their procurement procedures. There has been no official justification for the change, nevertheless we believe that local governments aimed at increasing the success ratio of the public projects assigned with these auctions by reducing the probability of a monetary loss by winning the auction and the winner's curse. The winner's curse is a severe empirical problem that has received attention both from theoretical and experimental economists. In case of procurement auctions, the winner's curse may arise due to an overly optimistic estimation of the total cost of carrying out the project and/or to the fierce competition among bidders. Although the winner's curse represents a systematic overestimation of the true value of the auctioned good, and therefore does not occur in a theoretical equilibrium, it represents a serious empirical problem.[1]

We believe that negative payoffs that do appear, although average out, in the theoretical equilibrium also endanger the fulfillment of public contracts. Even rational bidders who win the auction will often find that the price they have paid is higher than the real value of the project. As a consequence, paralyzed construction works and unexploited natural resources—among other problems—require the government to repeat the costly auction procedure. The lack of or late production may also reduce consumers surplus, therefore represents an efficiency loss for the society. Ganuza (2007) presents the empirical impact of the negative winning payoffs by listing European and US *horror stories* about procurement projects with long delays and huge cost overruns.[2]

[1]The number of cases in which companies claim they fell prey of the winner's curse is very large and present a large variety as for the market it occurred in. The early examples of oil companies appear in Capen, Clapp and Campbell (1971). There has been systematic overpayments in book publication rights auctions, on the market of professional sport players, also in numerous situation where the state sold out telecommunication rights.

[2]In his model, it is the sponsor, i.e. the seller's equilibrium strategy that makes these cost overruns likely due

The auction rule adopted by the Japanese local governments excludes some of the most optimistic bidders from the competition, i.e. those whose bid is among the highest price-bids or the lowest cost-bids. The exclusion is based on an endogenous price ceiling that is computed as the average of the most optimistic bids that is often corrected with a fixed scalar. For example, Nagano prefecture excludes those who send a cost-bid lower than the 80% of the five lowest cost-bids. With unchanged bidding behavior this measure looks promising as a means for reducing the probability of a financial loss. Nevertheless if participants are rational, we expect them to update their bidding behavior and adapt to the new rules. The question whether the new auction format is able to decrease the probability of negative payoffs is non-trivial. Based on numerical results that tackle the otherwise intractable mathematical problem, we show that excluding the overoptimistic can indeed reduce the probability of suffering a loss by winning the auction. However, this positive effect comes at the price of a smaller revenue for the seller.[3]

The idea of eliminating the overoptimistic is not a new one even it has not received enough attention in the academic literature. The European Commission, for example, identifies the so-called *abnormally low tenders* that "in the light of the client's preliminary estimate and of all the tenders submitted, it seems to be abnormally low by not providing a margin for a normal level of profit".[4] The Commission points out the potential risk behind these tenders and calls for their prevention, detection and elimination. Calveras et al. (2004) studies these abnormally low tenders from a theoretical point of view and concentrates on surety bonds as a possible solution.

to an underinvestment in design specifications. In ours, it is due to a similar uncertainty over the real cost of the project.

[3]Some authors, e.g. Ishii (2006) who uses empirical data, suggest that the Japanese procurement auctions suffer from collusion and bidding rings. Although it is an important question, with our one-stage common-value model we cannot address whether the specific auction rules have any effect on the possibility of collusion. Our paper focuses on how optimal bidding strategies and revenues change if the auction rules exclude some of the highest bids (and bidders) from the competition.

[4]Refer to http://ec.europa.eu/enterprise/construction/alo/altfin.htm for more details.

In this paper, we take a closer look at an other tool to cope with the problem that is based on large price deviations, i.e. when a submitted bid is considered as outlier when compared to some price (bid) average. Cox et al. (1994) consider a similar problem of cost overruns in procurement contracting with a model that includes both adverse selection and moral hazard and uses first- and second-price auctions to award contracts. Rather than studying the auction schemes, they compare fixed-price and cost-sharing contracts and find that although cost-sharing reduces the seller's expenses, it is inefficient as it induces cost overruns, i.e. negative payoffs. Abbink et al. (2006) study experimentally the so-called Spanish auction format used by the Bank of Spain to sell government bonds. The speciality of that auction is that for winning bids above the average winning bid, bidders are charged the average winning bid. They compare the Spanish auction in a multi-unit common-value environment to the discriminatory and the uniform auctions, and find that the Spanish auction, along with the uniform auction, raise higher revenue. Note that, although it is similar in its spirit to the Japanese format, the Spanish auction does not exclude overly optimistic bidders, it reduces the price they have to pay when winning the auction.

Our benchmark model is a first-price sealed-bid auction (FPSB). We compare its empirical properties to an auction with endogenous price ceiling (EPC) that mimics the procurement auction applied by the Japanese local governments. In both cases participants are required to simultaneously place a single bid for an object whose value is fixed, but unknown. Participants receive noisy signals about this value. In the first-price sealed-bid auction, the bidder with the highest bid receives the object in exchange for which she is required to pay her bid. In the auction with endogenous price ceiling, bids above the average of the highest three bids are excluded, and the winner is the bidder with the highest bid among the remaining bids.

In addition to the theoretical results, we also analyze data from laboratory experiments where we implemented four common-value auctions: two first-price sealed-bid auctions and two endogenous price-ceiling auctions with 5 and 10 participants.[5] Our data confirm the theoretical results that predict a lower probability of suffering a loss by winning the endogenous price-ceiling auction and a smaller revenue. As it is commonly observed in the experimental laboratory, subjects often make systematic mistakes and fall prey of the winner's curse.[6] Our treatments suggest that by introducing an endogenous price-ceiling the seller can also reduce the problem (probability) of the winner's curse.[7]

The article is organized as follows. Section 2 presents the theoretical results, while sections 3 and 4 the experimental ones. Section 5 concludes. The main theoretical results are stated in numbered *predictions*, while the experimental ones as numbered *observations* in the text. Tables appear in the text, while figures are in the appendix.

2 Theoretical results

The theoretical results detailed by Milgrom and Weber (1982) and Wilson (1977) offer a general solution to the bidding problem in common-value auctions (without price ceilings). Nevertheless, numerical examples with computed equilibrium strategies are rare due to the complexity of the calculations involved. In what follows, we present theoretical and experimental results for

[5]Apart from the our goal to study the effect of the endogenous price ceiling on the winner's curse, the use of the experimental method is due to the mathematical complexity of the theoretical model whose solution presented in this paper is based on approximation.

[6]While rational bidders apply a sufficiently high discount when observing the private signal and never suffer of this curse, it is a commonly observed problem in the experimental laboratory. Check for example Dyer et al. (1989) and Kagel and Levin (1986).

[7]The experimental literature has studied price ceilings (and floors) in a competitive environment induced by the double auction, e.g. refer to Isaac and Plott (1981), and Smith and Williams (1981). Differently from our case, they typically focus on non-binding price controls and find that they affect the competitive equilibrium in the lab even if in theory they should not. Gode and Sunder (2004) offer a simple dynamic model with "zero-intelligence" traders to explain the discrepancy.

the endogenous price-ceiling auction in a family of situations that are frequently implemented and studied in the experimental laboratory. Readers who are not interested in the technical details of obtaining the theoretical results may want to skip the next two subsections and follow our discussion from subsection 2.3.

We follow the common-value paradigm and assume that the value of the auctioned object, v, is not observable by bidders. In our information structure, it is assumed to be drawn from the uniform distribution over the $[0; 1]$ interval, and the signals, s, privately received by participants are independently drawn from the uniform distribution over $[0; 2v]$. The corresponding density function are g for the value of the object and f for the signal. This way, signals are unbiased, since their expected value coincides with the true value of the object, i.e. $E(s|v) = v$. However, their variance increases with the value of the object, since $Var(s|v) = \frac{v^2}{3}$, i.e. they are less informative for larger values.[8] These pieces of information, except for the value of the object, v, are assumed to be common knowledge in the auction as is the number of bidders, n.

2.1 Bidding behavior

In order to describe the formal model, we first introduce some additional pieces of notation following Wilson (1977). The equilibrium bidding function in the symmetric Bayes-Nash equilibrium of the auction with n bidders is denoted by $b_n(s)$, while its inverse by $\sigma_n(b)$.[9] Given the true value of the object, v, let $Q_n(s|v)$ be the conditional probability of winning the auction with signal s and by bidding $b_n(s)$. The support of $Q_n(s|v)$ is denoted by $\sum S(v)$, and it is the

[8]This is a special case ($\epsilon = v$) of the general $[v - \epsilon; v + \epsilon]$ specification. The literature, e.g. the seminal work by Kagel and Levin (1986), often chooses a fixed value for ϵ that implies a constant precision, $Var(s|v) = \frac{\epsilon^2}{3}$. We have explored both information structures and haven't found a qualitative difference. This is why we only present here the case that we believe to lie closer to reality.

[9]Since we are looking for a symmetric equilibrium, in which all bidders use the same bidding function, we do not have to include a subindex for bidders in our notation.

$[0; 2v]$ interval for our information structure.

Bidders are assumed to be risk-neutral and to maximize their expected payoffs after receiving the signal.[10] If a bidder is using the bidding function $b^*(s)$ while everybody else is bidding according to $b_n(s)$, her ex-ante expected utility can be written formally as

$$\int_0^1 \int_{\sum S(v)} [v - b^*(s)] \cdot Q_n(\sigma_n(b^*(s))|v) \cdot f(s|v) \cdot g(v) ds dv, \tag{1}$$

where in our uniform model $f(s|v) = \frac{1}{2v}$ whenever $s \in [0; 2v]$, and $g(v) = 1$ if $v \in [0; 1]$. Otherwise, both functions are equal to zero. The first term of the integrand is the net surplus that the winner of the auction enjoys (the value of the object minus her bid), while the others represent the ex-ante probability of winning the auction.[11] The interim expected utility, i.e. the expected utility for an observed and therefore fixed signal s is

$$\int_{\sum S(v)} [v - b^*(s)] \cdot Q_n(\sigma_n(b^*(s))|v) \cdot g(v|s) dv, \tag{2}$$

where Bayes' rule gives $g(v|s) = \frac{f(s|v)g(v)}{\int_{\sum S(v)} f(s|w)g(w)dw}$. Bidders are assumed to maximize this function by choosing the bidding function $b^*(s)$. The first order condition of the bidders' interim

[10]In the symmetric theoretical Bayes-Nash equilibrium of any auction, bidders are assumed to maximize their expected utility by using the same bidding strategy. The solution of this maximization problem, i.e. the equilibrium bidding function, is a fixed point, since given that all the others' are using that particular bidding function, the best an expected-profit maximizer agent can do is to opt for the same bidding function.

[11]$Q_n(s|v)$ is the conditional probability of winning the auction with signal s, while $f(s|v)$ is the conditional probability of receiving a signal s if the value of the object is v. Finally, $g(v)$ represents the probability of the value of the object being equal to v.

expected utility maximization problem yields the following equation:

$$\int_{\sum S(v)} [v - b^*(s)] \cdot Q_n'(\sigma_n(b^*(s))|v) \cdot \sigma_n'(b^*(s)) \cdot g(v|s)dv = \int_{\sum S(v)} Q_n(\sigma_n(b^*(s))|v) \cdot g(v|s)dv. \tag{3}$$

Since $\sigma_n(b_n(s)) = s$, and $\sigma_n'(b_n(s)) = \frac{1}{b_n'(s)}$, and in a symmetric Bayes-Nash equilibrium $b^* = b_n$, we can write the above condition as a differential equation.[12]

$$b_n'(s) \cdot \int_{\sum S(v)} Q_n(s|v) \cdot g(v|s)dv + b_n(s) \cdot \int_{\sum S(v)} Q_n'(s|v) \cdot g(v|s)dv = \int_{\sum S(v)} Q_n'(s|v) \cdot v \cdot g(v|s)dv \tag{5}$$

We assume that participants bid zero (the smallest possible bid) if they observe the smallest possible signal, i.e. $b_n(0) = 0$.[13] Now the solution to the differential equation that represents the equilibrium bidding function can be computed as

$$b_n(s) = e^{F(s)} \cdot \int_0^s e^{-F(t)} \frac{\int_{\sum S(t)} Q_n'(t|v) \cdot v \cdot g(v|t)dv}{\int_{\sum S(t)} Q_n(t|v) \cdot g(v|t)dv} dt, \tag{6}$$

with

$$F(t) = -\int_0^t \frac{\int_{\sum S(x)} Q_n'(x|v) \cdot g(v|x)dv}{\int_{\sum S(x)} Q_n(x|v) \cdot g(v|x)dv} dx. \tag{7}$$

Since the conditional probability of winning, $Q_n(s|v)$, itself depends on the equilibrium bid-

[12]For more details refer to Wilson (1977). For our information structure, this equation takes the form of

$$b_n'(s) \cdot \int_{\frac{s}{2}}^1 Q_n(s|v) \frac{1}{2v} dv + b_n(s) \cdot \int_{\frac{s}{2}}^1 Q_n'(s|v) \frac{1}{2v} dv = \frac{1}{2} \int_{\frac{s}{2}}^1 Q_n'(s|v) dv. \tag{4}$$

[13]Although a zero signal is possible for any value of the object in our information setup, this normalizing assumption seems plausible. Given the risk neutrality of the bidders it is not particularly restrictive and it allows for a unique solution.

ding function, $b_n(s)$, we are facing a difficult mathematical problem: $b_n(s)$ and $Q_n(s|v)$ need to be determined simultaneously. In a standard auction model, such as the first-price sealed-bid auction, this difficulty can be avoided by considering a strictly increasing equilibrium bidding function. If the equilibrium bidding function, $b_n(s)$, of the first-price sealed-bid auction is increasing, then independently of its exact form, $Q_n(s|v)$ will be simply the conditional probability that the bidder's signal is the highest, i.e. $Q_n(s|v) = (s/2v)^{n-1}$.[14] Then, the equilibrium bidding function can be computed according to equations 6 and 7. Given that the resulting bidding function is strictly increasing for $Q_n(s|v) = (s/2v)^{n-1}$, the previous technical assumption is typically justified.

In the endogenous price-ceiling auction, we cannot find the equilibrium $b_n(s)$ and $Q_n(s|v)$ in the same way. If $b_n(s)$ were linear, then $Q_n(s|v)$ would be the conditional probability that the bidder's signal is the highest among those that are not higher than the average of the three highest signals.[15] However, the optimal bidding function of the endogenous price-ceiling auction computed according to equations 6 and 7 is not linear even in our information setup where the value of the auctioned good, v, and the private signal, s, are uniformly distributed. Consequently, the probability of winning, $Q_n(s|v)$, in the endogenous price-ceiling auction cannot be traced back to the probability of receiving the highest signal. Moreover, even if the equilibrium bidding function were linear, the probability of winning the endogenous price-ceiling auction could not be derived in a straightfoward way (due to the existence of the endogenous price ceiling). It constitutes a real mathematical challenge for which we have not found any exact solution. We approximate $b_n(s)$ and $Q_n(s|v)$ in the following way.

[14]Note that if $b_n(s)$ is increasing, then s is the highest signals if and only if the corresponding $b_n(s)$ is the highest bids.

[15]Note that if $b_n(s) = c \cdot s + d$, $c > 0$, then $s \leq (s^1 + s^2 + s^3)/3 \Leftrightarrow b_n(s) \leq (b_n(s^1) + b_n(s^2) + b_n(s^3))/3$, where s^1, s^2, s^3 are the three highest signals.

First, although $b_n(s)$ is not linear, we interpret $Q_n(s|v)$ as the conditional probability of receiving the winning signal, i.e. the highest signal among those that are not higher than the average of the three highest signals.[16] Second, instead of deriving the exact functional form of $Q_n(s|v)$, we approximate it by a Beta distribution with parameters α and β. Third, we compute $b_n(s)$ using that Beta distribution as a proxy for $Q_n(s|v)$. Four, in order to evaluate the goodness of the approximation, we study again the empirical form of $Q_n(s|v)$ computed from the $b_n(s)$ by simulation and approximate it by Beta distribution. Finally, we compare the α and β parameters of the Beta distribution estimated in the second and the fourth steps. We consider that our method is justified if this comparison renders small differences between the estimated parameters. In what follows we present the detailed procedure to derive $b_n(s)$ and $Q_n(s|v)$.

Our choice of the Beta distribution is based on two arguments. On one hand, the Beta distribution with its two parameters is flexible enough to approximate asymmetric distributions. On the other hand, the kth order statistics (i.e., the kth largest of $n-1$ draws) of the uniform distribution follows the Beta distribution with parameters $\alpha = k$ and $\beta = n - k$. Therefore, while the Beta distribution offers a good approximation in the endogenous price-ceiling auction, it also represents the exact mathematical solution for auctions without price ceiling or with an exogenous price ceiling (e.g. the first-price sealed-bid auction). Since the Beta distribution is usually defined over the $[0; 1]$ interval, we use normalized signals defined as $\frac{s}{2v}$. When we say that the winning signal follows a Beta distribution given the value v, we refer to these normalized signals.

As for our particular endogenous price-ceiling auction, the use of the Beta distribution as a proxy is justified by a Monte Carlo experiment. Our Monte Carlo experiment involved 1 million

[16]This simplifying assumption is less severe for situations with a large number of bidders. Our numerical results show that as n increases, the equilibrium bidding function loses curvature.

independent cases. In each of these cases, given the number of bidders, n, we generated n independent draws from the uniform distribution over the $[0; 1]$ interval and selected the number that was not larger than the average of the three largest draws. We used the empirical distribution of these numbers to estimate the two parameters of the Beta distribution.[17] The upper part of table 1 contains the parameters of the Beta distribution that describes the distribution of the winning signal for 5, 10 and 20 bidders.[18] Although the Beta distribution does not produce a perfect fit, it closely follows the empirical distribution of the winning signal and captures its skewed shape.

Once the equilibrium bidding function is computed for the endogenous price-ceiling auction, it can be used to check the goodness of the above described approximation. Let us anticipate the equilibrium results and check here the precision of our approximation. We simulated the distribution of the winning bid for 10 possible values of the object, v, (between 0.1 and 1 with a step-length of 0.1) for the three studied group sizes. Then we re-estimated the parameters of the Beta distribution and report a summary of the results in the lower part of table 1. Since the estimates vary little, we only include the maximum and the minimum estimates in the table. The results suggest that the chosen approximation is adequate, especially for lower values of the object and for larger number of bidders.

Given the above simplifications in the endogenous prince-ceiling auction model, the equilibrium bidding functions can be computed. In other words, we use $Q_n(s|v) = B(\frac{s-(v-\epsilon)}{2\epsilon}, \alpha, \beta)$ in equations 6 and 7, where B is the cumulative distribution function of the Beta distribution.

[17]The two parameters of the Beta distribution were estimated using the method of moments, i.e. the following formula: $\hat{\alpha} = \bar{x}(\frac{\bar{x}(1-\bar{x})}{v} - 1)$ and $\hat{\beta} = (1-\bar{x})(\frac{\bar{x}(1-\bar{x})}{v} - 1)$, where $\bar{x}$ is the sample mean and v is the sample variance.

[18]In order to check the performance of the applied Monte Carlo algorithm we computed the empirical distribution of the winning bid for the other three auction formats, too, and compared them to the theoretical results. Our simulation results match the theoretical ones with a precision of at least 1 decimal.

Table 1: Estimated and re-estimated parameters, (α, β), of the Beta distribution that describe the distribution of the normalized winning signal given the value of the object. FPSB: first-price sealed-bid auction; EPC: endogenous price-ceiling auction. *Exact results. **Results based on Monte Carlo experiments.

number of bidders	5		10		20	
parameter	α	β	α	β	α	β
	parameters for equilibrium bids					
FPSB*	4.0	1.0	9.0	1.0	19.0	1.0
EPC**	2.4	2.9	7.5	2.8	17.8	2.8
	re-estimated parameters (EPC**)					
minimum	2.2	2.9	7.4	2.8	17.7	2.8
maximum	2.4	3.0	7.5	3.0	17.9	3.0

We present the theoretical results in the form of tabulated values based on numerical integrals in table 2. Since answering our main question related to the probability of suffering a monetary loss by winning the auction makes computer simulation and numerical methods unavoidable, we believe that this choice does not limit the practical interpretations of our results. In all computations we used the tabulated equilibrium bidding functions and applied linear interpolation. The equilibrium bidding functions gain slope and lose curvature as the number of bidders increases. The opposite pattern appears as the government changes the auction format and introduces protection by an endogenous price ceiling. For low signals, more protection implies more aggressive bidding behavior, but the pattern is the opposite for larger signals. Since the equilibrium bidding functions are strictly increasing, a higher signal will always induce more optimism, i.e. a higher bid. While the first-price sealed-bid auction assigns the object to the most optimistic bidder, the endogenous price-ceiling auction assigns it to the second or third most optimistic one.

Table 2: Tabulated equilibrium bidding functions. FPSB: first-price sealed-bid auction; EPC: endogenous price-ceiling auction.

auction	FPSB			EPC				FPSB			EPC		
number of bidders	5	10	20	5	10	20		5	10	20	5	10	20
signal	bid						signal	bid					
0.1	0.05	0.05	0.05	0.08	0.05	0.05	1.1	0.55	0.56	0.55	0.49	0.57	0.56
0.2	0.11	0.10	0.10	0.15	0.11	0.10	1.2	0.60	0.61	0.60	0.51	0.61	0.61
0.3	0.16	0.15	0.15	0.21	0.16	0.15	1.3	0.64	0.65	0.65	0.52	0.65	0.66
0.4	0.21	0.20	0.20	0.27	0.21	0.20	1.4	0.68	0.70	0.70	0.53	0.68	0.71
0.5	0.26	0.25	0.25	0.31	0.27	0.25	1.5	0.71	0.75	0.75	0.54	0.71	0.75
0.6	0.32	0.30	0.30	0.36	0.32	0.30	1.6	0.75	0.79	0.80	0.55	0.73	0.79
0.7	0.37	0.35	0.35	0.39	0.37	0.36	1.7	0.78	0.83	0.85	0.55	0.75	0.83
0.8	0.42	0.40	0.40	0.42	0.43	0.41	1.8	0.81	0.87	0.89	0.55	0.76	0.86
0.9	0.46	0.46	0.45	0.45	0.48	0.46	1.9	0.84	0.90	0.93	0.55	0.77	0.87
1.0	0.51	0.51	0.50	0.47	0.52	0.51	2.0	0.87	0.93	0.97	0.55	0.77	0.88

2.2 Endogenous price-ceiling auctions and the Japanese rules

Although the rules of our endogenous price-ceiling auction are inspired by the rules of the procurement auctions used by several Japanese local governments, they do not exactly coincide. The local governments usually exclude bidders who bid a cost below some k times the average of some of the highest bids, where k is typically less than 1. In our setup, given that we consider prices instead of costs, this rule can be translated into eliminating all those who bid above c times the average of the three highest bids, with $c \geq 1$. If c is large enough, the endogenous price-ceiling loses its importance and the distribution coincides with the distribution of the winning signal in the first-price sealed-bid auction. Although the changes we observe in the empirical distributions seem to be smooth, with the increase of c the densities tend to lose their bell shapes that makes the Beta approximation less accurate. The intuition behind the double peaks that appear in the histograms is that very large bids increase considerably the average of the three largest bids. When it is multiplied by a fixed c, for sufficiently large bids the endogenous price-ceiling stops being a binding constraint as it grows above the highest bid. Therefore the corresponding graphs are some combinations of two distributions: the one that belongs to our endogenous price-ceiling auction with $c = 1$, and the one that corresponds to the first-price sealed-bid auction. The complexity of this case made us leave the auction formats with $c > 1$ for further research and present the simplest, yet novel and interesting $c = 1$ case here.

2.3 Negative payoffs and the winner's curse

Since bidders only receive a noisy signal about the value of the auctioned object, in some occasions the winner, who is always the most optimistic (admitted) bidder, has to pay more than the real value of the object. Rational players apply a discount to take into consideration this informational problem. Nevertheless, negative payoffs occur even if players play according to the Bayes-Nash equilibrium strategies, as for a given signal extremely low values (for the value of the auctioned object) do appear with a positive, although relatively small, probability. The winner's curse occurs if players fail to correct their bids correctly, and bid above the expected value of the objects conditional on that the signal they hold is the winning one. Although the winner's curse does not occur in equilibrium, both analyzed auction formats are prone to negative winning payoffs.

Prediction 1. *The probability of negative payoff from winning the auction decreases with the introduction of a price ceiling, and with the number of bidders.*

Table 3 shows the probability of a negative winning payoff computed by a Monte Carlo experiment with 1 million draws. Although negative winning payoffs occur in all cases, their probability decreases as the number of bidders increases. More importantly, the results show that the endogenous price ceiling in fact reduces the probability of negative profits.

Table 3: The probability of obtaining a loss by winning the auction, Pr(loss), ex-ante expected utility, E(utility), and ex-ante expected revenue E(revenue). FPSB: first-price sealed-bid auction; EPC: endogenous price-ceiling auction.

auction	FPSB			EPC		
number of bidders	5	10	20	5	10	20
Pr(loss)	11.9%	7.3%	4.1%	8.3%	1.9%	0.3%
E(utility)	0.0175	0.0044	0.0012	0.0427	0.0119	0.0032
E(revenue)	0.4130	0.4535	0.4762	0.2876	0.3810	0.4361

2.4 Expected payoffs and revenue

Prediction 2. *The expected payoff of bidders increases with the introduction of a price ceiling, and decreases with the number of bidders.*

One expects that reducing the probability of suffering a loss by winning the auction increases bidders' expected payoff. We used equations 1 and 2 to confirm this hypothesis and tabulated the ex-ante expected payoffs in table 3. The numbers show that more competition reduces expected utility, while the implicit protection makes it to increase.

Prediction 3. *The expected revenue of the seller decreases with the introduction of a price ceiling, and increases with the number of bidders.*

Similarly to expected payoffs, we computed ex ante and interim expected revenues for the seller. Table 3 contains intuitive numerical results according to which more competition increases revenues, while more protection decreases it. Similar results hold for interim expected payoffs and interim expected revenue.

3 Experimental design

We conducted four experimental sessions to check the empirical properties of the analyzed auction formats. For each session we invited 20 subjects to a computer laboratory at the Institute of Social and Economic Research at Osaka University who participated in a 90-minute long experiment. We decided to adopt the instructions used by Kagel and Levin (1986) to make our result comparable with others from the literature. In order to avoid fluctuation in the number of participants, players received a monetary endowment in each period before learning their private signals and posing their bids in the auction. This feature made bankruptcy and a reduction in the number of active bidders impossible. This is in line with our theoretical model that describes a one-shot interaction between people, excluding any type of dynamic strategic considerations.

We used computers and zTree (Fischbacher, 2007) in all sessions. Table 4 offers a session summary showing the most important characteristics of the experimental design. In all cases the value of the object was generated by the uniform distribution over the $[0; 1000]$ interval, making experimental monetary units (EMU) close to real monetary units (Japanese Yen). Subjects received random draw—rounded to the closest integer—from the uniform distribution over the $[0; 2v]$ interval as private signals and were asked to bid. After the bidding we showed them all the bids, identified the winner and computed the payoffs. We used the same payment scheme (833 JPY show-up fee, and the 10 EMU = 1 JPY conversion rule) in all treatments.

Table 4: Experimental session summary. Number of practice rounds between parenthesis.

session	auction	rounds	group size	participants	net earnings (JPY)		
					min.	average	max.
1	FPSB	(3) + 20	5	20	1938	2019	2096
2	EPC	(3) + 20	5	20	1979	2038	2136
3	FPSB	(3) + 20	10	20	1797	2021	1987
4	EPC	(3) + 20	10	20	1937	2054	1999

4 Empirical results

Theory predicts that the bidding functions are strictly increasing in the private signal, therefore the winner of a first-price sealed-bid auction should be the person with the most optimistic estimate. According to our data, this is the case in 58% of the experimental markets in our FPSB session with 5 bidders, and 50% with 10.[19] Table 5 shows the distribution of the rank of the winner's signal. In the session with groups of 5 bidders, the rules of the endogenous price-ceiling auction managed to shift the distribution and to make that the person with the second highest bid become winner in 40% of the cases. Curiously, the empirical distributions in the sessions with 10 bidders are statistically identical for the two auction formats.[20]

Observation 1. *The expected payoff of bidders increases with the introduction of a price ceiling, and decreases with the number of bidders.*

Participants' net profits are the best numbers to give a quick overview of the empirical performance of the auctions. With 5 bidders, in the FPSB treatment their sum amounted to 953 EMU per group after the 20th period, while in the EPC treatment this number was equal to 1950 EMU. With 10 bidders, the fiercer competition reduced these numbers considerably and turned

[19] This results is comparable to the 42%-89% interval that includes the same proportion in the treatments reported by Kagel and Levin (1986).

[20] The statistical comparisons described in this section are based on one-sided parametric tests. The *usual* qualifier refers to a significance level of at most 15%.

Table 5: Empirical distribution of the auction winners according to their signal. Number of bidders between parenthesis.

auction	FPSB		EPC	
number of bidders	5	10	5	10
winning signal's rank	% of cases			
1	58%	50%	25%	50%
2	20%	28%	40%	30%
3	13%	15%	23%	10%
4	10%	3%	4%	3%
5	0%	5%	9%	8%

the average net profit into average net loss. The sum of net profit was -1314 EMU per group on average in the FPSB session, and -86 EMU per group in the EPC session.

Observation 2. *The probability of a negative winning payoff does not increase with the introduction of a price ceiling, and it increases with the number of bidders.*

As for the number of winners who achieved a net loss instead of a net gain, figure 2 plots the accumulated number of winners over the session who bid above the real value of the object. We estimate the probability of suffering a monetary loss by winning the auction using the cumulative data, and make a statistical comparison between the two auction formats. We find that the difference is either insignificant or shows that the endogenous price-ceiling auction implies a smaller probability independently from the number of bidders.

If we take all 20 round into account, the final point estimate for the probability of suffering a monetary loss by winning the auction with 5 bidders is 30% for both the first-price sealed-bid and endogenous price-ceiling auctions. With 10 bidders these estimates are much higher: 63% for the first-price sealed-bid and 48% for the endogenous price-ceiling auction. It is important to point out that all these numbers are higher than the expected probabilities for all usual significance levels. Moreover, it seems that the number of bidders increases the probability of suffering a loss in the laboratory instead of reducing it as suggested by the theoretical results.

Observation 3. *The probability of the winner's curse decreases with the introduction of a price ceiling, and it increases with the number of bidders.*

Systematic overbidding, i.e. winner's curse, and negative payoffs did occur in many different cases, however both problems typically appeared for small signals. Figure 1 shows the the empirical and the theoretical bidding functions and also includes the expected value of the object given a specific winning signal.[21] We can talk about the winner's curse when bids shoot over this expected value. According to our data this systematic mistake appears for signals between 0 and 300 in the first-price sealed-bid auction, and for signals below 100 in the endogenous price-ceiling auction if there are 5 bidders. More competition makes the situation worse for winners as the area of the winner's curse expands until signals around 600 in the first-price sealed-bid, and below 200 in the endogenous price-ceiling auction.[22] In the FPSB sessions the empirical bidding function practically coincides with the theoretical one for signals around 500 and above. In case of the endogenous price-ceiling auction, participants bid more aggressively than expected for especially small signals (below 300) and for especially large ones (above 1100). Although the winner's curse does not constitute a problem in theory, our theoretical results plotted in figure 1 suggest that participants in the EPC auction are less prone to suffer from it. The separation between the two grey curves, i.e. the equilibrium bidding function and

[21]In order to present a relatively smooth empirical bidding function we created 21 grid point over the $[0; 200]$ interval for signals using 100 EMU as distance and computed the average bid for the rounded signals.

[22]Although the estimated bidding function appears to stay above the expected value of the object for larger signals, too, the region reported in the text is characterized by statistically significant differences.

the expected value of the object (given that the observed signal is the winning one), is larger in case of the EPC auction than in case of the FPSB auction for a fixed number of bidders.

Theoretically, bidders' expected payoff is an increasing non-negative function of their signal. Our experimental data is partially in line with this result. It is the winner's curse that makes expected payoffs and the winner's payoff tend to be negative for small signals.

Observation 4. *The average revenue of the seller does not increase with the introduction of a price ceiling, and it does not decrease with the number of bidders.*

Both the theoretical and the empirical results suggest that the endogenous price-ceiling auction offers more protection and therefore a better situation for bidders for any given number of competitors. However this protection comes at a price as predicted by the drop in the revenue raised by the auction. Figure 3 shows the average revenue given the value of the auctioned object. The relatively small number of observations makes the picture incomplete and statistical comparison difficult. Nevertheless, our data confirms that the endogenous price-ceiling auction never achieves a higher revenue that the first-price sealed-bid auction for a given value of the object.[23] Similarly, the seller's revenue tend to increase with the competition.

5 Conclusions

We have presented theoretical and empirical results related to novel auction formats whose main purpose is to protect bidders from a financial loss by excluding the overoptimistic ones. Ours is the first step to systematically analyze and understand how this exclusion technique can reduce the probability of the winner's curse and/or suffering a monetary loss by winning the

[23]The statistical tests, where possible to complete, show either insignificant differences or the superiority of the first-price sealed-bid auction in raising revenue.

auction. Our laboratory data confirms that bidders indeed tend to be too optimistic and make systematic mistakes (as compared to theoretical results). Therefore the use of the proposed auction mechanisms by several authorities, like the local governments in Japan or the European Commission, is recommended to cope with the problem. Sellers, on the other hand, should be aware of the cost of this protection, since excluding the overoptimistic bidders reduces the revenue raised by the auction both in theory and in the experimental laboratory.

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Figures

Figure 1: Theoretical and empirical bidding functions, and the expected value of the object given that the signal is the winning one.

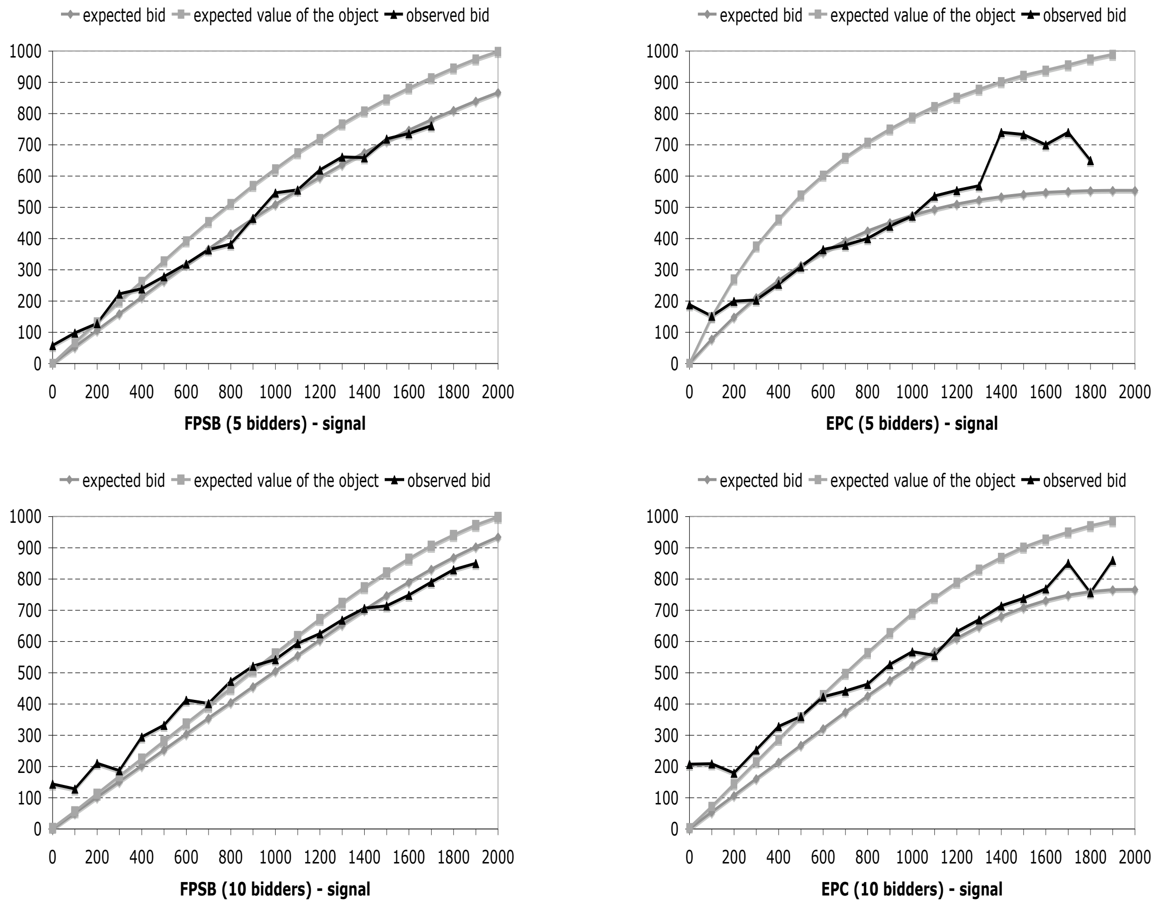


Figure 2: Accumulated number of negative winning payoffs over sessions.

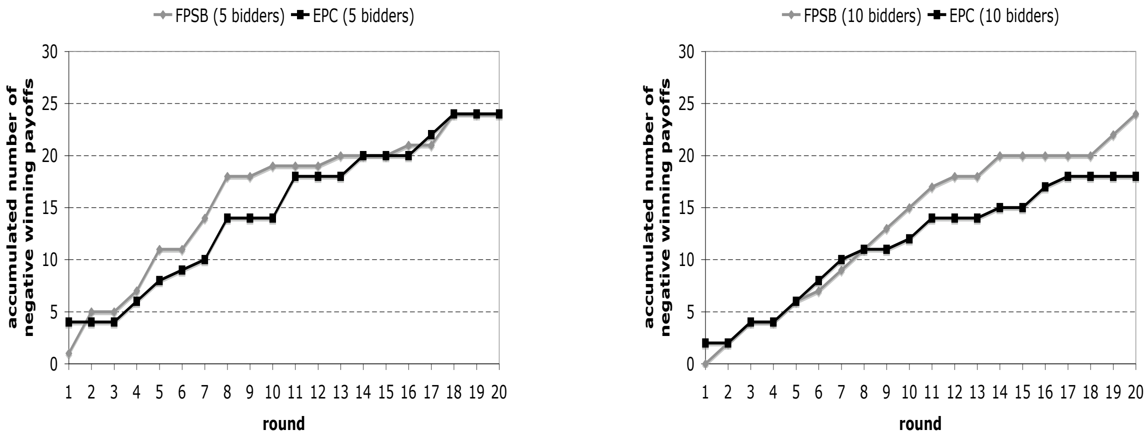
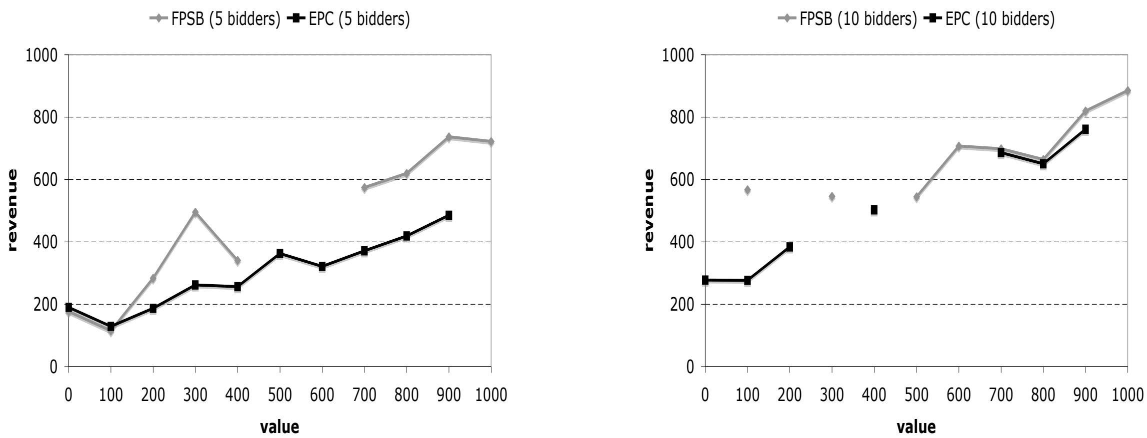


Figure 3: Revenue raised by the auctions given the value of the object



Supplementary materials

INSTRUCTIONS (for EPC)

This is an experiment about market decision making. The instructions are simple, and if you follow them carefully and make good decisions you may earn a CONSIDERABLE AMOUNT OF MONEY which will be PAID TO YOU IN CASH at the end of the experiment.

1. In this experiment we will create a market in which you will act as buyers of a fictitious commodity in a sequence of trading periods. A single unit of the commodity will be auctioned off in each trading period. There will be 3 trial periods and 20 paying periods that determine the amount of money that you will receive by the end of the experiment.

2. Your task is to submit written bids for the commodity in competition with other buyers. The precise value of the commodity at the time you make your bids will be unknown to you. Instead, each of you will receive information as to the value of the item which you should find useful in determining your bid. The process of determining the value of the commodity and the information you will receive will be described in Sections 6 and 7 below.

3. The highest bidder among all bidders whose bids are lower than the price ceiling gets the item and makes a profit equal to the difference between the value of the commodity and the amount they bid. The price ceiling is computed as the average of the 3 highest bids. That is,

(VALUE OF ITEM) – (HIGHEST BID AMONG ALL BIDS LOWER THAN THE PRICE CEILING) = PROFITS

for the highest bidder among all bidders whose bids are lower than the price ceiling. If this difference is negative, it represents a loss.

If you do not make the highest bid among all bids lower than the price ceiling on the item, you will earn zero profits. In this case, you neither gain nor lose money from bidding on the item.

4. You will be given 1,000 points of experimental cash at the beginning of each period. Any profit earned by you in each period will be added to these initial points, and any losses incurred will be subtracted from these initial points. The total profit of these transactions will be calculated and paid to you in CASH under the conversion rate of 1

point equal to 0.1yen at the end of the experiment. Finally, your final earnings will be calculated as follows:

$$\text{EARNINGS} = 0.1\times \{ \text{(TOTAL PROFITS)} - \text{(TOTAL LOSSES)} + \text{(20 PERIODS} \times \text{1,000 POINTS)} \}$$

5. At the beginning of each period groups of 5 participants will be formed by the computer in a random way. It means that you typically play with 4 different participants in every period. During each trading period you will be bidding in a market in which ***all*** the other participants are also bidding. You are asked in each period is to choose your bid, write it in the purple cell in the center of the screen, and click OK within 3 minutes. After all participants click OK, all bids in your group will be displayed on your screen. Then the computer will display the price ceiling, the highest value among all bids lower than the price ceiling, the value of the item, and your profit or loss. Once you reconfirm them, please click OK.

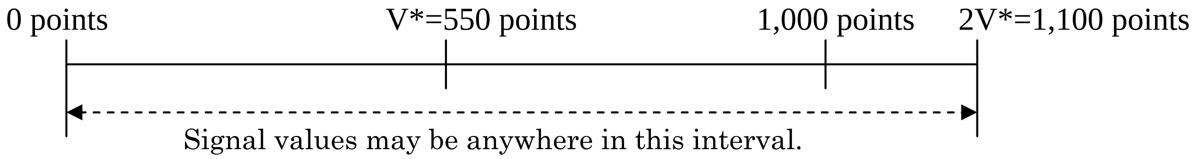
6. The value of the auctioned commodity (V*) will be assigned randomly and will lie between 0 points and 1,000 points inclusively. For each auction, ***any value*** within this interval has an ***equally likely chance*** of being drawn. The value of the item can never be less than 0 points or more than 1,000 points. The V* values are determined randomly and independently from auction to auction. As such a high V* in one period tells you nothing about the likely value in the next period whether it will be high or low. It doesn't even preclude drawing the same V* value in later periods.

7. Private Information Signals:

Although you do not know the precise value of the item in any particular trading period, you will receive a private information signal that is related to the V* value of the item in each auction. This signal is an integer between 0 and twice the V* value of the object (limits included). ***Any*** value within this interval has an ***equally likely*** chance of being drawn and being assigned to one of you as your private information signal.

For example, suppose that the value of the auctioned item is 550 points. Then each of you will receive a private information signal which will consist of a randomly drawn number that will be between 0 points and 2×550 =1,100 points. Any number in this interval has an equally likely chance of being drawn.

The line diagram below shows what's going on in this example.



The data below show the entire set of signals the computer generated for our sample. (Note we've ordered these signal values from lowest to highest.)

V* = 550 points. Signal values: 964 points,
914 points,
432 points
279 points
22 points

You will note that some signal values were above the value of the auctioned item, and some were below the value of the item. Over a sufficiently long series of auctions, the differences between your private information signal and the value of the item will average out to zero (or very close to it). For any given auction, however, your private information signal can be above or below the value of the item. That's the nature of the random selection process generating the signals.

8. Your signal values are strictly private information and are not to be revealed to anyone else during the whole session. Finally we will post all of the signal values drawn along with the bids.

9. No one may bid less than 0 points for the item. Any integral bid is acceptable. In case of ties for the highest bid among all bids lower than the price ceiling, computer will determine randomly who will earn the item.

10. You are not to reveal your bids, or profits, nor are you to speak to any other subject while the experiment is in progress.

Let's summarize the main points: (1) Highest bidder among all bidders whose bids are lower than the price ceiling earns the item and earns a profit = value of item –highest bid price lower than the price ceiling. The price ceiling is computed as the average of the 3 highest bids. (2) Profits in each period will be added to your initial experimental cash of 1,000 points, losses subtracted from it. Your total earnings at the end of experiment will be paid in cash. (3) Your private information signal is randomly drawn from the interval between 0 points and 2V*. (4) The value of the item will always be between 0 points and 1,000 points.

Are there any questions?

INSTRUCTIONS (for FPSB)

This is an experiment about market decision making. The instructions are simple, and if you follow them carefully and make good decisions you may earn a CONSIDERABLE AMOUNT OF MONEY which will be PAID TO YOU IN CASH at the end of the experiment.

1. In this experiment we will create a market in which you will act as buyers of a fictitious commodity in a sequence of trading periods. A single unit of the commodity will be auctioned off in each trading period. There will be 3 trial periods and 30 paying periods that determine the amount of money that you will receive by the end of the experiment.

2. Your task is to submit written bids for the commodity in competition with other buyers. The precise value of the commodity at the time you make your bids will be unknown to you. Instead, each of you will receive information as to the value of the item which you should find useful in determining your bid. The process of determining the value of the commodity and the information you will receive will be described in Sections 6 and 7 below.

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(VALUE OF ITEM) – (HIGHEST BID) = PROFITS

for the highest bidder. If this difference is negative, it represents a loss.

If you do not make the highest bid on the item, you will earn zero profits. In this case, you neither gain nor lose money from bidding on the item.

4. You will be given a starting capital credit balance of 1,500 yen. Any profit earned by you in the experiment will be added to this sum, and any losses incurred will be subtracted from this sum. The net balance of these transactions will be calculated and paid to you in CASH at the end of the experiment.

The starting capital credit balance, and whatever subsequent profits you earn, permits you to suffer losses in one auction to be recouped in part or in total in later auctions. You ***are*** permitted to bid in excess of your capital credit balance in any given period.

5. At the beginning of each period groups of 5 participants will be formed by the computer in a random way. It means that you typically play with 4 different

participants in every period. During each trading period you will be bidding in a market in which ***all*** the other participants are also bidding. You are asked in each period is to choose your bid, write it in the purple cell in the center of the screen, and click OK within 1 minutes. After all participants click OK, all bids in your group will be displayed on your screen. Then the computer will display the highest bid, the value of the item, and your profit or loss. Once you reconfirm them, please click OK.

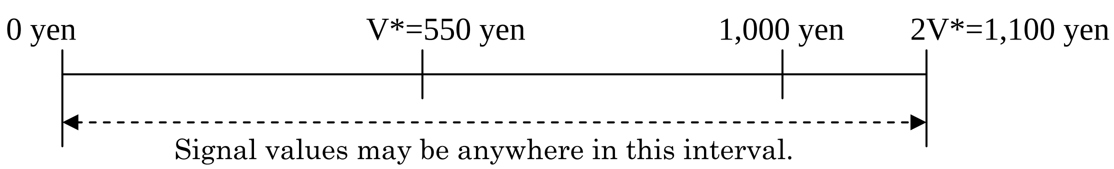
6. The value of the auctioned commodity (V*) will be assigned randomly and will lie between 0 yen and 1,000 yen inclusively. For each auction, ***any value*** within this interval has an ***equally likely chance*** of being drawn. The value of the item can never be less than 0 yen or more than 1,000 yen. The V* values are determined randomly and independently from auction to auction. As such a high V* in one period tells you nothing about the likely value in the next period whether it will be high or low. It doesn't even preclude drawing the same V* value in later periods.

7. Private Information Signals:

Although you do not know the precise value of the item in any particular trading period, you will receive a private information signal that is related to the V* value of the item in each auction. This signal is an integer between 0 and twice the V* value of the object (limits included). ***Any*** value within this interval has an ***equally likely*** chance of being drawn and being assigned to one of you as your private information signal.

For example, suppose that the value of the auctioned item is 550 yen. Then each of you will receive a private information signal which will consist of a randomly drawn number that will be between 0 yen and 2×550 =1,100 yen. Any number in this interval has an equally likely chance of being drawn.

The line diagram below shows what's going on in this example.



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432 yen

279 yen
22 yen

You will note that some signal values were above the value of the auctioned item, and some were below the value of the item. Over a sufficiently long series of auctions, the differences between your private information signal and the value of the item will average out to zero (or very close to it). For any given auction, however, your private information signal can be above or below the value of the item. That's the nature of the random selection process generating the signals.

8. Your signal values are strictly private information and are not to be revealed to anyone else during the whole session.

9. No one may bid less than 0 yen for the item. Any integral bid is acceptable. In case of ties for the highest bid, computer will determine randomly who will earn the item.

10. You are not to reveal your bids, or profits, nor are you to speak to any other subject while the experiment is in progress.

11. As promised, everyone will receive 750 yen irrespective of their earnings for participating in the experiment. Your net balance at the end of the experiment drop to zero (or less), you will receive only 750 yen for participating in the experiment. You will not pay your own money to the experimenter if your net balance at the end of the experiment less than zero.

Let's summarize the main points: (1) Highest bidder earns the item and earns a profit = value of item –highest bid price. (2) Profits will be added to your starting balance of 1,500 yen, losses subtracted from it. Your balance at the end of experiment will be paid in cash. If balance turns negative you're no longer allowed to bid. (3) Your private information signal is randomly drawn from the interval between 0 yen and 2 V*. (4) The value of the item will always be between 0 yen and 1,000 yen

Are there any questions?