Experimental Economics manuscript No.
(will be inserted by the editor)

Valuation Structure in First-Price and Least-Revenue Auctions: An Experimental Investigation

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Received: date / Accepted: date

Abstract In many auctions the valuation structure involves both private and common value elements. Existing experimental evidence (e.g. Goeree and Offerman (2002)) demonstrates that first-price auctions with this valuation structure tend to be inefficient, and inexperienced subjects tend to bid naively and fall prey to the winner's curse. In this paper, we compare first-price auctions with an alternative auction mechanism: the least-revenue auction. This auction mechanism shifts the risk regarding the common value of the good to the auctioneer. Such a shift is desirable when ex post negative payoffs for the winning bidder results in unfulfilled contracts, as is often the case in infrastructure concessions contracts. We directly these two auction formats within two valuation structures: 1) pure common value and 2) common value with a private cost. We find that, relative to first-price auctions, the winner's curse is significantly less prevalent in least-revenue auctions regardless of valuation structure. As a

Financial support from Gettysburg College and the Facultad de Ciencias Económicas at Universidad Francisco Marroquín is gratefully acknowledged. Thanks to Pedro Monzón for outstanding research assistance. We have benefited from comments and suggestions from participants in seminars at Chapman University, Universidad Francisco Marroquín, George Mason University, the Alhambra Experimental Workshop, the 2010 North-American ESA conference in Tuscon Arizona, the Eastern Economic Association 37th annual conference in New York City and the Sydney Experimental Seminar at UNSW.

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result revenue in first-price auctions is higher than in least-revenue auctions, contrary to theory. Further, when there are private and common value components, least-revenue auctions are significantly more efficient than first-price auctions.

Keywords Auctions · Winner's curse · Allocative Efficiency · Bidding
JEL Classification D44 C72

1 Introduction

For reasons of tractability, theorists typically make strong assumptions about the valuation structure of auctions. In particular, each bidder typically privately observes a signal, and her valuation of the available object is assumed to be a function of her signal, and possibly other unobserved signals. This basic framework is used to model auctions with a variety of valuation structures. In these models, the symmetric equilibrium bid function maps a bidder's one dimensional signal into bids.

However, in many auctions a bidder's valuation may have both private and common value components. That is, a bidder's valuation may be multidimensional. Auctions for infrastructure concession contracts can be modeled as having both private and common value components. The winner of such an auction receives the revenue generated by the contract (e.g. tolls from highway concessions, energy transmission tolls over a high-power grid, etc.) which has a common value Bain and Polakovic (2005); Flyvbjerg et al (2005). However, the winning bidder also incurs the cost of fulfilling the contract (e.g. building the highway, constructing the infrastructure for power lines, etc.). If bidders' costs of providing the infrastructure differ, these costs may represent an independent private value component of the valuation structure.

In auctions with common value components, it is well known that bidders are prone to the winner's curse. That is, bidders bid such that they guarantee themselves negative payoffs in expectation.[1] In this paper we experimentally consider auctions with an uncertain common value and private costs, and compare them to auctions with an uncertain common value and a common cost which is common knowledge. We compare these two valuation structures in a

[1] In the context of infrastructure concession contracts, the winner's curse might be used as a justification or as a reason to renegotiate the contract. Guasch (2004) reports that over 50% of concession contracts for transportation infrastructure are renegotiated. Athias and Nuñez (2008) find evidence that is consistent with bidders displaying more strategically opportunistic behavior in auctions for toll-road concessions in weaker institutional settings, pressumably due to a higher probability of contract renegotiation. The intuition is that when auctioneers face commitment and contract enforcement problems, winning bidders find it easier to say (truthfully or not) that they have fallen prey to the winner's curse and renegotiate better terms. In this sense, it is plausible that removing the common value risk to bidders might reduce the justification to renegotiate due to low realized values of concession contracts.

standard first-price sealed-bid auction, and in an alternative auction format, the Least-Revenue Auction (LRA).[2]

In an LRA, bidders simultaneously make sealed-bid offers which consist of the minimum amount (from the common value of the good) the bidder is willing to accept upon winning the auction.[3] Thus, the winner implicitly pays the difference between the realized common-value of the good and the offer. This mechanism renders private information bidders may hold regarding the common value of the good strategically irrelevant. Thus, in a purely common-value auction equilibrium bids are not a function of the private common-value signals that the bidders observe prior to placing their bids. The game is, in effect, a game of complete information. Similarly, in auctions with private and common values, the equilibrium bid function of an LRA maps bidders' private costs into bids, ignoring privately observed estimates of the common value. The LRA mechanism, in effect, transforms an auction with private and common values into an auction with purely private values.

It is important to note that in an LRA, uncertainty regarding the common value of the good is borne by the auctioneer rather than by the bidders. An LRA represents a contract in which the price the winning bidder pays is contingent on the realized value of the good; the auctioneer guarantees the winning bidder that she will earn her bid (provided the winning bid does not exceed the common value of the good). This transfer of risk may be desirable, and provides the original motivation for LRAs: Engel et al (1997, 2001) first proposed the Least Present Value of Revenue Auction (LPVRA), in which bidders submit the smallest present value of revenue they would require for a contract in which they build, operate and then transfer a highway to the government at the conclusion of the contract term. In an LPVRA, the duration of a contract is contingent on the stream of revenue which is generated by tolls collected on the highway. In particular, the contract lasts until the winning bidder obtains the present value (at a pre-determined discount rate) of the toll revenue that she bid. This flexible-term contract shifts most of the risk resulting from uncertain traffic patterns to the government, relative to a standard fixed-term contract. Engel et al (1997) estimates that the value of switching to LPVR auctions is about 33% of the value of the infrastructure investment. More generally, by eliminating ex ante uncertainty regarding payoffs conditional on winning the auction LRAs and LPVRAs reduce the ability of winners to attempt to renegotiate the contract on the grounds that the value of the good is less than expected. That is, the winning bidder is no longer able to claim that she fell victim to the winner's curse, and needs to renegotiate in order to fulfill the contract.

[2] This auction format follows the spirit fo the Least Present Value of Revenue Auction proposed in Engel et al (1997, 2001). We adopt the name least-revenue auction to reflect this similarity. However, we will, for resons of comparability, use the term revenue to refer to auctioneer's payoff.

[3] To put it in the context of Engel et al (2001), the future cash flows of toll revenue are a common unknown value, and bids consist of present value of toll revenue required by bidding firms.

It is important to note that in both the LRA and the LPVRA, the winning bidder does not have an incentive to maintain the value of the good because winning the auction guarantees the winning bidder her bid, and no more. That is, the benefits of maintaining or improving the value of the good ex post do not accrue to her. Monitoring the ex post behavior of the winning bidder, or imposing an enforceable contract, would be necessary to mitigate this problem. If neither of these are possible, LRAs and LPVRAs may not be ideal.

Our work differs from that of Engel et al (2001) in at least two important ways. First, their focus is on optimal risk-sharing contracts and not on bidding behavior or auction performance. Second, we allow for the possibility of private costs, and we analyze the common value of the good as the realization of a random variable in a single period rather than as a stream of revenue over time (with a high or low realized value in each period). However, the underlying intuition is the same. As such, the main contribution of this paper is to formally analyze and experimentally test bidding behavior and auction performance in an enviroment consistent with the motivation underlying LPVRAs. Although Chile has implemented LPVRAs on more than one occassion Vassallo (2006), to the best of our knowledge this is the first formal and empirical analysis of the allocative properties of this auction format and bidding behavior within it.

In addition, our paper contributes to the small but growing literature regarding auctions with private and common values Goeree and Offerman (2002); Boone et al (2009). The theoretical analysis of such auctions begins with Goeree and Offerman (2003). We rely on this analysis predictions in our experimental design. Goeree and Offerman (2002) (henceforth GO) present experimental evidence that first-price auctions with private and common values tend to be inefficient. The intuition behind this inefficiency is that subjects have to combine the information of two signals (the private value and the signal regarding the common value). If subjects were to ignore the common value signal, the auction would be fully efficient. This is precisely what the LRA offers. Ignoring the common-value signal presents a coordination problem for auction participants in a standard auction with private and common values. The LRA avoids this coordination problem by rendering common-value signals strategically irrelevant.[4]

Auctions with purely common value have been studied extensively in the experimental literature. It is typically observed that inexperienced bidders are prone to fall victim to the winner's curse. This observation is robust across numerous auction mechanisms, and these results cannot be explained by risk aversion, limited liability of losses or a non-monetary utility of winning.[5] This paper provides, to the best of our knowledge, the first attempt to link analysis

[4] GO also show that increasing competition (i.e. the number of bidders) exogenously or reducing the uncertainty (i.e. the variance) of the common value increases efficiency. Our results regarding LRAs are consistent with this finding, since LRA's eliminate the uncertainty regarding the common value of the good.

[5] See Kagel and Levin (2002) for an introduction to this literature.

of the winner's curse in auctions with only common values to auctions with both private and common value structures.

Our most dramatic result is a stark decrease in the prevalence of the winner's curse in LRAs relative to first-price auctions. Indeed, inexperienced bidders in LRAs very rarely fall victim to the winner's curse. Since these bidders do not face any uncertainty regarding their payoff conditional on winning the auction, this is perhaps not surprising. We also find that, when the value of the good has both private and common value components, there is a significant increase in efficiency in LRAs relative to first-price auctions. This is important because, as previously mentioned, efficiency is low in first-price auctions with this valuation structure. Thus, we demonstrate that in this environment increases in efficiency and a reduction of the winner's curse can be obtained by changing the auction mechanism. These findings support the use of LRAs or LPVRAs as a way to allocate concession contracts for infrastructure.

Contrary to theory, LRA generates less revenue than first-price auctions, regardless of valuation structure. This is largely due to the fact that bidders in first-price auctions tend to overbid aggresively, often to the point of guaranteeing negative profits in expectation. Correspondingly, bidders are better off in an LRA than in a first-price auction.

The remainder of the paper is organized as follows. Section 2 provides the theoretical background. Section 3 describes our experimental design. Section 4 provides our results. Section 5 contains the conclusion. Appendix A contains derivations of theoretical predictions. Appendix B contains a sample set of instructions.[6]

2 Theoretical Predictions

A set of risk neutral players $N \equiv \{1, ..., n\}$ compete for a good with a common but uncertain value, V, by simultaneously placing bids. Prior to placing her bid, bidder $i \in \mathbf{N}$ privately observes a signal v_i regarding the value of the good. Each of these signals is an independently drawn realization of the random variable v, which is distributed according to F and has support $[v_L, v_H]$. The value of the good is the average of the signals. That is, $V = \sum_{i \in \mathbf{N}} \frac{v_i}{n}$. Also, bidder i faces a cost c_i that must be paid if she wins the auction and obtains the good; bidders know their cost prior to placing bids, but may not know the value of c_j where $j \neq i$. Bidder $i \in N$ chooses a bid, $b_i \in \mathbb{R}_+$in an attempt to obtain the good. Bidders are not budget constrained; the strategy space of each player is $\mathbb{R}_+$. The vector of bids is $b \equiv b_1, ..., b_n$. Further, $b_{-i} \equiv b/b_i$ and $N_{-i} \equiv N/i$.

[6] The instructions used are in Spanish. The sample instructions found in Appendix B have been translated into English. The remaining instructions are available upon request.

2.1 First-Price Auctions with Private and Common Values

In a first-price auction with private and common values (FP-PC), costs are private information. In particular, each c_i, where $i \in N$, is an independent draw of the random variable d which is distributed according to G with support $[c_L, c_H]$. Thus, the value of the good has both private and common value components. To ensure that all bidders will participate in the auction, it is assumed that $c_H < v_L$. The net value of the good to bidder i is thus $V - c_i$. Note that each bidder privately observes two separate pieces of information regarding this net value, and that these pieces of information are independent. This information structure is analyzed in Goeree and Offerman (2003), and they demonstrate that the one dimensional summary statistic $s_i = \frac{v_i}{n} - c_i$ can be used to map both pieces of information into equilibrium bids in a first-price auction. We denote the random variable from which these summary statistics are (independently) drawn as s, and the corresponding distribution function as F_S. The symmetric equilibrium bid function is

$$\rho(s_i) = \frac{n-1}{n} E(v|s \le s_i) + E(y_1|y_1 \le s_i),$$

where $y_1$is the highest s_i of the other $n-1$ bidders. That is, $y_1 = max_{j \in N_{-i}} \frac{v_j}{n} - c_j$.

The expected profit of bidder i who observes s_i is $\Pi_i^{FP-PC}(s_i) = \int_{s_L}^{s_i} F_S(x)^{n-1} dx$. Integrating over $\Pi_i^{FP-PC}(s_i)$ yields the ex ante expected profit of bidder i: $E\left(\Pi_i^{FP-PC}(s_i)\right) = \frac{1}{n}\left(E(Y_1) - E(Y_2)\right)$, where Y_1 is the first order statistic of the n draws of s, and Y_2 is the corresponding second order statistic.

To find the expected revenue in an FP-PC auction we first note that the winner's net value of the good is $W = E(V) - E(E(c|s = Y_1))$. Subtracting the ex ante expected payoffs of the bidders yields the expected revenue of the auction $R^{FP-PC} = W - (E(Y_1) - E(Y_2))$[7].

2.1.1 Winner's Curse

It has been widely observed that inexperienced bidders in common value auctions fall victim to the winner's curse. That is, bidders are prone to bidding such that they guarantee themselves negative expected profits. According to this definition, a bidder falling victim to the winner's curse is bidding above the expected value of the good, conditional on winning the auction. The propensity of bidders to fall victim to the winner's curse in this environment, where there are common and private components of the net value, was observed by GO and is of interest in this study. We say that a bidder has fallen victim to the winner's curse if she has bid above the break-even bidding threshold, thus guaranteeing that she has negative expected profit. Note that this definition implies that a bidder can fall victim without actually winning the auction.

[7] For proof of these assertions, see Goeree and Offerman (2003).

This break-even bidding threshold is defined as

$$T^{FP-PC}(s_i) = s_i + \frac{n-1}{n} E(v \mid s \leq s_i).$$

2.1.2 Naive Bidding

In the symmetric Nash equilibrium of an FP-PC auction, winning the auction conveys information about the unknown common value of the good. In particular, since the equilibrium bid function is monotonically increasing, the bidder with the highest s_i will win the auction. If a bidder does not take the information that winning conveys into account, but otherwise adheres to the predicted Nash equilibrium bidding strategy, we call her (following GO) a naive bidder. The naive bidding strategy for FP-PC auctions is given by:

$$\eta(s_i) = \frac{n-1}{n} E(v) + E(y_1 | y_1 \leq s_i).$$

2.2 First-Price Auctions with Common Values

In a first-price auction with common values (FP-C), $c_i = E(c) \equiv \bar{c}$, and this is common knowledge. Since the cost that the winning bidder will have to pay is common knowledge and the same for each potential winner, these auctions effectively are purely common value. Such auctions have been widely studied in the literature. However, the presence of the (common) cost differentiates our work from the bulk of the literature. The symmetric equilibrium of this auction can be obtained by suitably specializing the results of Milgrom and Weber (1982).[8] The symmetric equilibrium bid function is

$$\beta(v_i) = \frac{n-1}{n} E(v | v \leq v_i) + \frac{1}{n} E(z_1 | z_1 \leq v_i) - \bar{c},$$

where $z_1$is the highest signal of the other $n-1$ bidders. That is, $z_1 = max_{j \in N_{-i}} v_j$.

The expected profit of bidder i who privately observes v_i, is $\Pi_i^{FP-C}(v_i) = \int_{v_L}^{v_i} F(x)^{n-1} dx$.

Taking the expectation of $\Pi_i^{FP-C}(v_i)$ yields the ex ante expected profit of bidder i, which is $E\left(\Pi_i^{FP-C}\right) = \frac{1}{n}(E(Z_1) - E(Z_2))$, where Z_1 is the first order statistic of the n draws of v, and Z_2 is the corresponding second order statistic. Subtracting the ex ante expected payoffs of the bidders yields the expected revenue of the auction $R^{F-PC} = E(V) - (E(Z_1) - E(Z_2))$.

[8] The derivations of the symmetric equilibrium bid function, equilibrium bidder profits, equilibrium auctioneer revenue, and the winner's curse threshold are found in Appendix A.

2.2.1 Winner's Curse

In an FP-C auction, a bidder falls victim to the winner's curse if she bids above the expected value of the good, conditional on winning the auction. When the symmetric equilibrium bidding function is monotonically increasing, as it is here, this is equivalent to bidding above the expected value of the good conditional on having the largest signal. Notice that bidding equal to this conditional expected value is a break-even bidding strategy. The functional form of this threshold is

$$T^{F-PC}\left(v_i\right) = \frac{v_i}{n} + \frac{n-1}{n} E\left(v | v \leq v_i\right).$$

2.2.2 Naive Bidding

When the valuation structure of a first-price auction is pure common values, winning the auction conveys information that, as discussed above, is often ignored by bidders. The naive bid function, in which bidders ignore this information but otherwise bid according to the Nash equilibrium bidding function, is given by:

$$\zeta\left(v_i\right) = \frac{n-1}{n} E\left(v\right) + \frac{1}{n} E\left(z_1 | z_1 \leq v_i\right) - \bar{c}.$$

2.3 Least-Revenue Auctions with Private and Common Values

In a least-revenue auction with private and common values (LR-PC), bidders simultaneously submit bids, the lowest of which wins the auction. Bids consist of the minimum amount (which would come from the common-value of the good) that a bidder is willing to accept, given that she wins the auction. The winner obtains the minimum of the realization of V and her bid. If the winning bid is less than the realized common value, the winning bidder implicitly pays the difference between the common-value and her bid. Recall that we assume $c_H < v_L$. This implies that the common value will always be sufficient to cover a bidder's cost.

When there are common and private values, the valuation structure is exactly the same as in FP-PC auctions. However, the price the winning bidder pays is contingent on the realized value of V. Provided her bid does not exceed V, the uncertainty regarding the common-value of the good does not affect the winning bidder's payoff. As a result, the private information that each bidder holds regarding V is strategically irrelevant. Since bidders each face a cost (should they win the auction) which is an independent draw from a common distribution, the problem that each bidder faces is strategically equivalent to a first-price independent private value procurement auction. The equilibrium bid function then maps c_i into $\mathbb{R}_+$. For bidder i who privately observes c_i this equilibrium bid function is

$$\zeta(c_i) = E(z_{n-1}|z_{n-1} \geq c_i)$$

where z_{n-1} is the smallest of $n-1$ draws of c.

The expected profit of bidder i who observes c_i is $\Pi_i^{LR-PC}(c_i) = \int_{c_i}^{c_H} (1 - G(t))^{n-1} dt$.

Integrating over $\Pi_i^{LR-PC}(c_i)$ yields the ex ante expected profit of bidder i, $\Pi_i^{LR-PC} = E\left(\Pi_i^{LR-PC}(c_i)\right)$. The expected revenue in LR-PC auctions is $R^{LR-PC} = E(V) - n\Pi_i^{LR-PC}$.

2.3.1 Winner's Curse

In an LRA, the realization of V is not relevant to the payoff of the bidder and the common-value signal does not enter into the equilibrium bid function. As such, the standard interpretation of the winner's curse, bidding in a common-value auction that guarantees negative expected profits by failing to take into account the information that is provided by having the highest signal, does not apply under this auction format.[9] However, for comparison purposes, we continue to call bidding, where expected profits conditional on winning are negative, the winner's curse.

In LR-PC auctions, any bid which is above the privately observed cost will guarantee the bidder positive profit upon winning the auction. Similarly, any bid that drops below the cost will guarantee negative profits. Thus, the break-even bidding threshold for a bidder in an LR-PC auction is

$$T^{LR-PC}(c_i) = c_i.$$

2.4 Least-Revenue Auctions with Common Values

In a least-revenue auction with common values and a common cost (LR-C), the game is, in effect, one of complete information. The unique equilibrium of this game is to bid $\bar{c}$. To see this, note that if any bidder were to bid below $\bar{c}$, they would earn negative profits upon winning. For any bid $b_i > \bar{c}$, bidder $j \in N_{-i}$ would have an incentive to bid $b_j \in (\bar{c}, b_i)$ and earn a positive profit. Notice that the equilibrium profit of bidder i is zero, and does not depend on v_i. Further, the equilibrium revenue in this game is $R^{LR-C} = E(V) - \bar{c}$.

2.4.1 Winner's Curse

Clearly, if a bidder were to bid less than $\bar{c}$, then her expected payoff would be negative. Thus, the break-even bidding threshold in LR-C auction is equal to the Nash equilibrium.

[9] Notice that winning does not convey any additional information about the value of the good. As such, the concept of naive bidding is also inaplicable in the context of LRAs.

Table 1 Summary of experimental design

	First-price auctions	Least-revenue auctions
Common and private value	4 sessions	4 sessions
Common value	4 sessions	4 sessions

3 Experimental Design

In every experimental session, twelve participants are randomly and anonymously matched into groups of three. In each round, every group participates in an auction. Each bidder submits a bid. The bidder who submits the winning bid obtains the good (ties are broken randomly). The other bidders receive payoffs of zero. Participants are randomly and anonymously re-matched after each round. This process is repeated for thirty rounds.[10]

In each auction the value of the good to each bidder is the difference between the common value and the cost the bidder faces if she were to win the auction. The common value of the good has an uncertain value. Each bidder $i \in \{1, 2, 3\}$ privately observes a signal, v_i, regarding this common value. Each of these signals is an independent draw from the uniform distribution with support $[100, 200]$. The common value, V, is the average of the private signals. That is, $V = \frac{1}{n} \sum_{i=1}^{3} v_i$. The realized value of the good is not observed by bidders before placing their bids, although bidders know the cost they must pay if they win the auction beforehand. The distribution from which the signals are drawn is common knowledge.

We employ a 2x2 between-subject design which varies the auction format and the valuation structure (This design is illustrated in Table 1).

1. *First-price auctions with private and common values (FP-PC):* In addition to the private signal that bidders observe regarding the common value of the good, each bidder privately observes the cost she must pay if she were to win the auction. Each of these costs is an independent draw from a uniform distribution with support $[0, 50]$. These costs represent the private value portion of the valuation structure. The auction format in this treatment is a standard first-price sealed-bid auction.
2. *First-price auctions with common values (FP-C):* In this treatment each bidder faces the same cost if she were to win the auction. This cost is equal to the expected value of the cost distribution in the FP-PC treatment ($\bar{c} = 25$). The auction format in this treatment is a standard first-price sealed-bid auction.
3. *Least-revenue auctions with private and common values (LR-PC):* In addition to the private signal that bidders observe regarding the common value of the good, each bidder privately observes the cost she must pay if she were to win the auction. Each of these costs is independently drawn

[10] One of the first ten periods is randomly selected to be paid. Each of the remaining 20 periods are paid. In the analysis that follows, data from the initial ten periods is not utilized.

from a uniform distribution with support $[0, 50]$. These costs represent the private value portion of the valuation structure. The auction format in this treatment is an LRA.

4. *Least-revenue auctions with common values (LR-C):* In this treatment each bidder faces the same cost if they were to win the auction. This cost is equal to the expected value of the cost distribution in the FP-PC treatment ($\bar{c} = 25$). The auction format in this treatment is an LRA.

In each of these four treatments, the valuation structure of the auction is common knowledge. That is, if a bidder observes a signal, this fact, as well as the distribution from which the signal is drawn, is common knowledge. At the conclusion of each auction each bidder observes V, all bids, her earnings from the auction, and the price paid by the winner.

All sessions were run at the Centro Vernon Smith de Economía Experimental at the Universidad Francisco Marroquín, and our participants were primarily matriculated undergraduates of the institution. The sessions were computerized using z-Tree Fischbacher (2007). Participants were separated by dividers such that they could not interact outside of the computerized interface. They were provided with instructions and were also shown a video which read these instructions aloud. Each participant then individually answered a set of questions to ensure understanding of the experimental procedures. We elicited risk attitudes using a measure that closely mirrors Holt and Laury (2002).[11] We varied the order in which subjects participated in the risk attitude elicitation procedure and the series of auctions. Each session lasted approximately one and a half hours. In half of the sessions, each participant began with a starting balance of Q62.5 ($1 Quetzal \approx US\$0.125$) to cover any losses; in the other half participants began with a starting balance of Q125. At the end of all thirty rounds, each participant was paid her balance, as well as a show-up fee of 20 Quetzales. If the balance of a participant became negative, she was permitted to continue provided she invested her show-up fee. If the show-up fee was also lost, she was permitted to continue, and received a payment of zero.[12] Within the reported sessions, there were two participants who went bankrupt ($\approx 1\%$ of participants) before the end of the experiment. The bids, signals and values were all denominated in Experimental Pesos (EP), which were exchanged for cash at a rate of $4E\$ = Q1 \approx US\$0.125$. The average payoff was $Q105$, with a minimum of $Q0$ and a maximum of $Q165$.

[11] Our risk attitude elicitation task differs from Holt and Laury (2002) in that, instead of choosing between two lotteries, subjects choose between a certain amount and a lottery.

[12] If more than one participant went bankrupt then the data from the session was not included in the reported analysis. We excluded the data from five sessions. In two of these, multiple subjects went bankrupt. In the remaining three, we were unable to complete all 30 auctions.

4 Results

4.1 Efficiency Levels

When the valuation structure is pure common value, any allocation of the good is efficient. As such, efficiency is not a concern in this valuation structure. When there are private costs, however, allocating the good to the bidder with the lowest cost is the efficient allocation.

Interestingly, when there are private and common value components in the first-price auction (FP-PC), the equilibrium allocation may not be efficient Goeree and Offerman (2003). This is because the equilibrium bid function is monotonically increasing in the summary statistic $s_i = \frac{v_i}{n} - c_i$. A bidder may have a high cost relative to the other bidders in the auction, but if she also has a relatively high common-value private signal (such that $s_i = \frac{v_i}{n} - c_i$ is larger than those of the other bidders) she is predicted to win the auction, which would result in an inefficient allocation.

However, in LR-PC auctions, equilibrium bids are monotonically decreasing in c_i. This implies that, in equilibrium, the bidder with the lowest cost will win with certainty. As such, the predicted efficiency level is 100%. This points to an important property of the LR-PC auction. Namely, by rendering the common value component strategically irrelevant, inefficiency concerns that arise in valuation structures with private and common values are, in theory, eliminated. That is, LR-PC auctions are predicted to be more efficient than FP-PC auctions.

Following GO, we define efficiency as

$$normalized\ efficiency = \frac{c_{max} - c_{winner}}{c_{max} - c_{min}},$$

where c_{winner} is the private cost of the winning bidder and $c_{max}(c_{min})$ is the maximal (minimal) private cost of the three bidders. This can be interpreted as the realized proportion of the difference between the most efficient and least efficient allocation.

Table 2 contains average efficiency levels in FP-PC and LR-PC auctions in ten period blocks, as well as aggregated across all twenty periods. Note that efficiency levels are considerably higher using the LRA format. In fact, efficiency is significantly higher in LR-PC than in FP-PC (robust rank order test, $U = -4.484$, $p = 0.029$). Figure 1 illustrates this difference by comparing the observed efficiency level to two benchmarks: the efficiency level predicted by equilibrium bidding behavior, and the efficiency level resulting from a random allocation of the good. Notice that in FP-PC auctions, the predicted efficiency level is much larger than that of the random allocation, while still being less than 100% efficient. Observed efficiency falls between predicted efficiency and that of a random allocation. While observed efficiency is much higher in LR-PC auctions than in FP-PC auctions, contrary to theory LR-PC auctions are not perfectly efficient. Figure 2 sorts the data into the first and last 10 periods. The difference in efficiency between LR-PC and FP-PC auctions can be largely

Fig. 1 Efficiency in FP-PC and LR-PC auctions

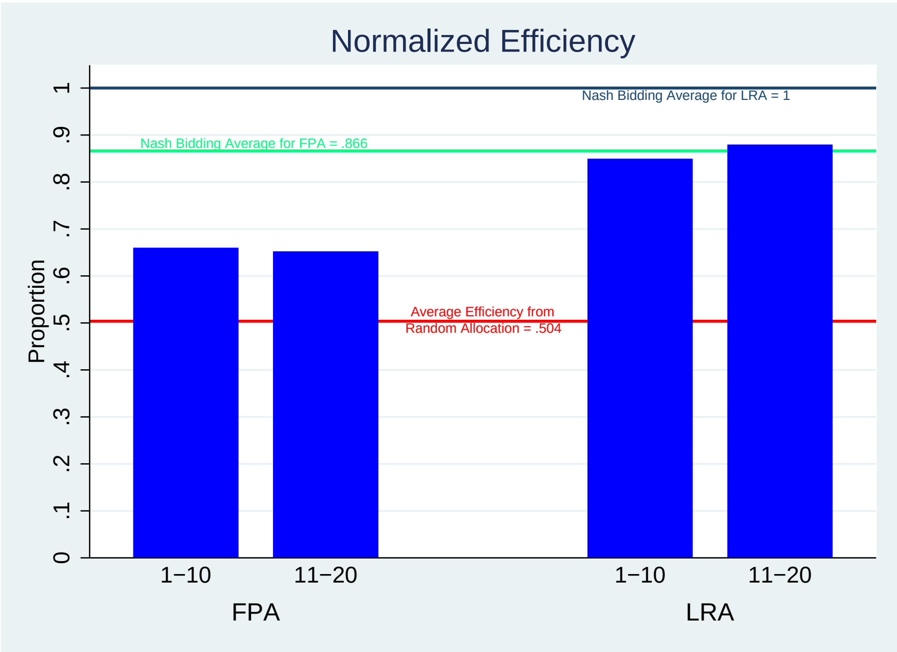

Fig. 2 Efficiency in FP-PC and LR-PC auction in the first and last ten periods

attributed to the fact that the uncertainty regarding the common value of the good has been shifted to the auctioneer in the LRAs.

4.2 Revenue

The effect of valuation structure and auction format on revenue ranking is of particular interest. Table 3 contains summary statistics regarding observed and predicted revenue in all four treatments aggregated over all twenty periods. Notice that, contrary to theory, FP-PC auctions, on average, generate the highest revenue, while LR-C auctions generate the least revenue.

Table 2 Summary statistics for efficiency

Efficiency Measure	FP-PC Periods 1-10	FP-PC Periods 11-20	FP-PC All Periods	LR-PC Periods 1-10	LR-PC Periods 11-20	LR-PC All Periods
Obseved	0.660	0.652	0.656	0.849	0.879	0.864
	(0.413)	(0.411)	(0.411)	(0.301)	(0.271)	(0.286)
Random Allocation	0.504	0.484	0.494	0.504	0.484	0.494
	(0.102)	(0.084)	(0.094)	(0.102)	(0.084)	(0.094)
Nash Bidding	0.878	0.839	0.858	1.000	1.000	1.000
	(0.258)	(0.297)	(0.278)	(0.000)	(0.000)	(0.000)

Notes: Table contains means with standard deviations in parentheses.

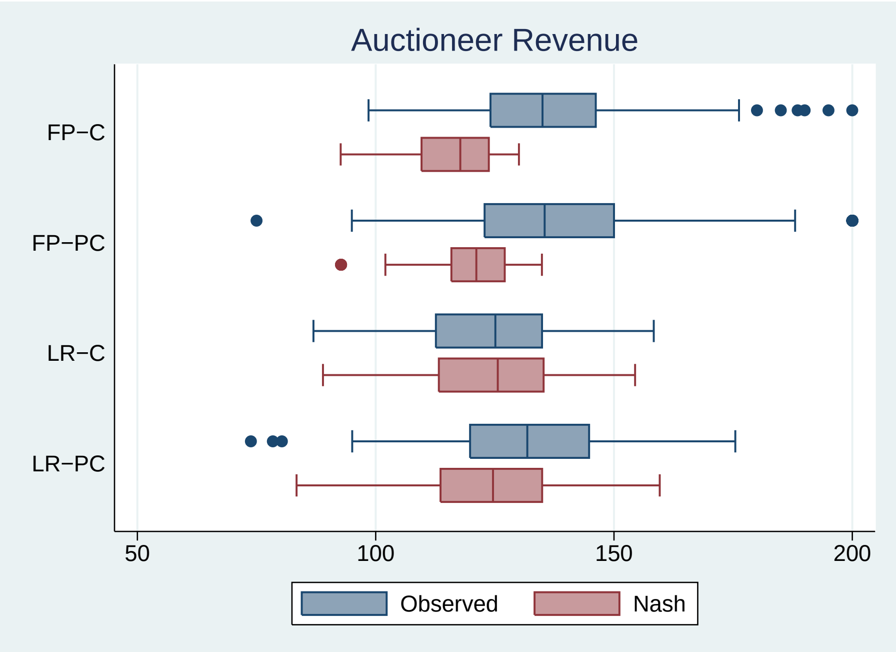

Fig. 3 Observed and predicted auctioneer revenue

Figure 3 compares observed revenue to predicted revenue. Note that in first-price auctions (under both valuation structures) and in LR-PC auctions, observed revenue is, on average, higher than the theoretical predictions. Further, note that in LR-C auctions, theory is, on average, a good predictor of observed revenue. That is, when bidders hold strategically relevant private information, revenue tends to exceed equilibrium predictions. When they do not, revenue is largely in line with predictions.

We find that valuation structure does not significantly affect revenue in first-price auctions (robust rank order test, $U = 0.000$, *n.s.*).[13] This result runs counter to the theoretical prediction that revenue is lower when there are

[13] *n.s.* indicates that the test is not significant at conventional levels.

Table 3 Revenue and bidder payoffs

Variable	FP-C	FP-PC	LR-C	LR-PC
Observed Revenue	135.492	138.634	124.267	132.024
	(17.379)	(23.300)	(14.975)	(17.070)
Predicted Revenue	116.319	120.367	124.558	124.028
	(9.170)	(8.858)	(14.832)	(15.241)
Observed Profits	-3.645	-3.105	0.097	0.565
	(11.365)	(14.683)	(0.896)	(6.570)
Predicted Profits	2.452	9.043	0.000	4.398
	(2.838)	(16.140)	(0.000)	(4.905)
Fraction of Auctions with Positive Payoffs	0.250	0.341	0.984	0.834
	(0.434)	(0.475)	(0.124)	(0.372)

Notes: Table contains means with standard deviations in parentheses.

private and common values as opposed to a pure common value structure in first price auctions. However, in LRAs the private and common value valuation structure generates more revenue than the pure common value valuation structure (robust rank order test, *n.d.*, $p < 0.001$). This is largely due to the fact that in LR-PC auctions the winning bidder is predicted to have the lowest cost, and the lowest cost is predicted to be below $\overline{c} = 25$.

Theory predicts that LRAs will generate more revenue than first-price auctions in both valuation structures. This is due to the fact that LRAs render the privately observed common value signal observed by bidders strategically irrelevant. As a result, bidders earn smaller information rents in LRAs than they do in first-price auctions. However, we find that, contrary to theory, revenue is lower in LRAs than in first-price auctions, regardless of valuation structure. When there are private and common value components, this difference is marginally significant (robust rank order test, $U = -1.568$, $p = 0.1$). On the other hand, in pure common value auctions this difference is highly significant (robust rank order test, *n.d.*, $p < 0.001$).[14] This result is due to the fact that bidders in first-price auctions tend to bid significantly above Nash predictions.[15] As a result, the revenue generated by first-price auctions is higher than predicted by theory. This is in contrast to LRAs in which bidders are much less likely to bid such that revenue increases relative to theory.

4.3 Bidder Profits

Bidder profits are, of course, closely related to revenue. As such, our results regarding bidder profits closely resemble those of revenue. Table 3 contains summary statistics of bidder payoffs in all four treatments. Figure 4 compares observed bidder profits to predicted bidder profits in all four treatments. Notice that in all treatments except LR-C bidders are, on average, worse off than

[14] When the lowest observation from one treatment is higher than the highest observation of the other treatment, the test statistic of the robust rank order test is undefined. We denote this highly significant case as *n.d.*

[15] This observed tendency to overbid is analyzed formally below in section 4.5.

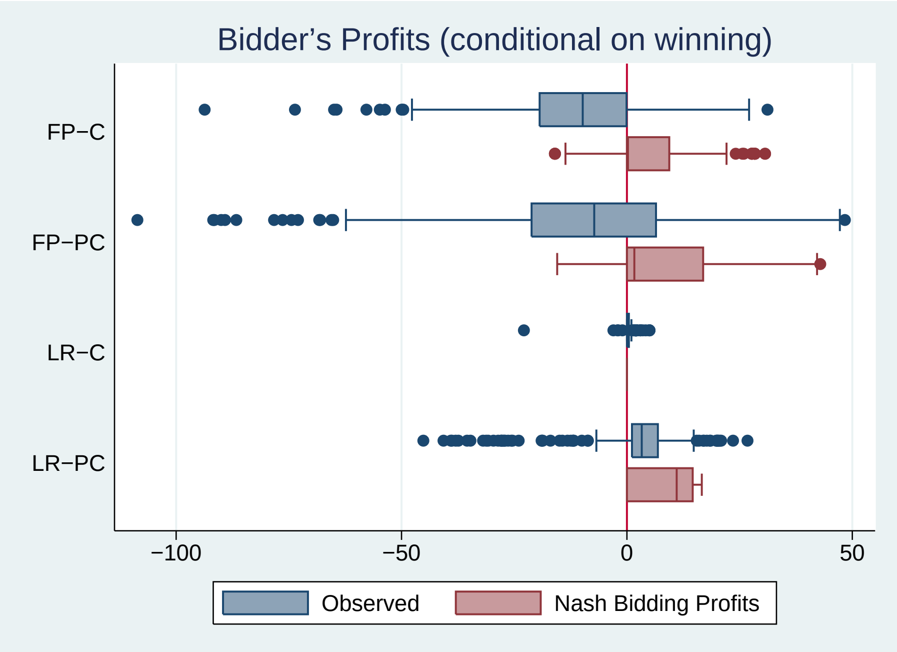

Fig. 4 Observed and predicted bidder profits

predicted by theory. In the case of LR-C auctions, theory is an excellent predictor. Also, note that in first-price auctions bidders are, on average, earning negative profits. This is in stark contrast to bidder profits observed in LRAs, in which bidders, on average, earn weakly greater than zero.

Theory predicts that bidders will be better of when there are private and common values than they would be in pure common value environments because the privately observed costs earn positive information rents. Contrary to this prediction, we find that valuation structure does not significantly affect payoffs in first-price auctions (robust rank order test, $U = -0.776$, *n.s.*) or in LRAs (robust rank order test, $U = -1.033$, *n.s.*).

We also find that bidders are better off in LRAs. When there are private and common values, this result is marginally significant (robust rank order test, $U = -1.568$, $p = 0.1$). However, this result is highly significant in the pure common values environment (robust rank order test, *n.d.*, $p < 0.001$). The intuition underlying this result mirrors the analogous finding for revenue. Namely, in first-price auctions bidders tend to substantially overbid relative to Nash predictions, often resulting in negative payoffs. In first-price auctions bidders must estimate the common value of the good, conditional on winning. By eliminating the uncertainty regarding bidder profit conditional on winning, LRAs eliminate the need for bidders to estimate this conditional expected value. A bidder in a LRA need only bid above her cost to ensure positive profits.

Table 4 Prevalence of the winner's curse (proportion of bids)

Variable	FP-C	FP-PC	LR-C	LR-PC
Prevalance of winner's curse	0.475	0.447	0.005	0.085
	(0.500)	(0.497)	(0.072)	(0.280)
Prevalence of winner's curse among winning bids	0.691	0.650	0.016	0.166
	(0.463)	(0.478)	(0.124)	(0.372)

Notes: Table contains means with standard deviations in parentheses.

4.4 Winner's Curse

In auctions with pure common values, the winner's curse is prevalent, particularly among inexperienced bidders such as those who participated in the experimental sessions for this paper. GO provide evidence that the winner's curse (bidding above the break-even threshold) is also prevalent in first-price auctions with private and common values. We replicate both these results, and compare them to the LRA format. Table 4 contains summary statistics of the prevalance of the winner's curse in all four treatments. Notice that, regardless of valuation structure, bidding above the break-even threshold is, on average, dramatically less prevalent in LRAs. Nonparametric tests confirm these results; bidding above the break-even threshold is significantly lower in LRAs than in first-price auctions with private and common value components (robust rank order test, $U = 11.314$, $p < 0.001$), as well as in the pure common value environment (robust rank order test, $U = 11.314$, $p < 0.001$). Figure 5 illustrates this result by showing the proportion of bids above the break-even bidding threshold for all four treatments. Figure 6 breaks this into five period blocks. Notice that bidding above the break-even threshold is almost entirely eliminated in LR-C auctions. The relative dearth of bidding above the break-even threshold in LRAs is largely attributable to the fact that the uncertain common value of the good does not translate into uncertainty regarding bidder profits. Indeed, conditional on winning the auction, there is no uncertainty regarding bidder profits in LRAs. The risk regarding this uncertain value has been completely shifted to the auctioneer.

We also find that the valuation structure does not significantly affect the prevalence of the winner's curse in first-price auctions (robust rank order test, $U = 1.016$, *n.s.*) or in LRAs (robust rank order test, $U = -1.206$, *n.s.*). This is not surprising because, holding the auction format constant, moving from the pure common-value environment to the private and common value environment does not change the level of uncertainty the bidder faces regarding the net value of the good.

4.5 Bids Relative to Theory

We now turn to comparing observed bidding behavior directly with theoretical predictions. In first-price auctions, we define overbidding as bidding above

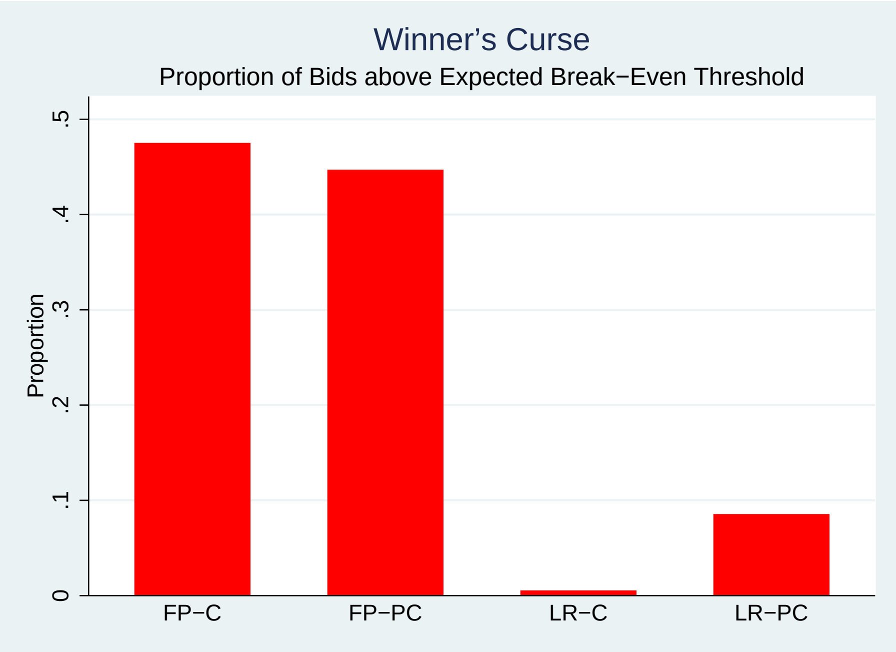

Fig. 5 Prevalence of the winners curse

Table 5 Observed bids relative to Nash and Naive bids

Variable	FP-C	FP-PC	LR-C	LR-PC
Observed Bids	14.085	111.929	34.160	29.959
	(27.243)	(32.455)	(24.606)	(18.064)
Nash Bids	102.532	104.936	25.000	33.357
	(15.568)	(19.739)	(0.000)	(9.927)
Naive Bids	119.346	114.961	-	-
	(6.227)	(12.287)		

Notes: Table contains means with standard deviations in parentheses.

the Nash equilibrium predictions. For comparability purposes, in LRAs we refer to bidding below the Nash equilibrium as overbidding. This is becasue by bidding below the Nash equilibrium, a bidder in an LRA is indicating that, upon winning the auction, they are willing to pay a higher implicit price than the respective Nash equilibrium bid. Table 5 contains summary statistics regarding observed bids, Nash equilibrium bids, and for first-price autions (where the defined naive bidding strategy is applicable), naive bids. Of note is the fact that, on average, bidders overbid relative to the Nash equilibrium in every treatment except LR-C. In first-price auctions this overbidding is, on average, less than the naive bidding strategy.

Figure 7 illustrates how observed bids in FP-C auctions compare to the Nash predictions, the naive bidding strategy, and the winner's curse threshold. Notice that bids tend to be well in excess of the equilibrium prediction. Indeed,

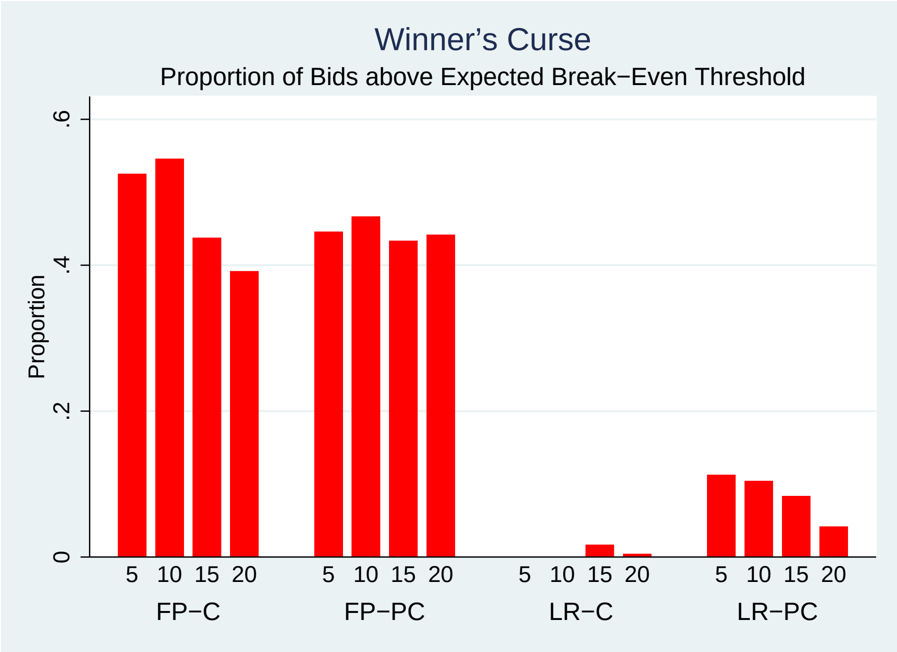

Fig. 6 Prevalence of the winners curse in five period blocks

bids well above the break-even bidding threshold, and above the naive biding strategy are common. In these FP-C auctions, we find that bids are greater than Nash predictions (sign test, $w = 41$, $p < 0.001$).[16] Further, FP-C bids are less than the naive bidding stategy (sign test, $w = 32$, $p = 0.015$).

Figure 8 provides the analogous graph for FP-PC auctions. Overbidding relative to Nash predictions, as well as bidding in excess of the winner's curse threshold, is also common in this enviroment. As in FP-C auctions, we find that bids in FP-PC auctions are greater than Nash predictions (sign test, $w = 39$, $p < 0.001$) but less than the naive bidding stategy (sign test, $w = 30$, $p = 0.056$).

Figure 9 illustrates observed bidding behavior in LR-C auctions against the Nash predictions as well as the break-even bidding strategy. Of note is the fact that overbidding (bidding below the Nash equlibrium) is largely nonexistant in this environment. In LR-C auctions, we find that bidders are underbidding relative to Nash predictions (sign test, $w = 47$, $p < 0.001$). This result could be an attempt to signal collusion at higher prices or it could be due to throwaway bids -bidders rebelling against competing for meager profits.

[16] The unit of observation used in the sign test is the individual participant. That is, the averge bid of a participant over all periods is compared with the average Nash equilibrium bid or the average naive bid. This unit of observation was used for all non-parametric tests regarding observed bidding relative to theory.

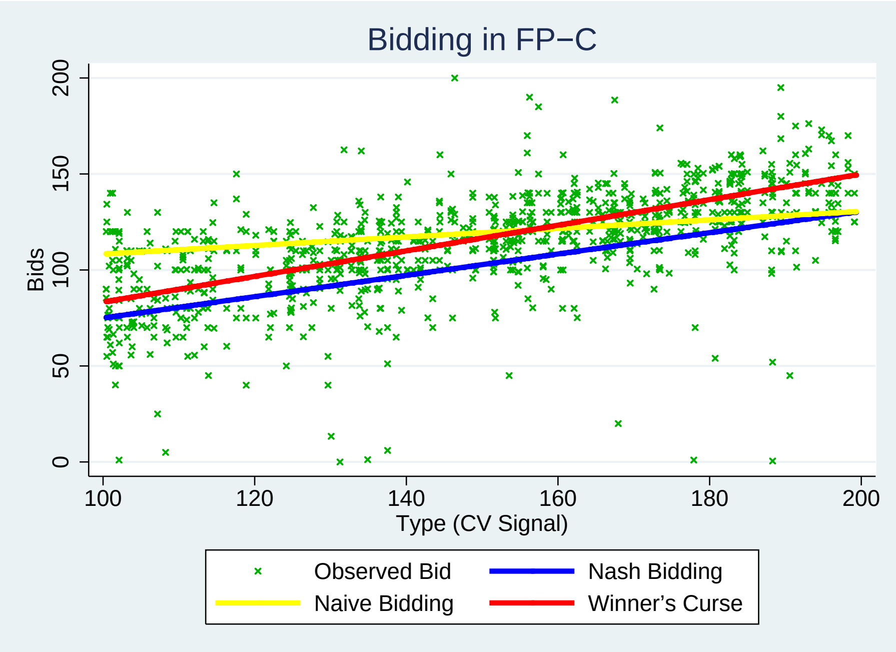

Fig. 7 Bidding in FP-C auctions

Figure 10 compares observed bids in LR-PC auctions to Nash predictions and the winner's curse threshold. In stark contrast to what is observed in first-price auctions, bidding such that expected profits are negative in expectation is almost non-existent. In LR-PC auctions, we find that bidders are overbidding relative to Nash predictions (sign test, $w = 38$, $p < 0.001$). That is, bidders are bidding more aggresivley than predicted by the Nash equilibrium. This is consistent with observed bidding behavior in first price auctions with independent private values.

4.6 Estimated Bid Functions

When estimating bid functions for the four treatments, we employ a random effects (at the individual level) specification, and cluster the standard errors to allow for intra-session correlation.[17] We control for the statistic upon which equilibrium bids are based as well as experience $(ln\,(t+1))$.[18] In LRAs, we also control for v_i, to test the hypothesis that the privately observed common-value signal does not enter into the bid function. We also estimate specifications

[17] As a robustness check, we also estimated bid functions with dummies for subjects who went bankrupt, and a dummy indicating whether or not a bankruptcy occurred in the session. These results are available upon request.

[18] Recall that the equilibrium bid of LR-C bidders does not depend on the private information held by bidders.

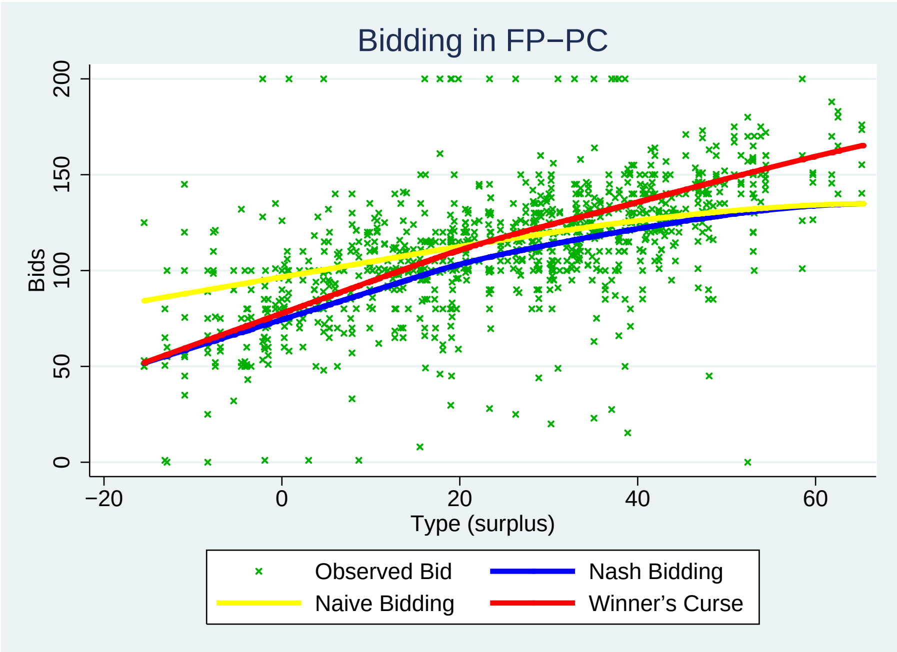

Fig. 8 Bidding in FP-PC auctions

which control for gender ($F_i = 1$ if the bidder is female, 0 otherwise), the interaction of gender and experience $F_i \cdot ln\,(t+1)$. We also control for the order of the risk attitude elicitation procedure (O_i), whether or not bidders started with an endowment of $E\$500$ (E_i), the number of safe choices in the risk elicitation procedure (R_i), and subject dummies.[19]

Table 6 contains the estimated bid functions for FP-C auctions. Several things are worth noting. First, the common value signal is, unsurprisingly, highly significant and positive in all specifications. Second, subjects do not seem to be reducing their bids over time, as evidenced by the insignificant coefficients on $ln\,(t+1)$. Notice that when we control for gender and the interaction between gender and $ln\,(t+1)$ the respective coefficients are insignificant (although when we only control for gender, the coefficient is positive and significnat). This is in contrast to the result of Casari et al (2007), which finds that women tend to initially overbid more than men, but also learn to reduce their bids faster than men in first-price common-value auctions.

[19] A subject is defined as the sequence of draws of v_i and, if applicable, c_i that a participant faced, as well as the sequence of unobserved draws that her opponents faced. That is, in each session we utilized the same set of (once random) draws as the other sessions. Thus, exactly one participant in each session observed each sequence of random draws. The dummy variable for a subject is equal to one for the set of participants who observed that sequence, and zero for the other participants.

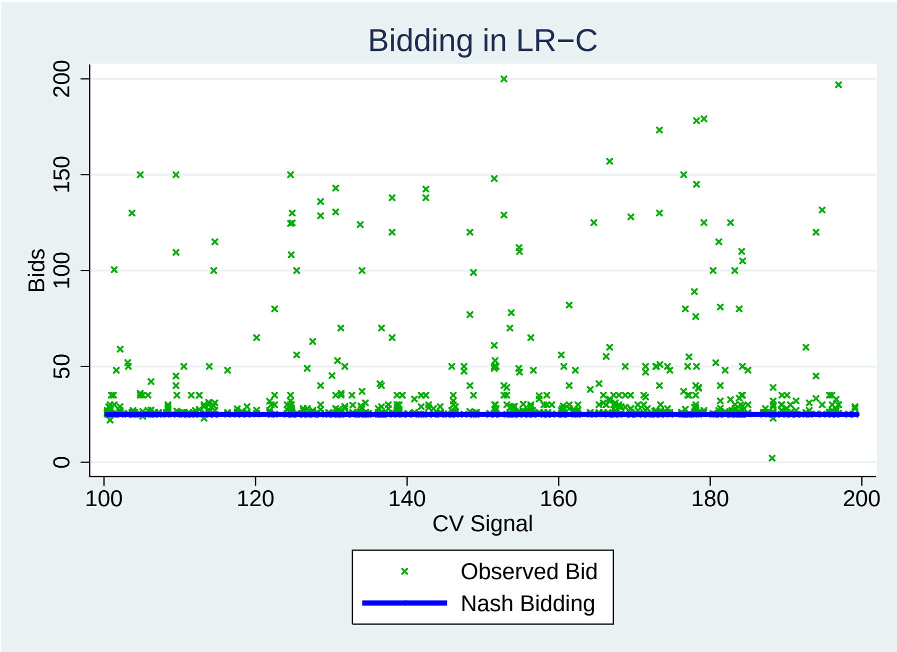

Fig. 9 Bidding in LR-C auctions

Table 7 contains the estimated bid functions for the FP-PC auctions.[20] Of interest is the fact that the coefficient on s_i is highly significant in all specifications, and approximently equal to one. Note that in the most inclusive specification the interaction between gender and $ln\,(t+1)$ is significant and positive, and that gender is (marginally) significant. This indicates that women are initially bidding less than men, but that as they gain experience they increase their bids more than men. This result is in stark contrast to that of Casari et al (2007).

Table 8 contains the estimated bid functions for LR-C auctions. As expected, the common-value signal is not significant. Also, the coefficient for $ln\,(t+1)$ is highly significant, and positive. That is, bidders are moving away from equilibrium, on average, as they gain experience. This may be an attempt by some bidders to send signals in order to tacitly collude with other bidders on a higher price. Since bidders were randomly and anonymously rematched every period, it would have been extremely difficult for this type of coordination to happen. At the same time, it would have been a very low-cost strategy, given the low profits observed in this auction. Alternatively, it might have been a case of *throw-away bidding* in which bidders simply express their

[20] The equilibrium bid function for FP-PC auctions is not predicted to be linear. However, for some values of s_i this bid fuction cannot be seperated into linear and nonlinear parts. We report linear bid functions, which we find to be a better fit for the data than nonlinear specifications. As such, the reported regressions should not be interpreted as an explicit test of the equilibrium bidding strategy.

Table 6 Estimated Bid Functions for FP-C Auctions

	(1)	(2)	(3)	(4)
v_i	0.595***	0.594***	0.594***	0.595***
	(0.033)	(0.033)	(0.033)	(0.035)
$ln\,(t+1)$	-4.135	-4.135	-3.527	-3.529
	(2.638)	(2.639)	(4.352)	(4.386)
F_i		2.488**	5.498	3.408
		(0.959)	(9.356)	(9.353)
$ln\,(t+1) \cdot F_i$			-1.327	-1.326
			(4.007)	(4.037)
R_i				-1.55
				(0.955)
E_i				-4.899*
				(2.361)
O_i				3.431+
				(2.032)
Subject Dummies	No	No	No	Yes
	-	-	-	-
Constant	34.547***	33.416***	32.043**	28.714*
	(9.285)	(8.958)	(10.870)	(14.515)
Observations	960	960	960	960

Notes: Standard errors (in parentheses) clustered to allow for intra-session correlation.
$^{+}p < 0.10$, $^{*}\,p < 0.05$, $^{**}\,p < 0.01$, $^{***}\,p < 0.001$

Table 7 Estimated bid functions for FC-PC auctions

	(1)	(2)	(3)	(4)
s_i	1.091***	1.091***	1.091***	1.091***
	(0.071)	(0.071)	(0.068)	(0.069)
$ln\,(t+1)$	-1.361	-1.361	-2.716	-2.715
	(1.869)	(1.870)	(1.926)	(1.941)
F_i		1.045	-8.171	-14.357+
		(5.252)	(7.309)	(8.138)
$ln\,(t+1) \cdot F_i$			4.062**	4.061**
			(1.331)	(1.341)
R_i				4.276*
				(1.897)
E_i				3.586*
				(1.708)
O_i				2.938
				(1.984)
Subject Dummies	No	No	No	Yes
	-	-	-	-
Constant	87.952***	87.604***	90.659***	64.064***
	(6.336)	(5.081)	(5.227)	(6.808)
Observations	960	960	960	960

Notes: Standard errors (in parentheses) clustered to allow for intra-session correlation.
$^{+}p < 0.10$, $^{*}\,p < 0.05$, $^{**}\,p < 0.01$, $^{***}\,p < 0.001$

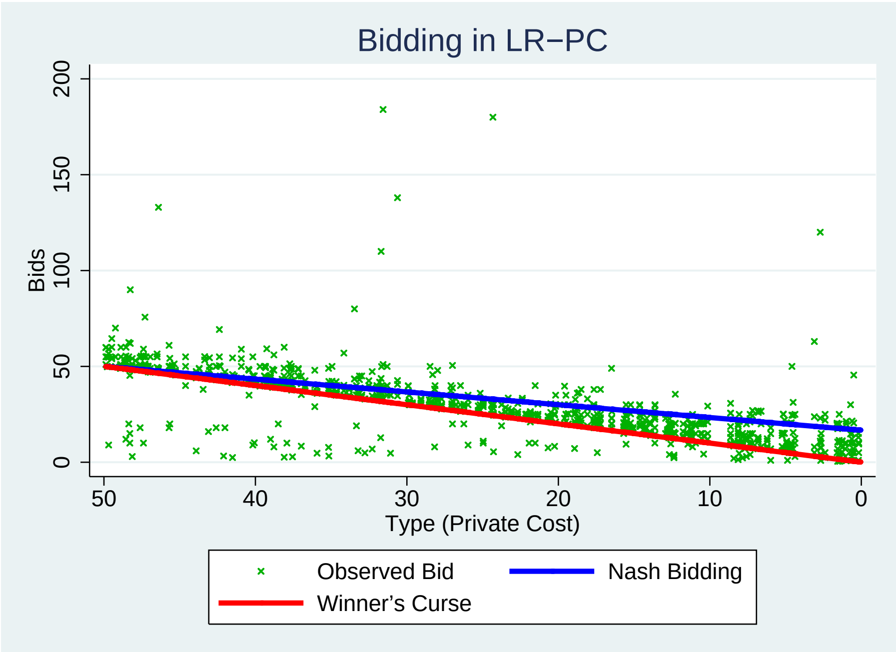

Fig. 10 Figure 10: Bidding in LR-PC auctions

frustration over competing for extremely low profits, conditional on winning. Additionally, in the most inclusive specification, the interaction between gender and $ln\,(t+1)$ is significant and negative. This implies that over time, the bids of male participants are increasing, and moving away from equilibrium. Once again, however, gender alone is not significant.

Table 9 contains the estimated bid functions for LR-PC auctions. Notice that, as predicted, the private cost observed by bidders is highly significant. Interestingly, the only significant coefficient is that of c_i. In particular, we find no significant gender effects, or learning.

5 Conclusion

In this paper we experimentally examine first-price and LRAs in two environments: one with private and common values, and other with pure common values only. In an LRA, a bidder's bid consists of the fixed amount of revenue from the common value of the good the bidder is willing to accept upon winning the auction. The lowest of these bids wins the auction. The winning bidder then incurs her cost.

Note that the uncertainty regarding the common value of the good is borne by the auctioneer in LRAs. The concept of such a risk sharing arrangement for infrastructure concession contracts has been theoretically studied in the past Engel et al (1997, 2001). Theory predicts that the allocative efficiency

Table 8 Estimated bid functions for LR-C auctions

	(1)	(2)	(3)	(4)
v_i	0.008	0.008	0.01	0.009
	(0.028)	(0.027)	(0.028)	(0.028)
$ln\,(t+1)$	3.750***	3.750***	7.110***	7.111***
	(1.135)	(1.135)	(2.074)	(2.090)
F_i		-7.657	5.911**	5.853
		(6.796)	(2.134)	(3.791)
$ln\,(t+1) \cdot F_i$			-5.980*	-5.979*
			(2.458)	(2.475)
R_i				5.818***
				(0.582)
E_i				-0.513
				(5.665)
O_i				-5.225
				(5.505)
Subject Dummies	No	No	No	Yes
	-	-	-	-
Constant	24.396***	28.698***	20.847***	3.634
	(3.011)	(4.938)	(1.573)	(7.330)
Observations	960	960	960	960

Notes: Standard errors (in parentheses) clustered to allow for intra-session correlation.
$^{+}p < 0.10$, $^{*}\,p < 0.05$, $^{**}\,p < 0.01$, $^{***}\,p < 0.001$

Table 9 Estimated bid functions for LR-PC auctions

	(1)	(2)	(3)	(4)
v_i	0.007	0.007	0.007	0.007
	(0.012)	(0.012)	(0.012)	(0.012)
c_i	0.865***	0.863***	0.863***	0.868***
	(0.038)	(0.039)	(0.039)	(0.037)
$ln\,(t+1)$	0.353	0.353	0.276	0.274
	(0.234)	(0.235)	(0.322)	(0.322)
F_i		-4.938	-5.432	-8.424
		(3.696)	(4.235)	(5.273)
$ln\,(t+1) \cdot F_i$			0.218	0.219
			(0.241)	(0.242)
R_i				0.170
				(0.491)
E_i				-4.651
				(2.831)
O_i				0.276
				(1.137)
Subject Dummies	No	No	No	Yes
	-	-	-	-
Constant	6.533***	8.337***	8.505**	7.261***
	(1.784)	(2.504)	(2.641)	(1.576)
Observations	960	960	960	960

Notes: Standard errors (in parentheses) clustered to allow for intra-session correlation.
$^{+}p < 0.10$, $^{*}\,p < 0.05$, $^{**}\,p < 0.01$, $^{***}\,p < 0.001$

of LRAs will be higher than in first-price auctions. Despite this advantage, a caveat regarding the general applicability of this format is in order: LRAs do not provide any incentive for the winner to invest in maintaining and enhancing the value of the good. This problem is mitigated if the ex-post value of the good is independent of the ex-post performance of the winning bidder. Alternatively, if the value of the good depends on easily monitored ex-post performance, a contract can be created which rewards and/or penalizes the winner contingent on ex-post performance.

This paper is the first to examine, both theoretically and experimentally, allocative efficiency, bidding behavior and auction performance in LRAs. This paper is also, to the best of our knowledge, the first direct comparison of bidding behavior in first-price auctions with these two valuation structures. We do not find any significant effect of the valuation structure on the prevalence of the winner's curse, the revenue generated, or bidder profits. This result is surprising, given that theory predicts that the additional private information held by bidders when there are private and common value components of the valuation structure will lower revenue and make bidders better off. This is important, because it shows that the general observations from pure common value auctions are robust and carry over to this valuation structure.

Perhaps the most interesting result is that, when there are private and common values, there are large increases in efficiency to be obtained by moving from a first-price auction to an LRA. The intuition underlying this result is clear: when there are private and common values, a bidder puts some weight on her common value signal when deciding her bid, while the efficiency is entirely determined by the private cost. As a result, the winning bidder may not have the lowest private cost, and thus the allocation may be inefficient. In an LRA, however, the common value signal is strategically irrelevant, and thus does not introduce inefficiency as in first-price auctions. This is, in effect, a limiting case of the finding in GO that a reduction in uncertainty regarding the common value component of the good reduces inefficiency.

The other noteworthy result is that, regardless of the valuation structure, bidding above the break-even threshold is significantly less prevalent in LRAs than in first-price auctions. Again, the intuition is due to the reduction of uncertainty in LRAs. In particular, in LRAs bidders do not need to estimate the expected common value of the good conditional on winning the auction in order to determine their expected profit. This is an important practical advantage, as it allows bidders to focus on their cost, as opposed to the uncertain common value and accounting for the information conveyed by winning the auction. Given the high rate of reported bankruptcy in infrastructure concessions allocated via traditional auction mechanisms (and the renegotiation that subsequently occurs), this result suggests that the use of LRAs may be preferred by policymakers.

A Derivation of Equilibria

Derivation of the Equilibrium in FP-C Auctions

Consider bidder i who privately observes v_i. The other bidders $j \neq i$ are bidding according to the differentiable and monotonically increasing bid function $\beta(v_j)$. Bidder i bids as though her signal were z. Her expected profit is then

$$\Pi(v_i, z) = F(z)^{n-1}\left(\frac{v_i}{n} + \frac{n-1}{n}E(v|v \le z) - \beta(z) - c\right).$$

The first order condition associated with this problem is

$$(n-1)F(z)^{n-2}f(z)\left(\frac{v_i}{n} + \frac{n-1}{n}E(v|v \le z) - \beta(z) - c\right) +$$

$$+F(z)^{n-1}\left(\frac{n-1}{n}\frac{\partial E(v|v \le z)}{\partial z} - \beta'(z)\right) = 0.$$

In equilibrium, it must be the case that $z = v_i$. Utilizing this, we are left with an ordinary differential equation:

$$(n-1)F(v_i)^{n-2}f(v_i)\left(\frac{v_i}{n} + \frac{n-1}{n}E(v|v \le v_i) - \beta(v_i) - c\right) +$$

$$+F(v_i)^{n-1}\left(\frac{n-1}{n}\frac{\partial E(v|v \le v_i)}{\partial v_i} - \beta'(v_i)\right) = 0.$$

The initial condition is $\beta(v_L) = v_L - c$. Notice that the above differential equation can be written as

$$\frac{d}{dv_i}\left(F(v_i)^{n-1}\left(\beta(v_i) - \frac{n-1}{n}E(v|v \le v_i)\right)\right) = (n-1)F(v_i)^{n-2}f(v_i)\left(\frac{v_i}{n} - c\right).$$

Integrating both sides leaves us with

$$\left(F(v_i)^{n-1}\left(\beta(v_i) - \frac{n-1}{n}E(v|v \le v_i)\right)\right) = \int_{v_L}^{v_i}(n-1)F(t)^{n-2}f(t)\left(\frac{t}{n} - c\right)dt.$$

Simplifying this yields the equilibrium bid function

$$\beta(v_i) = \frac{n-1}{n}E(v|v \le v_i) + \frac{1}{n}E(z_1|z_1 \le v_i) - c,$$

where z_1 is the highest signal of the other $n-1$ bidders. That is, $z_1 = max_{j \in N_{-i}} v_j$.

Derivation of the Equilibrium in LR-PC Auctions

Consider bidder i who privately observes c_i The other bidders $j \neq i$ are bidding according to the differentiable and monotonically decreasing bid function $\zeta(c_j)$. Bidder i bids as though her signal were z. Her expected profit is then

$$\Pi(c_i, z) = (1 - G(z))^{n-1}(\zeta(z) - c_i).$$

The first order condition associated with this problem is

$$-(n-1)(1 - G(z))^{n-2}g(z)(\zeta(z) - c_i) + (1 - G(z))^{n-1}\left(\zeta'(z)\right) = 0.$$

In equilibrium, it must be the case that $z = c_i$. Utilizing this, we are left with an ordinary differential equation

$$-(n-1)(1-G(c_i))^{n-2} g(c_i)(\zeta(c_i) - c_i) + (1-G(c_i))^{n-1}\left(\zeta'(c_i)\right) = 0.$$

The initial condition is $\zeta(c_H) = c_H$. Notice that the above differential equation can be written as

$$\frac{d}{dv_i}\left((1-G(c_i))^{n-1}(\zeta(c_i))\right) = -(n-1)(1-G(c_i))^{n-2} g(c_i)\, c_i.$$

Integrating both sides leaves us with

$$(1-G(c_i))^{n-1}(\zeta(c_i)) = \int_{c_i}^{c_H} (n-1)(1-G(t))^{n-2}\, tg(t)\, dt.$$

Simplifying this yields the equilibrium bid function

$$\zeta(c_i) = E(z_{n-1} | z_{n-1} \geq c_i),$$

where $z_{n-1}$is the smallest of $n-1$ draws of d.

B Instructions

A translated version of the instructions for the LR-PC treatment are below. Instructions for the remaining treatments are available upon request.

These instructions will explain how to earn money during this experiment, based on your decisions and the decisions of others. We recommend that you read carefully because your earnings may be affected if you do not understand the instructions.

If you have any questions regarding these instructions, please raise your hand and we will answer your question privately.

From now on, participants will only interact via computers. If you talk, laugh, exclaim out loud, etc., we will end the experiment and ask you to leave without payment. Monetary amounts in the experiment are denominated in Experimental Pesos (E$). At the end of the experiment, Experimental Pesos will be exchanged for Quetzales at a rate of Q1=E$4. The profits obtained during the experiment will be paid privately and in cash (Quetzales).

This experiment consists of a series of periods. The computer will act as a seller and participants will act as potential buyers of a good which has the same VALUE to all participants. For each seller there will be 3 potential buyers. All potential buyers will have a COST of obtaining the good, which will likely be different for each person.

You can make money if: 1) you make the lowest REQUEST and 2) the AMOUNT received is more than the COST of obtaining the good.

Each period, groups of 3 potential buyers are chosen randomly. Potential buyers can obtain a good that has a VALUE. This VALUE is the same for all potential buyers and represents how much the good being sold in that period is worth.

However, no one will know the VALUE of the good before the period begins.

At the beginning of the period each potential buyer will receive his own ESTIMATE of the VALUE. The ESTIMATE of the VALUE will be a number chosen at random between 100 and 200 (inclusive).

All numbers in this range have the same probability of being selected to be the ESTIMATE of the VALUE. Each ESTIMATE of the VALUE is independent from the ESTIMATES of the VALUE of other potential buyers and those of other periods.

In other words, in each period you will have an ESTIMATE of VALUE which is likely to be different from the ESTIMATES of VALUE of other potential buyers and ESTIMATES of VALUE in other periods.

Each period, the VALUE of the good will be the average of the ESTIMATEs of VALUE of the 3 potential buyers. Since all ESTIMATEs of VALUE are between 100 and 200, the actual VALUE will be in this interval as well, and will be the same for all 3 potential buyers.

For example, if your ESTIMATE of VALUE is 182.60 and the ESTIMATES of the other 2 potential buyers are 109.42 and 167.31, the VALUE of the good (for any of the 3 participants) would be 153.11.

$(182.60 + 109.42 + 167.31)/3 = 153.11$

Each potential buyer will have a COST of obtaining the good. This COST will likely be different for each potential buyer. This COST is only incurred by the buyer of the good, and is paid in addition to the PRICE of the good.

Each period, the COST to each buyer is assigned at random. All COSTs between E$0 and E$50 (inclusive) are equally likely to be assigned. Your COST does not depend on COSTs of other participants or the COSTs in other periods.

In other words, in each period you will have a COST (between E$0 and E$50) which will likely be different than the COST of other potential buyers and different from the COST(s) you had in previous periods.

When the period begins, each potential buyer will know his ESTIMATE of the VALUE of the good as well as his COST. Each potential buyer can then REQUEST an AMOUNT from the VALUE of the good. The person who makes the lowest REQUEST will buy the good. He will pay the difference between the VALUE and his REQUEST. In case of a tie between two or more REQUESTS, the buyer will be determined at random.

In other words, the buyer will get the AMOUNT of the VALUE of the good he REQUESTED (net of the price paid to the seller). The AMOUNT obtained by the buyer cannot be larger than the VALUE of the good. Whenever the REQUEST is less than the VALUE of the good, the buyer will get that AMOUNT. If the REQUEST is larger than the VALUE of the good, the AMOUNT obtained by the buyer will equal the VALUE.

At the end of the period, your screen will display the REQUESTS of all buyers (ranked from lowest to highest), as well as the VALUE of the good, the AMOUNT obtained by the buyer, and your PROFIT.

For the person with the lowest REQUEST, the PROFIT will be:

AMOUNT - COST = PROFIT

All others will have PROFIT: 0

Notice that the buyer will earn money if the AMOUNT is more than his COST. Also notice that the buyer will lose money if the AMOUNT is less than his COST.

For example, if you make a REQUEST of 34 and it is the lowest REQUEST, you will buy the good. If the VALUE is 163 in that period and your COST is 24, your PROFIT will be: 34 - 24 = 10

If your REQUEST is not the lowest, then you do not purchase the good and your PROFIT is 0. For example, if you REQUEST 42 and this is not the lowest REQUEST, you will not purchase the good and will have a PROFIT of 0 in that period.

Each period groups are randomly reassigned. That is, you will likely NOT interact with the same people every period.

Moreover, you will never know the identity of the other participants in your group nor will they know yours.

At the beginning of the experiment, all participants will receive an endowment of E$500.

If at any point during the experiment you have a loss greater than your balance, you cannot continue in the experiment. Please wait quietly until the end of the experiment to receive your participation payment.

At the end of the experiment, while we prepare your payments, you will be asked to quietly fill out a short questionnaire.

Summary: You and two other people will be potential buyers for a good that the computer will be selling.

Each period, you will make a REQUEST to try to buy the good.

The potential buyer with the lowest REQUEST buys the good. When the REQUEST is lower than the VALUE, the buyer will obtain the AMOUNT he REQUESTED. The buyer will also pay the COST of obtaining the good.

Whoever buys the good will make money if his REQUEST is larger than his COST. PROFIT (did buy the good) = AMOUNT – COST PROFIT(did not buy the good) = 0.

References

Athias L, Nuñez A (2008) Winner's curse in toll road concessions. Economics Letters 101(3):172–174

Bain R, Polakovic L (2005) Traffic forecasting risk study update 2005: through ramp-up and beyond. Tech. rep.

Boone J, Chen R, Goeree J, Polydoro A (2009) Risky procurement with an insider bidder. Experimental Economics 12(4):417–436

Casari M, Ham J, Kagel J (2007) Selection bias, demographic effects, and ability effects in common value auction experiments. American Economic Review 97(4):1278–1304

Engel E, Fischer R, Galetovic A (1997) Highway franchising: pitfalls and opportunities. American Economic Review 87(2):68–72

Engel E, Fischer R, Galetovic A (2001) Least-present-value-of-revenue auctions and highway franchising. Journal of Political Economy 109(5):993–1020

Fischbacher U (2007) z-Tree: Zurich toolbox for ready-made economic experiments. Experimental Economics 10(2):171–178

Flyvbjerg B, Holm M, Buhl S (2005) How (In)accurate Are Demand Forecasts in Public Works Projects? Journal of the American Planning Association 71(2):131–146

Goeree J, Offerman T (2002) Efficiency in auctions with private and common values: An experimental study. American Economic Review 92(3):625–643

Goeree J, Offerman T (2003) Competitive Bidding in Auctions with Private and Common Values. Economic Journal 113(489):598–613

Guasch J (2004) Granting and renegotiating infrastructure concessions: doing it right. World Bank Publications

Holt C, Laury S (2002) Risk aversion and incentive effects. American Economic Review 92(5):1644–1655

Kagel J, Levin D (2002) Common value auctions and the winner's curse. Princeton University Press

Milgrom P, Weber R (1982) A theory of auctions and competitive bidding. Econometrica 50(5):1089–1122

Vassallo J (2006) Traffic risk mitigation in highway concession projects: the experience of Chile. Journal of Transport Economics and Policy 40(3):359–381