Valuation Structure in First-Price and Least-Revenue Auctions: An Experimental Investigation[1]

Diego Aycinena
Centro Vernon Smith de Economía Experimental
Universidad Francisco Marroquín
Guatemala, Guatemala
diegoaa@ufm.edu

Rimvydas Baltaduonis
Department of Economics
Gettysburg College
Gettysburg, Pennsylvania
rbaltadu@gettysburg.edu

Lucas Rentschler
Centro Vernon Smith de Economía Experimental
Universidad Francisco Marroquin
Guatemala, Guatemala
lrentschler@ufm.edu

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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 above the break-even bidding threshold. 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 compare 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, bidding above the break-even bidding threshold is significantly less prevalent in least-revenue auctions regardless of valuation structure. As a 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.

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1 Introduction

Auctions for infrastructure concession contracts may be modeled as having both private and common components in the valuation structure. The winner of such an auction receives the revenue generated by the contract (e.g. tolls from highway concessions, energy transmission fees over a high-power grid, generation capacity payments, etc.) which has a common value (Bain and Polakovic (2005); Flyvbjerg et al (2005)), while also incurring the cost of fulfilling the contract (e.g. building the highway, constructing the infrastructure for power lines, building and maintaining power plants, etc.). If bidders' costs of providing the infrastructure differ, these costs may represent a private component of the valuation structure.

In auctions in which there is a common value component, it is well known that bidders are prone to the winner's curse.[1] That is, bidders bid such that they guarantee themselves negative payoffs in expectation. This is of particular concern in auctions for infrastructure concession contracts, as bidders who go bankrupt may cause costly delays in infrastructure development.

In this paper we experimentally compare the standard first-price sealed-bid auction with an alternative auction format which may reduce the prevalence of the winners curse, the Least-Revenue Auction (LRA).[2] We compare these two auction formats in two valuation structures with an uncertain common value. In the first, bidders face a private cost. In the second, bidders face a common cost which is common knowledge.

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] The bidder who submits the lowest amount wins the auction, and obtains that amount, provided the amount is less than the common value of the good. In the event that the winning amount is greater than the value of the good, the winning bidder only obtains this value. Thus, the winner implicitly pays the difference between the realized common-value of the good and the amount they submitted. This mechanism renders private information bidders may hold regarding the common value of the good strategically irrelevant, provided this information is not correlated with the private information of other bidders. The LRA is then strategically equivalent to a first-price procurement auction. In a purely common-value LRA 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

[1] See, e.g. Casari, Ham and Kagel (2007) and Goeree and Offerman (2002).

[2] This auction format follows the spirit of 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 reasons of comparability, use the term revenue to refer to the 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 the present value of toll revenue required by bidding firms.

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 reduces the possibility that the winning bidder, having failed to account for the informational content of winning the auction when formulating her bid, will subsequently go bankrupt.

An additional potential benefit of using LRAs is that if bidders anticipate that the contract is open to renegotiation ex post, they may bid more aggressively in a first price auction, with no intention of adhering to the contract ex post. Uncertainty regarding the common value component of the good may provide cover for such strategic behavior, since the winning bidder can claim that they simply fell victim to the winner's curse when demanding that the contract be renegotiated. Indeed, 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, presumably due to a higher probability of contract renegotiation. The LRA removes this cover, and thus may reduce reported bankruptcies in practice. We leave this interesting case to future research, and in the current paper focus on the case in which the contract is binding.

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 environment consistent with the motivation underlying LPVRAs. Although Chile has implemented LPVRAs on more than one occasion (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 this paper we test to see if an LRA can reduce the prevalence with which bidder's guarantee themselves negative profits in expectation. We leave for subsequent experimental research the question of optimal risk sharing between the auctioneer and bidders.

In addition, our paper contributes to the small but growing literature regarding auctions with private and common values (see e.g. Goeree and Offerman (2002); Boone et al (2009)). The theoretical analysis of such auctions begins with Goeree and Offerman (2003). We extend this analysis by deriving the cursed equilibrium in first price auctions. Cursed equilibrium was introduced in Eyster and Rabin (2005), and allows for the possibility that bidders do not fully take into account the link between the private information of other bidders and their when formulating their own bid. This model of bounded rationality includes Nash equilibrium and a naive bidding model as special cases. 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 (provided signals are independent).[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. That is, inexperienced bidders often bid above a break-even bidding threshold. This ob-

[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 LRAs eliminate the uncertainty regarding the common value of the good.

servation 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 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 frequency with which bidders bid above a break-even bidding threshold in LRAs relative to first-price auctions. Indeed, inexperienced bidders in LRAs very rarely bid above this threshold. 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 in bidding above the break-even bidding threshold 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 aggressively, 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 $j \neq i$. In particular, we consider environments in which the $c_i = c_j$ for $\forall i, j \in \mathbf{N}$, and this is common knowledge. We also

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

[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.

consider environments in which the cost of each bidder is an independent draw from a distribution that is commonly known. Each bidder observes their own cost, but not that of the other bidders. 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 $N_{-i} \equiv N/i$. We allow for the possibility that when a bidder is formulating her bid she does not fully take into account the information conveyed by the behavior of other bidders. In particular, we consider cursed equilibrium, as described in Eyster and Rabin (2005).[7] In a cursed equilibrium bidders only partially take into account the correlation between the bids and signals of their opponents. If bids are increasing in the common value signal, this can result in unrealistically high beliefs about the value of the good conditional on winning the auction. Following Eyster and Rabin (2005), we assume that each bidder correctly anticipates the probability distribution of other bids, but mistakenly believes that with probability χ each of the other bidders employ a strategy that is equal to their average bid. The crucial point is that with probability χ each bidder believes that the behavior of the other bidders is not correlated with their private signals. For simplicity we assume that χ is the same for all bidders. Note that when $\chi = 0$ predictions will correspond to the symmetric Bayesian Nash equilibrium. Further, when $\chi = 1$ bidders are naive in the sense that they do not account for the informational content of winning the auction. The special case where $\chi = 1$ is similar to the naive bidding model studied in GO.

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 c 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, with corresponding density and distribution functions f_s and F_s respectively. We denote the interval on which s is

[7] We do not consider a level-k model, because in three of our four treatments this model predicts Nash bidding behavior for all but level zero bidders (the exception is the first-price auction with common values and a private cost).

distributed as $[s_L, s_H] = \left[\frac{v_L}{n} - c_H, \frac{v_H}{n} - c_L\right]$. The symmetric cursed equilibrium bid function is

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

where $y_1$is the highest s_i of the other $n-1$ bidders. That is, $y_1 = max_{j \in N_{-i}} \frac{v_j}{n} - c_j$.[8]

The ex ante expected profit of bidder i in this cursed equilibrium is given by

$$E\left(\Pi_i^{FP-PC}(\rho(s), s)\right) = \left(\frac{1}{n}\right)\left(E(Y_1) - E(Y_2)\right) -$$
$$\chi\left(\frac{n-1}{n}\right)\left(\frac{1}{n}\right)\left(E(v) - E(v|s \le Y_1)\right),$$

where Y_1 is the first order statistic of the n draws of s, and Y_2 is the corresponding second order statistic. The corresponding ex ante expected profit of the winner is then

$$E\left(\Pi_{winner}^{FP-PC}\right) = E(Y_1) - E(Y_2) - \chi\left(\frac{n-1}{n}\right)\left(E(v) - E(v|s \le Y_1)\right).$$

Notice that $E\left(\Pi_{winner}^{FP-PC}\right)$is decreasing in χ.

To find the expected revenue in an FP-PC auction we first note that the winner's net value of the good is $W = E(V) - E(c|s = Y_1)$. Thus, expected revenue in this cursed equilibrium is $R^{FP-PC} = W - E\left(\Pi_{winner}^{FP-PC}\right)$. This means that R^{FP-PC} is increasing in χ.

2.1.1 Break-Even Bidding Threshold

It has been widely observed that inexperienced bidders in common value auctions bid such that they guarantee themselves negative expected profits. The propensity of bidders to bid above their break-even bidding threshold 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. The break-even bidding threshold is defined as

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

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

[8] Derivations of this cursed equilibrium as well as the corresponding expected profit and auctioneer revenue can be found in Appendix A.

been widely studied in the literature. However, the presence of the (common) cost differentiates our work from the bulk of the literature. The symmetric cursed equilibrium bidding function of this auction is given by:

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

where $z_1$is the highest signal of the other $n-1$ bidders. That is, $z_1=max_{j\in N_{-i}}v_j$.[9]

The ex ante expected profit of bidder i is given by

$$E\left(\Pi_i^{FP-C}\left(\beta\left(v\right),v\right)\right)=\left(\frac{1}{n^2}\right)\left(E\left(Z_1\right)-E\left(Z_2\right)\right)-$$
$$\chi\left(\frac{n-1}{n}\right)\left(\frac{1}{n}\right)\left(E\left(v\right)-E\left(v|v\leq Z_1\right)\right),$$

where Z_1 is the first order statistic of the n draws of v, and Z_2 is the corresponding second order statistic.

The ex ante expected profit of the winner in this cursed equilibrium is then

$$E\left(\Pi_{winner}^{FP-C}\right)=\left(\frac{1}{n}\right)\left(E\left(Z_1\right)-E\left(Z_2\right)\right)-\chi\left(\frac{n-1}{n}\right)\left(E\left(v\right)-E\left(v|v\leq Z_1\right)\right).$$

Total expected surplus in this auction is given by $X=E\left(V\right)-\bar{c}$. Thus, expected revenue in this cursed equilibrium is $R^{FP-C}=X-E\left(\Pi_{winner}^{FP-C}\right)$.

2.2.1 Break-Even Bidding Threshold

In an FP-C auction, a bidder is bidding above the break-even bidding threshold if she bids above the expected value of the good, conditional on winning the auction. When the symmetric cursed 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. The functional form of this threshold is

$$T^{FP-C}\left(v_i\right)=\frac{v_i}{n}+\left(\frac{n-1}{n}\right)E\left(v|v\leq v_i\right)-\bar{c}.$$

[9]The derivations of this cursed equilibrium bid function, equilibrium bidder profits, equilibrium auctioneer revenue can be found in Appendix A.

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, V) that a bidder is willing to receive, 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_L, the uncertainty regarding the common-value of the good does not affect the winning bidder's payoff conditional on winning. Note that in equilibrium predicted bids will fall below v_L.[10] Further, since we have assumed that private information is independent, a bidder's beliefs about the private information held by opponents will not be contingent on her own private information in equilibrium. Thus, the draws of v that each bidder observes are 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 procurement auction with independent private costs. Additionally, we assume that each bidder incorrectly believe that with probability χ her opponents will bid their average bid, rather than their type contingent strategy. However, as long as the resulting cursed equilibrium bidding strategy is monotonically decreasing in type, this will not affect expected payoffs. This is because the bidder with the lowest cost will win in equilibrium, and the probability of winning the auction is the same as the probability of having the lowest cost. As such, provided $\chi < 1$, the cursed equilibrium bid function will correspond to the Nash equilibrium bid function. Note that if bidders are cursed ($\chi > 0$), then using a LRA in place of a first price auction is predicted to reduce the frequency with which the winning bidder loses money.

The cursed (and Nash) equilibrium bid function is

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

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

The ex ante expected profit of bidder i is given by $E\left(\Pi_i^{LR-PC}(\zeta(c), c)\right) = \left(\frac{1}{n}\right) E(U_{n-1}) - \left(\frac{1}{n}\right) E(U_n)$, where U_{n-1} is the second lowest and U_n is the lowest of theof n draws of c. Thus the

[10] Since a bidder of type c_H will almost surely lose in any monotonically decreasing equilibrium, it must be the case that in equilibrium she will bid $c_H < v_L$. If a bidder of type c_H were to bid $b < c_H$ in equilibrium, she would earn a positive profit if she won the auction. She would then have an incentive to decrease her bid in order to have a positive probability of winning the auction. Thus the equilibrium bid of type c_H must be equal to c_H.

ex ante expected profit of the winner is given by $E\left(\Pi_{winner}^{LR-PC}\right) = E\left(U_{n-1}\right) - E\left(U_n\right)$. Since the total expected surplus in this auction is given by $D = E\left(V\right) - E\left(c|c = U_n\right)$, expected revenue in this equilibrium is $R^{LR-PC} = D - E\left(\Pi_{winner}^{LR-PC}\right)$.

2.3.1 Break-Even Bidding Threshold

In this environment, 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. 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

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

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. As a result, the value of χ is irrelevant. Since bidders place bids that do not depend on their private information (every type employs the same pure strategy), the average bid is the same. The unique symmetric (cursed) 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 $b_j \in \left(\bar{c}, b_i\right)$ and earn a positive profit. Notice that the ex ante equilibrium profit of bidder i is zero. Further, the equilibrium revenue in this game is $R^{LR-C} = E\left(V\right) - \bar{c}$.

2.4.1 Break-Even Bidding Threshold

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:

$$T^{LR-C} = 25.$$

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. After each round, all participants within a session are randomly and anonymously re-matched. The randomized group assignment was kept constant across all sessions. This process is repeated for thirty rounds.[11]

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 $[100, 200]$.[12] The common value, V, is the average of the private signals. That is, $V = \frac{1}{3}\sum_{i=1}^{3} v_i$. 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.

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 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

[11] One of the first ten periods (referred here as periods -9 to 0) is randomly selected to be paid. Each of the remaining 20 periods (referred to as periods 1 to 20) are paid. In the analysis that follows, data from the initial ten periods is not utilized.

[12] We used 360 (12 subjects $\times$30 rounds) iid draws that were kept constant across all sessions. That is, we had 12 types of subjects who saw the same sequence of signals constant across all sessions.

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 similar to that of Holt and Laury (2002).[13] 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 reported 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.[14] At the end of all thirty rounds, each participant was paid her balance which included 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 contine, and received a payment of zero.

[15] Within the 16 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 $Q165$.

[13]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.

[14]Low or high starting balance sessions are balanced across treatments. For each treatment we have 2 sessions with a low starting balance and two sessions with a high starting balance. The starting balance was increased due to the prevalence of bankrupt subjects with the lower starting balance. Bankruptcies only occurred in sessions with first-price auctions.

[15]If more than one participant went bankrupt then the data from the session was not included in the reported analysis. We exclude the data from six sessions. In two of these, multiple subjects went bankrupt. In the remaining four, one subject went bankrupt in each session, and additional problems prevented us from completing the session.

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 signal 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 1 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, $U = -4.484$, $p = 0.029$).[16] 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

[16] Unless otherwise noted, our non-parametric tests use average results from each session as an independent observation. Thus, we have 4 independent observations per cell. Given that the asymptotic p-value is not a good approximation when both samples have less than 12 observations, we rely on critical values of the test statistic for different levels of statistical significance calculated by Feltovich (2003).

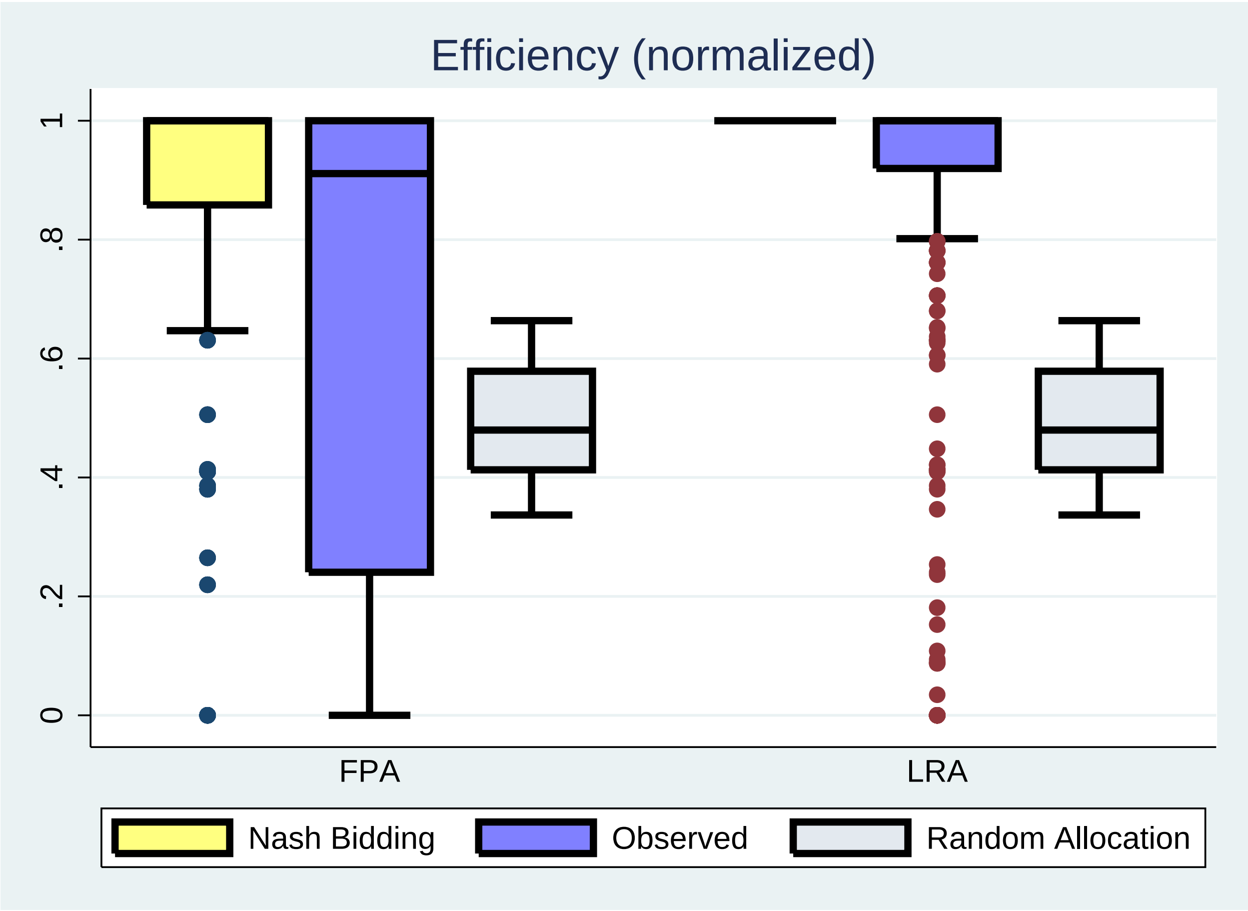

Figure 1: Efficiency in FP-PC and LR-PC auctions

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. The difference in efficiency between LR-PC and FP-PC auctions can be largely attributed to the fact that the uncertainty regarding the common value of the good has been shifted to the auctioneer in LRAs.

4.2 Bidder Profits

Table 2 contains summary statistics of bidder payoffs (and revenue) in all four treatments. Figure 2 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 predicted by theory. In the case of LR-C auctions, theory is an excellent predictor of bidder profits. 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 small but positive profits.

Theory predicts that bidders will be better off when there are private and common values than they would be in pure common value environments because the privately observed costs earn

Table 1: Summary statistics for efficiency

	FP-PC			LR-PC		
Efficiency Measure	Periods 1-10	Periods 11-20	All Periods	Periods 1-10	Periods 11-20	All Perioc
Observed	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.

Table 2: Bidder payoffs and revenue

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.

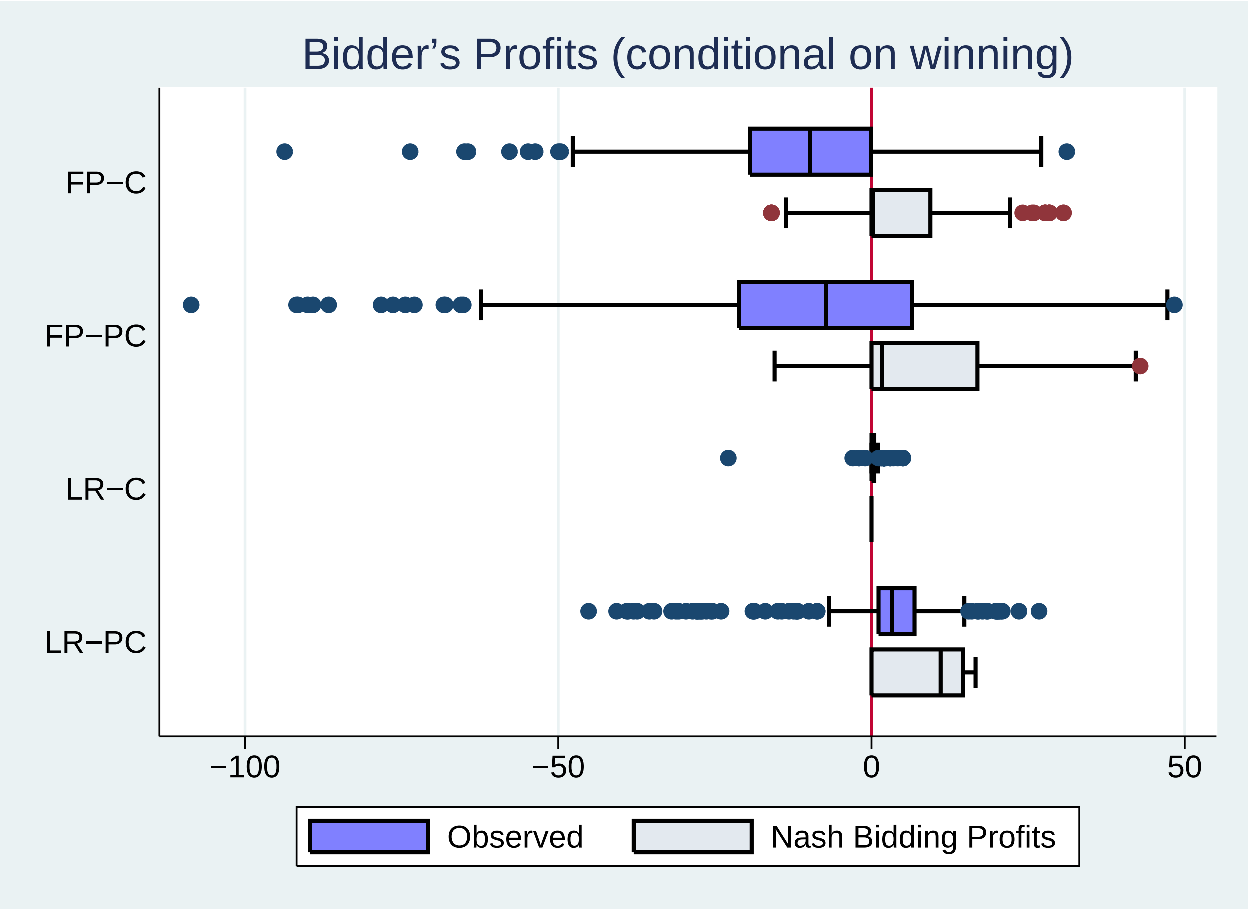

Figure 2: Observed and predicted bidder profits

positive information rents. We are unable to find evidence that valuation structure significantly affect payoffs in first-price auctions (robust rank order test, $U = -0.776$, *n.s.*)[17] or in LRAs (robust rank order test, $U = -1.033$, *n.s.*).[18]

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, $U = -1.586$, $p = 0.1$).[19] However, this result is highly significant in the pure common values environment (robust rank order test, *n.d.*, $p = 0.014$).[20] The intuition behind this is that in first-price auctions bidders tend to substantially

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

[18] As Figure 4 illustrates, in both auction formats, bidder profits are greater on average under private and common values than under pure common values. However, using session level data (with only four observations per cell), we cannot reject the null hypothesis of equality of means under using the robust rank order test. For FPAs, results are not robust to dropping 1 session in each treatment where a bankruptcy occurred: dropping those sessions, payoffs are significantly greater under FP-PC than under FP-C (robust rank order test, $U = -2.348$, $p = 0.1$). However, if we drop all periods after a subject went bankrupt rather than the entire session, we cannot reject equality (robust rank order test, $U = -0.776$, *n.s.*).

[19] If the session with bankruptcy in the FP-PC is dropped, this result is no longer significant ($U = -1.000$). If only the periods after the bankruptcy occurred are dropped, rather than the entire session, the result is unchanged.

[20] When the lowest observation from one treatment is higher than the highest observation of the other treatment, the

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 (weakly) positive profits.

Revenue is, of course, closely related to bidder profits. As such, our results regarding auction revenue closely mirror those of bidder profits. Contrary to theory, FP-PC auctions, on average, generate more revenue than LR-PC, although this result is only marginally significant (robust rank order test, $U = 1.586, p = 0.1$).[21] FP-C auctions generate more revenue than LR-C revenue (robust rank order test, $n.d.$, $p = 0.014$). The intuition underlying this result mirrors the analogous finding for profits. We also find that valuation structure does not significantly affect revenue in first-price auctions (robust rank order test, $U = 0.000$, *n.s.*). However, in LRAs the private and common value valuation structure generates more revenue than the pure common value valuation structure (robust rank order test, $n.d.$, $p = 0.014$).

4.3 Break-Even Bidding Threshold

In auctions with pure common values, bidders are widely observed to bid such that they guarantee themselves negative payoffs in expectation. This is particularly true among inexperienced bidders such as those who participated in the experimental sessions for this paper. GO provide evidence that 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 prevalence of the bidding above the break-even bidding threshold 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 FPAs with private and common value components (robust rank order test, $U = 11.314$, $p < 0.029$), as well as in the pure common value environment (robust rank order test, $U = 11.314$, $p < 0.029$). Figure 3 illustrates this result by showing the proportion of bids above the break-even bidding threshold for all four treatments. Figure 4 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

test statistic of the robust rank order test is undefined. We denote this highly significant case as *n.d.*

[21] If the FP-PC session in which a subject went bankrupt is dropped, this result is no longer significant. However, if periods after the subject went bankrupt are dropped, rather than the entire session, the result is unchanged.

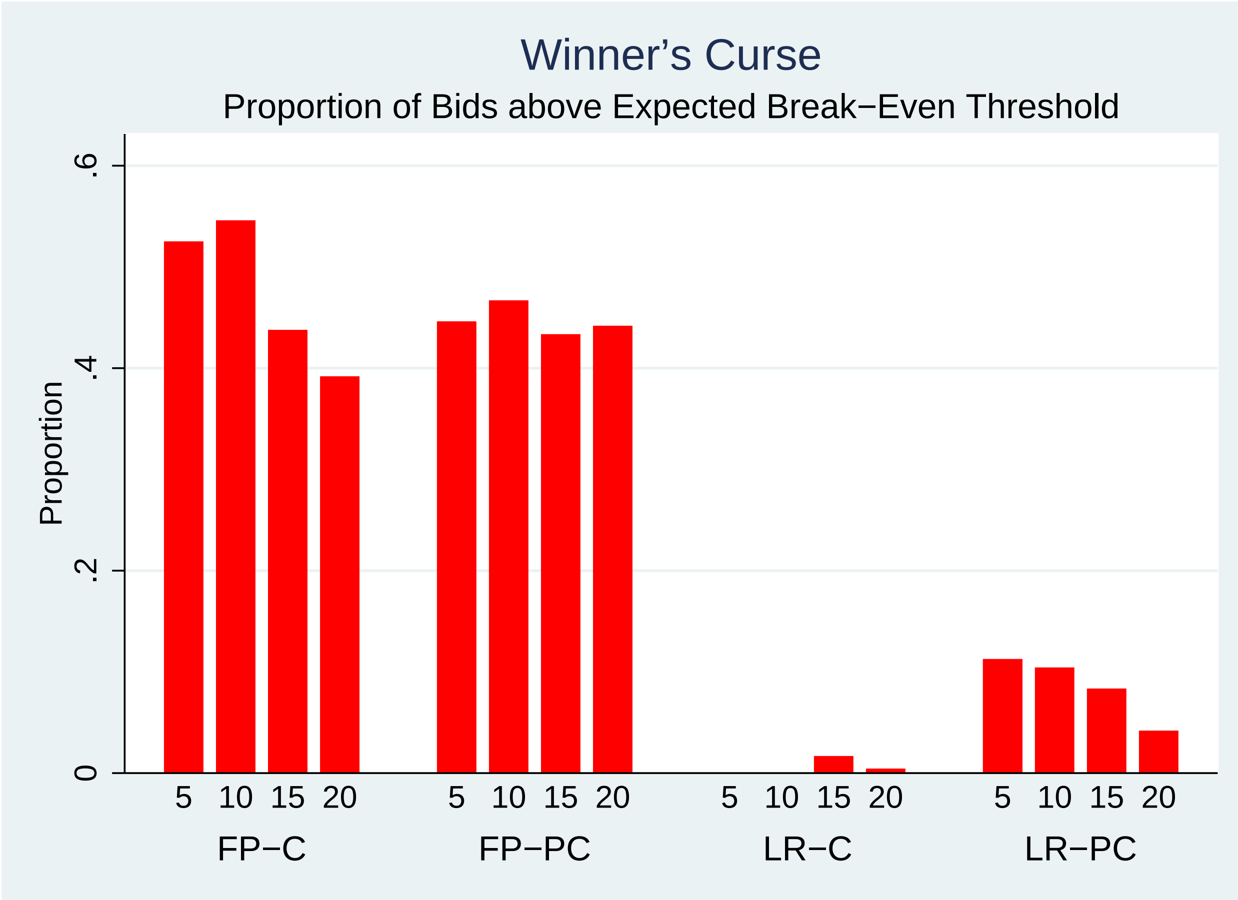

Figure 3: Prevalence of bids above the break-even threshold

risk regarding this uncertain value has been completely shifted to the auctioneer.

We also find that the valuation structure does not significantly affect the frequency with which bidders bid above the break-even bidding threshold in FPAs (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.

4.4 Cursed Equilibrium

We now turn to comparing observed bidding behavior directly with the cursed equilibrium predictions. Table 4 contains summary statistics regarding observed bids, as well as the two border cases in cursed equilibrium. These border cases are: Nash equilibrium bids (where $\chi = 0$), and for FPAs (where the equilibrium bid function depends on χ) the fully cursed equilibrium ($\chi = 1$). Of note is the fact that, on average, bidders overbid relative to the Nash equilibrium in every treatment

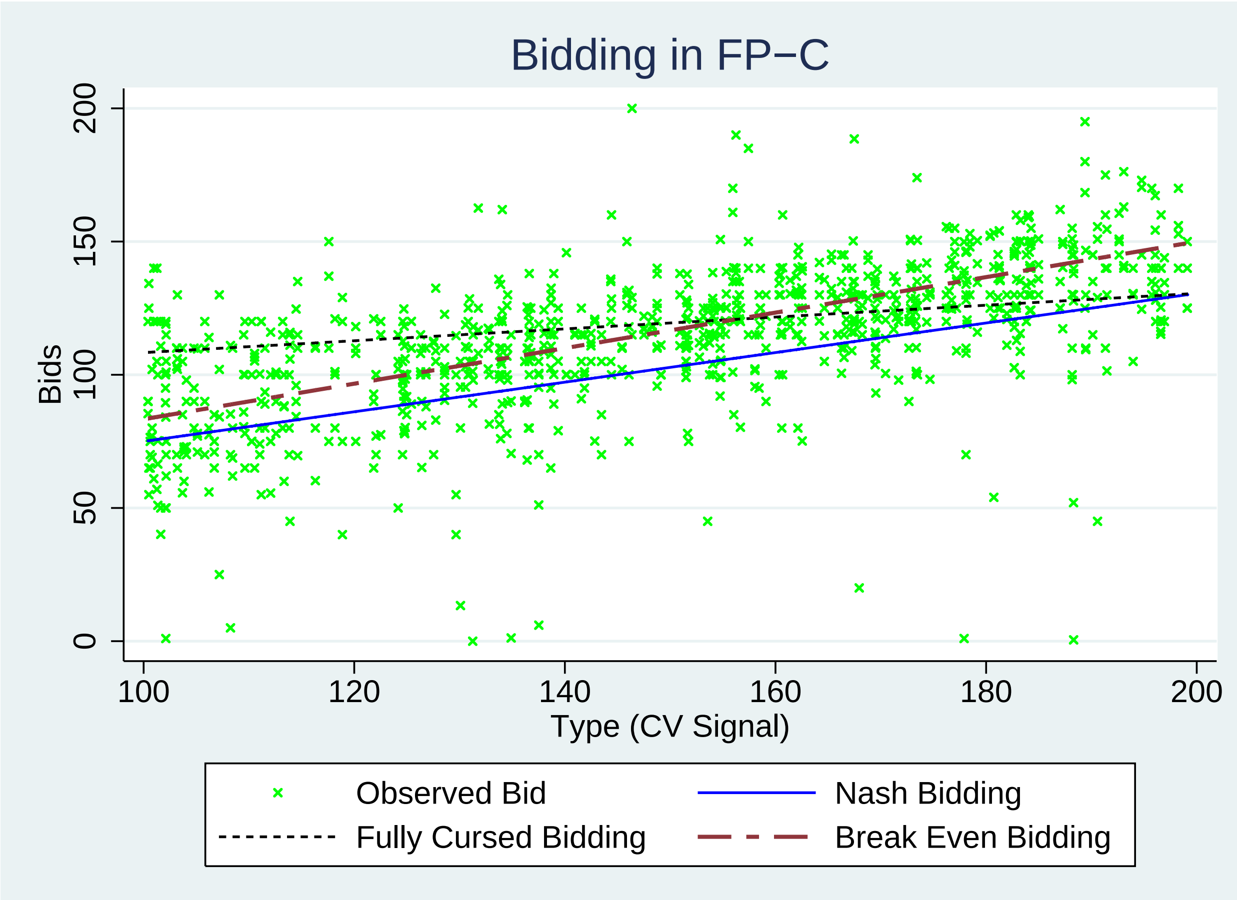

Figure 4: Prevalence of bids above the break-even threshold in five period blocks

except LR-C. In FPAs this overbidding is, on average, less than the fully cursed bidding strategy, indicating that a bidding may be explained by an intermediate level of cursedness.

Figure 5 illustrates how observed bids in FP-C auctions compare to the Nash predictions, the fully cursed bidding strategy, and the break-even bidding threshold. Notice that bids tend to be well in excess of the Nash equilibrium prediction. Indeed, bids well above the break-even bidding threshold, and above the fully cursed biding strategy are common. In these FP-C auctions, we find that bids are greater than Nash predictions (sign test, $w = 41$, $p < 0.001$). [22] Further, FP-C bids are less than the fully cursed bidding strategy (sign test, $w = 32$, $p = 0.015$).

Figure 6 provides the analogous graph for FP-PC auctions. Overbidding relative to Nash predictions, as well as bidding in excess of the break-even bidding threshold, is also common in this environment. 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 fully cursed bidding strategy (sign test,

[22] The unit of observation used in the sign test is the individual participant. That is, the average 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.

Table 3: Bidding above the break-even bidding threshold (proportion of bids)

Variable	FP-C	FP-PC	LR-C	LR-PC
Bids above break-even threshold	0.475	0.447	0.005	0.085
	(0.500)	(0.497)	(0.072)	(0.280)
Bids above break-even threshold 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.

Table 4: Observed bids relative to Nash and fully cursed bids

Variable	FP-C	FP-PC	LR-C	LR-PC
Observed Bids	114.085	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)
Fully Cursed Bids	119.346	114.961	-	-
	(6.227)	(12.287)		

Notes: Table contains means with standard deviations in parentheses.

$w = 30$, $p = 0.056$).

Figure 7 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 aggresive bidding (bidding below the Nash equlibrium) is largely nonexistant in this environment. In LR-C auctions, we find that bidders are submitting bids that exceed 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.

Figure 8 compares observed bids in LR-PC auctions to Nash predictions and the break-even bidding threshold. In stark contrast to what is observed in FPAs, bidding such that expected profits are negative in expectation is almost non-existent. In LR-PC auctions, we find that bidders are bidding more aggressively than predicted by the Nash equilibrium (sign test, $w = 38$, $p < 0.001$). This is consistent with observed bidding behavior in FPAs with independent private values.

The cursed equilibrium model that we consider depends on some behavioral parameters. In FPAs, the cursedness parameter χ predicts the extent to which bidders do not account for the correlation between their opponents private information and their behavior. In LRAs payoffs do not depend on χ. This provides a compelling theoretical rational for adopting the LRA in favor of the FPA; the LRA provides an environment in which the cursedness of bidders is predicted to not affect behavior.

Following Crawford and Ibiberri (2007), we estimate χ in FPAs and logit precision parameter

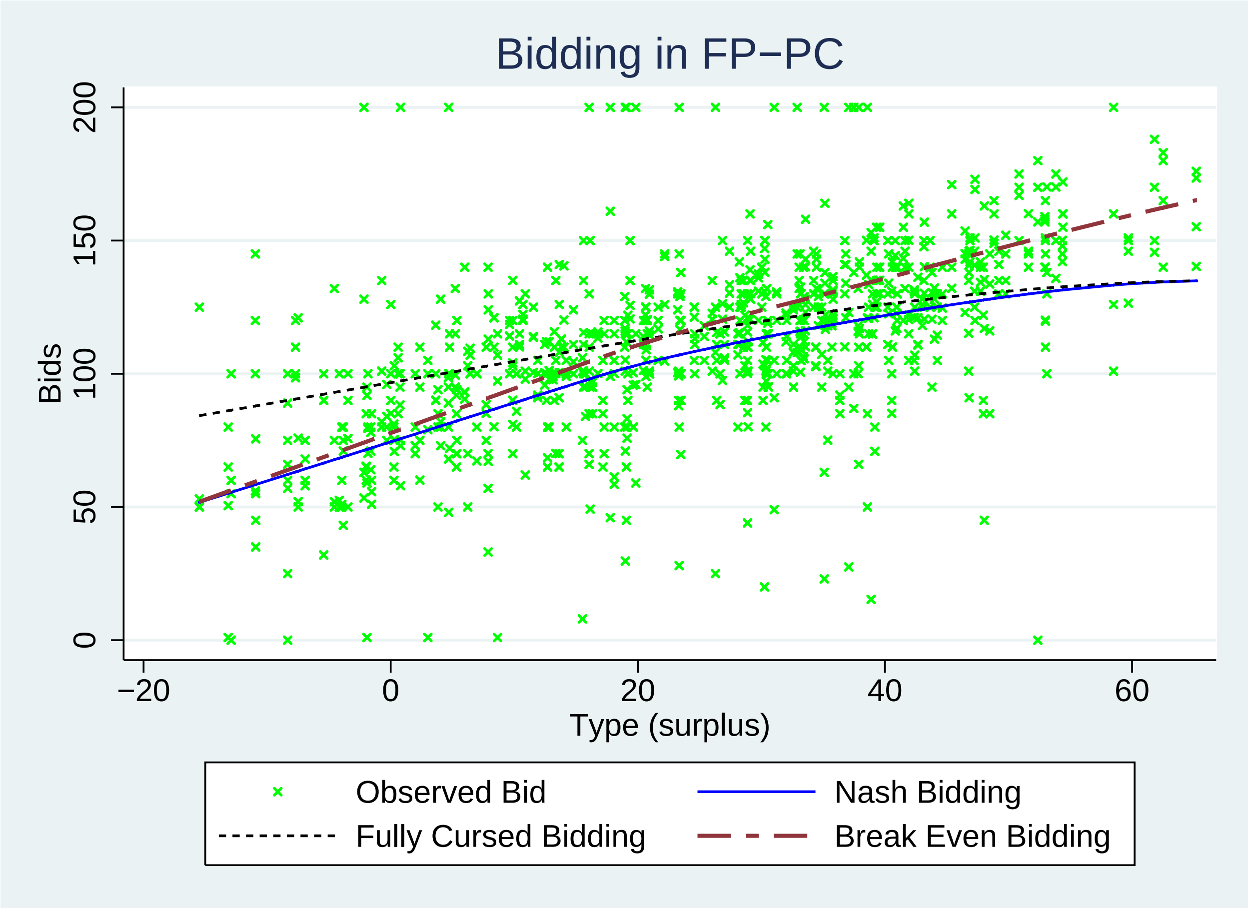

Figure 5: Bidding in FP-PC auctions

in all four treatments. These logit precision parameters, roughly speaking, give us a measure of how much noise must be added to the model in order for it to fit the data. Denoting the expected payoff that bidder i believes she has when she observes a common value signal v_{it} and a cost of c_{it} (note that in the pure common value environments $c_{it} = \bar{c}$) and who bids b_{it} in auction type k (where k is either FP-PC, FP-C, LR-PC or LR-C) as $\prod_{it}^{k}(b_{it}|v_{it}, c_{it})$. It is assumed that bidders make errors when formulating their bids. Every bid in the strategy space is played with positive probability, and this probability is increasing in the expected payoff that a bidder believes a bid would yield. In particular, the probability of observing bid b is assumed to be

$$Pr(b_{it}|v_{it}, c_{it}, \chi, \lambda) = \frac{exp\left(\lambda \prod_{it}^{k}(b_{it}|v_{it}, c_{it})\right)}{\int_{0}^{200} exp\left(\lambda \prod_{it}^{k}(x|v_{it}, c_{it})\right) dx}.$$

In the denominator we are integrating over the strategy space (the maximum allowed bid in our design was 200). λ is a logit precision parameter, which determines how sensitive the probabilities are to relative expected payoffs. Note that if $\lambda = 0$, then each strategy is played with equal

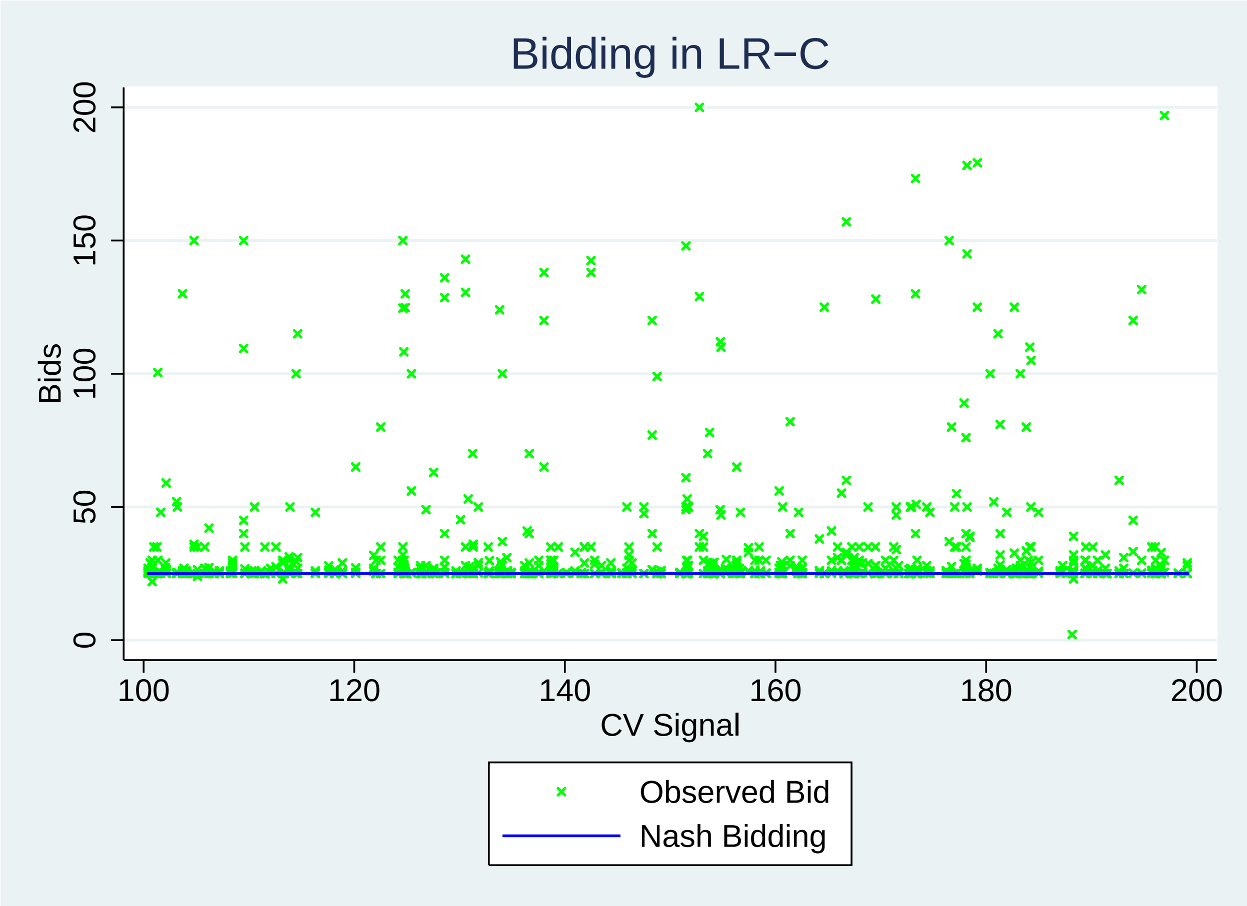

Figure 6: Bidding in LR-C auctions

probability, and that as $\lambda \to \infty$, bidders no longer make mistakes. We assume that errors are independent. Further, we assume that λ and χ do not vary over time or across subjects. For subject i in auction type k we observe a sequence of bids $b_i^k = \left(b_{i1}^k, b_{i2}^k, ..., b_{i20}^k\right)$. This subject observes a corresponding sequence of common value signals $v_i^k = \left(v_{i1}^k, v_{i2}^k, ..., v_{i20}^k\right)$ and costs $c_i^k = \left(c_{i1}^k, c_{i2}^k, ..., c_{i20}^k\right)$. Further, we have a total of 48 subjects in each auction type. The likelihood of observing our sample in auction type k is then given by

$$L = \prod_{i=1}^{48} \prod_{t=1}^{20} Pr\left(b_{it} | v_{it}, c_{it}, \chi, \lambda\right).$$

The corresponding log-likelihood is simply

$$LL = \sum_{i=1}^{48} \sum_{t=1}^{20} ln\left(Pr\left(b_{it} | v_{it}, c_{it}, \chi, \lambda\right)\right).$$

Table 5 shows observed bids by treatment as well as the theoretical bids predicted by the two

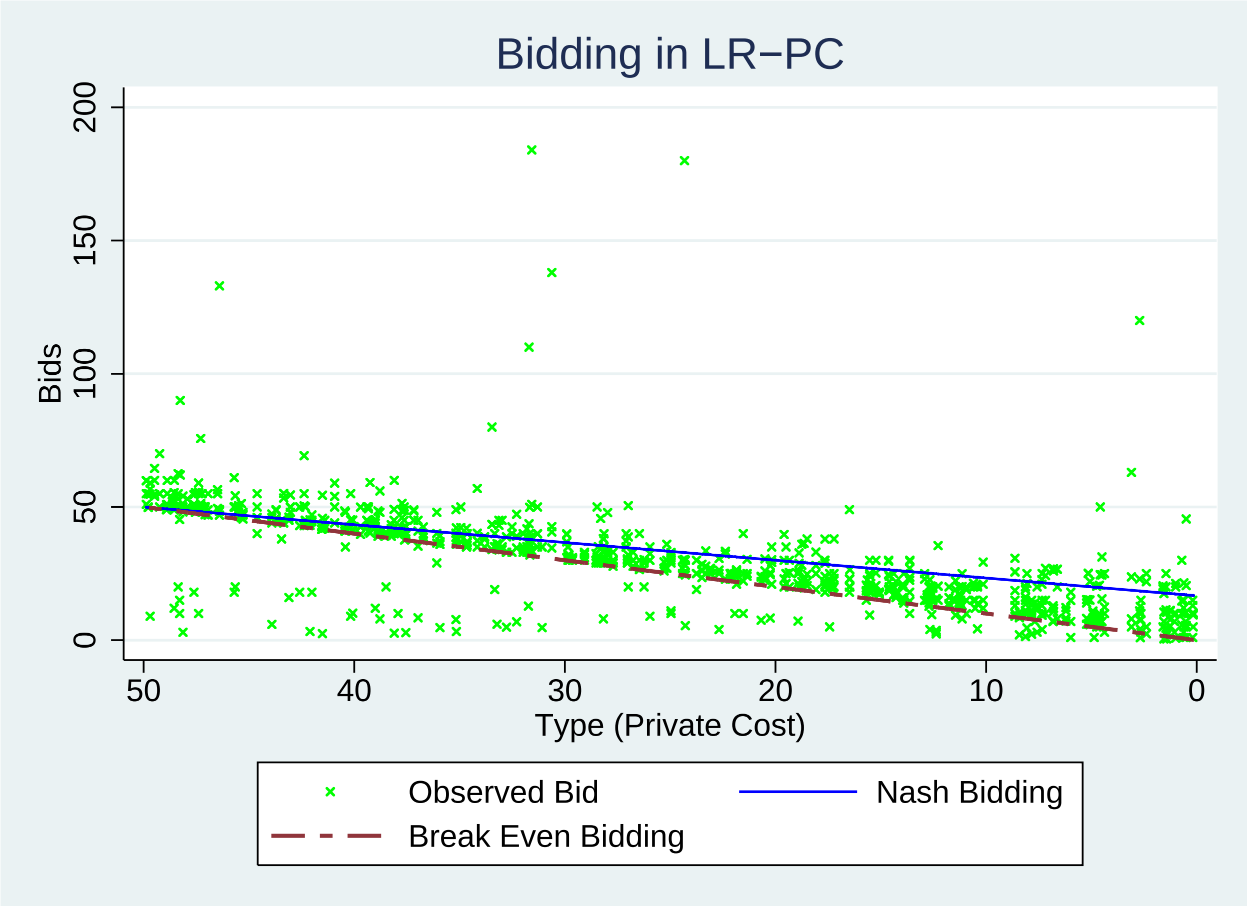

Figure 7: Figure 10: Bidding in LR-PC auctions

polar cases of our cursed equilibrium model. We break up the analysis by looking at three different blocks according to the magnitude of the relevant signal. [23] In addition to showing the average and standard deviation for observed and predicted (Nash and fully cursed) bidding, the table also reports the p-values for one sided sign tests between observed and predicted bids according to each model. [24] Notice that splitting the data into thirds allows us to check for differences in bidding away from the center of the distribution of relevant signals.[25] As the table shows, in FPAs, average

[23]For instance in FP-C, we split the data according to whether individuals observed a private signal about the common value of the good that was in the lower, mid or higher third of the theoretical distribution of signals. For FP-PC, the split is regarding the observed s_i relative to the theoretical distribution of the surplus summary statistic. For LR-C there is no relevant signal since the weakly dominant strategy ignores the private signal about the common value, but for comparability, we use the same blocks as in FP-C. Finally, for LR-PC, we split into blocks according to whether the observed private cost falls into the lower, mid or upper third of the theoretical cost distribution.

[24]For these sign tests, we use individual level data (i.e. the average bid of each individual when the observed relevant signal was in the specific block). For the test between observed and Nash bidding, the alternative hypothesis is that bidders bid more aggressively than the theory predicts: the median of observed bids exceed the median of Nash predicted bids. For the test between observed and fully cursed, the alternative hypothesis is that individuals bid more conservatively than predicted: the median of observed bids is below the median of fully cursed predicted bids.

[25]We thank an anonymous referee for suggesting this analysis

Table 5: Bidding relative to Nash and fully cursed, by signal magnitude

First Price Auctions	C				P&C			
Observed Bid	low	mid	high	all	low	mid	high	all
Mean	93.48	115.54	131.58	114.08	85.76	113.19	135.80	111.93
Std. Dev.	(24.12)	(21.29)	(22.43)	(27.24)	(30.57)	(27.50)	(23.68)	(32.46)
Nash Bid								
Mean	83.65	102.50	120.04	102.53	75.70	108.69	126.45	104.94
Std. Dev.	(5.93)	(5.48)	(5.07)	(15.57)	(9.94)	(8.55)	(3.91)	(19.74)
p-value	0.001	0.000	0.000	0.000	0.007	0.001	0.000	0.000
Fully Cursed Bid								
Mean	111.79	119.33	126.35	119.35	97.35	116.62	129.25	114.96
Std. Dev.	(2.37)	(2.19)	(2.03)	(6.23)	(5.42)	(5.76)	(2.66)	(12.29)
p-value	0.000	0.097	1.000	0.015	0.000	0.015	1.000	0.0557
Least Revenue Auctions								
Observed Bid								
Mean	34.02	33.13	35.39	34.16	15.64	30.78	44.38	29.96
Std. Dev.	(24.14)	(22.15)	(27.41)	(24.61)	(10.05)	(16.65)	(13.71)	(18.06)
Nash Bid								
Mean	25	25	25	25	22.21	33.65	44.93	33.36
Std. Dev.	(0)	(0)	(0)	(0)	(3.33)	(3.33)	(3.24)	(9.93)
p-value	0.000	0.000	0.000	0.000	0.000	0.000	0.015	0.000

observed bids tend to fall in between the two polar cases of the cursed equilibrium model. However, once we break it into blocks we see that when bidders have relevant signals in the upper third of the distribution, these bids tend to be statistically indistinguishable from the bids predicted by the fully cursed equilibrium. The table also illustrates that there is more dispersion among observed bids than among either theoretical prediction.[26]

Table 6 provides maximum likelihood estimates for all the behavioral parameters for all four treatments.[27] Recall that in LRAs, $\prod_{it}^{k}(b_{it}|v_{it}, c_{it})$ does not depend on χ. As such, in the LRA treatments we only estimate λ. There are several interesting results. First, χ is significant in both FP-PC and FP-C auctions. The degree of cursedness is higher in the pure common values environment. This indicates that the introduction of the private cost in first price auctions reduces cursedness. This is intuitive, because when the private cost is introduced, a subjects private information is more important in determining payoffs conditional on winning the auction. It is then not surprising that subjects are less likely to fail to recognize that private information and subsequent bids are related. Second, notice that the precision parameter λ is smaller in the FPA treatments than in the LRA treatments. This indicates that there is less error in formulating bids in LRAs.

[26]This suggests that either bid formulation is a noisy process, there is bidder heterogeneity, or both.

[27]The Gauss code we used to obtain these results is available upon request.

Table 6: Maximum likelihood estimates of behavioral parameters

Treatment	FP-PC	FP-C	LR-PC	LR-C
χ	0.663*	0.942***	–	–
	(0.312)	(0.106)		
λ	0.042***	0.044***	0.129***	0.418***
	(0.003)	(0.003)	(0.011)	(0.084)
Log likelihood	-466.407	-466.600	-470.360	-470.256

Notes: Standard errors (in parentheses)
$^{+}p < 0.10, ^{*}p < 0.05, ^{**}p < 0.01, ^{***}p < 0.001.$

This, combined with the fact that cursedness does affect perceived payoffs conditional on winning, offers support for using LRAs in favor of FPAs.

4.5 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.[28] We control for the statistic upon which equilibrium bids are based as well as experience ($ln\,(t+1)$).[29] 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 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.[30] Table 7 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 significant). 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

[28] 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.

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

[30] 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.

Table 7: Estimated Bid Functions for FP-C Auctions

	(1)	(2)	(3)	(4)
v_{it}	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.
$^{+}p < 0.10, ^{*}p < 0.05, ^{**}p < 0.01, ^{***}p < 0.001$

auctions. Table 8 contains the estimated bid functions for the FP-PC auctions.[31] Of interest is the fact that the coefficient on s_i is highly significant in all specifications, and approximately 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 9 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 re-matched 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,

[31] The equilibrium bid function for FP-PC auctions is not predicted to be linear. However, for some values of s_i this bid function cannot be separated 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 8: Estimated bid functions for FC-PC auctions

	(1)	(2)	(3)	(4)
s_{it}	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.
$^{+}p < 0.10, ^{*}p < 0.05, ^{**}p < 0.01, ^{***}p < 0.001$

Table 9: Estimated bid functions for LR-C auctions

	(1)	(2)	(3)	(4)
v_{it}	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.
$^{+}p < 0.10, ^{*}p < 0.05, ^{**}p < 0.01, ^{***}p < 0.001$

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 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 10 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,

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. 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

Table 10: Estimated bid functions for LR-PC auctions

	(1)	(2)	(3)	(4)
v_{it}	0.007	0.007	0.007	0.007
	(0.012)	(0.012)	(0.012)	(0.012)
c_{it}	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.
$^{+}p < 0.10, ^{*}p < 0.05, ^{**}p < 0.01, ^{***}p < 0.001$

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 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. For instance, some energy markets (e.g. the PJM market in the U.S., the strategic reserve market in Sweden and Finland, the French energy market, etc.) employ capacity markets to secure adequate level of generation capabilities for the demand peaks and system outages. Since these markets are organized by a third party - typically the independent system operator or the transmission system operator - it is relatively easy to monitor both the revenues and the quality of the procured back-up generation service. If a company fails to provide the service during the outage, the system operator observes the fact the very same second. A contract can be easily designed to penalize such occurrences.

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 bidding above the break-even bidding threshold, the revenue generated, or bidder profits. This 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. However, when estimating a cursed equilibrium bidding model, we find that the degree of cursedness is higher in the private and common 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 Cursed Equilibrium in FP-PC Auctions

Consider bidder i who privately observes common value signal v_i and private cost c_i (so that $s_i = \frac{v_i}{n} - c_i$). The other bidders $j \neq i$ are bidding according to the differentiable and monotonically increasing bid function $\rho(s_j)$ where $s_j = \frac{v_j}{n} - c_j$. Bidder i incorrectly believes that bidders $j \neq i$ only bid $\rho(s_j)$ with probability $(1-\chi)$ and bids $E(\rho(s))$ with probability χ. Bidder i bids b. Given χ, bidder i incorrectly believes her expected profit to be

$$\Pi_i^{\chi}(b, s_i) =$$

$$F_s\left(\rho^{-1}(b)\right)^{n-1}\left(s_i + \left(\frac{n-1}{n}\right)\left((1-\chi)E\left(v|s \leq \rho^{-1}(b)\right) + \chi E(v)\right) - b\right).$$

Taking the derivative with respect to b and noting that in a symmetric cursed equilibrium it must be the case that $b = \rho(s_i)$ leaves us with the differential equation

$$(n-1)F_s(s_i)^{n-2}\frac{f_s(s_i)}{\rho'(s_i)}(s_i - \rho(s_i)) +$$

$$(n-1)F_s(s_i)^{n-2}\frac{f_s(s_i)}{\rho'(s_i)}\left(\left(\frac{n-1}{n}\right)((1-\chi)E(v|s \leq s_i) + \chi E(v))\right) +$$

$$F_s(s_i)^{n-1}\left(\left(\frac{n-1}{n}\right)(1-\chi)\left((E(v|s = s_i) - E(v|s \leq s_i))\frac{f_s(s_i)}{F_s(s_i)\rho'(s_i)}\right)\right) -$$

$$F_s(s_i)^{n-1} = 0.$$

This can be written as

$$\frac{d}{ds_i}\left(F_s(s_i)^{n-1}\left(\rho(s_i)-\left(\frac{n-1}{n}\right)(1-\chi)E(v|s\leq s_i)\right)\right)=$$

$$(n-1)F_s(s_i)^{n-2}f_s(s_i)\left(s_i+\left(\frac{n-1}{n}\right)\chi E(v)\right).$$

Integrate both sides of this equation, and note that the initial condition is $\rho(s_L)=\left(\frac{n-\chi(n-1)}{n}\right)v_L+\chi\left(\frac{n-1}{n}\right)E(v)-c_H$. This leaves us with

$$F_s(s_i)^{n-1}\left(\rho(s_i)-\left(\frac{n-1}{n}\right)(1-\chi)E(v|s\leq s_i)\right)=$$

$$\int_{s_L}^{s_i}(n-1)F_s(t)^{n-2}f_s(t)\,tdt+$$

$$\left(\left(\frac{n-1}{n}\right)\chi E(v)\right)\int_{s_L}^{s_i}(n-1)F_s(t)^{n-2}f_s(t)\,dt.$$

This can be rewritten as

$$F_s(s_i)^{n-1}\left(\rho(s_i)-\left(\frac{n-1}{n}\right)(1-\chi)E(v|s\leq s_i)\right)=$$

$$F_s(s_i)^{n-1}E(y_1|y_1\leq s_i)+\left(\left(\frac{n-1}{n}\right)\chi E(v)\right)F_s(s_i)^{n-1},$$

where y_1 is the highest signal of the other $n-1$ bidders. That is, $y_1=max_{j\in N_{-i}}s_j$. Solving for $\rho(s_i)$ leaves us with the cursed equilibrium bid function:

$$\rho(s_i)=\left(\frac{n-1}{n}\right)((1-\chi)E(v|s\leq s_i)+\chi E(v))+E(y_1|y_1\leq s_i).$$

Plugging in the cursed equilibrium bid function, we see that the actual expected profit of bidder i in this cursed equilibrium is

$$\Pi_i(\rho(s_i),s_i)=$$

$$F_s(s_i)^{n-1}\left(s_i-E(y_1|y_1\leq s_i)-\chi\left(\frac{n-1}{n}\right)(E(v)-E(v|s\leq s_i))\right)$$

Integrating over s, we find that the actual ex ante expected profit of bidder i is

$$E\left(\Pi_i^{FP-PC}\left(\rho\left(s\right),s\right)\right)=\int\limits_{s_L}^{s_H}F_s\left(t\right)^{n-1}f_s\left(t\right)tdt-$$

$$\int\limits_{s_L}^{s_H}F_s\left(t\right)^{n-1}E\left(y_1|y_1\leq t\right)f_s\left(t\right)dt-$$

$$\chi\left(\frac{n-1}{n}\right)E\left(v\right)\int\limits_{s_L}^{s_H}F_s\left(t\right)^{n-1}f_s\left(t\right)dt+$$

$$\chi\left(\frac{n-1}{n}\right)\int\limits_{s_L}^{s_H}F_s\left(t\right)^{n-1}f_s\left(t\right)E\left(v|s\leq t\right)dt.$$

This can be written as

$$E\left(\Pi_i^{FP-PC}\left(\rho\left(s\right),s\right)\right)=$$

$$\left(\frac{1}{n}\right)E\left(Y_1\right)-\int\limits_{s_L}^{s_H}\int\limits_{s_L}^{t}\left(n-1\right)F_s\left(z\right)^{n-2}f_s\left(z\right)zdzf_s\left(t\right)dt-$$

$$\chi\left(\frac{n-1}{n}\right)E\left(v\right)\left(\frac{1}{n}\right)+\chi\left(\frac{n-1}{n}\right)\left(\frac{1}{n}\right)E\left(v|s\leq Y_1\right),$$

where Y_1 is the highest of the n draws of s. By changing the order of integration in the second term, this reduces to

$$E\left(\Pi_i^{FP-PC}\left(\rho\left(s\right),s\right)\right)=$$

$$\left(\frac{1}{n}\right)E\left(Y_1\right)-\int\limits_{s_L}^{s_H}\left(n-1\right)F_s\left(z\right)^{n-2}f_s\left(z\right)z\left(1-F_s\left(z\right)\right)dz-$$

$$\chi\left(\frac{n-1}{n}\right)E\left(v\right)\left(\frac{1}{n}\right)+\chi\left(\frac{n-1}{n}\right)\left(\frac{1}{n}\right)E\left(v|s\leq Y_1\right).$$

Since the density function for the second highest of the n draws of s (Y_2) is given by $n\left(n-1\right)F_s\left(\cdot\right)^{n-2}f_s\left(\cdot\right)\left(1-\right.$ this simplifies to

$$E\left(\Pi_i^{FP-PC}\left(\rho\left(s\right),s\right)\right)=\left(\frac{1}{n}\right)\left(E\left(Y_1\right)-E\left(Y_2\right)\right)-$$

$$\chi\left(\frac{n-1}{n}\right)\left(\frac{1}{n}\right)\left(E\left(v\right)-E\left(v|s\leq Y_1\right)\right).$$

The ex ante expected profit of the winner in this cursed equilibrium is then

$$E\left(\Pi_{winner}^{FP-PC}\right)$$

$$= E\left(Y_1\right) - E\left(Y_2\right) - \chi\left(\frac{n-1}{n}\right)\left(E\left(v\right) - E\left(v|s \le Y_1\right)\right).$$

Total expected surplus in this auction is given by $W = E\left(V\right) - E\left(c|s = Y_1\right)$. Thus, expected revenue in this cursed equilibrium is $R^{FP-PC} = W - E\left(\Pi_{winner}^{FP-PC}\right)$.

Derivation of the Equilibrium in FP-C Auctions

Consider bidder i who privately observes common value signal v_i. The cost of winning the auction is $\bar{c} \in (0, v_L)$. The other bidders $j \neq i$ are bidding according to the differentiable and monotonically increasing bid function $\beta\left(v_j\right)$. Bidder i incorrectly believes that bidders $j \neq i$ only bid $\beta\left(v_j\right)$ with probability $(1-\chi)$ and bids $E\left(\beta\left(v\right)\right)$ with probability χ. Bidder i bids b. Given χ, she incorrectly believes that her expected profit is

$$\Pi_i^{\chi}\left(b, v_i\right) =$$

$$F\left(\beta^{-1}\left(b\right)\right)^{n-1}\left(\frac{v_i}{n} + \left(\frac{n-1}{n}\right)\left(\left(1-\chi\right)E\left(v|v \le \beta^{-1}\left(b\right)\right) + \chi E\left(v\right)\right) - \bar{c} - b\right).$$

Taking the derivative with respect to b and noting that in a cursed equilibrium it must be the case that $b = \beta\left(v_i\right)$, we are left with an ordinary differential equation:

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

$$(n-1)\,F\left(v_i\right)^{n-2}\frac{f\left(v_i\right)}{\beta'\left(v_i\right)}\left(\frac{v_i}{n} - \bar{c} - \beta\left(v_i\right)\right) +$$

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

The initial condition is $\beta\left(v_L\right) = \left(\frac{n-\chi(n-1)}{n}\right)v_L + \chi\left(\frac{n-1}{n}\right)E\left(v\right) - \bar{c}$. Notice that the above differential equation can be written as

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

$$(n-1)\,F(v_i)^{n-2}\,f(v_i)\left(\frac{v_i}{n}+\left(\frac{n-1}{n}\right)\chi E(v)-\bar{c}\right).$$

Integrating both sides leaves us with

$$F(v_i)^{n-1}\left(\beta(v_i)-\left(\frac{n-1}{n}\right)(1-\chi)\,E(v|v\leq v_i)\right)=$$

$$\int_{v_L}^{v_i}(n-1)\,F(t)^{n-2}\,f(t)\left(\frac{t}{n}+\left(\frac{n-1}{n}\right)\chi E(v)-\bar{c}\right)dt.$$

Simplifying this yields the equilibrium bid function

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

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

Plugging in the cursed equilibrium bid function, we find the actual expected profit of bidder i in this cursed equilibrium:

$$\Pi_i(\beta(v_i),v_i)=$$
$$F(v_i)^{n-1}\left(\frac{v_i}{n}-\chi\left(\frac{n-1}{n}\right)(E(v)-E(v|v\leq v_i))-\left(\frac{1}{n}\right)E(z_1|z_1\leq v_i)\right).$$

Integrating over v we find the actual ex ante expected profit of bidder i is

$$E\left(\Pi_i^{FP-C}(\beta(v),v)\right)=\int_{v_L}^{v_H}F(t)^{n-1}\,f(t)\,\frac{t}{n}dt-$$

$$\left(\frac{1}{n}\right)\int_{v_L}^{v_H}F(t)^{n-1}\,E(z_1|z_1\leq t)\,f(t)\,dt-$$

$$\chi\left(\frac{n-1}{n}\right)E(v)\int_{v_L}^{v_H}F(t)^{n-1}\,f(t)\,dt+$$

$$\chi\left(\frac{n-1}{n}\right)\int_{v_L}^{v_H}F(t)^{n-1}\,f(t)\,E(v|v\leq t)\,dt.$$

This can be written as

$$E\left(\Pi_i^{FP-C}(\beta(v),v)\right)=\left(\frac{1}{n^2}\right)E(Z_1)-$$

$$\left(\frac{1}{n}\right)\int_{v_L}^{v_H}\int_{v_L}^{t}(n-1)\,F(u)^{n-2}\,f(u)\,udu f(t)\,dt-$$

$$\chi\left(\frac{n-1}{n}\right)E(v)\left(\frac{1}{n}\right)+\chi\left(\frac{n-1}{n}\right)\left(\frac{1}{n}\right)E(v|v\leq Z_1),$$

where Z_1 is the highest of the n draws of v. By changing the order of integration in the second term, this reduces to

$$E\left(\Pi_i^{FP-C}(\beta(v),v)\right)=\left(\frac{1}{n^2}\right)E(Z_1)-$$

$$\left(\frac{1}{n}\right)\int_{v_L}^{v_H}(n-1)\,F(u)^{n-2}\,f(u)\,u\,(1-F(u))\,du-$$

$$\chi\left(\frac{n-1}{n}\right)E(v)\left(\frac{1}{n}\right)+\chi\left(\frac{n-1}{n}\right)\left(\frac{1}{n}\right)E(v|v\leq Z_1).$$

Since the density function for the second highest of the n draws of v (Z_2) is given by $n\,(n-1)\,F(\cdot)^{n-2}\,f(\cdot)\,(1-F$ this simplifies to

$$E\left(\Pi_i^{FP-C}(\beta(v),v)\right)=\left(\frac{1}{n^2}\right)(E(Z_1)-E(Z_2))-$$

$$\chi\left(\frac{n-1}{n}\right)\left(\frac{1}{n}\right)(E(v)-E(v|v\leq Z_1)).$$

The ex ante expected profit of the winner in this cursed equilibrium is then

$$E\left(\Pi_{winner}^{FP-C}\right)=$$

$$\left(\frac{1}{n}\right)(E(Z_1)-E(Z_2))-\chi\left(\frac{n-1}{n}\right)(E(v)-E(v|v\leq Z_1)).$$

Total expected surplus in this auction is given by $X=E(V)-\bar{c}$. Thus, expected revenue in this cursed equilibrium is $R^{FP-C}=X-E\left(\Pi_{winner}^{FP-C}\right)$.

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 incorrectly believes that bidders $j\neq i$ only bid $\zeta(c_j)$ with probability $(1-\chi)$ and bids $E(\zeta(c))$ with probability χ. Bidder i bids b. Notice that for any given $\chi\in[0,1)$ the expected profit of bidder i is the same as if $\chi=0$. Thus, any symmetric cursed equilibrium will also be a symmetric Bayesian Nash equilibrium. This expected profit is given by

$$\Pi_i(b, c_i) = \left(1 - G\left(\zeta^{-1}(b)\right)\right)^{n-1}(b - c_i).$$

The first order condition associated with this problem is

$$-(n-1)\left(1 - G\left(\zeta^{-1}(b)\right)\right)^{n-2}\frac{g\left(\zeta^{-1}(b)\right)}{\zeta'\left(\zeta^{-1}(b)\right)}(b - c_i) +$$

$$\left(1 - G\left(\zeta^{-1}(b)\right)\right)^{n-1} = 0.$$

In equilibrium, it must be the case that $b = \zeta(c_i)$. Utilizing this, we are left with an ordinary differential equation

$$-(n-1)(1 - G(c_i))^{n-2} g(c_i)(\zeta(c_i) - c_i) +$$

$$(1 - G(c_i))^{n-1}(\zeta'(c_i)) = 0.$$

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

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

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

The equilibrium expected profit of bidder i is then

$$\Pi_i(\zeta(c_i), c_i) =$$

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

The ex ante expected profit of bidder i is found by integrating with respect to c.

$$E\left(\Pi_i^{LR-PC}\left(\zeta\left(c\right),c\right)\right)=$$

$$\int_{c_L}^{c_H}\int_{t}^{c_H}\left(n-1\right)\left(1-G\left(u\right)\right)^{n-2}ug\left(u\right)dug\left(t\right)dt-\int_{c_L}^{c_H}\left(1-G\left(t\right)\right)^{n-1}tg\left(t\right)dt.$$

This simplifies to

$$E\left(\Pi_i^{LR-PC}\left(\zeta\left(c\right),c\right)\right)=$$

$$\left(\frac{1}{n}\right)E\left(U_{n-1}\right)-\left(\frac{1}{n}\right)E\left(U_n\right),$$

where U_{n-1} is the second lowest of n draws of c. Thus the ex ante expected profit of the winner is given by $E\left(\Pi_{winner}^{LR-PC}\right)=E\left(U_{n-1}\right)-E\left(U_n\right)$. Since the total expected surplus in this auction is given by $D=E\left(V\right)-E\left(c|c=U_n\right)$, expected revenue in this equilibrium is $R^{LR-PC}=D-E\left(\Pi_{winner}^{LR-PC}\right)$.

B Instructions

What follows is an English translation of the instructions for least-revenue auctions with private and common values (LR-PC). Instructions from the remaining treatments are available upon request.

SLIDE No.1

These instructions will explain how you can earn money based on your decisions and the decisions of other participants during this part of the experiment. We recommend that you read the instructions carefully, because your earnings may be affected if you do not understand them. If you have any questions regarding there instructions, please raise your hand and we will answer your question privately.

SLIDE No.2

Earnings in the experiment

From now on, participants will interact only through computers. If you disobey the rules, we will end the experiment and ask you to leave without your accumulated earnings. The amounts in the experiment are denominated in Experimental Pesos (E$). At the end of the experiment we will convert your accumulated earnings to Quetzales (Q1=E$4) and we will pay it in cash (in Quetzales)

SLIDE No.3

The experiment consists in a series of periods. The computer will act as a seller and the participants will act as buyers of a good whose VALUE is the same for all participants. For each seller there will be 3 buyers. All 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 of the AMOUNT. 2) The AMOUNT received is higher than the COST of obtaining the good.

SLIDE No.4

Each period, groups of 3 buyers are chosen randomly. Buyers can obtain a good that has a VALUE. This VALUE is the same for all 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. When the period begins, each buyer will receive an ESTIMATE of the VALUE.

SLIDE No.5

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.

All ESTIMATES of the VALUE in the mentioned range have the same probability of being selected and are independent from the ESTIMATES of the VALUE of other buyers and those of other periods.

SLIDE No.6

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 buyers and ESTIMATES of VALUE in other periods.

In each period, the VALUE of the good will be the average of the ESTIMATES of VALUE of the 3 buyers of each group. Since all ESTIMATES of VALUE are between 100 and 200, the VALUE will be in this range, and will be the same for all 3 buyers.

SLIDE No.7

For example, if your ESTIMATE of VALUE is 182.60 and the ESTIMATES of the other 2 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) = 153.11 3

SLIDE No.8

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

In each period, the COST of each buyer is assigned randomly. All COSTS between E$0 and E$50 are equally likely to be chosen. COSTS do not depend on the 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 COSTS you had in previous periods.

SLIDE No.9

At the beginning of the period, each buyer will know his ESTIMATE of the VALUE of the good as well as his COST for obtaining the good. Each buyer can then make a REQUEST of an AMOUNT of the VALUE of the good. The person who makes the lowest REQUEST of an AMOUNT 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 randomly.

SLIDE No.10

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

SLIDE No.11

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

For the person with the lowest REQUEST of an AMOUNT, the EARNINGS will be: AMOUNT Obtained - COST = EARNINGS

All others will have PROFIT of: 0 Notice that the buyer could earn money if the AMOUNT obtained is lower than its COST. Also notice that the buyer could lose money if the AMOUNT is higher than its COST.

SLIDE No.12

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

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

SLIDE No.13

In each period, groups will be 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.

SLIDE No.14

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. You will then have to 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.

SLIDE No.15

Summary

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

In each period, you can make a REQUEST of an AMOUNT to try to buy the good.

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

SLIDE No.16

Summary

Whoever buys the good will make money if his REQUEST obtained is higher than the COST to obtain it.

EARNINGS (if you buy the good) = AMOUNT Obtained – COST

EARNINGS (if you do not buy the good) = 0

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