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

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Abstract

In many auctions for infrastructure concession contracts, the valuation structure involves private and common value elements. Existing experimental evidence (e.g. Goeree and Offerman (2002), Chui et al. (2010)) 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. In addition, we directly compare both auction formats with 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 valuations structure. Further, when there are private and common value components, least-revenue auctions are significantly more efficient than first-price auction.

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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 his valuation of the available object is assumed to be a function of his, and possibly other, signals. This basic framework is used to model auctions with a variety of valuation structures. In all of 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 multi-dimensional. 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 supplying the contract (e.g. building the highway, constructing the infrastructure for power lines, etc.). If bidders have different costs of providing the infrastructure, then these costs 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 Kagel and Levin (2002). That is, bidders bid such that they guarantee themselves negative payoffs in expectation. 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[1]. Athias and Nuñez (2008) find evidence that is consistent with

[1]For Latin America, the fraction of renegotiated contracts for transportation infrastructure

bidders displaying more strategically opportunistic behavior in auctions for toll-road concessions in weaker institutional settings, pressumably due to an 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, removing the common value risk to bidders might reduce the justification to renegotiate due to to low realized values of concession contracts.

In this paper we experimentally consider auctions with a common value and private costs, and compare them to auctions with a common value and a common cost which is common knowledge. We compare these two valuation structures in a standard first-price sealed bid auction, and in an alternative auction format: the Least Revenue Auction (LRA).

In a LRA, bidders simultaneously make sealed-bid offers which consist of the minimum revenue (from the common value of the good) the bidder is willing to accept upon winning the auction. 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 estimates of the common value 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 the 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 (two dimensional signals) into an auction with a (one dimensional) purely private

might have exceeded 2/3 by the end of 2005.

signal.

It is important to note that in a LRA uncertainty regarding the common value of the good is borne by the auctioneer rather than by the bidders. A 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 they will earn their bid[2]. This transfer of risk may be desirable, indeed even the motivation for using LRAs. This transfer of risk has been studied and proposed before by Engel et al. (1997, 2001). They first proposed the Least Present Value of Revenue auction (LPVR), in which bidders submit the smallest present value of revenue they would require for a contract in which they build, operate and then transfera highwayto the government at the conclusion of the contract. In a LPVR auction, the duration of contract is contingent on the stream of revenue that is generated by tolls 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 he bid. This flexible-term contract then shifts the risk resulting from uncertain traffic patterns to the government, relative to a standard fixed-term contract. Chile has implemented LPVR auctions on more than one occassionVassallo (2006), and Engel et al. (1996) estimates that the value of switching to LPVR auctions is about 33% of the value of the infrastructure investment.

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 (with a high or low realized value in each period) over time. However, the underlying

[2]As long as the winning bid does not exceed the common value of the good.

intuition is the same . As such, this paper can be seen as a complement that offers an experimental test of the premise underlying the motivation of LPVR auctions.

Perhaps 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 that in first-price auctions. This is significant because efficiency is low in first-price auctions with this valuation structure. Thus, we demonstrate that in this environment, increases in efficiency and reduction of the winner's curse can be obtained by changing the structure of the contract and the auction mechanisms to award contracts.

Contrary to theory, the LRA generates less revenue than expected. This is largely due to the fact that bidders in first-price auctions tend to overbid relative to Nash predictions, while such overbidding is rare in a LRA. Correspondingly, bidders are better off in a LRA than in a first-price auction.

The literature regarding auctions with private and common values is small, but growing quickly (e.g.Boone et al. (2009); Chui et al. (2010)). The theoretical analysis of such auctions begins with Goeree and Offerman (2003). The theoretical predictions utilized in our experimental design for first-price auctions with common and private values rely on this analysis. Goeree and Offerman (2002) 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 (private value and signal regarding the common value). If subjects were to ignore the common value signal, the auction would be fully efficient.[3] Goeree and Offerman (2002) 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. Namely, we eliminate the uncertainty regarding the common value of the good, and see a significant increase in efficiency.

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.[4] As such, the sharp reduction in the prevalence of the winner's curse we find in LRAs is notable.

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.

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

[3]This is precisely what the LRA does. 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]See Kagel and Levin (2002) for in introduction to this literature.

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 the value of their cost prior to placing bids, but may not know that value of c_j where $j \neq i$. Bidder $i \in N$ chooses a bid, $b_i \in \mathbb{R}_+$in an effort 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 $N_{-i} \equiv N/i$.

2.1 First-Price Auctions with Private and Common Values

In a first-price auction with private and common values (FPPC) 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

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

where $y_1$is the highest surplus 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 $\Pi_i^{FPPC}(s_i) = \int_{s_L}^{s_i} F_s(x)^{n-1}\,dx$. Integrating over $\Pi_i^{FPPC}(s_i)$ yields the ex ante expected profit of bidder i: $E\left(\Pi_i^{FPPC}(s_i)\right) = \frac{1}{n}\left(E(Y_1) - E(Y_2)\right)$, 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 a FPPC 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 $R^{FPPC} = W - (E(Y_1) - E(Y_2))$[5].

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 profit. 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 Goeree and Offerman (2002) and is of interest in this study. We say that a bidder has fallen victim to the winner's curse if they have bid above the break-even bidding threshold, thus guaranteeing that they have negative expected profit. Note that this definition implies that a bidder can fall victim without actually winning the auction. This break-even bidding threshold is defined as

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

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

2.2 First-Price Auctions with Common Values

In a first-price auction with common values (FPC) , $c_i = E(c) \equiv \bar{c}$, 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 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).[6] 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 $\Pi_i^{FPC}(v_i) = \int_{v_L}^{v_i} F(x)^{n-1} dx$.

Taking the expectation of $\Pi_i^{FPC}(v_i)$ yields the ex ante expected profit of bidder i, which is $E\left(\Pi_i^{FPC}\right) = \frac{1}{n}\left(E(Z_1) - E(Z_2)\right)$, 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 $R^{FPC} = E(V) - (E(Z_1) - E(Z_2))$.

2.2.1 Winner's Curse

In a first-price common-value 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

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

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

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

2.3 Least-Revenue Auctions with Private and Common Values

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

When there is common and private values, the valuation structure is exactly the same as in FPPC 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 drawn 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 functions is

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

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

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

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

2.3.1 Winner's Curse

In the least-revenue auction, 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 provided by having the highest signal- does not apply under this auction format. However, for comparison purposes, we continue to call bidding such that expected profits conditional on winning are negative the winners curse.

In LRPC auction, 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 a LRPC auction is

$$T^{LRPC}\left(c_i\right) = c_i.$$

2.4 Least-Revenue Auctions with Common Values

In a least-revenue auction with common values and a common cost (LRC), 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 $E(V) - \bar{c}$.

2.4.1 Winner's Curse

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

3 Experimental Design

Within a group of 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.[7]

In each auction the value of the good to each bidder is the sum of 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

[7] 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.

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 before placing their bids. 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 structure of the cost bidders face if they win the auction. (This design is illustrated in Table 1.)

1. *First-price auctions with common and private values (FPPC):* In addition to the private signal each bidder observes regarding the common value of the good, each bidder privately observes the cost they must pay if they were to win the auction. Each of these costs are independent draws 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 (FPC):* 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 distribution of costs in the FPPC treatment ($\bar{c} = 25$). The auction format in this treatment is a standard first-price sealed-bid auction.

3. *Least-revenue auctions with common and private values (LRPC):* In addition to the private signal each bidder observes regarding the common value of the good, each bidder privately observes the cost they must pay if they were to win the auction. Each of these costs are independent draws 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 least-revenue auction.

4. *Least-revenue auctions with common values (LRC):* 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 distribution of costs in the FP-PC treatment ($\bar{c} = 25$). The auction format in this treatment is a least-revenue auction.

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, their 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 shown a video which read these instructions aloud. Each participant then individually answered a set of questions to ensure understanding of the experimental procedure. We also elicit risk attitudes using a measure that closely mirrors Holt and Laury (2002)[8]. We varied the order in which subjects participated in the risk attitudes elicitation procedure and the series of auctions.. Each session lasted approximately one and a half hours. In half the sessions, each participant began with a starting balance of 62.5 Quetzales (about $7.75) to cover any losses; in the other half participants

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

began with a starting balance of 125 Quetzales. At the end of all thirty rounds, each participant was paid their balance, as well as a show-up fee of 20 Quetzales. If the balance of a participant became negative, she was permitted to continue, but was only paid the show-up fee of 20 Quetzales. Within the data sessions we use, there are only 2 participants who went bankrupt (approximately 1% of participants)[9]. The bids, signals and values were all denominated in Experimental Pesos (EP), which were exchanged for cash at a rate of $4EP = 1Q \approx US\$0.125$.

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 need 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 he also has a relatively high common-value signal (such that $s_i = \frac{v_i}{n} - c_i$ is larger than the those of the other bidders), he will win the auction, resulting in an inefficient allocation.

However, in LR-PC auctions, the equilibrium bid function is 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

[9]We drop from the data 4 sessions where multiple subjects went bankrupt. We only use data from 16 sessions where no more than one subject went bankrupt.

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 Goeree and Offerman (2002), 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 in the group.

Table 2 contains the average efficiency level of FP-PC and LR-PC auctions over all twenty periods. Note that efficiency levels are considerably higher using the Least Revenue auction 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 observed efficiency levels to two benchmarks: the efficiency level predicted by equilibrium bidding behavior, and the efficiency levels resulting from a random allocation of the good. Notice that in first-price 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 efficiency predicted by theory and that of a random allocation.Observed efficiency is much higher in the LR-PC auctions, but are not perfectly efficient, as predicted by theory. Figure 2 sorts the data into the first and last 10 periods. The proportion of efficient allocations increases slightly in the last ten periods of least-revenue auctions, while decreasing slightly in first-price auctions. The difference in efficiency between least-revenue auctions and first-price 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 least-revenue auctions.

4.2 Revenue

The effect of valuation structure and auction format on revenue is of particular interest. Table 2 also contains summary statistics regarding observed revenue in all four treatments, aggregated over all twenty periods. Notice that FP-PC auctions generate the highest revenue, on average. Further, note that LR-C auctions generate less revenue than the remaining treatments on average.

Figure 3 provides histograms of revenue for all four treatments, and Figure 4 compares observed revenue to predicted revenue. Note that for first-price auctions and 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. Figure 5 further illustrates this point by displaying observed revenue in the last ten periods of all four treatments, normalized by the predicted revenue.

We find that valuation structure does not significantly affect revenue in either first-price auctions (robust rank order test, $U = -0.776$, *n.s.*) or least-revenue auctions (robust rank order test, $U = -1.033$, *n.s.*). This result contradicts the theoretical prediction that revenue is lower when there are private and common values as opposed to a pure common value structure. In particular, the additional private information held by bidders, in the form of private costs, does not translate into lower revenue.

Theory predicts that least-revenue auctions will generate more revenue that first-price auctions in both valuations structures analyzed here. This is due to the fact that least-revenue auctions render the privately observed common value signal observed by bidders strategically irrelevant. As a result, bidders earn smaller information rents in least-revenue auctions than they do in first-price auctions. However, we find that, contrary to theory, revenue is lower in least-revenue auctions 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, , $p < 0.001, n.d.$).[10] This result is due to the fact that bidders in first-price auctions tend to overbid significantly. As a result, the revenue generated by first-price auctions is higher than predicted by theory. This is in contrast to least-revenue auctions, 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 our revenue results. Table 2 contains summary statistics of bidder payoffs in all four treatments. Figure 6 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. Also note that in first-price auctions bidders are, on average, earning negative profits. This is in stark contrast to bidder profits observed in least-revenue auctions, in which bidders, on average earn weakly greater than zero. Figure 7 shows observed bidder profits in ten period blocks. Notice that on average bidders are better off in the second ten periods than in the first ten for all treatments except LR-C. Indeed, in the second ten periods we observe more negative

[10] 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 $n.d.$.

profits in LR-C auctions than we do in the first ten periods. Figure 8 displays histograms of bidder payoffs, conditional on winning, for all four treatments. Of note is the fact that negative payoffs are much more common in first-price auctions.

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 least-revenue auctions (robust rank order test, $U = -1.033$, *n.s.*).

We also find that bidders are better off in least-revenue auctions. 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 when 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, 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, least-revenue auctions eliminates the need for bidders to estimate this conditional expected value. A bidder in a least-revenue auction need bid above his cost to ensure positive profits.

4.4 Winner's Curse

In auctions with common value components, the winner's curse is prevalent, particularly among inexperienced bidders such as those who participated in the experimental sessions for this paper. Goeree and Offerman (2002)provide evidence for prevalence of winner's curse in first-price auctions with private and common values.

We observe that bidders in first-price auctions often fall victim to the winners curse, at levels comparable to those observed in the existing literature. However, we find strong evidence that the winner's curse is significantly lower in least-revenue auctions than it is in first-price auctions. This is true when there are private and common value components (robust rank order test, $U = 11.314$, $p < 0.001$), and in the pure common-value environment (robust rank order test, $U = 11.314$, $p < 0.001$). Figure 9 illustrates this result by showing the proportion of bids above the break-even bidding threshold for all four treatments. Figure 10 breaks this into ten period blocks. Notice that the winner's curse is almost entirely eliminated in LR-C auctions. The relative dearth of the winner's curse in least-revenue auctions is largely attributable to the fact that the uncertain common value of the good does not translate into uncertainty regarding bidder payoffs. Indeed, conditional on winning the auction, there is no uncertainty regarding bidder payoffs in least-revenue auctions. 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 least-revenue auctions (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 Nash Predictions

We now turn to comparing observed bidding behavior directly with Nash predictions. Table 2 contains summary statistics regarding the observed bids, as well as Nash bids. Of note is the fact that, on average, bidders overbid relative to the Nash equilibrium in every treatment except LR-C. Note that in first-price auctions, overbidding implies bidding above certain reference bid (i.e. above Nash bidding). For comparability purposes, we reffer here to overbidding in least-revenue auctions as bidding *below* the nash equilibrium. This way, in both cases overbidding implies paying a higher explicit or implicit price. In first-price auctions this overbidding often corresponds to winning the auction and obtaining negative profits in the process.

Figure 11 illustrates how observed bids compare to the Nash predictions in FP-C auctions. Notice that bids tend to be well in excess of the equilibrium prediction. Indeed, bids well above the break-even bidding threshold are very common. Figure 12 provides the analogous graph for LR-C auctions. In stark contrast to what is observed in FP-C auctions, bidding such that expected profits are negative in expectation are almost non-existent. Figures 13 and 14 yield a similar comparison when there are private and common value components.

4.6 Estimated Bid Functions

We now turn to the estimation of bid functions for the four treatments.We employ a random effects (at the individual level) specification which controls for the the statistic upon which equilibrium bids are based (note that this is not constant across treatments), nonlinear components of the equilibrium bid functions (when applicable), gender, experience ($ln\,(t+1)$), the interaction of gender and experience, the order of the Holt and Laury risk elicitation procedure, whether or not bidders started with an endowment of $EP500$, session dummies, and subject dummies.[11]

Table 3 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. Second, participants learn to reduce their overbidding in this treatment over time, as evidenced by the significant and negative coefficient for $ln\,(t+1)$. Interestingly, neither gender, nor the interaction of gender and $ln\,(t+1)$ are 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 faster than men.

Table 4 contains the estimated bid functions for the FP-PC auctions. Note that here, the interaction between gender and $ln\,(t+1)$ is significant and negative, but that gender itself is not significant.

Table 5 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 implicitly 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, 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. Additionally, note that the interaction between gender and $ln\,(t+1)$ is highly significant and negative. This implies that

[11] A subject is defined as the sequence of draws of $v_i$and, if applicable, c_i that a participant could face. 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.

over time, the bids of male participants are increasing. Once again, however, gender alone is not significant.

Table 6 contains the estimated bid functions for LR-PC auctions. Notice that, as predicted, the private cost observed by bidders is highly significant. Interestingly, this is the only treatment for which $ln\,(t+1)$is not significant in the most inclusive specification. Also, gender is significant in this specification; women tend to bid less than men in this environment.

5 Conclusion

In this paper we experimentally examine first-price and least-revenue auctions under two environments: with private and common values, and with pure common values. In a least-revenue auction 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 least-revenue auctions. While the concept of such a risk sharing arrangement for infrastructure concession contracts has been theoretically studied in the past (see Engel et al. (1997, 2001)), this paper is the first to examine theoretically and experimentally bidding behavior and auction performance for this mechanism.

This paper is also, to the best of our knowledge, the first direct comparison of bidding behavior in first-price auctions with these valuation structures. We find that the valuation structure does not have a significant effect on the prevalence of the winner's curse, the revenue generated, or bidder payoffs. This result is suprising, 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 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 a least-revenue auction. The intuition underlying this result is clear: when there are private and common values, a bidder puts some weight on his common-value signal in deciding his bid. As a result, the winning bidder need not have the lowest private cost, and thus the allocation may be inefficient. In a least-revenue auction, however, the common-value signal is strategically irrelevant, and thus does not introduce inefficiency as in first-price auctions. This is, in effect, a border case of the finding in Goeree and Offerman (2002) that a reduction in the uncertainty regarding the common-value component of the good reduces inefficiency.

The other noteworthy result is that, regardless of the valuation structure, the winner's curse is significantly less prevalent in least-revenue auctions than in first-price auctions. Again the intuition is due to the reduction of uncertainty in least-revenue auctions. In particular, in least-revenue auctions 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 reduces the cognitive demandsof the auction,the winner's curse falls as a result, and allows bidders to focus on what they have comparative advantage (i.e. building highways at a low cost).

Our results offer tentative support for shifting the risk in infrastructure concession contract auctions to the auctioneer (the government). Given the observed high levels of bankruptcies and renegotiation by winners of such contracts, our results suggest that, at the least, the implementation of least-revenue auctions might eliminate one justification of contract holders to opportunistically renegotiate under the premise that the value of the contact is less than expected. Despite the aforementioned advantages that LRA offer, a caveat is in place as to the general applicability of this format: note that the LRA does not provide any incentive for the winner to invest in the maintenance and enhancment of 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. Or if the value of the good depends on ex-post performance that can be easily monitored and as such a contract can be put in place with rewards and penalties contingent on ex-post performance. This seems to be the case for infrastructure concession contracts.

Appendix A

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 his signal were z. His expected profit is then

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

The first order condition associated with this problem is

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

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

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

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

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

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

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

Integrating both sides leaves us with

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

Simplifying this yields the equilibrium bid function

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

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. The other bidders $j\neq i$ are bidding according to the differentiable and monotonically decreasing bid function $\zeta\left(c_j\right)$. Bidder i bids as though his signal were z. His expected profit is then

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

The first order condition associated with this problem is

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

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

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

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

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

Integrating both sides leaves us with

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

Simplifying this yields the equilibrium bid function

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

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

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Table 1: Summary of Experimental Design

	2x2between subject design	
	First-price auctions	Least-revenue auctions
Common and private value	4 sessions	4 sessions
Common value	4 sessions	4 sessions

Table 2: Summary Statistics (periods 1 - 20)

	FP-C		FP-PC		LR-C		LR-PC	
Variables	mean	*std. dev.*	mean	*std. dev.*	mean	*std. dev.*	mean	*std. dev.*
Observed Bid	110.9	*26.9*	111.7	*31.9*	36.8	*29.1*	29.1	*15.2*
Nash Bid	102.7	*15.6*	105.9	*19.1*	25.0	*0.0*	32.9	*10.0*
Winner's Curse Threshold	116.6	*18.7*	115.9	*24.2*	25.0	*0.0*	24.3	*15.0*
% of Winner's Curse Bids	41.5%	*0.49*	43.8%	*0.50*	1.0%	*0.10*	6.3%	*0.24*
% of Winner's Curse winning Bids	69.1%	*0.46*	65.0%	*0.48*	1.6%	*0.12*	16.6%	*0.37*
Profits for winning bidders	-11.2	*18.3*	-9.5	*24.7*	0.3	*1.7*	1.8	*11.4*
(Normalized) Efficiency	.	.	65.2%	*0.41*	.	.	87.9%	*0.27*
Revenue	132.0	*16.0*	137.7	*22.7*	124.7	*15.5*	132.7	*17.1*

Notes -- Table presents means and standard devaitions (in italics) of main variables by treatment for all periods.

Table 3:

Estimated Bid Functions for First Price Common Value Auctions with Random Effects at the individual level

Dependent Variable: Estimated Bid	(1)	(2)	(3)	(4)	(5)	(6)
CV signal	0.5946***	0.5945***	0.5946***	0.5945***	0.5944***	0.5952***
	[0.0000]	[0.0000]	[0.0000]	[0.0000]	[0.0000]	[0.0000]
Ln Period + 1	-4.1354***	-4.1353***	-4.2741***	-3.5271**	-3.5271**	-3.5291**
	[0.0000]	[0.0000]	[0.0001]	[0.0071]	[0.0071]	[0.0071]
Session						
Dummy for Female		2.488		5.4982	4.2832	3.5358
		[0.4168]		[0.3044]	[0.4225]	[0.5373]
Female * Ln (Period + 1)			0.3026	-1.3267	-1.3267	-1.3265
			[0.7847]	[0.4929]	[0.4929]	[0.4931]
500 initial endowment dummy						-5.8466+
						[0.0656]
Order of H&L elicitation						3.0978
						[0.3224]
Subject						
Constant	34.5473***	33.4158***	34.5479***	32.0426***	35.2832***	21.4861*
	[0.0000]	[0.0000]	[0.0000]	[0.0000]	[0.0000]	[0.0136]
Number of Observations (N)	960	960	960	960	960	960

p-values in parenthesis

+ p<0.10, * p<0.05, ** p<0.01, *** p<0.001

Table 4:

Estimated Bid Functions for First Price Private and Common Value Auctions
with Random Effects at the individual level

Dependent Variable: Estimated Bid	(1)	(2)	(3)	(4)	(5)	(6)
PC surplus (region 1) * Treatment 2	1.4146***	1.4144***	1.4164***	1.4187***	1.4187***	1.4180***
	[0.0000]	[0.0000]	[0.0000]	[0.0000]	[0.0000]	[0.0000]
PC surplus (region 2) * Treatment 2	0.7960***	0.7958***	0.7976***	0.7999***	0.7997***	0.7955***
	[0.0005]	[0.0005]	[0.0005]	[0.0005]	[0.0005]	[0.0005]
PC surplus (region 3) * Treatment 2	1.2997***	1.2995***	1.3004***	1.3025***	1.3025***	1.3017***
	[0.0000]	[0.0000]	[0.0000]	[0.0000]	[0.0000]	[0.0000]
Non-linear portion (region 2 - PC) Treatment 2	0.1185	0.1186	0.119	0.119	0.119	0.1206
	[0.1082]	[0.1080]	[0.1061]	[0.1061]	[0.1059]	[0.1021]
Non-linear portion (region 3 - PC) Treatment 2	-0.1138+	-0.1137+	-0.1140+	-0.1151+	-0.1151+	-0.1149+
	[0.0983]	[0.0986]	[0.0972]	[0.0942]	[0.0941]	[0.0956]
Ln Period + 1	-1.4049	-1.4049	-2.3015*	-2.8212*	-2.8212*	-2.8206*
	[0.1505]	[0.1505]	[0.0384]	[0.0181]	[0.0181]	[0.0184]
Session						
Dummy for Female		0.8635		-8.7901	-9.131	-11.1409
		[0.8799]		[0.2348]	[0.2284]	[0.1703]
Female * Ln (Period + 1)			2.6927+	4.2526*	4.2527*	4.2544*
			[0.0921]	[0.0398]	[0.0398]	[0.0401]
500 initial endowment dummy						4.1206
						[0.4767]
Order of H&L elicitation						2.1504
						[0.7153]
Subject						
Constant	86.8847***	86.5972***	86.8494***	89.7554***	90.4567***	78.7723***
	[0.0000]	[0.0000]	[0.0000]	[0.0000]	[0.0000]	[0.0000]
Number of Observations (N)	960	960	960	960	960	960

p-values in parenthesis
+ p<0.10, * p<0.05, ** p<0.01, *** p<0.001

Table 5:

Estimated Bid Functions for Least Revenue Common Value Auctions with Random Effects at the individual level

Dependent Variable: Estimated Bid	(1)	(2)	(3)	(4)	(5)	(6)
CV signal	0.0084	0.0084	0.0098	0.0099	0.01	0.0095
	[0.6569]	[0.6555]	[0.6029]	[0.5960]	[0.5957]	[0.6133]
Ln Period + 1	3.7504***	3.7503***	6.6637***	7.1104***	7.1104***	7.1110***
	[0.0000]	[0.0000]	[0.0000]	[0.0000]	[0.0000]	[0.0000]
Session						
Dummy for Female		-7.6571		5.911	3.0041	7.1407
		[0.1627]		[0.3690]	[0.6610]	[0.2528]
Female * Ln (Period + 1)			-5.1850***	-5.9799***	-5.9799***	-5.9791***
			[0.0001]	[0.0002]	[0.0002]	[0.0002]
500 initial endowment dummy						-0.1891
						[0.9686]
Order of H&L elicitation						1.0242
						[0.8297]
Subject						
Constant	24.3959***	28.6978***	24.1990***	20.8469***	27.6647***	16.4037
	[0.0000]	[0.0000]	[0.0000]	[0.0002]	[0.0003]	[0.1799]
Number of Observations (N)	960	960	960	960	960	960

p-values in parenthesis

+ p<0.10, * p<0.05, ** p<0.01, *** p<0.001

Table 6:

Estimated Bid Functions for Least Revenue Private and Common Value Auctions
with Random Effects at the individual level

Dependent Variable: Estimated Bid	(1)	(2)	(3)	(4)	(5)	(6)
Cost	0.8643***	0.8626***	0.8631***	0.8626***	0.8617***	0.8674***
	[0.0000]	[0.0000]	[0.0000]	[0.0000]	[0.0000]	[0.0000]
Ln Period + 1	0.3691	0.3691	0.834	0.2962	0.2962	0.2963
	[0.5049]	[0.5056]	[0.1701]	[0.6678]	[0.6680]	[0.6670]
Session						
Dummy for Female		-4.9382*		-5.4051	-4.9621	-8.1240*
		[0.0129]		[0.1011]	[0.1231]	[0.0178]
Female * Ln (Period + 1)			-1.3126+	0.2058	0.2058	0.2057
			[0.0604]	[0.8592]	[0.8592]	[0.8590]
500 initial endowment dummy						-4.5780*
						[0.0272]
Order of H&L elicitation						0.2364
						[0.9221]
Subject						
Constant	7.4845***	9.2743***	7.5139***	9.4399***	11.1919***	8.7891+
	[0.0000]	[0.0000]	[0.0000]	[0.0000]	[0.0000]	[0.0755]
Number of Observations (N)	960	960	960	960	960	960

p-values in parenthesis
+ p<0.10, * p<0.05, ** p<0.01, *** p<0.001

Figure 1: Observed and predicted efficiency relative to a random allocation

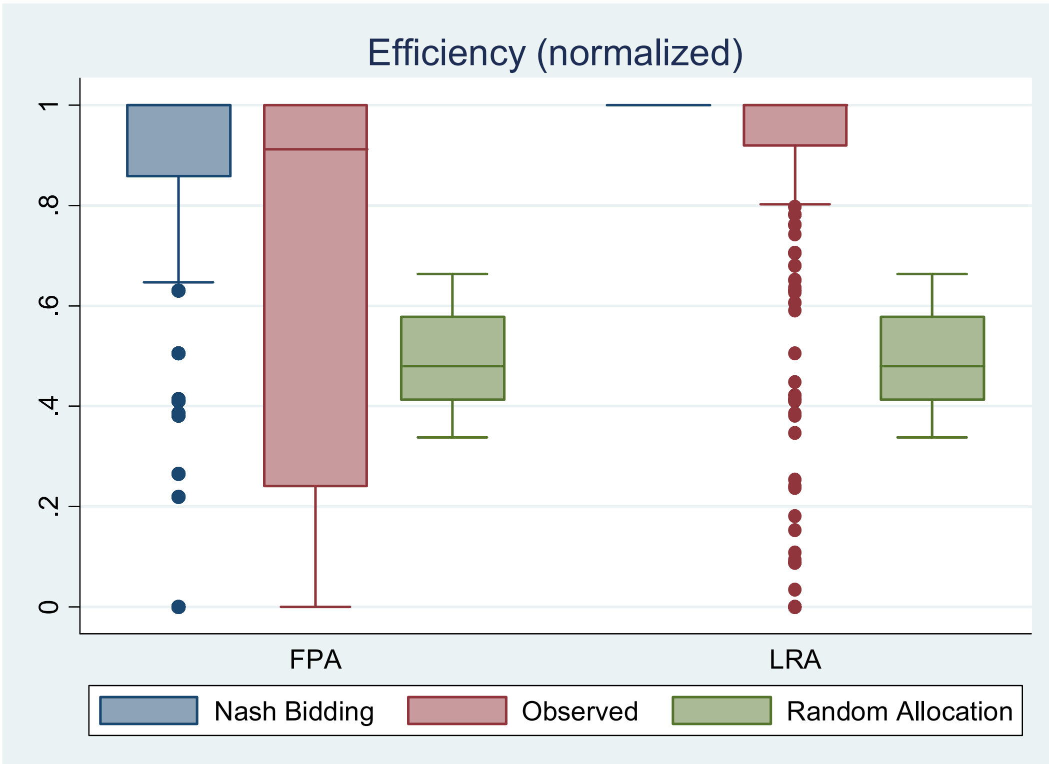


Figure 2: Observed efficiency in the first and last 10 periods

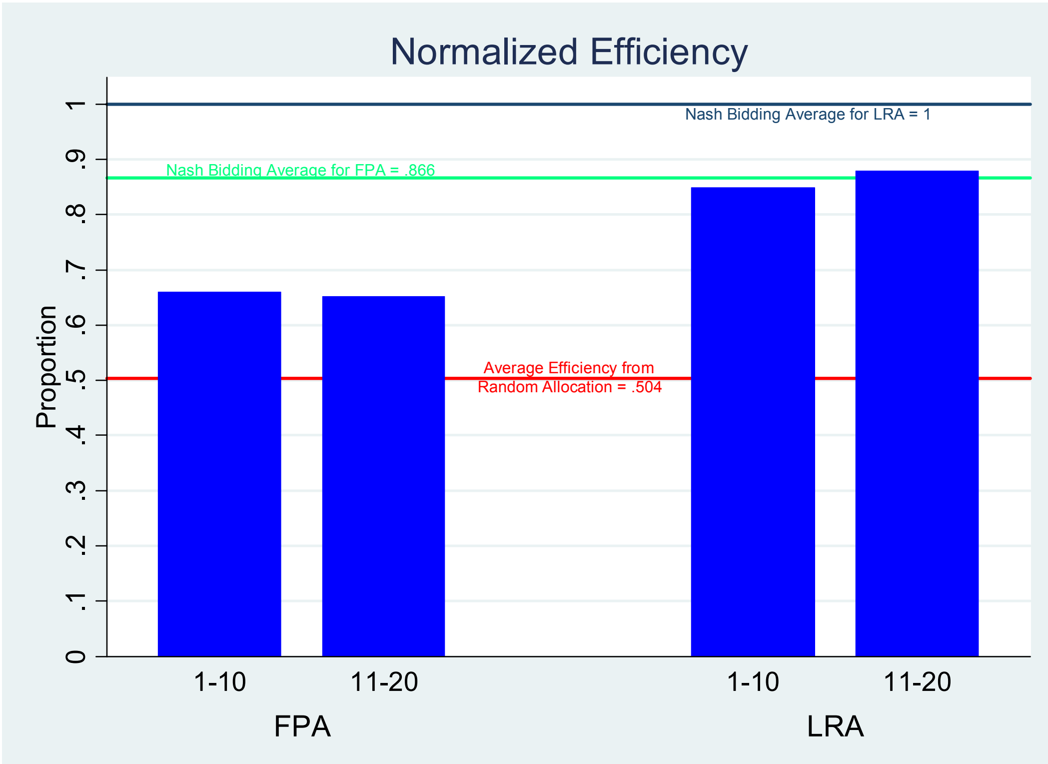


Figure 3:

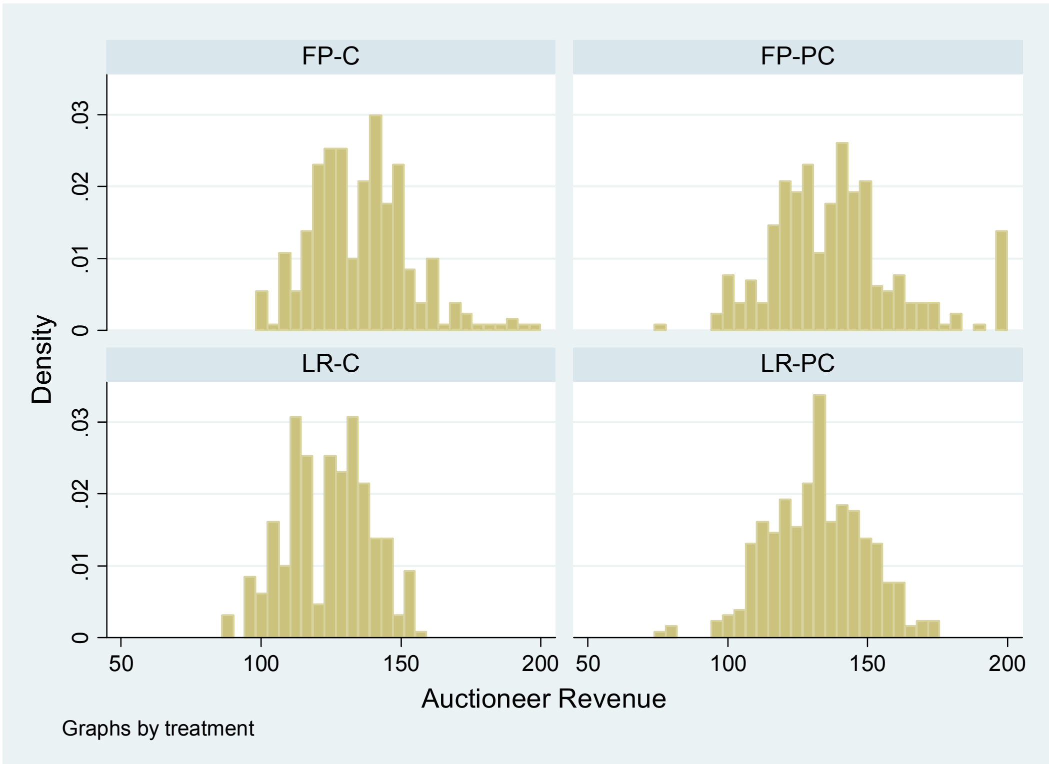

FP-C
FP-PC
LR-C
LR-PC
Density
0
.01
.02
.03
50
100
150
200
Auctioneer Revenue
Graphs by treatment

Figure 4:

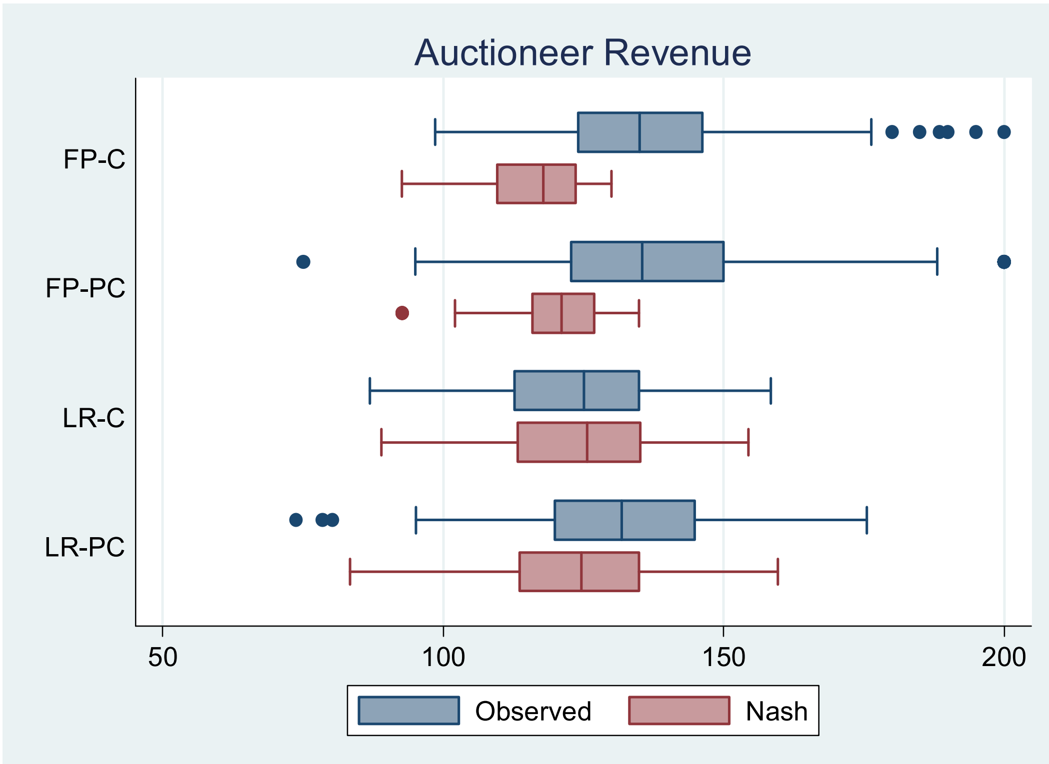

Auctioneer Revenue
FP-C
FP-PC
LR-C
LR-PC
50
100
150
200
Observed
Nash

Figure 5:

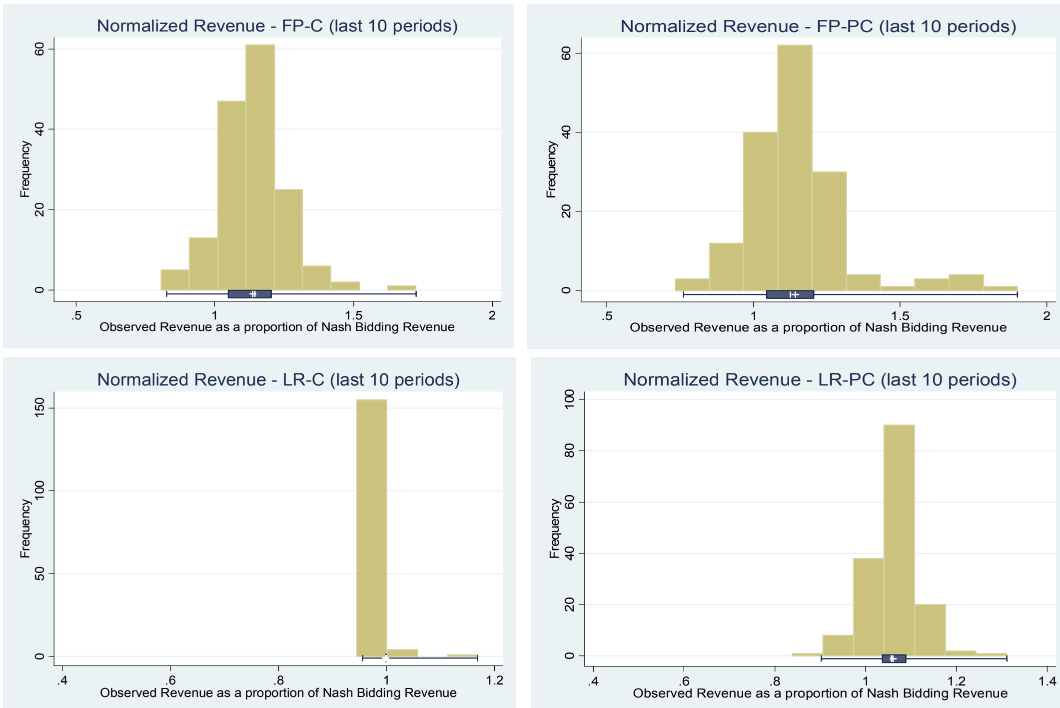

Normalized Revenue - FP-C (last 10 periods)
Frequency
0
20
40
60
.5
1
1.5
2
Observed Revenue as a proportion of Nash Bidding Revenue
Normalized Revenue - FP-PC (last 10 periods)
Frequency
0
20
40
60
.5
1
1.5
2
Observed Revenue as a proportion of Nash Bidding Revenue
Normalized Revenue - LR-C (last 10 periods)
Frequency
0
50
100
150
.4
.6
.8
1
1.2
Observed Revenue as a proportion of Nash Bidding Revenue
Normalized Revenue - LR-PC (last 10 periods)
Frequency
0
20
40
60
80
100
.4
.6
.8
1
1.2
1.4
Observed Revenue as a proportion of Nash Bidding Revenue

Figure 6:

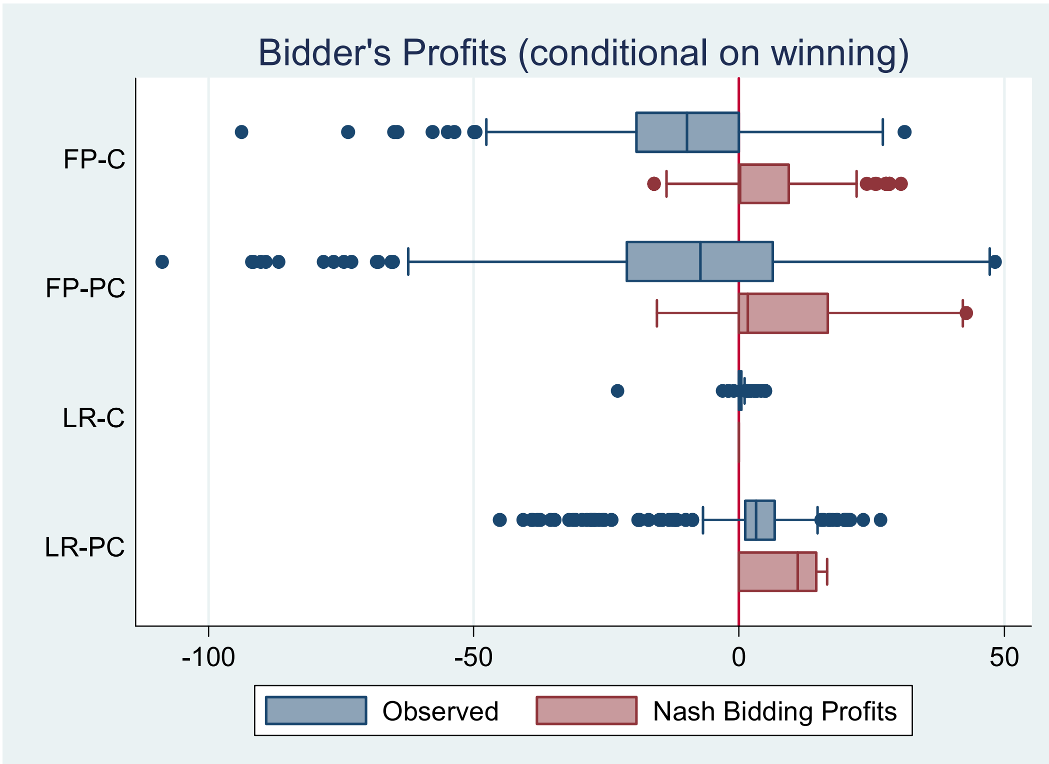

Bidder's Profits (conditional on winning)
FP-C
FP-PC
LR-C
LR-PC
-100
-50
0
50
Observed
Nash Bidding Profits

Figure 7:

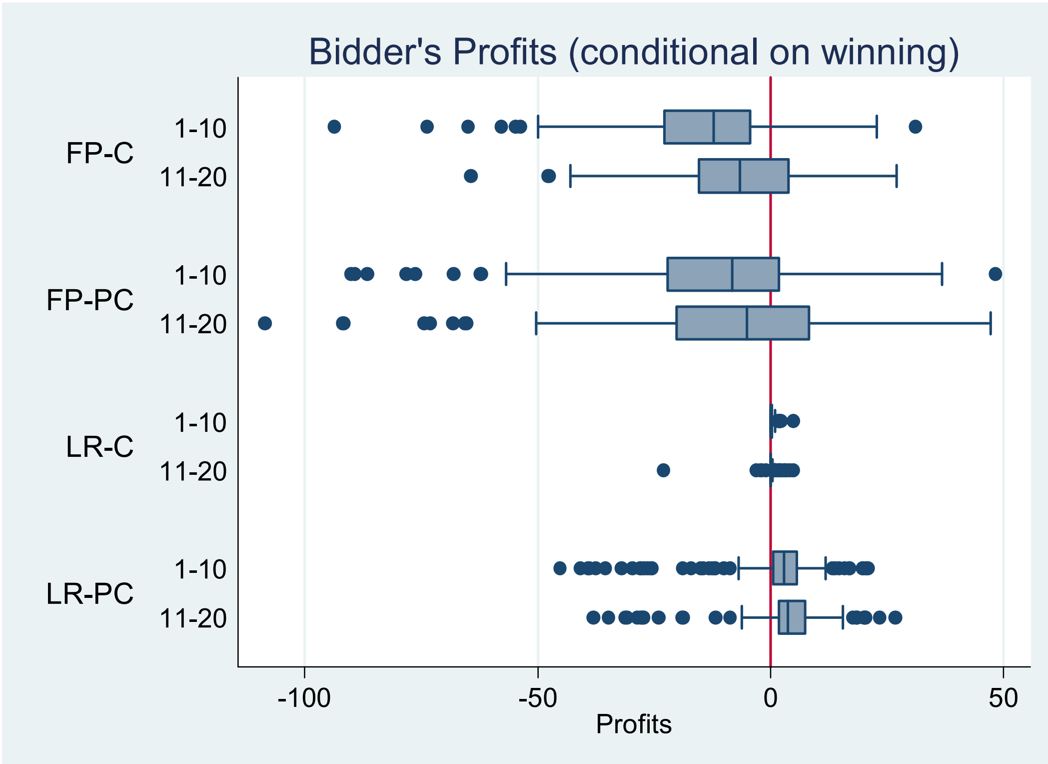

Bidder's Profits (conditional on winning)
FP-C
1-10
11-20
FP-PC
1-10
11-20
LR-C
1-10
11-20
LR-PC
1-10
11-20
-100
-50
0
50
Profits

Figure 8:

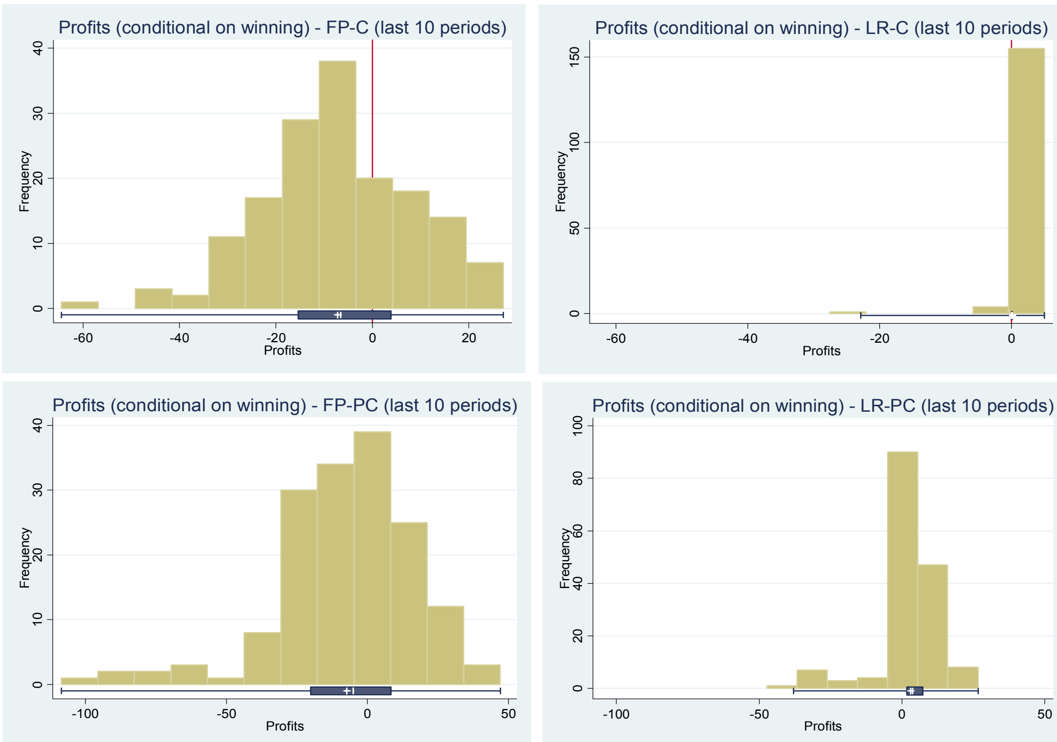
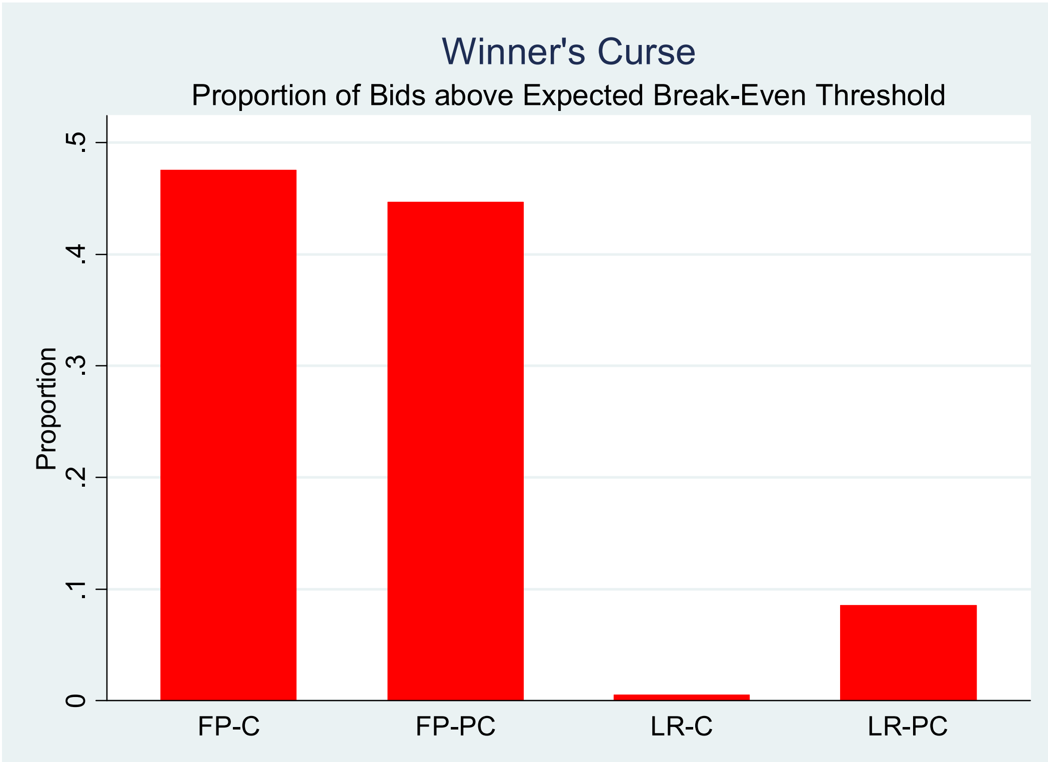

Profits (conditional on winning) - FP-C (last 10 periods)
Frequency
Profits
Profits (conditional on winning) - LR-C (last 10 periods)
Frequency
Profits
Profits (conditional on winning) - FP-PC (last 10 periods)
Frequency
Profits
Profits (conditional on winning) - LR-PC (last 10 periods)
Frequency
Profits

Figure 9:



Winner's Curse
Proportion of Bids above Expected Break-Even Threshold
Proportion
0
.1
.2
.3
.4
.5
FP-C
FP-PC
LR-C
LR-PC

Figure 10:

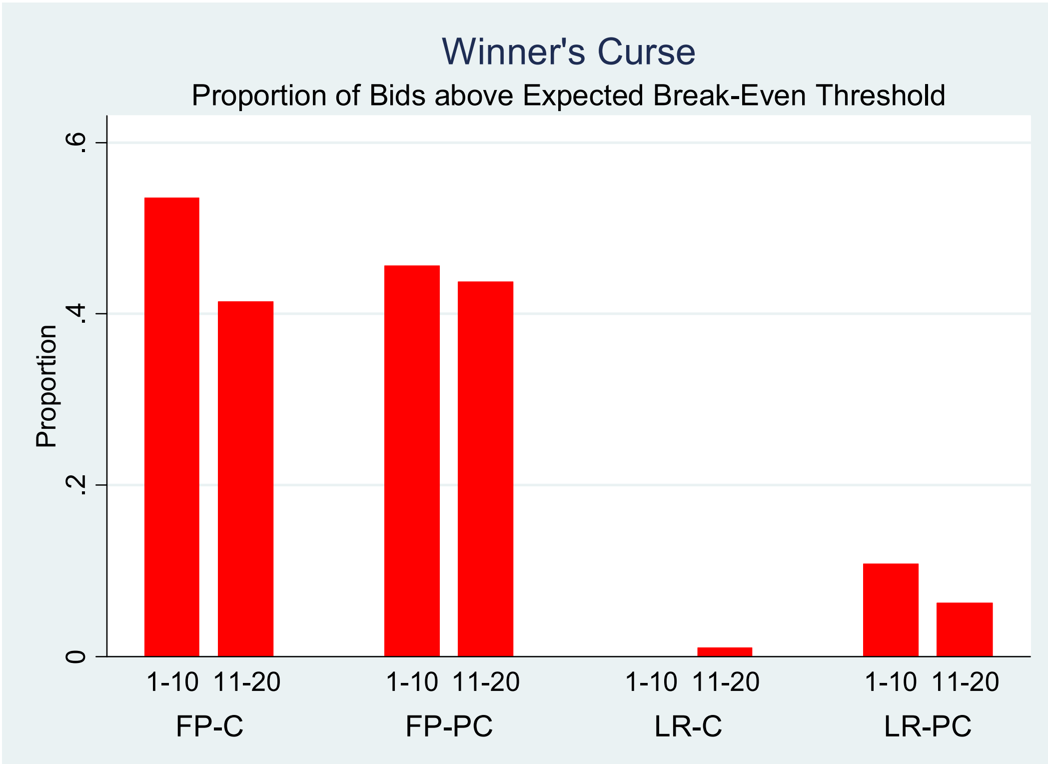

Winner's Curse
Proportion of Bids above Expected Break-Even Threshold
Proportion
0
.2
.4
.6
1-10
11-20
FP-C
FP-PC
LR-C
LR-PC

Figure 11:

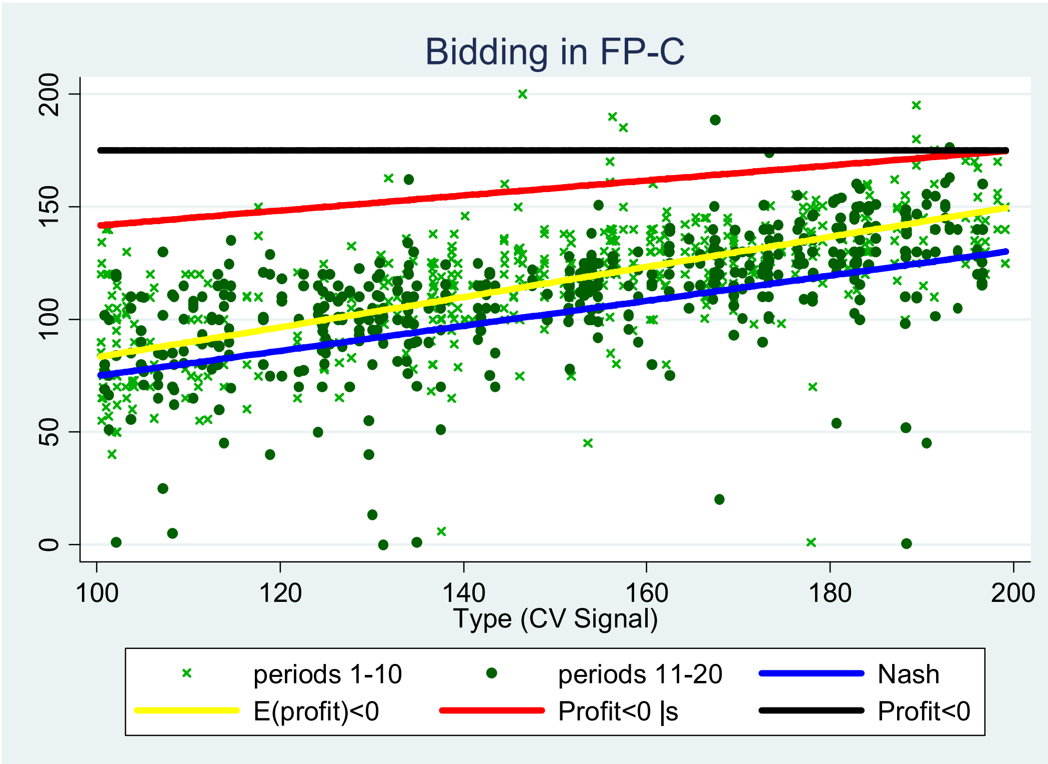

Bidding in FP-C
0
50
100
150
200
100
120
140
160
180
200
Type (CV Signal)
periods 1-10
periods 11-20
Nash
E(profit)<0
Profit<0 |s
Profit<0

Figure 12:

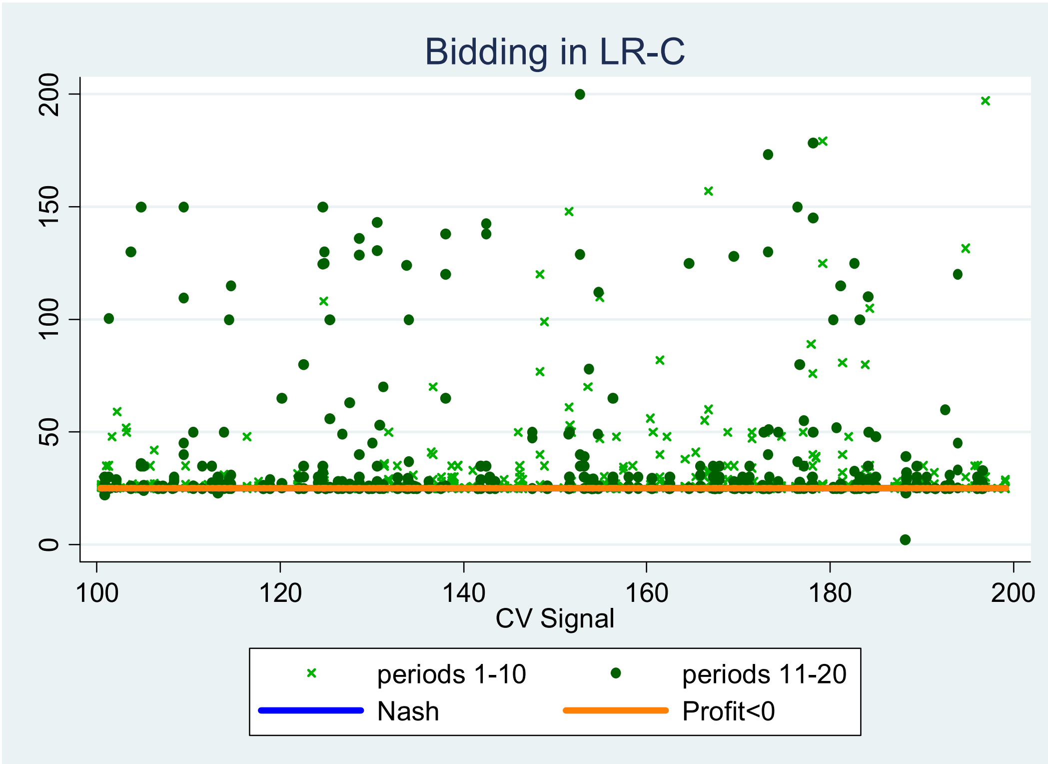

Bidding in LR-C
0
50
100
150
200
100
120
140
160
180
200
CV Signal
periods 1-10
periods 11-20
Nash
Profit<0

Figure 13:

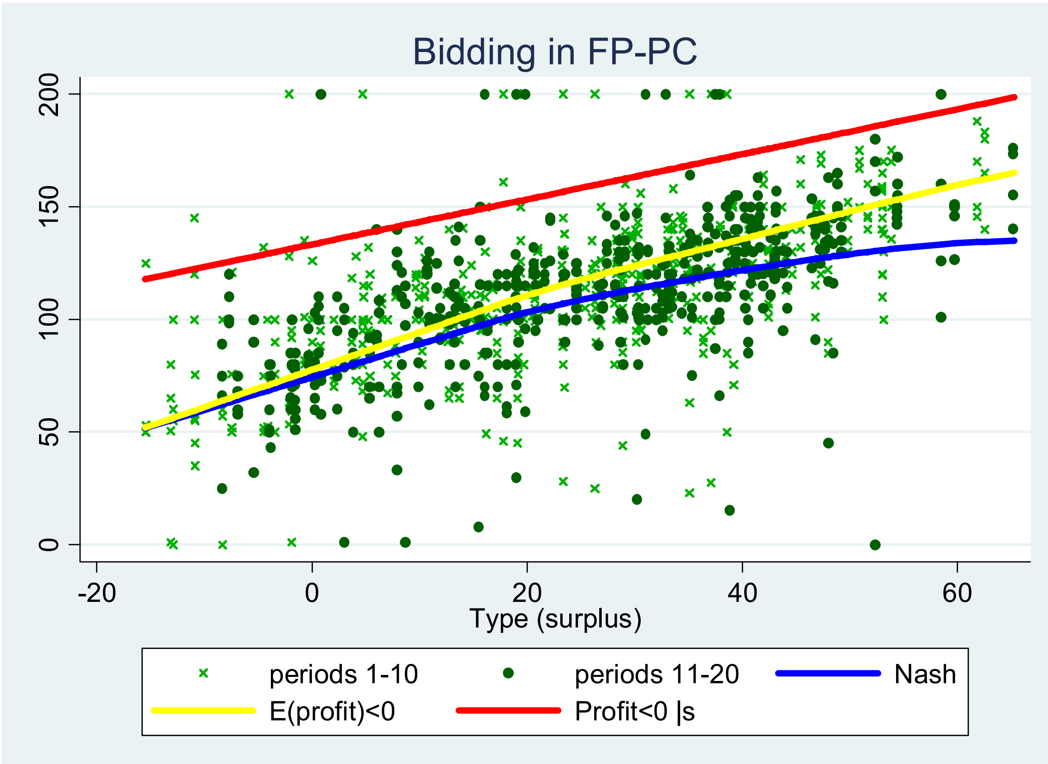
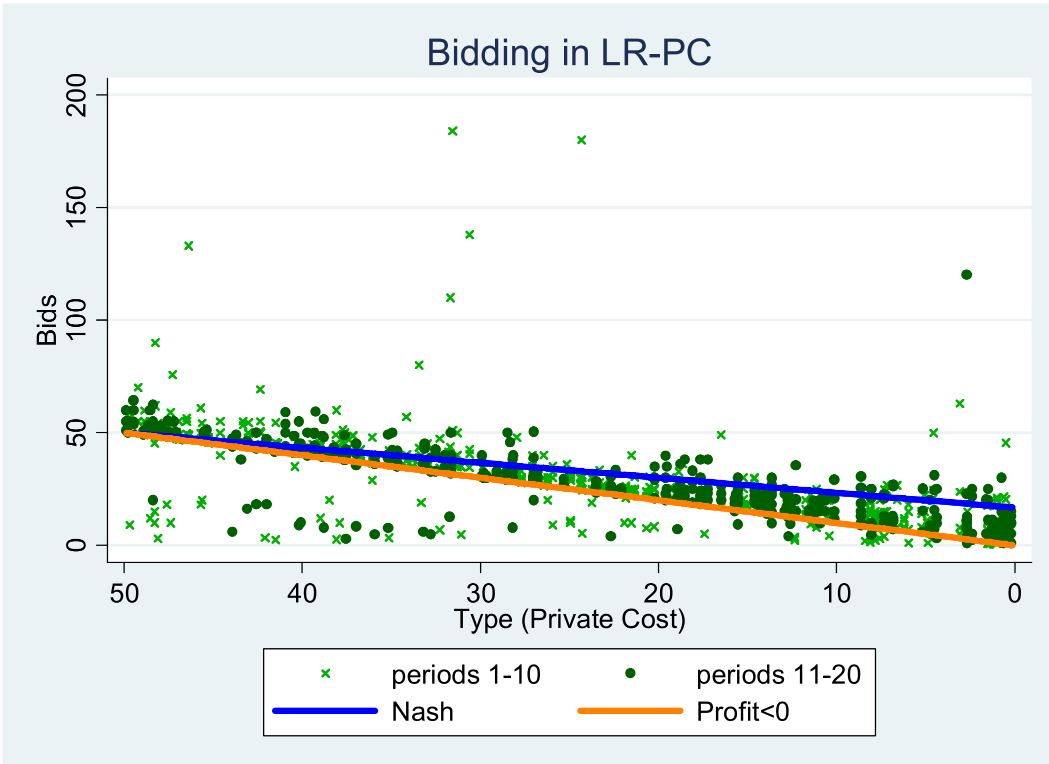

Bidding in FP-PC
0
50
100
150
200
-20
0
20
40
60
Type (surplus)
periods 1-10
periods 11-20
Nash
E(profit)<0
Profit<0 |s

Figure 14:


Bidding in LR-PC
Bids
0
50
100
150
200
50
40
30
20
10
0
Type (Private Cost)
periods 1-10
periods 11-20
Nash
Profit<0