DO AUCTIONEERS MATTER IN COMMON VALUE AUCTIONS?*

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Abstract

In common value auctions an auctioneer can enhance the seller's revenue by making all the private information she possesses regarding the item's value available to bidders before the bidding takes place. This prediction relies on the bidders being rational. On the other hand, if bidders have naïve beliefs regarding the item's value and suffer the winner's curse, an auctioneer would maximize the seller's revenue by not making any information publicly available to bidders before the bidding takes place. In other words, conditional on the auction mechanism, an auctioneer only affects auction results by her choice of public information disclosure policy. This paper tests the above prediction in a first-price common value auction in a laboratory setting, and demonstrates that, contrary to the theoretical prediction, the mere presence of an auctioneer reduces occurrences of winner's curse, and thus, lowers the seller's revenue. We fit a structural level-k model of reasoning which confirms that players apply more thinking steps to formulate their bids in auctions with the presence of an auctioneer, and behave more in accordance with Nash equilibrium predictions.

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1 INTRODUCTION

The value of goods exchanged each year by auctions is enormous. As an example, in modern market economies, governments purchases from private firms, typically in the form of auction procurement, account for about ten percent of GDP(McAfee and McMillan, 1987). Auctions are also important from a theoretical perspective since they play a primary role in the theory of price determination among players with asymmetric information and in the absence of a market intermediary. Not surprisingly, the theoretical and empirical literature on auctions is vast and growing. In practice, most auctions take place either live (as in most charity events or auction houses) or on-line. The main difference between these two forms of auctions is the presence of an auctioneer who calls the bids in live auction formats. Given the economic and theoretical significance of auctions, it is surprising that the role played by auctioneers has not been investigated empirically by the literature. This paper begins to fill that gap.

Common value auctions (CVA) are auctions where the value of the item is the same to everyone, but bidders have different (asymmetric) information about the underlying value of the item when they place their bids. Most real auctions have common value elements to them, as auction winners can (almost) always sell items purchased in auctions in a secondary market. A robust phenomenon in CVA is the persistence of the winner's curse. In CVA, the winner is typically the one with the highest or one of the highest private information signals about the value of the item. For any bidder, winning against other bidders following similar bidding strategies, implies that her private information signal is an overestimate of the value of the item, conditional on the event of winning. The winner's curse is the systematic failure to account for this adverse selection effect, and, on average, it produces below equilibrium or negative profits. There are many real world examples of the pervasiveness of the winner's curse (mineral exploration rights, signing of free-agent professional sports players, competition for book publishing rights, et cetera.) and many aspects of the phenomenon have been extensively studied in a laboratory environment (Kagel and Levin, 2002 offers the most comprehensive review). However, to the extent of our knowledge there are no known studies (field or laboratory) reporting how auctioneers affect CVA auction outcomes.

The role that an auctioneer can play in CVA was first studied theoretically by Milgrom and Weber (1982). When bidders have affiliated private signals with respect to the item's value (which roughly means that larger values of a bidder's valuation makes it more likely that rivals' valuations are also large rather than small), in CVA, revealing information about the item's expected value removes uncertainty which makes low signal holders bid more aggressively, and in essence puts more pressure on the high signal holders not to shade their bids as much. Consequently, in the presence of rational bidders, an auctioneer should always commit to a policy of revealing all the information available to her (make it public) about the item's value to all bidders before the bidding takes place so as to eliminate the maximum amount of uncertainty possible from the low signal holders, and thus, raise the seller's (and the auctioneer's) revenue. Ashenfelter (1989) reports that professional auctioneers largely behave in accordance with theoretical predictions in auctions for wine. On the other hand, if bidders have naïve beliefs with respect to the item's value and suffer the winner's curse, revealing public information causes high signal holders to update downward the expected value of the item. In most cases this force is stronger than the one causing high signal holders not to shade their bids as much out of strategic considerations, and consequently, an auctioneer who wants to maximize revenue should not reveal any public information about the item's value to bidders. Therefore, theory indicates that an auctioneer can influence auction results by her public information disclosure policy choice.

The main purpose of this paper is to test the principle of "public information disclosure policy" formally. We do that by means of laboratory experiments where we replicate the seminal Kagel and Levin, 1986 (hereafter KL) first-price sealed-bid common value auction design. KL's design consists of a two-step procedure where in the first step the value of a commodity *(V)* is drawn from uniform distribution, and in the second step, private information signals *(x)* about V are generated for each bidder by drawing values from a uniform distribution centered on V but with a narrower support than the first step distribution. In each session three bidders (the minimum necessary to maintain an interesting auction) participated in between 21-30 auction rounds. We divided the sessions into three experimental conditions in all of which we maintained the same values of V and x*'s* for each corresponding auction round. The conditions were the following: two control conditions (without the presence of an auctioneer); one where only private information (x*'s*) was revealed to bidders before the bidding took place (private information), and another one where public information was revealed to bidders before the bidding took place in addition to the *x's* (public information). Finally, in the treatment condition an auctioneer chose what public information disclosure policy to follow, but before gaining access to the information herself.

Unlike KL and other papers who replicated that design without the presence of an auctioneer and whose main purpose was the demonstrate the existence of the winner's curse, our main focus was to compare auction outcomes in the presence versus the absence of an auctioneer whose only task was to commit to a public information disclosure policy. As in KL we find that the winner's curse is a prevalent phenomenon even for auctions with as few as three bidders. However, contrary to the theoretical prediction whereby an auctioneer only influences the auction outcome by the public information disclosure policy, we find that: 1- the mere presence of an auctioneer reduces occurrences of the winner's curse, and 2- that auctioneers often commit to the incorrect public information disclosure policy, further depressing theirs and the seller's revenues. In other words, we document an "auctioneer effect" whereby the presence of an auctioneer significantly reduces instances of the winner's curse in common value auctions.

To account for the above behavioral regularities we fit a structural non-equilibrium level-k model of reasoning (Crawford and Iriberri, 2007) applicable to initial responses. Level-k belongs to the "number of thinking steps" class of models which also include Stahl and Wilson (1995) and Cognitive Hierarchy (Camerer, Ho and Chong, 2004). This class of models is based on strategic players that act rationally but depart from equilibrium in that players have non-equilibrium beliefs about the distribution of other players' types. In particular, players believe that they understand the game better than other players. This class of models rationalizes data better than equilibrium and alternative non-equilibrium models for a large set of games with complete information. In addition, level-k rationalizes data in common value auctions (first and second-price) as well as in independent private value auctions (PVA) more satisfactorily than alternative competing non-equilibrium structural models. The results of fitting level-k to our data indicate that bidders who participated in auctions where the auctioneer was present employed a deeper level of reasoning (i.e. more thinking steps) to formulate their bids, and behaved more in accordance with Nash equilibrium predictions than bidders in both control conditions (no auctioneer present).

In summary, this paper contributes to the auction literature by isolating one key aspect of auctions which had been ignored by the empirical literature in economics and marketing so far: the auctioneer. We demonstrate via laboratory experiments the "auctioneer effect" whereby the presence of an auctioneer reduces instances of the winner's curse (and thus lowers the seller's revenue), not only by committing to the incorrect public information disclosure policy, but simply by her mere presence. Furthermore, we fit a non-equilibrium structural level-k model of iterative reasoning and identify that the mechanism by which the winner's curse is mitigated in the the presence of an auctioneer is through players' increased number of thinking steps, so that bidding becomes more in line with Nash equilibrium predictions.

The rest of the paper is organized as follows: The next section reviews the theory of common value auctions, describes Kagel and Levin (1986) seminal experimental design, reviews the role of public information, describes our experimental set-up, and presents our findings. Section 3 describes the level-k model and fits the experimental data from our first-price common value auctions. Finally section 4 concludes and outlines possible next steps for future research.

2 COMMON VALUE AUCTIONS

This section briefly reviews the economic theory of common value auctions, formulates two theory-based hypotheses about the possible role of auctioneers, describes a laboratory experiment designed to test those hypotheses, and finally, presents the experimental results and conclusions.

2.1 THEORY & HYPOTHESIS

Common value auctions (CVA) are auctions in which the value of the item V is the same to all bidders, but bidders are unaware of that value at the time they place their bids. Bidders base their bids on private estimates x typically correlated to the value of the item. As demonstrated by KL, CVA constitute a market setting in which participants are particularly susceptible to judgment failures. Although participants obtain unbiased estimates of the the item's value, assuming symmetric bid functions, they only win in cases where they have the highest or one of the highest signals. The systematic failure to account for this adverse selection problem in bidding, will result in winning bids that produce below equilibrium or even negative profits and is referred to in the literature as the winner's curse. There are several examples of the winner's curse in real life auctions. Some of the most cited examples come from the book-publishing industry (Dessauer, 1989), the rights for offshore oil exploration (Capen, Clapp and Campbell, 1971), and from the market for free-agent baseball players (Cassing and Douglas, 1980) in which auction winners typically overpay. Thaler (1994) provides further examples and offers a review of the literature on this phenomenon.

The winner's curse

There are several possible definitions of the winner's curse ranging from less stringent (bidding above Nash equilibrium bidding) to more stringent (bidding above expected value of the item conditional on winning). In this paper we adopt a stringent definition of the winner's curse which is the same adopted by KL. In first-price common value auction with risk neutral bidders, Nash equilibrium requires bidding as if one holds the highest signal, since the result of the auction only counts when one's bid is the highest. Define $E[V|x_i]$ as an unbiased estimate of the value of the item before bidding and $E[V|X_i = x_1]$ as the expected value of the item conditional on having the highest signal. As per KL, an auction market exhibits a winner's curse when:
(i) there is a positive rank-order correlation between bids and private information signals, and
(ii) individual bids exceed $E[V|X_i = x_1]$.
As stated by KL, "the above two conditions characterize the mechanism underlying the market outcomes: namely that the winner's curse results from an adverse selection problem in that (1) bidders generally win the auction when they hold the highest signal, and (2) they fail to account for this fact in formulating their bids."

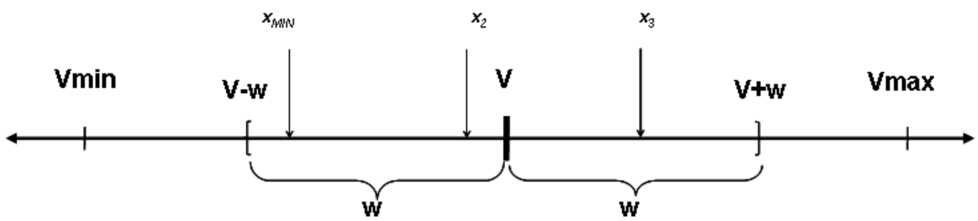


Figure 1: KL Design

2.1.1 KL EXPERIMENTAL DESIGN

KL seminal design consists of a two step procedure: first the random value V is generated by drawing a number from the uniform distribution $U[V_{min}, V_{max}]$. Second, all N bidders receive unbiased private information signals x about the possible value of V. Those signals are generated from a uniform distribution centered at V and of width equal to $2w$ (i.e. $U[V-w, V+w]$), where w is a fixed number (see figure 1 for illustration).

2.1.2 BIDDING UNDER PRIVATE INFORMATION

The following theory follows directly from KL paper. For signals positively associated in the interval:

$$V_{min} + w \leq x \leq V_{max} + w \tag{1}$$

Rational players expected value of the item and optimal bidding strategy are defined by:

$$E[V|x_i = x_1] = x_i - \frac{w(N-1)}{(N+1)} \tag{2}$$

$$b^r(x_i) = x_i - w + Y \tag{3}$$

where the term Y is given by the following expression:

$$Y = \left[\frac{2w}{(N+1)}\right] \exp^{[-(\frac{N}{2w}(x_i-(V_{min}+w))]} \tag{4}$$

Notice that Y contains a negative exponential which quickly approaches zero for $x_i > V_{min} + w$, and therefore, it has been largely ignored by most experimenters and so do we.

Cursed bidders have naïve beliefs about the item's value. Their expected value of the item and corresponding optimal bidding strategy are given by:

$$E[V|x_i] = x_i \tag{5}$$

$$b^c(x_i) = x_i - \left(\frac{2w}{N}\right) + \left(\frac{Y}{N}\right) \tag{6}$$

Comparing equation 6 with equation 2 it is easy to see that cursed bidders will experience the winner's curse when $N > 3$. In addition symmetric bidding according to 6 results in expected negative profits.

2.1.3 BIDDING UNDER PUBLIC INFORMATION

When private information is released, as described by KL (section II.B), on average, for the bidder holding the highest information signal:

$$E\left[V|X_i = x_1\right] = E[V|X_i = x_1, X_p] \tag{7}$$

Since all symmetric RNNE requires agents bidding as if $x_i = x_1$, and due to affiliation of signal values, bidders whose private info $x_i < x_1$will, ex-post, raise the average expected value of the item, which induces an upward revision of the bids. This in turn puts pressure on the bidder with the highest signal information (x_1), to bid more out of strategic considerations. For signals in 1 the expected value of the item for a RNNE bidder is:

$$E[V|X_i = x_1, X_p = x_{min}] = \frac{(x_i + x_{min})}{2} \tag{8}$$

The RNNE bid function with public information is:[1]

$$b(x_i, x_{min})^{pub} = \frac{N}{2(N-1)} x_{min} + \frac{(N-2)}{2(N-1)} x_i \tag{9}$$

Cursed players hold naïve beliefs about the expected value of the item. For cursed players that expectation is:

[1]This Nash bidding strategy has been corrected in Campbell, Kagel and Levin (1999) but the actual difference is negligible for the purpose of this paper so we continue to use equation 9 above.

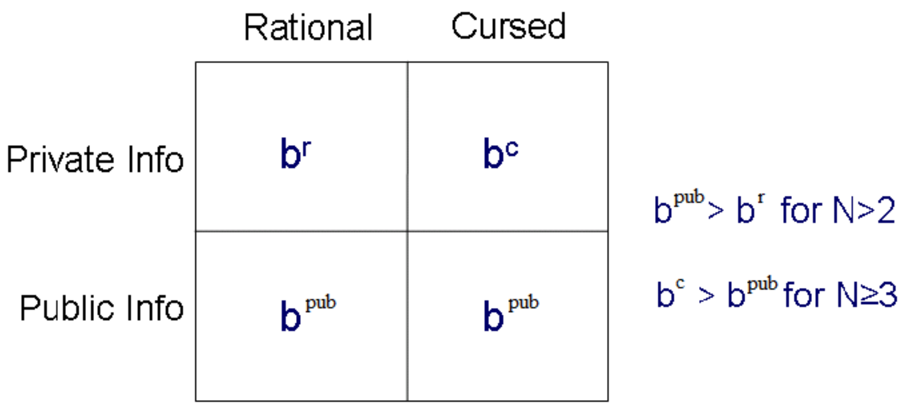


Figure 2: Theoretical predictions revenue ranking

$$E[V|x_i, x_{min}] = \frac{(x_i + x_{min})}{2} \tag{10}$$

Comparing the above equation with 8 we see that both types of players hold the same beliefs. Consequently the RNNE and cursed bid functions coincide.

The above framework allows us to derive precise theoretical predictions (summarized in figure 2):

1. Under private information, comparing equation 6 with equation 3 we see that $b^c > b^r$ for $N > 2$.
2. Comparing rational bidders across information condition (i.e. equations 3 and 9) we see that $b^{pub} > b^r$ for any $N > 1$
3. Comparing bidders with cursed beliefs across information conditions (i.e. equations 6 and 9) we see that $b^r > b^{pub}$ for $N \geqslant 3$.

In summary, in first-price CVA, an auctioneer is better off by releasing public information if bidders are rational, but the auctioneer is better off by not releasing public information if bidders have cursed beliefs and would likely suffer the winner's curse. Previous laboratory findings (Kagel et al., 1989, Garvin and Kagel, 1994) with inexperienced bidders (i.e. where subjects did not participate in previous auction experiments) show that even in small auctions with four bidders, players suffer the winner's curse. Consistent with auction theory, a rational auctioneer will choose the correct information policy to maximize her expected profits, and, in addition, the auctioneer would only affect auction outcomes through the public information disclosure policy. Thus,

- H1: Rational auctioneers will choose the correct public information disclosure policy.
- H2: Conditional on the auction mechanism, the auctioneer only influences auction results through the public information disclosure policy.

2.2 EXPERIMENTS

Our CVA experiments replicate KL seminal design, but with a different goal in mind. Our main objective is to test the effect of the presence of an auctioneer and how the outcomes are affected by the public information policy choice. The experimental design consists of three conditions: two control condition without the presence of an auctioneer, and a treatment condition with the presence of an auctioneer. The control condition experiments were further divided into two types of sessions where we manipulate the public information displayed to bidders: in one manipulation (private information) no public information was revealed to bidders before they submitted their bids, and in the other manipulation (public information), $x_{min}$was always revealed to participants, in addition to their private estimates x, before they submitted their bids. In the treatment condition the sole task of the auctioneer was to commit to a policy of either revealing x_{min} or not revealing x_{min} to all the bidders before the auction started, but the auctioneer had no access to the information herself, and this was common knowledge.

This papers reports the result of 12 experimental sessions divided into 8 control conditions (4 private information and 4 public information) and 4 treatment conditions. In total 47 bidders participated in the 8 control conditions and 24 in the treatment conditions. Bidders were given a US $5 participation fee and a starting balance of US $12 to bid. Gains from each auction were added to the starting balance and losses subtracted from this balance in each period, and bidders could continue participating in the experiment as long as their balances were positive. Since we had anticipated the possibility of bidders going bankrupt (as was the case in KL and other similar experiments with four or more bidders), each session consisted of a pool of six bidders, only three of which were active in any given auction, and bidders were paired in each round in random order. In addition, in the treatment condition we had 3 additional subjects who played the role of auctioneers, and whose sole task was to commit to reveal or not to reveal public information to the bidders. A total of 12 auctioneers took part in all 4 treatment sessions, and each one of them was the auctioneer between eight to ten auction rounds.

Following KL, the choice of public information was x_{min}, both because the optimal bid strategy can be solved analytically, and because the amount of information x_{min} conveys reduces bidders uncertainty substantially.

2.2.1 ORDER OF PLAY

1. In each round 3 bidders were randomly chosen to participate in the auction as long as they had a positive overall balance.

2. The value V was generated following step one of the two-step procedure described in 2.1.1.

3. The 3 *x's* were generated following step two of the the two-step procedure.

4. In the control condition x_{min} was either not revealed (private information) or was revealed (public information) to bidders (bidders were informed of these in the experiment instructions beforehand). In the treatment condition an auctioneer chose to reveal or not to reveal $x_{min}$to the bidders, though the auctioneers did not know x_{min} themselves.

5. Bidders submitted their bids.

6. All participants received the following feedback after each round: V, the 3 bids in decreasing order, profits to the winner(i.e. ***[High bid - V]*** , all othe bidders made zero profit in that round), and profits to the auctioneer ***(i.e. 3%*High Bid)***.

Table 1: CVA Summary Statistics *(all profit figures in USD)*

	Control Private Info.	Control Public Info.	Treatment	Overall
RNNE expected round profit	6	3	4.7	4.6
Actual avg.round profit	-0.59	-0.66	0.73	0.18
Number of bidders bankrupt	14 (of 47)		5 (of 24)	19 (of 71)
Avg. profit to survivors	15.1		17.0	15.7
Avg. profit to auctioneers	15.4		15.1	15.2
Money recovered from starting budget (%)	10.3		5.9	8.8

2.3 CVA RESULTS

Table 1 presents the summary statistics for all three conditions. In four sessions in the control condition (45 auction rounds) subjects played a mix of private and subsequently public information rounds (or viceversa). In the remaining control sessions (60 auctions rounds) subjects played all rounds either under private information or under public information. Consequently, this table reports the RNNE expected round profits, and the actual average round profits for each condition separately, but combines the rest of the statistics for both control conditions.

The table gives us a preview of the most important results. On average winning bidders made \$6.59 per round less than equilibrium predictions under private information, and \$3.66 less under public information. Negative average profits suggests that players suffered from the winner's curse, but less so in the control condition where on average winners made money (\$0.73) as opposed to lost money (approximate \$0.60) in both control conditions. A higher percentage of bidders went bankrupt in the control conditions versus the treatment condition (30% versus 20%), and consequently, subjects ended-up returning more money to the experimenter from their original endowment in the control conditions (10% vs. 6%).

Table 2 quantifies the winning bidder's average round profit in each control condition separately (top row), and compares auctions rounds where the public information disclosure choice of the treatment condition matched the

Table 2: Winning Bidder Average Round Profits *(all figures in USD)*

	Control Private Info.	Control Public Info.	Treatment	Δ	Obs.	t-test (power, α=0.05)
Control conditions	-0.59	-0.66		0.07	105	0.11 (0.05)
Control (combined) versus treatment	-0.66		0.73	1.39	105	2.85[a] (0.13)
Private Info. Only	-0.04		0.83	0.87	60	1.19 (0.13)
Public Info. Only		-2.21	0.57	2.78	45	4.84[a] (0.75)

[a]*significant at 1% level, 2-sided paired t-test*

corresponding control condition auction round (bottom 2 rows). Therefore for these last two comparisons, all the information to bidders was identical (auctioneers chose to display x_{min} in 45 auctions of the 105 auctions). There was essentially no difference in round profits in both control conditions (-$ 0.59 versus -$0.66, t-test=0.11). However, comparing the combined control conditions to treatment reveals that, on average, the winning bidder makes $1.39 less per round when the auctioneer was not present (2 sided, paired t-test= 2.85, p>0.01). As the bottom two rows indicate this difference was mainly driven by the difference in average profits under public information.

Table 3 reports deviations from RNNE bidding for all players and it shows that not only did auction winners bid in accordance with cursed beliefs, but that all players did so on average in the control condition. In the treatment condition bidders bid higher than equilibrium under private information, though significantly less than in the control condition ($2.59 vs. $3.42, t=1.65*). Under public information that difference was even larger (-$1.98 vs. $0.99, t=5.49***) with bidders in the treatment condition bidding below RNNE. Clearly, the auctioneer's presence caused all bidders, on average, to bid more conservatively regardless of the auctioneer's public information policy decision.

Table 4 shows the auctioneer's average round profits and further demonstrates that her mere presence reduces her profits (and the seller's) as evidenced by the 2.4 percent higher average round profits in the control versus

Table 3: Deviations from RNNE bidding - all bidders *(all figures in USD)*

	Control Private Info.	Control Public Info.	Treatment	Δ	Obs.	t-test (power, α=0.05)
Control condition	3.80	0.58		3.22	315	7.82[b] (1.00)
Deviation from b^r	3.42		2.59	0.83	180	1.65[a] (0.34)
Deviation from b^c		0.99	-1.98	2.97	135	5.49[b] (0.75)

[a]*significant at 10% level, 2-sided paired t-test;* [b]*significant at 1% level, 2-sided paired t-test*

the treatment condition ($1.71 vs. $1.67, t=2.81***). Since bidders, on average, suffered the winner's curse, a rational auctioneer should have chosen not to display public information (at least in the early rounds of play). However, they chose to reveal public information in more that 43 percent of the auctions. In so doing, auctioneers hurt the seller (and themselves) even more. Table 5, shows regression results from regressing the seller's revenue on the auctioneer's public information policy choice (dummy variable =1 when she showed public information, and 0 otherwise) for the treatment data only. In this regression we control for all the private signals to bidders and the round number. The regression results show that, on average, the incorrect decision (to show public information to bidders) cost the seller $1.44 (or 2.6 percent in revenues).

In summary, our auction results indicate that even in CVA with 3 bidders, the winner's curse is a prevalent phenomenon. In addition, auctioneers could have made more money by not revealing public information to bidders (as suggested by theory if bidders are cursed) and thus we reject H1. Finally, we also reject H2 since the mere presence of an auctioneer reduced the seller's revenues and caused bidders to bid more conservatively, regardless of the auctioneer's public information policy choice and in clear violation of the theory.

Table 4: Auctioneer's Profits *(all figures in USD)*

	Control Private Info.	Control Public Info.	Treatment	Δ	Obs.	t-test (power, α=0.05)
Control conditions	1.71	1.71		~ 0	105	0.10 (0.01)
Control (combined) versus treatment	1.71		1.67	-0.04	105	2.81^{a} (0.08)
Private Info.	1.64		1.61	-0.03	60	1.16 (0.06)
Public Info.		1.84	1.75	-0.08	45	4.81^{a} (0.11)

^{a}*significant at 1% level, 2-sided paired t-test*

Table 5: Regression - DV. Auctioneer's Profits (treatment data only)

Indep. Var.	Coeff. *(robust s.e.)*	t-stat.
const.	2.26 (1.429)	1.58
x_1	0.32 (0.056)	5.67^{a}
x_2	0.31 (0.047)	6.52^{a}
x_3	0.36 (0.047)	7.51^{a}
Round	-0.11 (0.051)	2.24^{b}
Show	**-1.44 (0.051)**	**1.73^{c}**
Obs.	105	
F(5,99)	739.9	
Prob. > F	0.0000	
R^2	0.96	

$^{a,\ b,\ c}$ *significant at the 1%, 5%, and 10% level respectively*

3 A MODEL OF BIDDING

Several models have attempted to explain departures from risk-neutral Nash equilibrium bidding in order to explain the winner's curse phenomena in common value auctions. In addition to KL's cursed players explanation, Holt and Sherman (1994) (HS) propose a model similar to KL in which "naïve" bidders do not adjust their value estimates by the information revealed by winning. Eyster and Rabin (2005)'s "cursed equilibrium" model generalizes both KL and HS models to allow for intermediate levels of value adjustment ranging from full-equilibrium to "fully-cursed equilibrium" with no adjustment. All three models allow players to deviate from equilibrium only to the extent that they do not draw the correct inference from the auction outcomes, but do not explain non-equilibrium behavior in private value auctions.

In addition, other models have attempted to explain overbidding in independent private value auctions, but with the potential to offer an explanation for the presence of the winner's curse in CVA. Some of the most cited are: risk aversion (Cox, Smith and Walker, 1988), the "joy of winning" (Cox, Smith and Walker, 1992), or McKlevey and Palfrey (1995) quantal response equilibrium (QRE is a generalization of equilibrium that allows players choices to be noisy, with the probability of each choice increasing in expected payoff). However, there are several reasons why one would expect these models not to be entirely satisfactory in our case. As noted by Lind and Plott (1991) and Kagel and Roth (1992), common value auctions with risk aversion are not well understood theoretically, and risk aversion cannot be the only factor (and may not be the most important) in explaining overbidding in first-price private value auctions (PVA). In addition, HS does not find strong evidence for the "utility of winning." Finally, all these explanations for overbidding assume perfect coordination of beliefs about others' strategies which is characteristic of equilibrium analysis. But neither field nor laboratory evidence make equilibrium a plausible hypothesis for rationalizing data in first-price CVA, especially with inexperienced bidders, and particularly in the early rounds of play when players had not had sufficient opportunity to learn. In addition, equilibrium requires strategic thinking, but thinking may not follow the circular fixed-point logic of equilibrium in complicated incomplete-information games such as CVA, but rather it might follow a step-by-step reasoning procedure (Selten, 1998).

More promising alternatives to explain both the winner's curse in CVA and overbidding in PVA (as well as in other incomplete-information games) are models which depart from equilibrium but which accurately describe initial responses to games. One set of such models which accurately rationalize data for a large class of games is based in degrees of reasoning or thinking steps. Such models were first introduced by Stahl and Wilson (1995) and include Cognitive Hierarchy (Camerer, Ho and Chong, 2004), and level-k thinking (Crawford and Iriberri 2007, hereafter CI). All these model assume that players believe they understand the game better than their adversaries, an assumption consistent with psychological findings that demonstrate that people are over-confident about their own relative abilities (Camerer and Lovallo, 1999). In particular, Cognitive Hierarchy (CH) and the level-k models are very similar in nature and mainly differ from each other in that players best respond to either a mixture of lower type players (CH) or to the type immediately below (level-k). Both these models explain behavior better than equilibrium for a large class of normal-form games of complete-information. The next section describes level-k thinking, which in addition, rationalizes empirical data better than equilibrium and cursed equilibrium in CVA, but also performs better than equilibrium and QRE, in first-price independent PVA.

3.1 Level-K

Learning and survival pressure can lead bidders in small auctions to approach equilibrium bidding in a long series of auctions (as evidence in KL and in our data). Therefore, an appropriate model to capture the mechanism underlying the winner's curse in CVA needs to correctly describe initial bidding behavior. One such model is the level-k model (see CI for a complete model description), which is a structural non-equilibrium model of initial responses to incomplete-information games based on k-levels of thinking steps. Level-k allows behavior to be heterogeneous, but it assumes that each player's behavior is drawn from a common distribution over a particularly hierarchy of decision types.

Each type Lk for k>0, anchor its beliefs in a non-strategic L0 type and adjusts those beliefs via an iterated process of best responses. L1 best responds to L0, L2 to L1, et cetera. CI confine attention only to L0, L1, and L2, simply because they suffice to demonstrate the model's power to explain auction behavior, but also because experimental evidence suggests that higher types are rare, particularly in incomplete-information games.

All Lk for k>0 have accurate models of the game and are rational; they only depart from equilibrium by basing their beliefs on simplified models of other types. Thus, these players follow equilibrium considerations to the extent that they take into account value adjustment (information revealed by winning) vs. bidding trade-off (a higher bid's cost vs. increased probability of winning) when formulating their bids. The deviations from equilibrium are mainly explained by these type's non-equilibrium beliefs. The k-types are the following (the optimal bids for each type can be found in table 1, row 7 of CI):

- L0 is non-strategic and represents the key to the model explanatory power. Two kinds of L0 are considered:

    1. Random L0 (RL0) is the most general type, and bids uniformly random over the feasible range of bids.
    2. Truthful L0 (TL0) bids the value of its private information signal taken by itself, so they neither adjust for the curse nor shade their bids (in practice these players are rare).

- Random L1 (RL1) follows RL0. Because RL0 bids are independent of its signal, RL1 ignores the information revealed by winning. On average, this causes it to overbid with respect to equilibrium.

- Truthful L1 (TL1) believes that to win it must bid higher than all other TL0 bids, not just higher than their equilibrium bids. Thus, value adjustment considerations make them believe that the curse is more severe than in equilibrium so they underbid relative to equilibrium. But bidding trade-off considerations can make them bid higher or lower relative to equilibrium. In first-price CVA, TL1 bids lower than equilibrium or coincides with it.

- Random L2 (RL2) follows RL1, but, unlike them, RL2 adjusts value estimates by the information revealed by winning, because RL1 bidding strategy is an increasing function of its private information signal. RL2 believes that to win it must bid higher than all other RL1 bids, not just higher than their equilibrium bids, thus RL2 believes the curse is more severe than in equilibrium, and in general this tends to make it underbid relative to equilibrium, but the bidding trade-off might reinforce or work against the tendency to underbid.

- Truthful L2 (TL2). Since TL1 bids approximately coincide with equilibrium, TL2 can not profitably deviate from this strategy and therefore follows (approximately) equilibrium bidding as well.

Notice that Random or Truthful Lk for k>0 are not random or truthful themselves. The notation simply identifies the types associated with the corresponding L0 (i.e. RL0 or TL0).

As per CI, subjects of type k, normally follow bids $b_k(x)$ but subject to logistic errors of precision λ assumed independent across auctions. A player expected payoff for bid b given his signal x with type-k beliefs is $S_k(b|x)$. Thus the probability of observing a bid b within the range of possible bids $[\underline{b}, \overline{b}]$ for a type- k bidder is:

$$Pr(b|k, x, \lambda) = \frac{exp(\lambda S_k(b|x)}{\int_{\underline{b}}^{\overline{b}} exp(\lambda S_k(a|x)da} \tag{11}$$

With independent errors conditional on a bidder's type, the likelihood of observing the t observation sample $b_i = (b_{i1}, ..., b_{iT})$ for player i of type k with signal x and precision λ is:

$$L_k(b_i|k, x, \lambda_{ik}) = \prod_{t=1}^{T} Pr(b_{it}|k, x, \lambda_{ik}) \tag{12}$$

and the log-likelihood function for each player conditional on his type is :

$$LL_k = \sum_{t=1}^{T} Pr(b_{ik}|k, x, \lambda_{ik}) \tag{13}$$

Because the payoff function is quasi-concave and the logit term increases with payoff, the likelihood treats a bid as stronger evidence for a type the closer it is to a type's bid or the better the deviations are explained given its beliefs.

3.2 Level-k Results

The main purpose of fitting the model is to compare the distribution of k-types bidders from our experimental data in the presence versus the absence

Table 6: Level-k Distribution Types

	Obs. 1-5 (all bidders)				**Min 3 & Max 8 obs.**			
	No Auctioneer		Auctioneer		No Auctioneer		Auctioneer	
Types	Count	%	Count	%	Count	%	Count	%
R.L0	7	15	2	8	5	11	0	0
R.L1	31	66	17	71	35	78	17	74
R.L2	6	13	0	0	2	4	0	0
T.L1	1	2	4	17	1	2	2	9
T.L2 (∼Eq.)	2	4	1	4	2	4	4	17
Total	47	100	24	100	45	100	23	100
LR - Chi2 (4)	10.08, $p < 0.04$				9.84, $p < 0.05$			

of auctioneers. Since level-k is a model of initial responses, to carry out this comparison we mainly use data from the first half of the experiments. We report two model specifications: following CI we report data for each player's first five individual observations (rounds of play), and in addition, to verify distribution types with more precise cost parameter λ, we also compare k-type distributions by only retaining bidders that took part in a minimum of 3 auction rounds, but with a maximum of 8 observations. This last specification eliminates players which had gone bankrupt in the very early rounds of play due to large mistakes, and therefore only compares bidders that applied more thinking steps from the start of the game.

Table 6 reports both the count and the proportion for each k-type of players for the control versus the treatment conditions and for both specifications. A likelihood-ratio χ^2 test rejects the hypothesis that the sample of players come from the same distribution (LR-chi2(4) = 10.08, p<0.04 for specification 1, and LR-chi2(4) = 9.84, p<0.05 for specification 2) for the control (no auctioneer) versus the treatment condition (auctioneer). The table clearly shows that there is smaller proportion of zero level players in the treatment condition, and that in general that there are a larger proportion of higher k-types in the presence of auctioneers. A simple weighted average of the types (using the second specification as an example) yields for the distributions of players without versus with the auctioneer, modes of k=1 and k=1.2 respectively. These numbers are in agreement with CH findings where typical values of τ(the mean of the Poisson distribution) range from 1 to 2.

Table 7: Level-k Distribution Types (Only Random)

	Bidders with min 3/max 8 obs.			
	No Auctioneer		Auctioneer	
Types	Count	%	Count	%
R.L0	5	11	0	0
R.L1	35	78	17	74
R.L2	2	4	0	0
Equilibrium	3	7	6	26
Total	45	100	23	100
LR - Chi2 (4)	9.84, $p < 0.03$			

Since T.L0 players (those that bid exactly their private signals) are practically nonexistent and because the previous two specifications comparisons yield similar results, we also compare the control versus the treatment condition in the absence of truthful k-types for one of the previous specifications. Table 7 shows that comparison for the specification with players with a minimum of 3 and a maximum of 8 observations. Like in the previous case, we reject the hypothesis that the sample of bidders is drawn from the same distribution (LR-chi2(3) = 9.84, p<0.03) and we clearly observe that players in the treatment condition are of higher k-types, and thus, use a deeper level of thinking at the time of formulating their bids.

The results from fitting the k-level model to our CVA experimental data identify that the mechanism by which the presence of an auctioneer reduces the instances of the winner's curse amongst bidders is through players applying more reasoning steps at the moment of formulating their bids.

4 Conclusion and Next Steps

Common value auctions are of economic significance to most advanced economies. First and second-price sealed bid CVA contests are the mechanisms most typically used by governments and firms to award procurement contracts. Given the economic importance of these auctions as a medium of exchange of goods and services, it is somewhat surprising that the empirical literature in marketing and economics has ignored a feature of these auctions that has the potential to significantly affect auction outcomes: the role played by auctioneers.

CVA are instances where bidders have been known to be particularly susceptible to judgment failures which typically give rise to the winner's curse. This paper contributes to the auction literature by being the first to formally investigate the role played by auctioneers in first price-common value auctions in a laboratory environment. Theoretical predictions state that an auctioneer affects CVA auction outcomes by the choice of public information disclosure policy. Our main contribution was to demonstrate the "auctioneer effect" whereby the mere presence of an auctioneer reduces occurrences of the winner's curse, and thus, reduces the seller's revenue. This effect is further enhanced by auctioneers' incorrect public information policy choices. The second contribution of this paper is to demonstrate through a level-k model of non-equilibrium behavior that the mechanism by which the "auctioneer effect" mitigates the winner's curse, is through players applying higher number of thinking steps at the moment of formulating their bids.

A logical next step would be to demonstrate that an auctioneer's presence can actually hurt the seller in a real auction environment. Our preliminary findings in an English auction (the most common auction for the transaction of goods) with common value elements suggest that the presence of a professional auctioneer with deep product expertise can indeed hurt the seller. Further field evidence documenting instances of this effect would be of great interest, as well as experiments that identify the conditions under which this effect is likely to be stronger.

In addition, there are many real case CVA (such as in auctions for mineral rights exploration) where the auctioneer (or the seller) would have conducted their own independent study to estimate the approximate value of the item before the auction takes place. An interesting extension to this study would be to investigate the "auctioneer effect" in such cases, where the auctioneer gains access to private information with respect to the item's value first and then decides which public information disclosure policy to pursue. In these cases, theoretical considerations dictate following the same information policy as the one in our experiments, but in this new scenario there are other strategic considerations at play that could affect outcomes. It would be worthwhile to formally investigate how bidders react in the presence versus the absence of that information and whether the auctioneer's policy choice mitigates or enhances the “auctioneer effect” documented in this paper.

Finally, it would be worthwhile to extend our studies to private value auctions. In this settings, the winner’s curse is not an issue since there are not item’s valuation considerations to take into account at the moment of formulating the bids. Rational players, only use the bidding trade-off to formulate their optimal bids in first-price auctions, and thus, in principle, an auctioneer play a negligible role in affecting auction outcomes. An interesting extension to this paper would be to investigate if and when does an auctioneer’s information policy choice affect auction results and whether the “auctioneer effect” is also prevalent in this auction setting.

APPENDIX 1 - CVA INSTRUCTIONS

This is an experiment in economic decision making. The instructions are simple and if you follow them carefully and make good decisions, you could earn a considerable amount of money which will be paid to you in check before you leave today. Different subjects may earn different amounts of cash. What you earn today partly depends on your decisions, partly on the decisions of others, and partly on chance. Your compensation is variable and will be described in section II & III below.

I. GENERAL INSTRUCTIONS

Nine subjects will participate in this experiment. The experiment task involves buying and selling a fictitious product through an auction format. Participants' roles are either A(Auctioneers) or B(Bidders). Three of you will be randomly assigned to be A players (and will be located in the room next door) and the rest of you (five) will be B players (and will stay in this room).

You have been randomly selected to play the role of:
PLAYER A / B (one circled).

The experiment consists of **30 decision rounds.** In each decision round**,** we will auction a single unit of the fictitious product. One A player will be randomly selected to act as the Auctioneer and **three B players will act as bidders in each round**. A random selection scheme has been designed such that each A player will be the auctioneer in 10 decision rounds (i.e., 1/3 of the time). In addition, the order in which B players will act as bidders is also random and will be announced before every round. Each bidder will have the chance to bid in at least 12 rounds (exceptions will be explained in section II).

In each decision round, B players will bid for the fictitious product **whose value (V) will be unknown to both Players A and B until the auction ends.** The bidder who places the highest bid (**HB**) in a decision round will win the item in that round. The winner will automatically sell the product to the experimenter and make a profit equal to **[V - HB]**. If the difference is positive it will represent a gain to the winner, and if it is negative it will represent a loss. All other bidders will make zero profit in that round. The auctioneer's profit in each decision round is based on a commission and will be **[3% * HB].**

Each round consists of five steps

STEP 1: The software generates the value of the fictitious product (V).

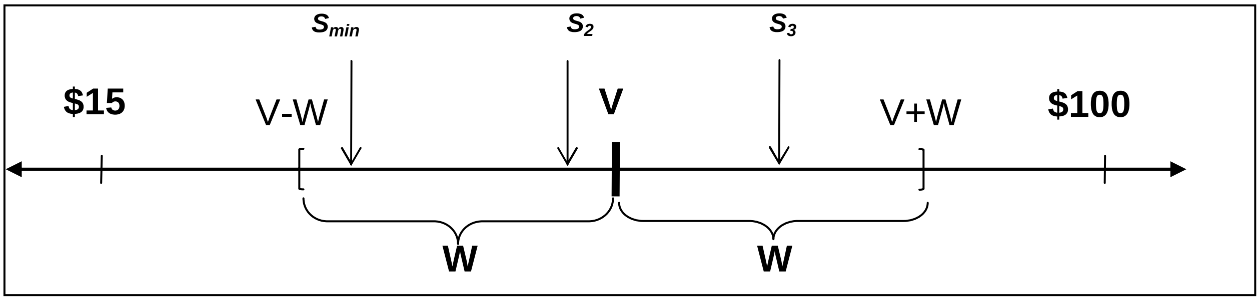
The computer program will generate V by randomly drawing a number from an interval whose **minimum value is $15** and whose **maximum value is $100 inclusively** (rounded to the nearest penny). In each round, **any number within this interval has an equal chance of being drawn**. Since V in each decision round is determined randomly and independently, the drawn value V in one round tells you nothing about its likely value in another round.

STEP 2: The software generates individual private estimates of V.

Although you do not know V until the auction has ended, B players **will each receive an individual estimate of V which will help them narrow down the range of possible values of V.** For each B player i this estimate (S_i) is private information. All S_i's will be drawn randomly and independently in every round from an interval centered at V and of width equal to (2*W), where W=$12. Thus, the lower bound of the range is (V-W), and its upper bound is (V+W).

Any number (rounded to the nearest penny) within that interval has an equal chance of being drawn and assigned to B players as their individual private estimate of V (see Figure1).

FIGURE 1



Note: S_{min} thru S_3 designate the lowest to the highest private estimates in this example.

Note that every private estimate (S_i) is within W of V. In a sufficiently long series of auctions, the difference between the average of each B player's private estimates (S_i) and the average of Vs will be zero (or close to it), but for any specific auction, S_i can be above or below V. That is the nature of the random selection process generating the estimates.

Also, notice that it is possible for S_i to be outside the range ($15, $100). There is nothing strange about this, it simply indicates that V is close to $15 or $100 relative to the size of W.

Player A will not receive any private information about V.

STEP 3: Player A makes a decision.

In each round, Player A moves first and **chooses between two options**: 1) to announce the lowest of the all the private estimates (S_{min}) to all bidders or 2) not to announce S_{min} to all bidders. Notice that at the time of this decision, **player A <u>does not know</u> either the value of S_{min} or the identity of the bidder holding that estimate.**

If Player A chooses to announce (S_{min}) all B players will receive that information on their screen before submitting their bids for the item. However, the identity of the B player holding that estimate will remain anonymous to all participants.

STEP 4: Players B submit their bids.

No one may bid less than $ 0 for the item, nor may anyone bid more than their private estimate (S_i) plus W ($12). **Any bids within this interval are valid bids**. Any bids outside that interval will be rejected by the system and you will be asked to enter a valid bid. Bids must be rounded to the nearest penny.

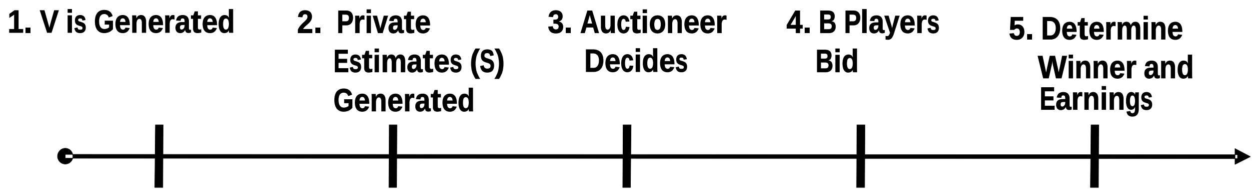
STEP 5: A winner is declared and earnings are estimated**.**

After all players B submit their bids, a winner for the auction will be determined. The winner will be the bidder who submits the highest bid (HB) for the product. In case of a tie, the software will randomly select amongst the highest bidders the B player who wins the item in that round.

Earnings for each participant in each round are as follows:

- The winning bidder: Earnings = *(V – HB)*
- Other bidders: Earnings = *$0*
- Auctioneer: Earnings = *(3% * HB)*

SUMMARY OF EACH ROUND STEPS



II. INSTRUCTIONS FOR B PLAYERS

You will be given a **starting balance of $12**. Any profit earned by you during the experiment will be added to your balance, and any losses incurred will be subtracted from this balance. **Your compensation for this experiment will be the net balance at the end of all the rounds** and it will be paid to you in cash, at the end of the experiment.

You have been provided with a record keeping sheet. Please write down your bidder number, circle every round in which you participate as a bidder, write down the station # (1-3) for that round, write down the round profit and update your balance after every round.

Should your net balance at any time during the experiment become negative, you will no longer be permitted to bid for the rest of the experiment. You are, however, permitted to bid in excess of your balance in any given auction, as long as your balance is positive.

III. INSTRUCTIONS FOR A PLAYERS

Each player A will play the role of the auctioneer for **10 rounds** determined in random order. However, all A players will be able to see the decisions of the other A players, and the results of all auctions rounds (S_{min} if chosen to display, V, all 3 bids bid, earnings to the winner of the item, and earnings to the auctioneer).

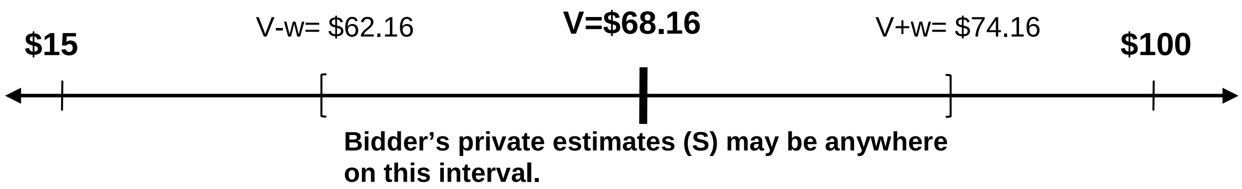
Auctioneers have an starting balance of $0. Your compensation consists of your earnings from the all the rounds in which you will act as the auctioneer and it will be paid to you in cash at the end of the experiment.

IV. EXAMPLE

The numbers used in the example are simply for illustration purposes and in no way they are suggestive of the correct values, estimates, or the actions that you should follow during the experiment.

STEP 1: Program Generates V

V_{min}	V_{max}	w	V (not announced)
$15	$100	$6	**$68.16**



STEP 2: Suppose Private Estimates (S) for each player are as follows (in $)

3 Bidders

S_1	S_2	S_3	S_{min}
63.38	62.57	73.07	62.57

STEP 3: Auctioneer's Decision
Suppose the auctioneer in this example chooses to announce S_{min}; now every bidder knows that the lowest estimate possessed by a bidder is $62.57.

STEP 4: Bidding
Every bidder submits a bid between $0 and (S + W), rounded to the nearest penny (for example bidder 6 can not bid above $75.11 for the item).

STEP 5: Winner and Earnings

Suppose the winning bid is placed by Bidder 3 who bids places a bid (for example) B_3= $72.07. Bidder 3 earns $68.16 (V) – $72.07 = – $3.91 (note that this is negative); all other bidders earn $0. The Auctioneer earns 3% * $72.07 = $2.16.

V. AUCTION SOFTWARE TOOL

We will now play two practice rounds so that you can become familiarized with the auction software before the real experiment begins.

Are there any questions?

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