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COMMON VALUE AUCTIONS WITH INSIDER INFORMATION[1]

BY JOHN H. KAGEL AND DAN LEVIN

Bidding is studied in first-price common value auctions where an *insider* is better informed than other bidders (outsiders) about the value of the item. With inexperienced bidders, having an insider does not materially reduce the severity of the winner's curse compared to auctions with a *symmetric information structure* (SIS). In contrast, super-experienced bidders, who have largely overcome the winner's curse, satisfy the comparative static predictions of equilibrium bidding theory: (i) average seller's revenue is *larger* with an insider than in SIS auctions, (ii) insiders make substantially greater profits, conditional on winning, than outsiders, and (iii) insiders increase their bids in response to more rivals. Further, changes in insiders' bids are consistent with directional learning theory (Selten and Buchta (1994)).

KEYWORDS: Common value auctions, asymmetric information structure, winner's curse, learning.

THIS PAPER INVESTIGATES BIDDING in first-price, sealed bid common value auctions with an asymmetric information structure (AIS). Two types of AIS auctions have been analyzed in the literature. In both cases a single insider (I) has superior (often exact) information about the value of the item. In one case I's have a double informational advantage; they are better informed, and less informed bidders (outsiders; O's) only have access to *public* information. In this case, O's employ mixed strategies earning zero expected profits in equilibrium (Wilson (1967), Weverberg (1979), Englebrecht-Wiggans, Milgrom, and Weber (1983), Hendricks, Porter, and Wilson (1994)). In the second case, I's do not have access to the private information O's have, which provides O's with positive expected profits in equilibrium (Wilson (1985), Hausch (1987)).

The AIS auction studied here corresponds to the second category. The primary motivation for this was to maintain comparability with the vast amount of "baseline" data on auctions with a symmetric information structure (SIS).[2] I's were provided with a signal equal to the true value of the item, while O's received *private* information signals distributed around the true value as in previous SIS experiments. This design yields a number of interesting compara-

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[2]AIS common value auctions have been used to analyze oil and gas drainage lease auctions. Arguably, as in our design, less informed bidders in drainage lease auctions have some proprietary information as they have conducted their own seismic readings and their own analysis of the data, conclusions of which are not available to the insider.

tive static predictions that differ in important ways from the double informational advantage model. First, and foremost, for the parameter values employed, AIS auctions increase expected revenue relative to SIS auctions. In contrast, in the double informational advantage model, the insider *always* reduces the seller's expected revenue.[3] Further, unlike the double informational advantage model, O's earn informational rents, albeit, substantially smaller rents than in corresponding SIS auctions. Increases in the number of O's result in I's bidding higher in our model. In contrast, in the double informational advantage model, I's bidding strategy is unaffected by increases in the number of O's. Finally, both models imply that, conditional on winning, I's expected profits are larger than O's and larger than in SIS auctions.

Our experimental design also permits us to investigate possible ways in which the winner's curse is attenuated or eliminated in field settings. Inexperienced bidders in SIS auctions are subject to a strong winner's curse, consistently bidding above the expected value of the item conditional on winning and earning large negative average profits (Kagel, Levin, Battalio, and Meyer (1989), Dyer, Kagel, and Levin (1989), Lind and Plott (1991). Such losses clearly characterize markets that are out of equilibrium. In field settings with a common value element, one or more agents are often better informed than others. Although this will typically create a stronger adverse selection effect than in a SIS setting, it is entirely plausible that the need to hedge against a known insider is more intuitive and transparent than the need to correct for winning against equally well informed rivals. Thus, having an insider may actually reduce the severity of the winner's curse for inexperienced bidders. This would be true, for example, if O's view the situation as being closer in structure to a lemon's market (see Akerlof (1970)), where it seems reasonably clear there is no rampant winner's curse (our culture warns us to beware of used car salesmen).[4] On the other hand, inexperienced subjects may bid higher, rather than lower, in order to make up for their informational disadvantage, thus exacerbating the winner's curse.

Our main experimental results are: Super-experienced bidders, who have learned to overcome the worst effects of the winner's curse, generally satisfy the comparative static predictions of the theory. In contrast, for inexperienced O's the winner's curse is alive and well in AIS auctions as bids are consistently above expected value conditional on winning the item. More importantly, the introduction of an insider does not result in significantly lower bidding than in SIS auctions. However, the theoretical prediction that I's earn larger profits conditional on winning than O's do holds (superior information is valuable outside of equilibrium). Finally, I's adjustments to past outcomes are generally consistent

[3]Note that increased seller's revenue is *not* a general characteristic of AIS auctions in which O's maintain some proprietary information. However, it is true for the parameter values of our experiment and in other cases as well (see Kagel and Levin (1998) and Campbell and Levin (1997)).

[4]"Presentation format" effects of this sort have been found in a number of game theoretic contexts. See, for example, Andreoni (1995), Cooper, Garvin, and Kagel (1997), and Schotter, Weigelt, and Wilson (1994).

with Selten and Buchta's (1994) "directional learning theory," with some important differences in the quantitative pattern of the adjustment process relative to previously reported results.

1. STRUCTURE OF THE AUCTIONS

Each experimental session consisted of a series of auctions in which a single unit of a commodity was awarded to the high bidder in a first-price sealed bid auction. The value of the item, x_o, was unknown at the time bids were submitted. In each auction period, x_o was drawn randomly from a uniform distribution on $[\underline{x}, \bar{x}]$.

In SIS auctions, each bidder received his own private information signal, x, drawn iid from a uniform distribution on $[x_o - \varepsilon, x_o + \varepsilon]$. In AIS auctions one bidder—the insider—chosen at random in each auction, received private information signal $x = x_o$ and was told $x = x_o$. Each of the other bidders, the O's, received a private information signal as in the SIS auctions. I's did not know the realizations of O's signals. O's knew they were O's, that there was a single I who knew x_o, and the way that other O's got their signals (but not their realizations). The total number of bidders (n) and the values of ε and $[\underline{x}, \bar{x}]$ were publicly posted prior to each auction.

At the end of each auction all bids were posted from highest to lowest along with the corresponding signal values (bidders identification numbers were suppressed) and the value of x_o. In AIS auctions, the value of ε associated with each bidder's private information signal was also reported so that bidders could readily identify I's bid. Profits were calculated for the high bidder and reported to all bidders.

To cover the possibility of losses, bidders were given starting capital balances of \$10.00. Losses were subtracted from this balance and profits added to it. If a subject's balance became nonpositive, they were no longer allowed to bid. To hold n constant, while dealing with the possibility of bankruptcies, there were typically several extra bidders in each session, with the active bidders in each auction determined randomly or through a rotation rule. Bidder identification numbers were suppressed throughout, so subjects did not know who they were competing against in any given auction.[5] Bidders were paid their end of session balances in cash, along with a \$4 or \$5 participation fee.

All inexperienced sessions began with $\varepsilon = \$6$ and progressed to higher values of ε. Each of these sessions employed a minimum of two "dry runs" to familiarize subjects with the procedures and the consequences of bidding too much. The instructions pointed out that, given x, ε, and the endpoint values, subjects had their own upper and lower bound estimates for x_o ($\min\{x + \varepsilon, \bar{x}\}$; $\max\{x - \varepsilon, \underline{x}\}$), which were reported to them along with x. Thus, under both

[5] These procedures were maintained with super-experienced bidders, thereby preserving some degree of independence between auctions within a given experimental session.

TABLE I

TREATMENT CONDITIONS

Condition	Experience[a]	Number of Bidders	Number of Experimental Sessions	Information Structure
1	None	4	2	Asymmetric
2	Super Experienced	4	4	Asymmetric
3[b]	None	4	5	Symmetric
4[c]	Super Experienced	4	8	Symmetric
5	None	7	2	Asymmetric
6[d, e]	Super Experienced	7	8	Asymmetric and Symmetric
7[b, d]	None	7	5	Symmetric

[a] In super-experienced bidder sessions all bidders had participated in two or more first-price sealed bid auction sessions with equal numbers of bidders.
[b] Data have been previously reported in Garvin and Kagel (1994).
[c] Data have been partially reported in Levin, Kagel, and Richard (1996).
[d] Includes some periods with $n = 6$. Earlier work shows that pooling $n = 6$ and 7 is justified (Kagel and Levin (1986), Kagel, Levin, and Harstad (1995)).
[e] In 7 of 8 sessions both SIS and AIS auctions were conducted using the same subjects.
$\text{Min}(\bar{x} - \underline{x}) = \$200$; $\text{Max}(\bar{x} - \underline{x}) = \$330$.

information conditions, imperfectly informed bidders always had a "safe haven" strategy of bidding $\max\{x - \varepsilon, \underline{x}\}$, which completely protected them from losses.

Bidding was studied under two different values of n (4 and 7), five different values of ε (6, 12, 18, 24, and 30), and two different levels of bidder experience (inexperienced and super-experienced). Super-experienced bidders are defined as having been in at least two previous SIS or AIS first-price auction series. Table I cross-classifies experimental sessions by subjects' experience, the number of active bidders, and information structure.

Subjects were primarily senior undergraduate economics majors and MBA students at the University of Houston and the University of Pittsburgh. In establishing a pool of super-experienced bidders, all bidders were invited back, with the exception of the few bidders who went bankrupt early on in both of the first two auction sessions. Each experimental session lasted approximately two hours and had a minimum of 20 auctions.

2. THEORETICAL CONSIDERATIONS

Our focus here and throughout the data analysis is on $x_o \in [\underline{x} + 2\varepsilon, \bar{x} - 2\varepsilon]$ (referred to as region 2) for which we have clear bounds on behavior in the AIS auctions.

A. *The Winner's Curse*

For SIS auctions, we define a bidder as falling prey to the winner's curse when her bid is so high that it yields negative expected profits conditional on having the highest signal value, i.e., bids greater than

$$E[x_o | x = x_1^n] = x - \frac{n-1}{n+1}\varepsilon, \tag{1}$$

where x_1^n is the highest of the n private signals. In auctions where x_1^n always wins the item, bidding above (1) insures negative expected profit. In auctions where symmetry is not satisfied, but all bidders bid above (1), negative expected profits are insured as well. One or both of these initial conditions is reasonably well satisfied in our data so that bidding above (1) serves as a good *ex ante* indicator of a winner's curse.

For AIS auctions, O's bidding above

$$E\left[x_o | x = x_1^{n^o}\right] = x - \frac{n^o - 1}{n^o + 1}\varepsilon \tag{2}$$

(where n^o is the number of O's bidding) can expect to earn negative profits just competing against other O's. Further, if all O's bid according to (2), and I's employ their best response to these bids then, conditional on winning, O's would earn average *losses* of over \$1.50 per auction. As such, bidding above (2) provides a first, very conservative, definition of the winner's curse. A second definition of the winner's curse which accounts for I's best responding to O's bids is developed below.

B. *Auctions with Symmetric Information Structure* (*SIS*)

In SIS auctions the symmetric risk neutral Nash equilibrium (RNNE) bid function $\gamma(x)$ in region 2 is given by[6]

$$\gamma(x) = x - \varepsilon + g(x), \qquad \underline{x} + \varepsilon \leq x \leq \bar{x} - \varepsilon, \tag{3}$$

where

$$g(x) = \frac{2\varepsilon}{n+1}\exp\left[-\frac{n}{2\varepsilon}[x - (\underline{x} + \varepsilon)]\right].$$

Equilibrium bidding combines strategic considerations similar to those involved in first-price private value auctions and item valuation considerations. The latter involves anticipating the adverse selection effect associated with winning. Both factors promote bidding below x in region 2, with expected profit for the high bidder approximately equal to $2\varepsilon/(n+1)$.

3. AUCTIONS WITH ASYMMETRIC INFORMATION STRUCTURE (AIS)

Let $b(x)$ and $B(x_o)$ be the bid functions for O's and I's, respectively, and define $h(B)$ and $H(B)$ to be their inverse. When both $h(B)$ and $H(B)$ are in region 2, bidding in AIS auctions yields the following system of differential

[6] Derivation of the RNNE bid function over the entire support can be found in an appendix to Levin, Kagel, and Richard (1996).

equations, where we assume symmetry among the O's:

$$\text{(4a)} \qquad h'(B) - \frac{h(B) + \varepsilon - H(B)}{n^o[H(B) - B]} = 0,$$

$$\text{(4b)} \qquad [H'(B) - h'(B)][H(B) - B]\Theta^{n^o - 1} + [h'(B) - 1]\frac{2\varepsilon}{n^o}(1 - \Theta^{n^o}) + h'(B)[h(B) - (B + \varepsilon)] = 0,$$

where

$$0 \leq \Theta \equiv \frac{h(B) + \varepsilon - H(B)}{2\varepsilon} \leq 1,$$

and H' and h' represent the first derivatives of the inverse bid functions. This system of differential equations defies analytical solution under the initial condition that the lowest possible bid is $\underline{x}$ (namely, $h(\underline{x}) = \underline{x} - \varepsilon$ and $H(\underline{x}) = \underline{x}$).[7] Numerical solution of this system of differential equations is nontrivial since the slopes of both I's and O's bid functions approach zero in a neighborhood around $\underline{x}$ (see Marshall, et al. (1994); these zero slopes mean that the solution to (4a–b) need not be unique). Instead, we use an alternative approach based on boundedly rational bidding strategies which, as it winds up, provides a good approximation to the Nash equilibrium in region 2.

Assume that because O's are boundedly rational, their bids in region 2 are restricted to a bidding strategy of the form

$$\text{(5a)} \qquad b(x) = x - \beta\varepsilon, \qquad 0 < \beta \leq 1.$$

Inspecting (4a), I's best response to this bidding strategy is

$$\text{(5b)} \qquad B(x_o) = x_o - \alpha(\beta)\varepsilon = x_o - [(1 + \beta)/n]\varepsilon.$$

We will refer to this pair of bid functions as a *β-discount bid factor* (β-DBF), as it involves O's and I's discounting their bids, relative to their signal values, by the *bid factors* $\beta\varepsilon$ and $\alpha\varepsilon$.

In the special case where $\beta = 1$, (5a–b) become

$$\text{(6a)} \qquad b(x) = x - \varepsilon,$$

$$\text{(6b)} \qquad B(x_o) = x_o - \frac{2\varepsilon}{n}.$$

Note that (6a–b) satisfy the necessary conditions, (4a–b), for equilibrium in region 2. That is, (6a–b) constitute an equilibrium in region 2 in cases where O's, because of bounded rationality (e.g., limited computational abilities), are restricted to employing the bid function (5a). Also note that Laskowski and Slonim (in press) show that the unique pair of Nash equilibrium bid functions satisfying (4a–b) converges to (6a–b) as region 2 becomes larger and larger.[8]

[7]Note that for $\underline{x} - \varepsilon \leq x \leq \underline{x} + \varepsilon$ equation (4b) changes, but 4a remains unchanged.

[8]O's bid function, (5a), corresponds to Laskowski and Slonim's assumption of a translation invariant bid function.

Further, examination of bidding in region 2, for both inexperienced and experienced O's, shows that equation (5a) provides a remarkably good fit to the data, yielding R^2 values of .99 or better and with coefficient estimates for x always within one standard deviation of 1.00 (see Tables III and V below).[9]

Finally, we can establish a second, tighter definition of the winner's curse that accounts for I's best responding to O's bids. This involves calculating the values of β_0 and α_0 (where $\alpha_0 = [1 + \beta_0]/n$) for equations (5a–b) that result in zero expected profit for O's. These are: for $n = 4$, $\alpha_0 = .421$ and $\beta_0 = .690$ and for $n = 7$, $\alpha_0 = .261$ and $\beta_0 = .825$. One can show that if O's employ a bid factor $\beta < \beta_0$, and I's best respond, O's would earn negative expected profits. These β_0 values are larger than the bid factors required to avoid the winner's curse in SIS auctions with the same total number of bidders.

Equilibrium under β-DBF has several interesting comparative static predictions:

1. As n increases from 4 to 7, I's must employ larger bid factors, while O's bid factors remain unchanged.[10]

2. I's earn higher expected profits, conditional on winning, than O's do. For example, with $n = 4$ and $\varepsilon = \$18$, O's expected profit, conditional on winning, is \$4.07. For I's, it is \$9.00.[11]

3. Expected profits, conditional on winning, are substantially lower for O's in AIS than in corresponding SIS auctions. For example, with $n = 4$ and $\varepsilon = \$18$, these average around \$7.20 in the SIS auctions versus \$4.07 in the AIS auctions.[12]

4. I's earn higher expected profits, conditional on winning, than in corresponding SIS auctions. However, the expected differences here are smaller than the differences reported in (2) and (3) above. For example, with $\varepsilon = \$18$ and $n = 4$, the expected difference is \$1.80 versus expected differences of \$4.93 between I's and O's in (2) and of \$3.13 between SIS auctions and O's in (3).

5. Seller's expected revenue is *higher* in AIS than in corresponding SIS auctions for both $n = 4$ and 7. For example, with $n = 4$ and $\varepsilon = \$18$ seller's expected revenue in AIS auctions is $x_o - \$6.16$ compared to $x_o - \$7.20$ in SIS auctions. With $n = 7$ and $\varepsilon = \$18$ these values are $x_o - \$3.40$ in AIS compared to $x_o - \$4.50$ in SIS auctions. Note, sellers would be unambiguously better off in SIS compared to AIS auctions if I's won *all* the time. However, in our AIS auctions, the seller gains additional revenue because when O's win, they only win with relatively high signals, which yields more revenue than when I's win.

[9] Further, Kagel and Richard (1998) show that for SIS auctions a piecewise linear bid function, with a single piece (5a) for region 2, provides a far better fit to the data than does the Nash bid function (bidders totally ignore $g(x)$).

[10] Wilson's (1985) model, which is closest in structure to ours, yields similar results for I's.

[11] Positive economic rents for O's result from the private nature of their information.

[12] For SIS auctions we assume x_o is in region 2 and employ the approximation that profits, conditional on winning, are equal to $2\varepsilon/(n+1)$.

These higher revenues more than offset the lower revenues when I's win (see Kagel and Levin (1998), for details of this argument).

Finally, with β-DBF bid functions, assuming that O's avoid the winner's curse and β in (5a) is no greater than 1.00, predictions 1–5 hold even if play does not converge to equilibrium.[13] Thus, the comparative static predictions 1–5 are quite robust.

3. EXPERIMENTAL RESULTS

A. *Auctions with Inexperienced Bidders*

Table II presents summary statistics for inexperienced bidders for both AIS auctions and SIS auctions (top and bottom part of Table II, respectively). For inexperienced subjects within session experience covaries systematically with ε, as all sessions started with 6 to 8 auctions with $\varepsilon = \$6$ and then switched to $\varepsilon = \$12$. Thus, differences between different values of ε may reflect within session learning and/or bankruptcy and elimination of the most aggressive bidders. In what follows we first address the question of whether an insider helps inexperienced bidders to overcome, or at least attenuate, the winner's curse relative to SIS auctions. We then examine which, if any, of the predictions of the β-DBF bidding model hold for inexperienced bidders.

First, looking at the top of Table II (part A) we see that the winner's curse is alive and well. Consider auctions with $\varepsilon = \$6$, which were used to start each session. With $n = 4$, almost 60% of the high O's bids were above our first measure of the winner's curse (equation 2), so that these bids would have lost money, on average, just competing against other O's. Further, 94% of the high O bids were subject to a winner's curse under our second, tighter measure of the winner's curse. With $n = 7$, the adverse selection effect is stronger and the winner's curse was more pervasive: 100% of the high O bids and 85.2% of *all O* bids fell prey to the winner's curse just considering competition with other O's (equation 2). The net result was large negative profits for O's when they won ($-\$1.68$ per auction with $n = 4$; $-\$3.68$ with $n = 7$). Although somewhat diminished in frequency, a strong winner's curse is also reported for higher values of ε as O's continued to earn negative profits throughout, with at least 47% of all bids subject to the winner's curse, by the tighter measure, for any value of ε.

Comparing the bidding of O's in the AIS auctions (Table IIA) to bidding in SIS auctions (Table IIB), the raw data suggests a more extreme winner's curse in AIS auctions with $n = 7$, but just the opposite result with $n = 4$. Rather than belabor the raw data, we go directly to Table III, which compares estimated bid functions between SIS and AIS auctions.[14] Dummy variables are used to capture

[13] See our working paper (Kagel and Levin (1998)) for details. The single exception is that we cannot bound O's bid factor.

[14] Random effects error specifications were employed in all cases, with subject as the random error component.

TABLE II
INEXPERIENCED BIDDERS

A: Auctions with Asymmetric Information Structure (AIS)

Number of Bidders	ε	Outsiders' Bids: Average Earnings Conditional on Winning (S_m)	Outsiders' Bids: Frequency of Winning (raw data)	Frequency of Winner's Curse (raw data), Against Outsiders Only: High Outsider Bid	Against Outsiders Only: All Bids	Against Outsiders and Insiders: High Outsider Bid	Against Outsiders and Insiders: All Bids	Average Bid Factor[a] (S_m)	Frequency High Outsider Bid from High Outsider Signal Holder (raw data)	Insiders' Bids: Average Earnings Conditional on Winning (S_m)	Insiders' Bids: Average Bid Factor (S_m)
4	6	−1.68	70.6%	58.8%	39.2%	94.1%	70.6%	1.16	52.9%	0.71	1.46[b]
		(0.93)	(12/17)	(10/17)	(20/51)	(16/17)	(36/51)	(0.62)	(9/17)	(0.35)	(0.26)
	12	−1.40	65.2%	39.1%	23.2%	65.2%	47.8%	6.00	73.9%	2.74	2.25
		(0.50)*	(15/23)	(9/23)	(16/69)	(15/23)	(33/69)	(0.77)	(17/23)	(0.77)*	(0.35)
	24	−6.56	71.4%	28.6%	14.3%	85.7%	57.1%	11.61	100%	5.05	5.09
		(3.07)	(5/7)	(2/7)	(3/21)	(6/7)	(12/21)	(2.78)	(7/7)	(3.50)	(1.27)
7	6	−3.68	100%	100%	85.2%	100%	92.6%	−0.61[c]	66.7%	—	1.09[b]
		(0.61)**	(9/9)	(9/9)	(46/54)	(9/9)	(50/54)	(0.62)	(6/9)	—	(0.29)
	12	−2.47	78.9%	89.5%	69.7%	89.5%	79.8%	4.85	73.7%	1.93	1.91[b]
		(1.03)*	(15/19)	(17/19)	(78/112)	(17/19)	(91/114)	(1.03)	(14/19)	(0.61)**	(0.33)

B: Auctions with Symmetric Information Structure (SIS)

Number of Bidders	ε	Average Earnings Conditional on Winning (S_m)	Frequency of Winner's Curse (raw data): High Bidders	Frequency of Winner's Curse (raw data): All Bidders	Average Bid Factor[a] (S_m)	Frequency High Bid from High Signal Holder (raw data)
4	6	−2.40	88.4%	70.2%	0.13	57.7%
		(0.55)**	(23/26)	(73/104)	(0.51)	(15/26)
	12	−1.10	74.3%	66.4%	5.02	80.0%
		(0.85)	(26/35)	(93/140)	(0.63)	(28/35)
	24	0.25	38.9%	37.5%	12.98	72.2%
		(1.84)	(7/18)	(27/72)	(2.20)	(13/18)
7	6	−3.63	84.9%	68.4%	0.56	57.6%
		(0.57)**	(28/33)	(158/231)	(0.48)	(19/33)
	12	−2.27	72.1%	43.5%	5.06	60.7%
		(0.69)**	(44/61)	(185/425)	(0.62)	(37/61)

Notes: S_m standard error of the mean; *significantly different from 0 at the 5% level, two-tailed test; **significantly different from 0 at the 1% level, two-tailed test.
[a] High bids only.
[b] A single outlier bid less than $x_o - \varepsilon$ was dropped.
[c] In this treatment high O's actually bid *above* their signal values, on average.

the response to changes in ε since it is clear that bid factors do not change proportionately with ε.

Looking at O's bid functions, with the exception of the $n = 4$, $\varepsilon = \$24$ treatment, the bid factors are too small to avoid the winner's curse.[15] More relevant, however, are differences in bid factors between AIS and SIS auctions. These are found in the regressions pooling data for O's and SIS auctions, with the *DASY*EPS* dummies testing for differences in the bid factors for different values of ε. For $n = 4$, the *DASY*EPS6* and *DASP*EPS12* dummies are both negative, but neither coefficient is, by itself, significantly different from zero, and a test of the null hypothesis that all three coefficients are zero cannot be rejected either ($\chi^2 = 0.68$, d.f. $= 3$). For $n = 7$, both *DASY*EPS* dummies are positive, but here, too, neither dummy is significantly different from zero by itself, and a test of the null hypothesis that both coefficients are zero cannot be rejected ($\chi^2 = 0.59$, d.f. $= 2$). As such, we conclude that, contrary to our initial conjecture, the existence of an insider did not induce significantly less aggressive bidding for inexperienced O's.

Raw data for inexperienced I's is shown in the right-hand most columns of Table IIA, with estimated bid functions reported in the right-hand most columns of Table III. Note, first, that the functional form of I's bid function is consistent with equation (5b), indicating that they are close to best responding to O's.[16] However, I's employed a significantly smaller bid factor than the one employed in our tighter winner's curse measure, so that O's actually faced an even stronger adverse selection problem, and higher incidence of the winner's curse, than our second tighter measure implies.[17] I's smaller bid factors were, however, consistent with the overly aggressive bidding by O's, although I's did deviate marginally from best responses. The latter resulted in average losses with $\varepsilon = \$12$ (for which we have the most data) of 3.6¢ per auction with $n = 4$ and 4.9¢ with $n = 7$.[18]

The right-hand most column in Table III tests for differences in I's bid factors in auctions with $n = 4$ versus $n = 7$. Both of the *DN*EPS* dummies are

[15] Estimated bid factors and minimum bid factors needed to avoid the winner's curse (accounting for I's bids) are as follows: $n = 4$, $\varepsilon = \$6$ (2.67 vs. 4.14; $p < .04$), $\varepsilon = \$12$ (6.92 vs. 8.28; $p < .07$), $\varepsilon = \$24$ (16.38 vs. 16.56); $n = 7$, $\varepsilon = \$6$ (2.03 vs. 4.95; $p < .01$), $\varepsilon = \$12$ (6.84 vs. 9.90; $p < .01$) (1-tailed significance levels reported).

[16] R^2 values of .99 or better and coefficient estimates for x_o always within two standard deviations of 1.00, both here and for experienced bidders as well.

[17] I's estimated bid factors versus best response values associated with O's earning zero expected profits are: $n = 4$, $\varepsilon = \$6$ (0.67 vs. 2.53, $p < .01$), $\varepsilon = \$12$ (1.39 vs. 5.05, $p < .01$), $\varepsilon = \$24$ (4.10 vs. 10.10, $p < .01$); $n = 7$, $\varepsilon = \$6$ (0.27 vs. 1.57, $p < .17$), $\varepsilon = \$12$ (1.33 vs. 3.13, $p < .07$) (1-tailed tests for estimated probabilities being significantly below predicted values).

[18] Expected losses are calculated on the basis of estimated bid factors. Given O's estimated bid factor we can compute, analytically, I's best response bid factor and I's expected profits. Given I's and O's estimated bid factors, we compute, analytically, actual expected earnings. The difference between these two earnings measures constitute expected losses. These procedures are consistent with those of Fudenberg and Levine (1997) for estimating deviations from best responses in normal form, complete information games.

TABLE III

ESTIMATED BID FUNCTIONS: INEXPERIENCED BIDDERS
(STANDARD ERRORS OF ESTIMATES IN PARENTHESES)

	Outsiders & SIS					Insiders		
	$n = 4$		$n = 7$			$n = 4$	$n = 7$	$n = 4\&7$
Variable	O's	O's & SIS	O's	O's & SIS	Variable			
x	1.001	1.003	1.000	0.998	x_o	0.995	0.988	0.997
	(0.004)	(0.002)	(0.007)	(0.002)		(0.003)	(0.007)	(0.002)
EPS6	−2.672	−2.791	−2.031	−2.102	EPS6	−0.673	−0.268	−1.042
	(0.826)**	(0.744)**	(0.943)*	(0.527)**		(0.599)	(1.323)	(0.724)
DEPS12	−4.249	−3.816	−4.807	−5.102	DEPS12	−0.724	−1.064	−0.760
	(0.675)**	(0.518)**	(0.484)**	(0.287)**		(0.521)	(0.552)+	(0.495)
DEPS24	−13.707	−14.052	—	—	DEPS24	−3.429	—	−3.519
	(0.939)**	(0.614)**				(0.720)**		(0.673)**
DASY*EPS6	—	−0.161	—	0.215	DN*EPS6	—	—	−0.103
		(0.997)		(0.834)				(0.993)
DASY*EPS12	—	−0.633	—	0.537	DN*DPS12	—	—	−0.365
		(0.936)		(0.761)				(0.896)
DASY*EPS24	—	0.099	—	—	R^2	.999	.995	.999
		(1.217)						
R^2	.998	.997	.991	.998	Number of Observations	46	27	73
Number of Observations	141	461	168	810	Number of Subjects	12	9	21
Number of Subjects	13	50	16	60				

Notes: + significantly different from zero at $p < .10$ level, 2-tailed test; *significantly different from zero at $p < .05$ level, 2-tailed test; **significantly different from zero at $p < .01$ level, 2-tailed test. EPS6 = intercept of bid function. DEPS12 = 1 if EPS = 12; 0 otherwise. DEPS24 = 1 if EPS = 24 or 30; 0 otherwise. DASY = 1 if AIS auction; 0 if SIS auction. DN = 1 if $n = 7$; 0 if $n = 4$.

negative, indicating somewhat larger bid factors with $n = 4$ than $n = 7$, contrary to the theory's prediction. However, neither coefficient is statistically significant by itself, and they are not significant in combination. This lack of responsiveness may well reflect the fact that both O's and I's had yet to converge to any sort of sustainable equilibrium.[19]

Table IV reports the change in seller's revenue, normalized for variation in x_o, between AIS and SIS auctions. In three of five cases seller's revenue is *lower* in AIS compared to SIS auctions, *contrary* to the β-DBF model's prediction. Of the two remaining cases, there is essentially no change in revenue for $n = 7$ and $\varepsilon = \$6$, and the increase in revenue for $n = 4$, $\varepsilon = \$24$ is not significant at

[19] Given the obvious failure to converge to equilibrium, one might question why we have not broken up the data analysis, considering early versus later auctions separately. However, differences between early versus later auctions coincide with changes in ε, and our data analysis already distinguishes between different values of ε.

TABLE IV

CHANGE IN SELLER'S REVENUE: AIS VS. SIS AUCTIONS WITH INEXPERIENCED BIDDERS (IN DOLLARS)

	$n = 4$			$n = 7$		
		Mean Profits (σ^2)			Mean Profits (σ^2)	
	Change in Revenue: AIS − SIS Auctions[a] (t stat)[b]	AIS	SIS	Change in Revenue: AIS − SIS Auctions[a] (t stat)[b]	AIS	SIS
$\varepsilon = \$6$	−1.425	−0.975	−2.400	0.045	−3.680	−3.635
	(−1.588)	(8.474)	(7.995)	(0.054)	(3.386)	(10.616)
$\varepsilon = \$12$	−1.098	−0.005	−1.130	−0.715	−1.550	−2.265
	(−1.063)	(7.879)	(25.331)	(0.622)	(16.128)	(28.846)
$\varepsilon = \$24$	3.503	−3.257	.246	—	—	—
	(1.060)	(67.716)	(61.256)			

[a] Change in seller's revenue, normalized for variation in x_o, is bidder profits in SIS auctions less bidder profits in AIS auctions.
[b] t statistics calculated for populations with unknown and unequal variances (Guenther (1964)). Auction period is unit of observation.

conventional levels.[20] This failure of the model's prediction can be directly attributed to the winner's curse. Recall that seller's revenue, normalized for variation in x_o, is simply the converse of bidder's profits. The relatively strong winner's curse for inexperienced bidders in both AIS and SIS auctions results in approximately the same negative average profits, conditional on winning. However, when I's win an item they earn positive profits. The net effect is an overall reduction in seller's revenue in AIS compared to SIS auctions.[21]

B. *Super-Experienced Bidders*

Table V reports data for super-experienced bidders. Looking at the top half of Table V (part A), the data for AIS auctions, the negative average earnings for inexperienced O's have been replaced by positive average earnings. Further, using our tighter definition of the winner's curse, it has been reduced to the point that it hardly exists in auctions with $n = 4$ and has been reduced substantially, compared to inexperienced bidders, with $n = 7$. (We have dropped our looser winner's curse measure, equation (2), since these numbers were less than

[20] The reader may also notice the substantially larger variance in mean profits in SIS compared to AIS auctions. Our working paper (Kagel and Levin (1998)) shows that this is a derivative implication of our AIS model that is closely related to the propensity to raise seller's revenue compared to SIS auctions.

[21] The winner's curse also results in reversals of the SIS model's prediction regarding the ability of public information to raise seller's revenue (Kagel and Levin (1986)) and English auctions to raise revenue compared to first-price auctions (Levin, Kagel, and Richard (1996)). There are different mechanisms at work in these cases compared to the present case, but what they have in common is that a key comparative static prediction of the theory fails in the presence of the winner's curse.

TABLE V
SUPER-EXPERIENCED BIDDERS

A: Auctions with Asymmetric Information Structure (AIS)

		Outsiders' Bids						Insiders' Bids	
				Frequency of Winner's Curse: Against Outsiders and Insiders (raw data)					
Number of Bidders	ε	Average Earnings Conditional on Winning (S_m)	Frequency of Winning (raw data)	High Outsider Bid	All Bids	Average Bid Factor[a] (S_m)	Frequency High Outsider Bid from High Outsider Signal Holder (raw data)	Average Earnings Conditional on Winning (S_m)	Average Bid Factor (S_m)
4	12	0.65	53.7%	9.3%	4.9%	10.05	92.6%	3.30	3.60[c]
		(0.43)	(29/54)	(5/54)	(8/162)	(0.23)	(50/54)	(0.23)**	(0.19)
	18	0.87	63.3%	3.3%	1.1%	15.29	93.3%	4.13	5.80[c]
		(0.68)	(19/30)	(1/30)	(1/90)	(0.26)	(28/30)	(0.37)**	(0.50)
	30	3.67	42.1%	5.3%	3.5%	27.04	94.7%	7.94	8.24
		(2.32)	(8/19)	(1/19)	(2/57)	(0.65)	(18/19)	(0.69)**	(0.61)
7[b]	18	0.52	64.5%	22.4%	17.2%	15.86	86.8%	3.24	4.35
		(0.34)	(49/76)	(17/76)	(77/453)	(0.26)	(66/76)	(0.36)**	(0.26)
	30	3.90	41.7%	16.7%	19.4%	26.95	83.3%	4.95	5.98
		(3.07)	(5/12)	(2/12)	(14/72)	(0.85)	(10/12)	(0.80)**	(0.67)

B: Auctions with Symmetric Information Structure (SIS)

			Frequency of Winner's Curse (raw data)			
Number of Bidders	ε	Average Earnings Conditional on Winning (S_m)	High Bidders	All Bidders	Average Bid Factor[a] (S_m)	Frequency High Bid from High Signal Holder (raw data)
4	18	3.82	20.5%	10.9%	13.56	87.5%
		(0.67)**	(23/112)	(49/448)	(0.40)	(98/112)
	30	8.88	0%	0%	25.27	91.7%
		(2.22)**	(0/12)	(0/48)	(1.07)	(11/12)
7	18	2.23	13.0%	6.1%	14.98	82.9%
		(0.36)**	(19/146)	(61/1007)	(0.32)	(121/146)
	30	5.44	20.0%	8.6%	26.85	80.0%
		(1.78)*	(1/5)	(3/35)	(2.03)	(4/5)

Notes: S_m standard error of the mean; *significantly different from 0 at the 5% level; two-tailed t-test; **significantly different from 0 at the 1% level, two-tailed t-test.
[a] High bids only.
[b] Includes several auctions with $n = 6$.
[c] A single outlier bid less than $x_o - \varepsilon$ was dropped.

TABLE VI

ESTIMATED FUNCTIONS: SUPER-EXPERIENCED BIDDERS
(STANDARD ERRORS OF ESTIMATES IN PARENTHESES)

	Outsiders and SIS Auctions					Insiders		
	$n = 4$		$n = 7$			$n = 4$	$n = 7$	$n = 4\&7$
ariable	Outsiders	Outsiders & SIS	Outsiders	Outsiders & SIS	Variable			
x	1.001	1.001	1.000	1.000	x_o	0.994	1.000	0.996
	(0.001)	(0.001)	(0.001)	(0.001)		(0.003)	(0.003)	(0.002)
EPS18	−15.933	−14.973	−16.025	−15.625	EPS18	−4.466	−4.007	−4.920
	(0.360)**	(0.357)**	(0.331)**	(0.333)**		(0.746)**	(0.711)**	(0.655)**
DEPS30	−11.307	−10.869	−10.563	−11.330	DEPS30	−2.648	−1.740	−2.634
	(0.231)**	(0.373)**	(0.247)**	(0.266)**		(0.613)**	(0.727)*	(0.611)**
DEPS12	5.470	4.302	—	—	DEPS12	2.193	—	2.161
	(0.188)**	(0.562)**				(0.470)**		(0.469)**
DASY*EPS18	—	−1.165	—	−0.332	DN*EPS18	—	—	1.587
		(0.590)*		(0.437)				(0.589)**
DASY*EPS30	—	−1.584	—	0.425	DN*EPS30	—	—	2.454
		(0.672)*		(0.557)				(0.864)**
R^2	.999	.999	.999	.999	R^2	.999	.999	.999
Number of Observations	309	805	523	1562	Number of Observations	101	88	189
Number of Subjects	24	67	60	114	Number of Subjects	23	50	73

Notes: + significantly different from zero at $p < .10$ level, 2-tailed test; *significantly different from zero at $p < .05$ level, 2-tailed test; **significantly different from zero at $p < .01$ level, 2-tailed test. EPS18 = intercept of bid function. DEPS30 = 1 if EPS = 30; 0 otherwise. DEPS12 = 1 if EPS = 12; 0 otherwise. DASY = 1 if AIS auction; 0 if SIS auction. DN = 1 if $n = 6$ or 7; 0 if $n = 4$.

1% with $n = 4$ and less than 6% with $n = 7$ for all values of ε.) This sharp reduction in the winner's curse is the result of more aggressive bidders declining invitations to return for additional sessions, and less aggressive bidding by those who did return. Further, no new, inexperienced, bidders were permitted to enter the auctions, as might occur in field settings.

Table VI reports estimated bid functions for super-experienced bidders.[22] O's bid factors were more than enough to avoid the winner's curse (accounting for I's bids) in all cases: for $n = 4$, estimated versus required bid factors are \$10.46 versus \$8.28 ($\varepsilon = \$12$), \$15.93 versus \$12.42 ($\varepsilon = \$18$), and \$27.24 versus \$20.70 ($\varepsilon = \$30$); for $n = 7$ the corresponding values are \$16.01 versus \$14.85 ($\varepsilon = \$18$) and \$26.58 versus \$24.75 ($\varepsilon = \$30$). Further, comparing O's bids with bids in SIS auctions, for $n = 4$, O's bid less as both *DASY*EPS* dummies are significantly below zero at the .05 level. In contrast, for $n = 7$, there are no significant differences in O's bids versus bids in SIS auctions. Larger bid factors for O's than in SIS auctions with $n = 4$ may well be the result of I's bid factors being

[22] Regressions testing for differences in bid functions between early versus late auctions within a given experimental session, holding ε constant, show no systematic differences in bidding by either I's or O's. Thus, there were no systematic, statistically significant adjustments in bidding within these sessions.

far smaller than what best response dictates (see below). Note, however, that in both cases O's were not best responding to I's bids, or to overly aggressive bids of other O's, as this calls for bidding close to $x - \varepsilon$. However, the opportunity cost of an individual O's failure to best respond was relatively small, averaging less than 10¢ per auction, in large measure because no individual O stood much of a chance of winning.[23]

Looking at Table V again, consistent with one of the most basic equilibrium predictions, conditional on winning, I's earned significantly greater profits than O's did for all values of ε and n (these differences are statistically significant in 4 of 5 cases).[24] I's profits, conditional on winning, were larger than in SIS auctions for both $n = 4$ and $n = 7$ with $\varepsilon = \$18$, treatments for which we have the most data, with significantly higher profits for I's in the $n = 7$ case ($t = 1.99$, d.f. $= 88$, $p < .05$, 1-tailed test).[25] However, average profits for I's were lower (but not significantly so), compared to profits in SIS auctions for $\varepsilon = \$30$. I's failure to earn consistently higher profits, conditional on winning, than in SIS auctions may be partially accounted for by that fact that under our design these differences are relatively small.

Turning to Table VI, for $n = 4$, I's bid factors were consistently smaller than the best (risk neutral) response to Os' bids. These opportunity costs averaged 54.7¢ per auction with $\varepsilon = \$18$ and 59.1¢ per auction with $\varepsilon = \$12$ (18.3% and 30.4% of best response earnings).[26] Notably, for the parameter set for which we have the most data, and with which our super-experienced subjects had the most experience ($n = 7$ and $\varepsilon = \$18$), there is essentially no difference between best response and actual bidding, with average opportunity costs of 2.7¢ per auction (just under 2% of best response earnings).[27] Unfortunately, we cannot determine whether this superior performance is a function of greater experience or a matter of chance.[28]

The comparative static prediction regarding I's response to increased numbers of rivals is satisfied as well. Looking at the raw data in the right-hand most column of Table V, I's average bid factor is smaller for $n = 7$ versus $n = 4$ for both values of ε. This is consistent with the regression results reported in the

[23] Opportunity costs were relatively large in percentage terms, averaging close to 30% of best response earnings. Opportunity costs for O's were calculated using estimated bid factors from Table VI and running Monte Carlo (MC) simulations in which a single O unilaterally adjusts his bid factor.

[24] For $n = 4$: $\varepsilon = \$12$, $t = 5.20$, $p < .01$, $\varepsilon = \$18$, $t = 3.45$, $p < .01$, $\varepsilon = \$30$, $t = 1.76$, $p < .10$; for $n = 7$: $\varepsilon = \$18$, $t = 5.15$, $p < .01$, $\varepsilon = \$30$, $t = 0.33$ (1-tailed t tests in all cases). Auction period is the unit of observation in each case.

[25] t statistic calculated for populations with unknown and unequal variances (Guenther (1964)).

[26] Our expected cost measures implicitly assume that all O's use the same bid factor (see footnote 18 above). Further analysis shows that these cost estimates are robust to the observed heterogeneity in O's bid factors.

[27] I's estimated bid factor is 4.01 versus a best response bid factor of 4.70 ($Z = 1.20$, $p > .10$).

[28] However, these results are not unlike those found in private value auctions, in which bidding above the RNNE is substantially greater, in both absolute and percentage terms, as the number of bidders decreases (Kagel, Harstad, and Levin (1987)).

TABLE VII

CHANGE IN SELLER'S REVENUE: AIS VS. SIS AUCTIONS WITH SUPER-EXPERIENCED BIDDERS

	$n = 4$			$n = 7$		
		Mean Profits (σ^2)			Mean Profits (σ^2)	
	Change in Revenue: AIS − SIS Auctions[a] (t stat)[b]	AIS	SIS	Change in Revenue: AIS − SIS Auctions[a] (t stat)[b]	AIS	SIS
$\varepsilon = \$18$	1.759	2.063	3.822	0.739	1.492	2.231
	(2.057)*	(8.561)	(49.972)	(1.573)+	(6.770)	(19.221)
$\varepsilon = \$30$	2.734	6.148	8.876	0.919	4.517	5.436
	(1.097)	(24.334)	(59.731)	(0.425)	(17.978)	(15.839)

[a] Change in seller's revenue, normalized for variation in x_o, is bidder profits in SIS auctions less bidder profits in AIS auctions.
[b] t statistics calculated for populations with unknown and unequal variances (Guenther (1964)). Auction period is unit of observation.
*Significantly different from 0 at $p < .05$, one-tailed test; + significantly different from 0 at $p < .10$, one-tailed test.

right-hand most column of Table VI, which show the coefficients for both *DN*EPS* dummies to be positive and significantly different from zero at $p < .01$. In our design, I's are, effectively, participating in a first-price private value auction. There is an extensive experimental literature demonstrating that subjects in first-price private value auctions increase their bids when faced with more rivals, as the theory predicts (Kagel and Levin (1993), Kagel (1995)). This strategic sensitivity extends to I's bidding in AIS common value auctions.

Table VII reports average revenue in AIS versus SIS auctions. In all four cases average revenue is higher in the AIS auctions, with these differences statistically significant for both $n = 4$ and 7 when $\varepsilon = \$18$ (for which we have the most data). Thus, this prediction of the theory is satisfied with experienced bidders who have generally learned to avoid the winner's curse.

C. *Learning and Adjustments in Insider's Bids Over Time*

This section examines adjustments in I's bids over time in relation to Selten and Buchta's (1994) (SB) "direction learning" theory, first applied to bidding in private value auctions.[29] Within direction learning theory players are assumed to be boundedly rational and to respond "sensibly" to the direct reinforcement effects of their bids in the previous auction period. As applied to our auctions, direction learning theory predicts: (a) If I wins, her bid factor will increase in reaction to money left on the table, (b) if she loses and O's winning bid is below x_o, so that there is a lost profit opportunity, I's bid factor will decrease in the next period, and (c) if I loses and O's winning bid is above x_o, so that there was

[29] Adjustment processes in SIS auctions have been discussed extensively elsewhere (Garvin and Kagel (1994); Kagel and Richard (1998)). O's adjustments no doubt follow a similar pattern.

no opportunity to earn a profit (the outpriced case), there will be no systematic effect on I's bid in the next auction period.[30] We anticipate, as earlier studies have found (SB and Cason and Friedman (1997)), that (b) dominates (a), promoting higher bids over time. Finally, there is no formal consideration within direction learning theory for threshold effects; e.g., when I wins but her bid is only slightly above (say less than 5 cents) the next highest bidder, she might well feel "Wow, that was too close" and decide to *reduce* her bid factor in the next period. Threshold effects of this sort seem eminently reasonable for case (a), so we test for them as well.[31]

Table VIII reports I's qualitative responses for these three cases.[32] For super-experienced bidders changes in I's bid factors are completely consistent with directional learning theory: I's winning and leaving money on the table increased their bid factor 68% of the time with $n = 7$ ($p < .05$), 69% of the time with $n = 4$ ($p < .01$).[33] In contrast, after a lost profit opportunity, bid factors decreased 61% of the time with $n = 7$ ($p = .11$), 64% of the time with $n = 4$ ($p < .01$). However, the average absolute size of these responses was approximately equal (see the last column in Table VIII) so that in both cases, unlike the results reported in SB and Cason and Friedman (1997) (CF), there was no systematic tendency to respond more strongly to lost earning opportunities than to money left on the table.

For auctions with $n = 4$, data from sessions leading up to I's super-experienced status are reported in the bottom panel of Table VIII. Like the super-experienced bidders, I's increased their bid factor following winning (68%, $p < .10$) and decreased it following a lost profit opportunity (59%, $p = .20$). However, unlike the super-experienced bidders, but like the results reported in SB and CF, the reaction to lost profit opportunities was substantially stronger than to money left on the table (the net effect of these changes being an average reduction in the bid factor of 5% per auction). Since our super-experienced bidders had substantially more experience than the subjects in SB and CS, this

[30] Whether or not (c) is integral to SB's model or is a result of the limited information feedback subjects had in their experiment (they only learned the market price) is an open question. Garvin and Kagel (1994) report strong observational learning effects as subjects increased their bid factors substantially following auctions in which they would have lost money applying their bid factor to the high bidder's signal value. This is inconsistent with (c).

[31] SB eliminate no change responses in evaluating their directional learning model. These responses may capture some of these threshold effects. We see no motive for a similar threshold effect in case (b).

[32] Since I is determined randomly in each auction, our analysis is based on changes in bid factors (normalized for any changes in ε) between different individuals across adjacent auction periods. An alternative analysis, based on the same individual across nonadjacent auction periods yields similar results, but fewer observations.

[33] No change outcomes are excluded from these percentages. Probabilities calculated test the null hypothesis of no systematic change in the bid factor versus a change whose sign is consistent with directional learning theory.

TABLE VIII

EFFECT OF PAST OUTCOMES ON CHANGE IN INSIDERS' BIDS

Bidder Experience	Outcome in period $t-1$	Change in I's bid factor: period $t-1$ to t[a] Decrease	Increase	No Change	Average Change
Super-experienced bidders: $n=7$	I wins: ("Money left on the table")	11	23	1	0.059
	I loses and O bids below x_o (lost profit opportunity)	25	16	2	−0.049
	I loses and O bids above x_o (outpriced valuation)	11	6	1	−0.041
Super-experienced bidders: $n=4$	I wins: ("Money left on the table")	17	37	2	0.206
	I loses and O bids below x_o (lost profit opportunity)	21	12	2	−0.315
	I loses and O bids above x_o (outpriced valuation)	10	10	0	0.007
Less-experienced bidders: $n=4$	I wins: ("Money left on the table")	9	17	0	0.058
	I loses and O bids below x_o (lost profit opportunity)	20	14	1	−0.165
	I loses and O bids above x_o (outpriced valuation)	16	21	1	−0.006

[a]Bid factor is computed as $[x - b(x)]/\varepsilon$.

suggests that with experience subjects become attuned to the more subtle strategic implications of winning and paying more than is necessary to win.

Testing for threshold effects in case (a), we regressed the change in I's bid factor between periods t and $t-1$ against the amount of money left on the table in period $t-1$. Direction learning theory implies a positive slope coefficient for the variable "money left on the table," with the existence of the predicted threshold effect indicated by a negative intercept value. There is no evidence for a threshold effect as (i) the regressions for experienced bidders have very low R^2 values (less than .05) and (ii) in all cases the intercept values, although not significantly different from zero, have the wrong sign.

4. SUMMARY AND CONCLUSIONS

We examined bidding in asymmetric information structure (AIS) auctions and compared it to bidding in symmetric information structure (SIS) common value auctions. In the AIS auctions a single insider (I) knows the value of the item with certainty, and outsiders (O's) are provided proprietary information affiliated with the value of the item. The existence of a perfectly informed insider did not significantly reduce the frequency or intensity of the winner's curse for inexperienced bidders compared to SIS auctions. Further, the only comparative static prediction of the AIS model consistently satisfied for these inexperienced bidders was that I's earned greater profits than O's. In contrast, super-experienced O's learn to overcome the worst effects of the winner's curse, generally bidding below the expected value conditional on winning. In this case the comparative static predictions of the theory are generally satisfied: (i) I's earn greater profits conditional on winning than O's do, (ii) with increased numbers of O's, I's bid more aggressively, (iii) O's earn positive average profits, but these are substantially less than earnings in SIS auctions, and (iv) AIS auctions *increase* seller's revenue compared to SIS auctions.

The predicted increase in seller's revenue in AIS auctions seems, at first blush, to be counterintuitive. This prediction of the model rests critically on the fact that in our experimental design less informed bidders have some proprietary information. Although this is not a sufficient condition for AIS auctions to raise revenue compared to SIS auctions, it clearly is a necessary condition. In contrast, models that start with bidders having only public information predict that the introduction of an insider will unambiguously reduce seller's average revenue. In many cases a model in which O's have some proprietary information is more realistic than one in which they only have public information. In these circumstances, it may well be the case, as in our experiment, that the introduction of an insider increases seller's revenue, and that both I's and O's earn economic rents. This potential for insider information to raise average seller's revenue has not been explicitly recognized in the auction literature prior to this.

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REFERENCES

AKERLOF, GEORGE (1970): "The Market for Lemons: Qualitative Uncertainty and the Market Mechanism," *Quarterly Journal of Economics*, 89, 488–500.

ANDREONI, JAMES (1995): "Warn-Glow versus Cold-Prickle: The Effects of Positive and Negative Framing on Cooperation in Experiments," *Quarterly Journal of Economics*, 110, 1–22.

CAMPBELL, COLIN, AND DAN LEVIN (1997): "Can the Seller Benefit from an Insider in Common Value Auctions?" Mimeographed, Ohio State University.

CASON, TIMOTHY N., AND DANIEL FRIEDMAN (1997): "Price Formation in Single Call Markets," *Econometrica*, 65, 311–346.

COOPER, DAVID J., SUSAN GARVIN, AND JOHN H. KAGEL (1997): "Adaptive Learning vs. Equilibrium Refinements in an Entry Limit Pricing Game," *RAND Journal of Economics*, 28, 662–683.

DYER, DOUGLAS, JOHN H. KAGEL, AND DAN LEVIN (1998): "A Comparison of Naive and Experienced Bidders in Common Value Offer Auctions: A Laboratory Analysis," *Economic Journal*, 99, 108–115.

ENGELBRECHT-WIGGANS, RICHARD, PAUL R. MILGROM, AND ROBERT J. WEBER (1983): "Competitive Bidding and Proprietary Information," *Journal of Mathematical Economics*, 11, 161–169.

FUDENBERG, DREW, AND DAVID K. LEVINE (1997): "Measuring Players Losses in Experimental Games," *Quarterly Journal of Economics*, 112, 507–536.

Garvin, Susan, and John H. Kagel (1994): "Learning in Common Value Auctions: Some Initial Observations," *Journal of Economic Behavior and Organization*, 25, 351–372.

Guenther, William C. (1964): *Analysis of Variance*. Englewood Cliffs, N.J.: Prentice-Hall.

Hausch, Donald B. (1987): "An Asymmetric Common Value Auction Model," *RAND Journal of Economics*, 18, 611–621.

Hendricks, Kenneth, Robert H. Porter, and Charles A. Wilson (1994): "Auctions for Oil and Gas Leases with an Informed Bidder and a Random Reservation Price," *Econometrica*, 62, 1415–1444.

Kagel, John H. (1995): "Auctions: A Survey of Experimental Research," in *The Handbook of Experimental Economics*, ed. by J. H. Kagel and A. E. Roth. Princeton: Princeton University Press.

Kagel, John H., Ronald M. Harstad, and Dan Levin (1987): "Information Impact and Allocation Rules in Auctions with Affiliated Private Values: A Laboratory Study," *Econometrica*, 55, 1275–1304.

Kagel, John H., and D. Levin (1986): "The Winner's Curse and Public Information in Common Value Auctions," *American Economic Review*, 76, 894–920.

——— (1993): "Independent Private Value Auctions: Bidder Behavior in First-, Second- and Third-Price Auctions with Varying Numbers of Bidders," *Economic Journal*, 103, 868–880.

——— (1998): "Common Value Auctions with Insider Information," Mimeographed, University of Pittsburgh.

Kagel, John H., D. Levin, R. Battalio, and D. J. Meyer (1989): "First-Price Common Value Auctions: Bidder Behavior and the Winner's Curse," *Economic Inquiry*, 27, 241–258.

Kagel, John H., D. Levin, and R. M. Harstad (1995): "Comparative Static Effects of Number of Bidders and Public Information in Second-Price Common Value Auctions," *International Journal of Game Theory*, 24, 293–319.

Kagel, John H., and J. F. Richard (1998): "Super-experienced Bidders in First-price Common Value Auctions: Rules-of-thumb, Nash Equilibrium Bidding and the Winner's Curse," Mimeographed, University of Pittsburgh.

Levin, D., John H. Kagel, and J. F. Richard (1996): "Revenue Effects and Information Processing in English Common Value Auctions," *American Economic Review*, 86, 442–460.

Lind, B., and C. R. Plott (1991): "The Winner's Curse: Experiments with Buyers and with Sellers," *American Economic Review*, 81, 335–346.

Laskowski, M. C., and R. L. Slonim (in press): "An Asymmetric Solution for Sealed Bid Common-Value Auctions with Bidders Having Asymmetric Information," *Games and Economic Behavior* (in press).

Marshall, Robert C., Michael J. Meurer, Jean-Francois Richard, and Walter Stromquist (1994): "Numerical Analysis of Asymmetric First Price Auctions," *Games and Economic Behavior*, 7, 193–220.

Milgrom, Paul R., and Robert J. Weber (1982): "A Theory of Auctions and Competitive Bidding," *Econometrica*, 50, 1089–1122.

Schotter, A., K. Weigelt, and C. Wilson (1995): "A Laboratory Investigation of Multi-person Rationality and Presentation Effects," *Games and Economic Behavior*, 8, 164–212.

Selten, Reinhard, and Joachim Buchta (1994): "Experimental Sealed Bid First Price Auctions with Directly Observed Bid Functions," Discussion Paper No. B-270, University of Bonn.

Weverbergh, M. (1979): "Competitive Bidding with Asymmetric Information Reanalyzed," *Management Science*, 25, 291–294.

Wilson, Robert (1967): "Competitive Bidding with Asymmetric Information," *Management Science*, 13, 816–820.

——— (1985): "Analytical Foundations of Pricing Strategy: Trading Procedures," Mimeographed, Stanford University.