The Winner's Curse and Public Information in Common Value Auctions

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Experienced bidders show sensitivity to the strategic considerations underlying common value auctions, but not to item valuation considerations. Auctions with large numbers of bidders (6–7) produce more aggressive bidding than with small numbers (3–4), resulting in negative profits, the winner's curse. Providing public information about the value of the item increases seller revenue in the absence of a winner's curse, but produces the contrary result in its presence.

Common value auctions constitute a market setting in which participants may be particularly susceptible to judgment failures that affect market outcomes. In a common value auction, the value of the auctioned item is the same to all bidders. What makes the auction interesting is that bidders are unaware of the value of the item at the time the bids are placed. Mineral lease auctions, particularly the federal government's outer continental shelf (OCS) oil lease auctions, are common value auctions. There is a common value element to most auctions. Bidders for an oil painting may purchase for their own pleasure, a private value element, but they may also bid for investment and eventual resale, reflecting an uncertain common value element.

Judgmental failures in common value auctions are known as the "winner's curse." Assume that all bidders obtain unbiased estimates of an item's value and that bids are an increasing function of these estimates. The high bidder then tends to be the one with the most optimistic estimate of the item's value. Unless this adverse-selection problem is accounted for in the bidding process, it will result in winning bids that produce below normal or even negative profits. The systematic failure to account for this adverse selection problem is referred to as the "winner's curse."

Oil companies claim they fell prey to the winner's curse in early OCS lease sales (E. C. Capen, R. V. Clapp, and W. M. Campbell, 1971; John Lorenz and E. L. Dougherty, 1983; and references cited therein). Similar claims have been made in auctions for book publication rights (John Dessauer, 1981) in professional baseball's free agency market (James Cassing and Richard Douglas, 1980) and in corporate takeover battles (Richard Roll, 1986). Economists typically treat such claims with caution as they imply that bidders repeatedly err, in violation of basic notions of economic rationality. This caution is justified given the inherent problems in interpreting field data, self-serving motives of many of the claimants, and the general absence of conventional statistical tests documenting these claims. However, common value auction experiments using financially motivated, but inexperienced, subjects demonstrate a strong

*Department of Economics, University of Houston-University Park, Houston, TX 77004. Financial support was received from the Information Science and Technology Division and the Economics Division of NSF; the Energy Laboratory and the Center for Public Policy of the University of Houston-University Park. Ray Battalio, Don Meyer, and Carl Kogut ran auction series 1 and 2; Ron Harstad and Doug Dyer assisted in series 3–8. Doug Dyer and Susan Garvin provided valuable research assistance. This paper has benefited from discussions with Badi Baltagi, Ron Harstad, Mark Issac, Asbjord Moseidjord, Jim Smith, and Philip Sorensen, the comments of Daniel Friedman, Robert Wilson, two referees, and participants in seminars at the University of Houston, Texas A&M University and the University of Indiana. An earlier version of this paper was presented at the 1985 Winter Econometric Society meetings. We alone are responsible for errors and omissions.

and nearly ubiquitous winner's curse which continues to significantly depress profits after as many as 15–20 auction periods (Kagel et al., 1986).

It is one thing to find that inexperienced bidders commit a winner's curse. It is another to find that experienced bidders do the same. Here we report the results of common value auction experiments with experienced subjects, survivors of one or more initial series of experiments. With continued experience, bidders' judgment improve. In auctions involving a limited number of competitors (3–4 bidders), average profits are consistently positive and closer to the Nash equilibrium bidding outcome than to the winner's curse hypothesis: behavior consistent with traditional notions of the effects of repeated exposure to market conditions, in conjunction with profit incentives and survival pressures. However, learning is situationally specific as bids are found to be an increasing function of the number of rivals faced, in clear violation of risk-neutral Nash equilibrium bidding theory under our design. This contributes to a reemergence of the winner's curse, with bankruptcies and negative profits, in auctions with large numbers (6–7) of bidders.

Just as Nash equilibrium bidding theory predicts, experimental manipulations providing public information reducing uncertainty about item value reliably result in higher winning bids and increased seller's revenues in the absence of a winner's curse. However, in the presence of a winner's curse, this same public information generates lower average winning bids and reduced seller's revenues. The differential response to public information conditional on the presence or absence of a winner's curse has practical implications which have largely gone unrecognized in the literature.

The paper is organized as follows. Section I describes the structure of the experiments. Section II characterizes the Nash equilibrium bidding strategies for the auction, provides a formal definition of the winner's curse, and states the research hypotheses that guided our investigations. The results of the experiments are reported and discussed in Section III. Section IV extends the analysis to field settings where our experimental results help explain a puzzling outcome of OCS lease sales: namely, that public information reducing item uncertainty increased bidder's profits, just as observed in our laboratory experiments in the presence of a winner's curse. A concluding section summarizes our research results and poses questions for further research.

I. Structure of the Auctions

A. *Basic Auction Structure*

Subjects were recruited for two-hour sessions consisting of a series of auction periods. In each auction period, a single unit of a commodity was sold to the high bidder at the high-bid price, with bidders submitting sealed bids for the item (a first-price, sealed-bid procedure). The high bidder earned profits equal to the value of the item less the amount bid; other bidders earned zero profits for that auction period.

In each auction period, the value of the item, x_0, was drawn randomly from a uniform distribution on the interval $[\underline{x}, \bar{x}]$. Subjects submitted bids without knowing the value of x_0. Private information signals, x_i, were distributed prior to bidding. The x_i were randomly drawn from a uniform distribution centered on x_0 with upper bound $x_0 + \varepsilon$ and lower bound $x_0 - \varepsilon$. As such, the x_i constitute unbiased estimates of the value of x_0 (or could be used to compute unbiased estimates in conjunction with the endpoint values $\underline{x}, \bar{x}$). Given x_i, ε, and the endpoint values, each bidder could compute an upper and lower bound on the value of x_0; these were min $\{x_i + \varepsilon, \bar{x}\}$ and max $\{x_i - \varepsilon, \underline{x}\}$, respectively. The bounds associated with a given x_i were computed and reported along with the x_i.

The distribution underlying the signal values, the value of ε, and the interval $[\underline{x}, \bar{x}]$ were common knowledge. The value of ε varied across auctions (see Table 1). All changes in ε were announced and posted. With signal values drawn independently relative to x_0, they satisfy the criteria of strict positive affiliation (Paul Milgrom and Robert Weber, 1982) which, roughly speak-

TABLE 1—EXPERIMENTAL CONDITIONS[a]

Auction Series	Subject Population (no. starting exp.)	Market Period	ε	$\underline{x}$	$\bar{x}$	Public Information[b] (market periods)	Number Active Bidders (market periods)	Experience
1	Texas A&M Undergraduates (5)	1–18	$12	$15	$100	Random signal (10–18)	5(1–18)	First-price common value
2	Texas A&M Undergraduates (4)	1–18	$12	$15	$100	Random signal (10–18)	4(1–18)	First-price common value
3	U. Houston Graduate/Senior Undergraduates (7)	1–8 9–17, 24–25 18–23	$12 $18 $30	$25	$225	Low signal (12–25)	7(1–4) 6(5–6) 5(7–11) 4(12–25)	Second-price common value, some first-price common value
4	U. Houston Graduate/Senior Undergraduates (8)	1–6 7–14 15–25	$12 $18 $30	$25	$225	Low signal (8–25)	7(1–10) 6(11–25)	Second-price common value, some first-price common value
5	U. Houston Graduate/Senior Undergraduates (9)	1–9 10–15, 24–26 16–23	$12 $18 $30	$25	$225	Low signal (7–26)	7(1–26) 7(1–26)	First and Second-price common value
6	U. Houston Graduate/Senior Undergraduates (4)	1–5 6–16, 28–31 17–21 22–27	$12 $18 $24 $30	$25	$225	Low signal (9–31)	4(1–11) 4(1–11) 3(12–31)	First and Second-price common value
7	U. Houston Graduate/Senior Undergraduates (6)	1–5 6–13, 26–32 33–37 14–25	$12 $18 $24 $30	$25	$225	Low signal (9–32)	4(1–19) 6(20–37)	First and Second-price common value
8	U. Houston Graduate/Senior Undergraduates (7)	1–6 7–16 17–23	$12 $18 $30	$30	$500	None	4(1–23)[c] 7(10–23)	First-price common value, some private value

[a]Starting balances were $8 in experiments 1 and 2, $10 in all others.

[b]Profits were earned in markets with both public and private information in experiments 1 and 2; in only one market in experiments 3–8. The market paying profits was determined by a coin flip in experiments 3–8.

[c]Period 10 on involved a bidding in two markets with 4 subjects bidding first in a "small" market and all 7 subjects bidding in a "large" market.

ing, requires that large values for a given signal make it more likely that rivals signal values, and x_0, are large rather than small.

Bids were restricted to be nonnegative and rounded to the nearest penny. After all bids were collected, they were posted on the blackboard in descending order next to the corresponding signal values, x_0 was announced, subjects' profits were calculated, and balances were updated.[1] Earnings of the high bidder were also announced, but his/her identity was not. The x_0 values and the associated signal values were all determined randomly strictly according to the process described to the subjects.

To cover the possibility of losses, subjects were given starting balances of $8.00 in auction series 1–2, and $10.00 in series 3–8. Profits and losses were added to this balance. If a subject's balance went negative, he was no longer permitted to bid; he was paid the $4.00 participation fee and free to leave the experiment. The auction survivors were paid their end of experiment

[1]In auction series 1 and 2, the top three bids were posted, and the signal values underlying the bids were not revealed.

balance in cash, along with their participation fee.[2]

Given the information structure and uncertainty inherent in common value auctions, negative profits will occasionally be realized even if the market immediately locks into the risk-neutral Nash equilibrium outcome. The starting capital balance served to account for this possibility, and to impose clear opportunity costs on overly aggressive bidding. Balances were set so that: (*i*) subjects could commit at least one gross bidding error, learn from their mistake, and still have a large enough balance to actively participate in the auctions, and (*ii*) conservative bidders who were shut out from winning by overly aggressive counterparts would earn a reasonable return for participating.

B. *Auctions with Public Information*

Approximately one-third of the way through auction series 1–7, we introduced bidding in two separate auction markets simultaneously. Bidding in the first auction market continued as before under private information conditions. After these bids were collected, but before they were posted, we introduced a public information signal and asked subjects to bid again. (Subjects retained their original private information signals; no new private information signals were distributed.) We employed two types of public information signals. In series 1 and 2, we randomly drew an additional signal, x_i, from the interval $[x_0 - \varepsilon, x_0 + \varepsilon]$, and posted it. In series 3–7, the lowest of the private information signals distributed, x_L, was posted. Bidders were always accurately informed of whether the public information signal was random or the lowest private information signal.

Profits were paid (or losses incurred) in only one of the two auction markets, determined on the basis of a coin flip after all bids were collected.[3] Subjects were told that they were under no obligation to submit the same or different bids in the two markets, but should bid in a way they thought would "maximize profits." All bids from both markets were posted along with the corresponding private information signals.

The dual market bidding procedure, involving the same set of bidders with the same item value and the same set of private information signals, has the advantage of directly controlling for between subject variability and extraneous variability resulting from variations in item value and private information signals. Some critics have mistakenly concluded that the procedure involves a "portfolio" problem so that the optimal bid in one market affects bids in the other market. This conclusion is unwarranted, however. There is no way that bids in the private information market can be used to hedge bids in the public information market any more than bids in the private information market in period t can be used to hedge bids in the private information market in period $t+1$. In analyzing each member of a set of auctions, $t = 1, 2, \dots, T$, as a single-shot auction (which we do below), we are assuming that the utility function is intertemporally separable in profits from the auction, $U = \sum_{t=1}^{T} u(\Pi_t)$. Similarly we are assuming separability in bidding between the dual markets. The breakdown of the separability assumption in either case (for example, $U = u(\sum_{t=1}^{T} \Pi_t)$) has comparable implications, namely no effect in the case of risk-neutral bidders, while risk-averse bidders will tend to be less risk averse than under separable preferences, as they can rely on the law of large numbers to smooth the variance in profits across auctions.

Of course, it is another matter entirely whether bidders actually bid as if their preferences are separable between the dual markets or over time. Experiments 1 and 2 explicitly tested for separability, holding ε constant throughout and having a relatively

[2] Series 1 and 2 had a \$3 participation fee. Many subjects in series 3–7 had signed a contract to participate in 3 different auction series, for which they were paid a single participation fee of \$25 at the end of the last series.

[3] Once again, series 1 and 2 involved an exception to these procedures as profits and losses were computed and paid in both the public and private information markets.

large number of private information auctions (9) before introducing dual markets. Regression analysis using dummy variables showed no systematic response to bids in the private information market under the dual market procedure.[4] Similar tests, conducted in a related series of first-price auctions, showed no systematic effects in going from private information markets only to dual markets with public information, and from dual markets to markets with public information only (Kagel, Ronald Harstad, and Levin, 1986). Bid patterns over time are presented in reporting our results.

C. *Varying Numbers of Bidders*

A number of tactics were employed to study the effects of varying the number of bidders. Auction series 1–6 used a between-groups design with different series having different numbers of active bidders. In pursuit of this objective, series 4 and 5 had more subjects than active bidders, in order to control for bankruptcies, with a simple rotation rule to determine which subjects would be active in any given auction period.[5] Variations in the number of active bidders in these series (see the eighth column in Table 1) resulted from bankruptcies.

Auction series 7 and 8 involved planned variations in the number of active bidders. Series 7 employed a crossover design, starting with 4 active bidders rotating among a set of 6 total bidders. In auction period 20, the rotation procedure ceased, and all 6 bidders were active in the remaining auction periods. Auction series 8 employed a within-subjects design, starting out with 4 active bidders rotating between 7 total bidders. In auction period 10, dual market bidding procedures similar to those used to study the effects of public information were introduced; only numbers of active bidders varied between markets.[6] We refer to the different market sizes here as series 7 and 8 small, and 7 and 8 large. Auction series 3 involved a large unplanned variation in number of active bidders due to bankruptcies in early auction periods. Our analysis distinguishes between these early auction periods with 5 or more active bidders (series 3 large), and the later periods with 4 active bidders (series 3 small), as market outcomes were distinctly different between the two situations.

D. *The Experience Factor*

All auctions employed experienced subjects. In series 1 and 2, all subjects had been in one earlier first-price common value auction series using similar design parameters (see Kagel et al., 1986, auction series 4–6). These earlier auctions all began with 6 active bidders, but as a result of bankruptcies ended with 3–5 bidders. Recruitment into these experiments was restricted to subjects who had not gone bankrupt in the initial auction series.

Auction series 3–8 are numbered in chronological order as they involved a common core of subjects, recruited in varying combinations, in the different series. Thirteen of the 15 bidders in series 3 and 4 had participated in an earlier series of second-price

[4] The bid function had the form $b_{it} = \alpha_0 + \alpha_1 x_{it} + \alpha_2 Y_{it}$ as suggested by equation (2), where α_i were constants to be estimated (ε was constant in these auctions). The function was fit to individual subject data for signals in the interval (1), and a dummy variable added to account for simultaneous bidding in two auctions. Combining independent t-tests on the dummy variable coefficient using the z statistic suggested in Ben Winer (1971, p. 50), we were unable to identify any systematic effects associated with simultaneous bidding ($z = -.124$).

[5] For example, with 9 subjects and 7 active bidders, in period 1, subjects 1–7 were active; in period 2, subjects 2–8 were active, etc. Inactive subjects received signals and bid, but these bids were discarded (the latter was common knowledge).

[6] Using a single set of private information signals and a single true value, x_0, 4 subjects first bid in a small market. Then, before these bids were opened, all 7 subjects bid in a large market. The 4 subjects in the small market continued to be determined through rotation, and bids only counted in one of the two markets using a coin flip rule. Raymond Battalio, Carl Kogut, and Donald Meyer (1983) report tests of the separability assumption underlying the dual market technique in private value auctions with varying numbers of bidders. They found no systematic biases associated with the dual market technique.

common value auction experiments with similar design parameters. (The distinguishing characteristic of these second-price auctions was that the high bidders earned the item and paid the second-highest bid price.) Most of these subjects had been in two or more second-price series, at least one of which involved 6–7 active bidders throughout. The two remaining subjects had been in a first-price common value series involving 5–6 active bidders throughout (Kagel et al., 1986, auction series 11). Seven of the 9 subjects in series 5 were recruited from series 3 and 4, with the remaining 2 having extensive second-price experience. All 6 bidders in series 7 had been in both auction series 3 and 5, or 4 and 5. Three of the 4 bidders in series 6 had been in series 4, with the fourth bidder having been in series 3 and 5. Series 8 was conducted several months after the others and involved 3 veterans of series 7, 2 from series 6, and 2 bidders with experience in first-price auctions with positively affiliated private values (Kagel, Harstad, and Levin). Several subjects in this series had gone bankrupt in their initial common value auction series, but were included provided the bankruptcy occurred after a fair number of auction periods (15 or more periods was the rule of thumb employed).[7] Subjects were recruited into later series in this sequence without regard to performance earlier in the sequence.

II. Theoretical Considerations

A. *Private Information Conditions*

1. *The Nash Equilibrium*. The most common equilibrium bidding model in the economic's literature is that of a noncooperative Nash equilibrium with risk-neutral bidders (hereafter RNNE). Robert Wilson (1977) was the first to develop a Nash equilibrium solution for first-price common value auctions, while Milgrom and Weber provide some significant extensions and generalization of the Wilson model.

We restrict our analysis in the text to signals in the interval

$$\underline{x} + \varepsilon \le x_i \le \bar{x} - \varepsilon. \tag{1}$$

The optimal bid function in this interval is, of course, affected by the bid function in the interval $x_i < \underline{x} + \varepsilon$, which in turn is affected by the added information associated with the end-point value, $\underline{x}$.[8] Assuming risk neutrality on bidder's part, the Nash equilibrium bid function for signals in (1) is

$$b(x_i) = x_i - \varepsilon + Y, \tag{2}$$

where $Y = [2\varepsilon/(N+1)]\exp[-(N/2\varepsilon)(x_i - (\underline{x}+\varepsilon))]$ and N stands for the number of active bidders in the market. Y contains a negative exponential, and diminishes rapidly as x_i moves beyond $\underline{x} + \varepsilon$.

Under (2), expected profits for the high bidder are

$$E[\Pi | W] = 2\varepsilon/(N+1) - Y. \tag{3}$$

In addition, the model predicts that the high signal holder always wins the auction. This follows directly from the assumption that all bidders use the same bid function, the only

[7]In a private value auction, bidders know their value for the item with certainty, but only the distribution of their rivals' values. Under the first-price rule, the high bidder wins the item and earns profits equal to his private value less the bid price; others earn zero profits.

[8]For $x_i < \underline{x} + \varepsilon$, the RNNE bid function is

$$b(x_i) = \underline{x} + (x_i + \varepsilon - \underline{x})/(N+1)$$

and yields zero expected profits. This equilibrium bid function is obtained from Wilson (1977) under the initial condition $b(x_i) = \underline{x}$ for $x_i = \underline{x} - \varepsilon$. The initial condition for the bid function in (2) exploits continuity in the bid function at the junction point $x_i = \underline{x} + \varepsilon$. For $x_i > \bar{x} - \varepsilon$, the optimal bid function defies analytic solution. For observations in this interval, we employ the bid function (2) in comparing performance with the RNNE model. This tends to overstate the RNNE bid, hence underestimate the discrepancy between actual and predicted bids. Since the bias is small, and favors the null hypothesis, correcting for it will not change the conclusions reached. These bid functions are explicitly derived in Kagel et al. (1984).

difference being their private information, x_i, regarding the value of the item.[9]

Accounting for risk aversion on bidder's part complicates the model's predictions, as equilibrium bids can lie to either side of the RNNE prediction, depending upon the form of the utility function and the degree of risk aversion assumed. We do not pursue these extensions here, as they appear secondary to understanding the experiments' outcomes.[10] Note that under the RNNE there is no winner's curse as bidders fully account for the adverse-selection problem in determining their bids. The RNNE bidding model provides a convenient benchmark against which to compare the experiments' outcomes.

2. *Judgmental Failures: The Winner's Curse.* In common value auctions, bidders usually win the item when they have the highest, or one of the highest, estimates of value. Under these conditions an unbiased estimate of value, $E[x_0|x_i)$, is biased as

$$E[x_0|x_i] > E[x_0|X_i = x_1] \qquad \text{for } N>1$$

where $E[x_0|X_i = x_1]$ is the expected value conditional on having the highest private information signal. Assuming that the highest signal holder always wins the auction and risk neutrality, or risk aversion, bids in excess of $E[x_0|X_i = x_1]$ will insure negative profits on average, and can only result from failure to recognize the adverse-selection problem inherent in winning the auction. Since we have no reason to assume risk loving, and the highest signal holder usually wins the auction, bids in excess of $E[x_0|X_i = x_1]$ will be attributed to such judgmental failures, and will be referred to as the winner's curse.[11]

For signal values in the interval (1),

$$(4) \quad E[x_0|x_i] = x_i;$$

$$(5) \quad E[x_0|X_i = x_1] = x_i - \varepsilon(N-1)/(N+1).$$

Avoiding the winner's curse requires considerable discounting of bids relative to signal values.[12] Further, the size of the discount is an increasing function of both N and ε.

In first-price sealed-bid auctions, strategic considerations generally dictate discounting of bids relative to the expected value of the item. Strategic discounting results strictly from known dispersion in rivals' values. It is informative to compare the bid function (2), and the size of the discount in (5), with strategic discounting based on the dispersion in the x_i values. Suppose that bidders completely ignore the adverse-selection problem inherent in the auction, employing (4) to compute the expected value of the item: they act as if they are in an auction with positively affiliated private values, where the x_i represents the value of the item to bidder i, and values are independently distributed over the interval (1). Under risk neutrality, the bid function here is[13]

$$(6) \quad b^s(x_i) = x_i - (2\varepsilon/N) + (Y/N),$$

[9]The model can be generalized to account for both private value and common value elements (see Wilson, 1981, for example). In this case, the high signal holder does not always win the item, even assuming identical bidding strategies. Undoubtedly, actual auction sales, even OCS lease sales, contain both private and common value elements. Developments in Section III suggest that the Nash equilibrium model must be generalized to account for individual differences in risk attitudes and/or information-processing capacities, as well as simple random errors on bidder's part. Developing and testing such a model lies beyond the scope of the present paper.

[10]Milgrom and Weber, section 8, and Steven Matthews (1986) develop some results for risk-averse bidders.

[11]Results from private value auction experiments generally support an assumption of risk neutrality or risk aversion (James Cox, Bruce Roberson, and Vernon Smith, 1982; Kagel, Harstad, and Levin).

[12]The size of the discount seems remarkably large, particularly for larger N's. To get an idea of the adverse-selection bias involved here, compared to alternative distributions, we normalize it in terms of the standard error of the underlying distribution. For x_i in (1) the standard error of the uniform distributions is $\sigma = 2\varepsilon/\sqrt{12}$. From (5), knowing that your estimate is the maximum of N such estimates, means that it is biased upwards by the amount $\sqrt{12}(N-1)\sigma/2(N+1)$. For $N = 2$–8, the resulting bias is quite similar to what would be found if the x_i were normally distributed around x_0.

[13]Kagel, Harstad, and Levin experimentally investigate first-price sealed bid auctions with positively affili-

where the expression Y is the same as in (2) above.

Comparing equation (5) with (6) shows that strategic discounting produces a winner's curse whenever $N > 3$. Further, strategic considerations (6), item valuation considerations (5), and the RNNE bid function (2) all call for greater discounting of bids relative to signal values with increases in ε.[14] Since evidence from private value auctions shows bidders to be sensitive to the strategic considerations inherent in these auctions (James Cox, et al.; our 1985 paper), we expect bidders to be sensitive to variations in ε.

However, with increasing numbers of bidders, equations (2), (5), and (6) give conflicting directions. Differentiation of (6) shows that strategic considerations require higher bids in the presence of more rivals as signal values are more congested. Item valuation considerations as expressed in (5) require less aggressive bidding as the adverse-selection problem becomes more severe. The net effect of these two forces, expressed in the RNNE bid function, is for bids to remain constant or decrease in the presence of more rivals.[15] This conflict between item valuation and strategic considerations suggests that structural variations in numbers of bidders is critical to determining whether experienced bidders learn to avoid the winner's curse in small groups out of a trial and error survival process that is situationally specific, as opposed to "understanding" the adverse-selection problem as it applies to new situations. If the survival process results in generalized learning (one interpretation of optimality via survival arguments in economics), behavior in both large and small groups should show comparable deviations from the RNNE reference point.[16] However, in the absence of generalized learning, behavior is likely to be markedly different, to the extent that the winner's curse, having been largely or entirely eliminated in small groups, will reemerge with increases in group size.

B. *Effects of Public Information*

1. *The Nash Equilibrium.* Extensions of the common value auction model show that public information reducing item valuation uncertainty will increase average seller's revenues (reduce bidder's profits) under the RNNE (Milgrom and Weber). This holds even though public information signals of the sort employed here, x_p, will on average lie below the maximum private information signal, x_1. The economic forces at work here are roughly as follows: On average,

$$E[x_0 | X_i = x_1] = E[x_0 | X_i = x_1, X_p]$$

for the bidder actually holding the highest private information signal, x_1. (All symmetric, noncooperative Nash equilibria involve agents bidding as if $x_i = x_1$, since their bid only "counts" when this presumption is satisfied.) However, due to the affiliation of the signal values, for bidders whose private information signals $x_i < x_1$, the public information signal will, *ex post*, raise the average expected value of the item. This will induce an upward revision of these bids, which in

ated private values, where private values were generated using exactly the same procedures generating the x_i values here. Equation (6) corresponds to the bid function developed there. Note, these private value experiments show bids commonly in excess of (6) with $N = 6$.

[14] In addition, an increase in ε increases the variance associated with the naive expectation (4). Thus to the extent that bidders are generally risk averse and bid more cautiously in the face of increased risk, but are poor Bayesians so that they continue to employ the naive expectation (4), they will respond correctly (at least directionally) to changing ε.

[15] Differentiation of (2) with respect to N shows the Y term to require lower bids in the presence of more rivals.

[16] An earlier reader of this paper argued that optimality by survival arguments implied "correct" responses under all possible states of the world, as survivors had experienced all relevant states and had learned to adapt to them. While acknowledging the validity of this interpretation, it seems to rob the survival argument of empirical content as: 1) the survival process would never be complete as real economies are repeatedly subject to changing conditions and changes in the set of agents, and 2) there would be no role left for economic theory in terms of understanding behavioral processes or in predicting responses to novel economic conditions.

turn puts pressure on the bidder with the highest private information signal, x_1, to bid more out of strategic considerations.

As an experimental device, the use of the low private information signal, x_L, as the public information signal has several advantages. First, the RNNE bid function with public information is readily solved analytically with x_L. Second, x_L provides a substantial amount of information concerning the location of x_0, and the signal values rivals are likely to have. For signals in the interval (1),

$$(7) \quad E\left[x_0|X_i = x_1, X_p = x_L\right] = (x_L + x_i)/2$$

provides a sufficient statistic for the value of x_0 given the set of private information signals distributed, under the presumption that $x_i = x_1$. From (7), it is clear that announcing x_L should reduce the average spread in beliefs about the underlying value of the item between any two bidders by one-half. Under private information conditions, a similar reduction in beliefs would require halving ε, as this halves the average spread between any two private information signals (as well as the spread in expected values under (5)). Thus, announcing x_L induces strong competitive pressures on the high bidder and translates into relatively large increases in seller's revenues, or reduced bidder's profits (see equation (9) below), while still maintaining an interesting auction.

The RNNE bid function with, public information, x_L, and private information signals in the interval (1) is[17]

$$(8) \quad b(x_i, x_L) = x_L + \left[\frac{N-2}{N-1}\right] \times \left[\frac{x_i + x_L}{2} - x_L\right] = \frac{N}{2(N-1)}x_L + \frac{(N-2)}{2(N-1)}x_i.$$

Expected profits are substantially diluted, being

$$(9) \quad E[\Pi|W, X_L] = \varepsilon/(N+1).$$

This is a little more than one-half of the expected profits under private information conditions (3).

With risk aversion we cannot unambiguously determine whether public information will increase or decrease average seller's revenues (Milgrom and Weber). The impact depends upon the particular form of the utility function assumed, the degree of risk aversion displayed, and the extent to which public information dilutes private information differences. Nevertheless, we would anticipate that under most plausible scenarios, the relatively large dilution of private information differentials inherent in releasing x_L, would cause seller's revenues to increase, or at least not to decrease.

2. *Judgmental Failures: The Winner's Curse.* The judgmental error underlying the winner's curse consists of the high bidder's systematic overestimation of the item's value. To the extent that the magnitude of these judgmental errors decreases as the uncertainty concerning the value of the item decreases, public information will result in a downward revision in the most optimistic bidder's valuation of the item. This introduces a potentially powerful offset to any strategic forces tending to raise bids.[18] This effect is well illustrated through extending the notion of strategic discounting to auctions with public information, and comparing the resultant discount function with (6).

[17]For x_i in the interval (1), the RNNE equilibrium bid function is obtained under the initial condition that $b(x_L) = x_L$. Note that ε is not explicitly represented in (8). However, the average difference $(x_i + x_L)/2 - x_L$ depends directly on ε.

[18]Note that unbiased random errors, even if they do not result in high bids in excess of $E[x_0|X_i = x_1]$, will *not* cancel out here in terms of their effects on seller's revenues. This results from the auction selection mechanism whereby market outcomes overrepresent bids with upward biases, resulting in average bids in excess of the RNNE. Consequently, if public information reduces the magnitude of these item valuation errors, public information will still result in a downward revision of the market price, which offsets the strategic forces promoting increased revenues. High bids in excess of $E[x_0|X_i = x_1]$ can constitute an extreme form of these errors and/or a systematic tendency, on at least some bidder's part, to overestimate the item's value.

Under strategic discounting, we continue to assume that bidders employ naive expectations to determine the value of the item, to the point that they ignore the positional information inherent in announcing x_L, and act as if they are in a private value auction. For x_i and x_L in the interval (1), a naive expectation of x_0 is the same as (7):

$$(10) \qquad E[x_0|x_i, x_L] = (x_i + x_L)/2.$$

Consequently, under risk neutrality, the strategic discount function and the RNNE bid function (8) coincide here. Note that this follows directly from the fact that the naive (10) and sophisticated expectations (7) coincide. In markets with private information, the two bid functions differ as the expectations differ.

Comparing (6) with (8), $b^s(x_i) > b(x_i, x_L)$ on average for all $N \geq 3$. In auctions where bidders employ naive expectations, but strategic discounting, announcing x_L will result in *reductions* in average seller's revenues (increases in average bidder's profits) with 3 or more bidders. Finally, given that previous experimental studies indicate sensitivity to the strategic implications inherent in auction markets, and the coincidence of the strategic bid function with the RNNE bid function, the RNNE model should provide a fairly good predictor of market performance with x_L announced, irrespective of its predictive adequacy in comparable markets with private information only.

C. *Summary of Research Questions of Primary Interest*

We conclude this section by summarizing the research questions of primary interest in the form of hypotheses to be tested.

HYPOTHESIS 1: *Under private information conditions market outcomes for experienced bidders are observationally indistinguishable from the RNNE as* (i) *the high signal holder usually wins the auction, and* (ii) *prices do not deviate substantially or systematically from the RNNE prediction.*

HYPOTHESIS 2: *Announcing x_L, the lowest private information signal, raises average seller's revenues by the average amount predicted under the RNNE model.*

HYPOTHESIS 3: *Under private information conditions, experienced bidders avoid the winner's curse as average profits are closer to the RNNE level than the zero/negative profits predicted under the winner's curse.*

HYPOTHESIS 4: *Public information raises average seller's revenue.*

HYPOTHESIS 5: *Hypotheses* 3 *and* 4 *apply uniformly to experiments with small and large numbers of bidders.*

HYPOTHESIS 6: *Bidders are sensitive to the strategic implications of the auctions so that when the strategic discounting model and the RNNE model coincide, the RNNE model provides a reasonable characterization of the data.*

Hypotheses 1 and 2 involve strong predictions, which if satisfied would imply satisfaction of all the other hypotheses as well. Hypotheses 3–5 involve weaker predictions which may be satisfied even though Hypotheses 1 and 2, strictly interpreted, fail. Nevertheless confirmation of these weaker predictions would indicate that the RNNE model provided a reasonable "ballpark" characterization of behavior in general: that for experienced bidders, at least, the repeated nature of market decision processes in conjunction with survival pressures and profit opportunities, eliminate the judgmental failures underlying the winner's curse. Further, conditional on the confirmation of Hypotheses 3–5, one of the key policy implications of the theory, the revenue-enhancing effects of public information, would be reasonably accurate as well.

Finally, Hypothesis 6 captures the notion that bidders in private value auction experiments have been shown to be sensitive to the strategic implications inherent in these auctions. Hence, we would expect the RNNE model to perform well here when its predictions coincide with strategic discounting. If Hypothesis 6 is satisfied, but Hypotheses 1–5 are not, we have indirect evidence that it is the judgmental errors underlying the

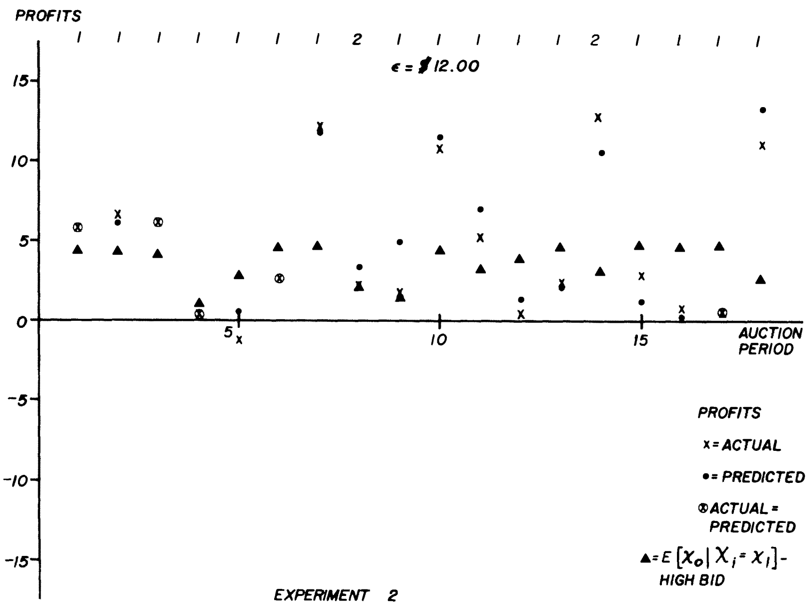


FIGURE 1

winner's curse that are responsible for the breakdown in the model's performance.

III. Experimental Results

A. *Bidding Patterns with Private Information*

Figures 1–5 provide representative data for market outcomes over time. The rank of the high bidder's signal value is shown at the top of each figure: 1 for the highest signal value, 2 for the second highest, etc. Closed triangles show the difference between $E[x_0|X_i = x_1]$ for the high bidder and the high bid. A negative (positive) value here indicates that the high bid exceeded (fell below) $E[x_0|X_i = x_1]$, implying negative (positive) expected profits should the high signal holder win the auction. Cross marks show actual profits earned, with closed circles showing profits predicted under the RNNE: cross marks below (above) closed circles indicate that the actual bid exceeded (was less than) the RNNE prediction and by how much. Eyeballing the data, there appears to be little systematic variation in bids over time, within a given auction series, independent of variations in N and ε.

Table 2 provides summary statistics of auction outcomes.[19] Columns 4–6 show, respectively, actual profits earned, profits predicted under the RNNE, and profits earned as a percentage of the RNNE prediction. For comparative purposes, column 3 shows profits predicted under the strategic discounting formulation (profits predicted using the bid function 6, assuming that the highest signal holder always won the auction). The last two columns report the average frequency with which the high signal holder won the item, and the frequency with which the high bid exceeded $E[x_0|X_i = x_1]$.

[19]Our computations include all auctions under dual market procedures, regardless of whether bidders actually made profits (or losses) as a consequence of our coin flip procedure. Since the coin flip was made after bids from both markets had been accepted, its outcome should not affect decisions. Experiments involving experienced, as opposed to super-experienced, subjects had one or more dry runs with no money at stake. These auction periods are *not* included in the analysis.

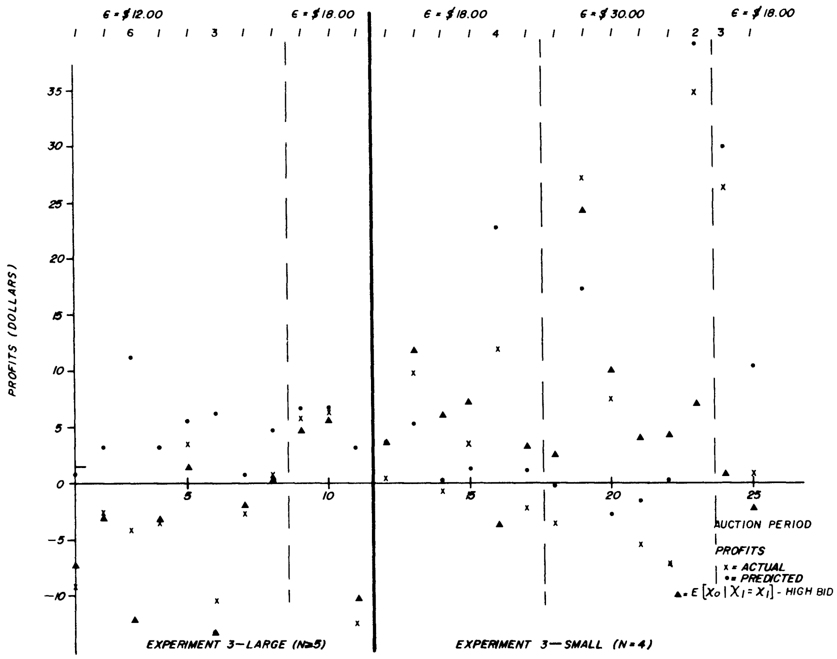


FIGURE 2

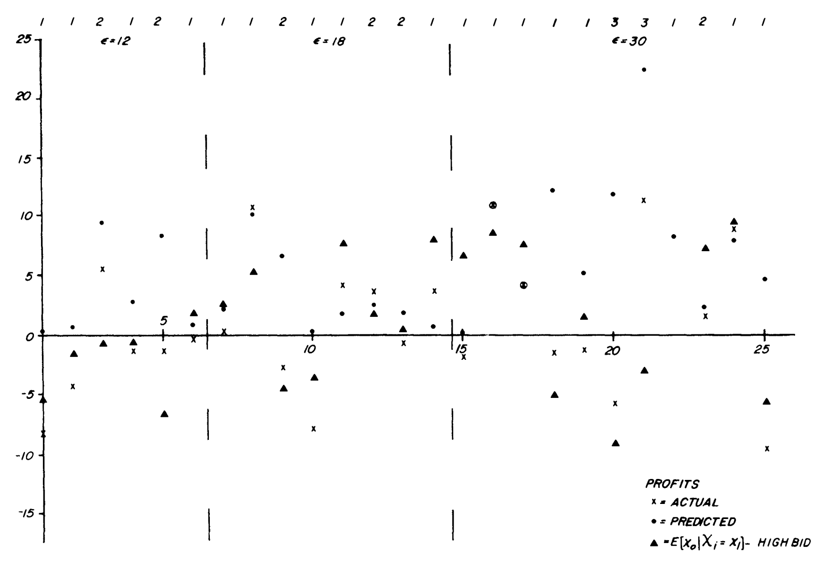


FIGURE 3

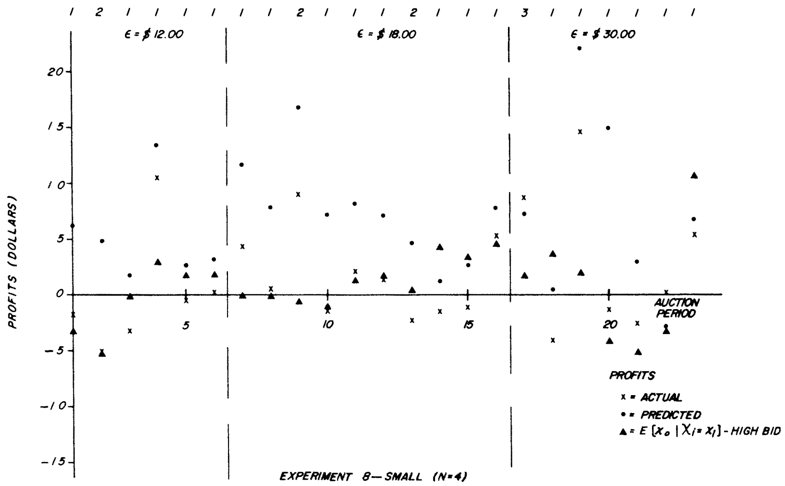


FIGURE 4

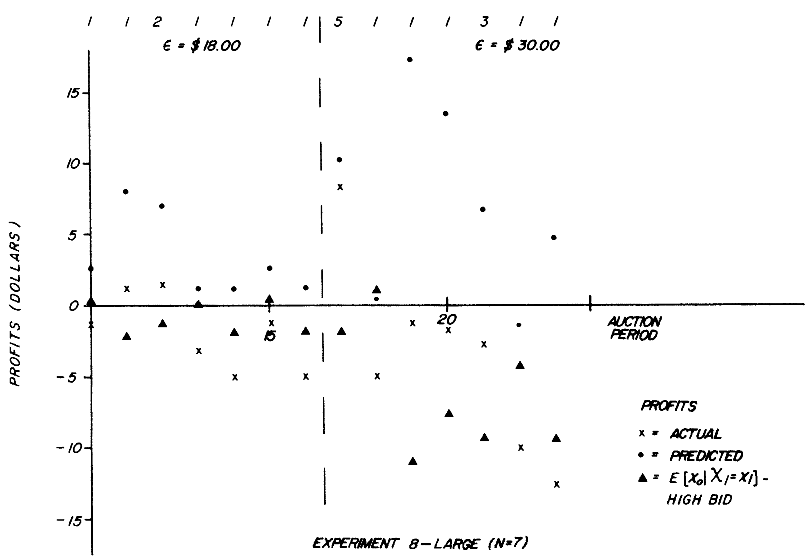


FIGURE 5

The auction series were ordered by the number of active bidders, beginning with the small group experiments, as we kept drawing the same conclusion: there were substantial differences in the ability of the RNNE bidding model to provide a ballpark characterization of the data in auctions involving small numbers (3–4) of bidders compared to those with large numbers (6–7) of bidders. In auction series that began with small numbers of bidders, one can observe bankruptcies (series 6) and some bidding in excess of $E[x_0|X_i = x_1]$. There was at least one large group series where average profits were positive and bidding was generally below $E[x_0|X_i = x_1]$ (series 7 large). However, the

TABLE 2—PROFITS AND BIDDING BY EXPERIMENT AND NUMBER OF ACTIVE BIDDERS: PRIVATE INFORMATION CONDITIONS (Profits measured in dollars)

Auction Series (No. of Periods)	No. of Active Bidders	Average Profits with Strategic Discounting (standard error of mean)	Average Actual Profits (t-statistic)[a]	Average Profits Under RNNE (standard error of mean)	Profits as a Percentage of RNNE Prediction	Percentage of Auctions Won by High Signal Holder	Percentage of High Bids $b_1 > E[x_0 \mid X_i = x_1]$
6 (31)	3–4	3.25 (1.51)	3.73 (2.70)[b]	9.51 (1.70)	39.2	67.7	22.6
2 (18)	4	−.75 (1.07)	4.61 (4.35)[c]	4.99 (1.03)	92.6	88.9	0.0
3 small (14)	4	−3.82 (2.40)	7.53 (2.07)	6.51 (2.65)	115.7	78.6	14.3
7 small (19)	4	−.12 (1.56)	5.83 (3.35)[c]	8.56 (2.07)	68.1	63.2	10.5
8 small (23)	4	−2.24 (1.05)	1.70 (1.56)	6.38 (1.21)	26.6	84.6	39.1
1 (18)	5	−1.90 (.85)	2.89 (3.14)[c]	5.19 (.86)	55.7	72.2	27.8
3 large (11)	5–7	−5.19 (.55)	−2.92 (−1.49)	3.65 (.62)	−80.5	81.8	63.6
7 large (18)	6	−10.11 (.96)	1.89 (1.67)	4.70 (1.03)	40.2	72.2	22.2
4 (25)	6–7	−10.03 (1.05)	−.23 (−.15)	4.78 (.92)	−4.8	69.2	46.2
5 (26)	7	−8.07 (1.04)	−.41 (−.44)	5.25 (1.03)	−7.8	42.3	65.4
8 large (14)	7	−11.04 (1.35)	−2.74 (−2.04)	5.03 (1.40)	−54.8	78.6	71.4

[a]Tests null hypothesis that mean is different from 0.0.
[b]Significant at 5 percent level, 2-tailed t-test.
[c]Significant at 1 percent level, 2-tailed t-test.

general pattern was one of positive average profits in small groups which, while well below the RNNE criteria, were clearly closer to the RNNE prediction than the zero/negative profit levels of the winner's curse: profits averaged across experiments with 3–4 bidders were \$4.68 per auction period, about 65.1 percent of the RNNE models prediction of \$7.19 per auction period.[20] In contrast, auctions involving 6–7 bidders had average actual profits of −\$.88 per auction period. While this is substantially better than profits predicted under strategic discounting, −\$8.89, indicating considerable adjustment to the adverse-selection problem, these adjustments were far from complete, as profit levels were negative, closer to the winner's curse prediction than the RNNE prediction of \$4.68 per auction period. Further, comparing large and small group auctions, actual profits decreased substantially more than profit opportunities as measured by the RNNE criteria. The latter profit criteria dropped by \$2.51 per auction period, while actual profits fell by \$5.56. Thus, in going from small to large groups, profit perfor-

[20]Averages reported here and elsewhere in the text are simple, unweighted averages across experiments, unless noted otherwise. All RNNE profit calculations are exact, based on the bid function in (2) and fn. 8.

TABLE 3—PROFITS AND BIDDING UNDER VARYING LEVELS OF ε
(All profits in dollars)

No. of Bidders	ε	Average Profits with Strategic Discounting (standard error of mean)	Average Actual Profits (t-statistics)[a]	Average Profits Under RNNE[b] (standard error of mean)	Profits as a Percentage of the RNNE Prediction
3–4	12	−1.24	2.60	4.52	57.5
		(.69)	(1.74)	(1.44)	
	18	−.24	3.98	7.20	55.4
		(1.03)	(3.71)[d]	(1.05)	
	24/30	.60	6.75	11.22	60.2
		(1.94)	(3.33)[d]	(2.06)	
6–7	12	−3.68	−1.86	3.46	−53.8
		(.54)	(−2.21)[c]	(.56)	
	18	−8.51	−.95	3.19	−29.8
		(.52)	(−1.00)	(.51)	
	24/30	−12.31	.60	7.12	8.4
		(.89)	(.51)	(.94)	

[a] Tests null hypothesis that mean is different from 0.0.
[b] Based on sample of signal values drawn.
[c] Significant at 5 percent level, 2-tailed t-test.
[d] Significant at 1 percent level, 2-tailed t-test.

mance deteriorated above and beyond that predicted under the RNNE.

In both small and large groups, the bidder with the high private information signal generally won. Averaging across auction series, the percentages were 76.6 and 68.8 percent for small and large groups, respectively. Thus, the adverse-selection mechanism hypothesized to underly the winner's curse was present for both group sizes. The high bid, b_1, was below $E[x_0|X_i=x_1]$ in 82.7 percent of all auctions involving small number of bidders, but was below this value in only 46.2 percent of those auctions involving large numbers. The judgmental errors underlying the winner's curse were largely absent in small groups, but were quite prevalent in larger groups.[21]

Table 3 shows the relationship between profits and ε where the averages are computed over auction periods. We continue to distinguish between auctions involving small (3–4) and large (6–7) numbers of bidders, and pool the data for $\varepsilon=24$ and $\varepsilon=30$ as there were relatively few observations at $\varepsilon=24$. In auctions involving small numbers of bidders, actual profits increased with increases in ε and constituted a relatively stable fraction of the profits predicted under the RNNE. With large numbers of bidders (6–7), average losses decreased with increases in ε, with positive average profits earned at $\varepsilon=24$–30. Reduced losses with ε increasing implies that bids were reduced proportionately more relative to signal values. A stable proportionate discount in terms of ε would have resulted in larger absolute dollar losses as ε increased.[22] Instead, sub-

[21] The adverse-selection discount identifying the winner's curse fails to account for the high signal holder not always winning the item. Bidders should have been responsive to this and used a smaller adverse-selection discount based on actual frequencies with which different ranked signal holders won. Since over 90 percent of all auctions were won by the first- or second-highest signal holder, $E[x_0|X_i=x_2]$ serves as a reasonable *upper* bound on the relevant discount. Using this measure, less than 1 percent of all small group auctions had a winner's curse, while 28.7 percent of all large group auctions did. Our conclusion regarding the differential frequency of the winner's curse in large and small groups is unaffected, although the overall frequency is reduced substantially.

[22] Recall that $E[x_0|X_i=x_1]$ is decreasing in ε.

jects took advantage of the increased profit opportunities inherent in the increased value of ε.

We used multiple regression analysis to summarize and quantify the influences on bidding in the private value auctions. Using an error components model, and restricting our analysis to signal values in the interval (1), Table 4 shows the results of two alternative bid function specifications.[23] The first regression involves a generalized version of the bid function (2), allowing for a nonzero intercept and including numbers of bidders as a right-hand side variable. Under this specification, both the intercept coefficient and the coefficient associated with the variable Y in (2) were not significantly different from zero. The second regression drops these two terms. Under both specifications, the x_i critically influences bids with an estimated coefficient value close to 1.0, as implied under the RNNE bid function and under strategic bidding. Further, bidders were clearly sensitive to changes in ε, so that we can soundly reject any naive bidding models which postulate a constant, fixed discount relative to x_i. On the other hand, the coefficient on ε is significantly below unity, and this contradicts the RNNE bid function. These results parallel those from private value auctions, where increases in the distribution of underlying values resulted in lower bids, but these bids were not reduced as much as predicted under the risk neutrality hypothesis (Kagel, Harstad, and Levin). Finally, the aggressive forces associated with increased numbers of bidders win out over the item valuation influences, as we find a statistically significant, positive coefficient associated with N under both specifications. The increased aggressiveness of individual bids with increases in N is in direct contradiction to the predictions of the RNNE bidding model. It adds to the dilution of bidders profits associated with increased N predicted under the RNNE, with the net result a persistent winner's curse with $N=6$ or 7.

TABLE 4—ERROR COMPONENTS ESTIMATES OF BID FUNCTION IN PRIVATE INFORMATION MARKETS[a]

$$b(x_i) = -\underset{(3.36)}{4.30} + \underset{(.002)}{1.00x_i} - \underset{(.03)}{.73\varepsilon} + \underset{(.16)}{.70N} - \underset{(.14)}{.02Y} \qquad R^2 = .99 \quad \sigma_\eta = 4.94$$

$$b(x_i) = \underset{(.002)}{1.00x_i} - \underset{(.03)}{.74\varepsilon} + \underset{(.15)}{.65N} \qquad R^2 = .99 \quad \sigma_\eta = 4.94$$

[a]Standard errors are shown in parentheses.

Learning patterns over time are not explored in detail here. The interested reader should consult Kagel et al. (1986) where individual learning patterns of inexperienced bidders are analyzed. The data reported there show considerable learning on survivors part, as most start out bidding in excess of $E[x_0|X_i=x_1]$. Comparing the results here with end-of-experiment performance for these inexperienced bidders shows continued learning as well: averaging over the last 5 periods of 5 auction series of 3–4 inexperienced bidders shows 28 percent of all high bids in excess of $E[x_0|X_i=x_1]$ (compared to 17.3 percent here) with profits averaging 27.5 percent of the RNNE prediction (compared to 65.1 percent here).[24] It is important to note, however, that the learning resulting in the strong performance of the RNNE model in small groups appears to be situationally

[23]An error components specification was employed, with error term

$$\eta_{it} = u_i + v_{it} \qquad i=1,\dots,N; \quad t=1,\dots,T;$$

where u_i is a subject-specific error term, assumed constant subject across auction series, and v_{it} is an auction period error term. Standard assumptions were employed: $u_i \sim (0,\sigma_u^2)$ and $v_{it} \sim (0,\sigma_v^2)$ where u_{it} and v_{it} are independent among each other and among themselves. Badi Baltagi's (1986) weighted least squares computational procedure was used to invert the variance-covariance matrix. A fixed-effects error specification generated similar coefficient estimates and standard errors. Permitting the u_i to vary with subject participation in different auction series yields similar estimates except for the variable N, which increases in value with no loss in statistical significance.

[24]There are no large group end-of-experiment data from the inexperienced subject experiments to compare with the results reported here, as bankruptcies precluded keeping groups of 6–7 bidders intact for very long.

TABLE 5–EFFECTS OF PUBLIC INFORMATION ON SELLER'S REVENUES
(All revenue figures in dollars)

Acution Series (No. of Periods)	No. of Active Bidders	Average Change in Revenues: Actual (t-statistic)[a]	Predicted (standard error of mean): RNNE Model	Predicted (standard error of mean): Strategic Discounting
6	3–4	4.38	7.62	1.38
(23)		(2.71)[b]	(1.54)	(1.41)
3 small	4	−2.71	3.83	−6.51
(14)		(−.99)	(2.05)	(1.58)
7 small	4	6.58	7.46	−3.46
(11)		(2.79)[b]	(1.74)	(1.52)
7 large	6	.22	1.64	−13.16
(18)		(.15)	(.87)	(1.26)
4	6–7	−3.20	1.25	−15.75
(18)		(−1.36)	(.82)	(1.07)
5	7	−2.40	2.43	−12.34
(20		(−1.83)	(.86)	(1.30)

[a] Tests null hypothesis that mean is 0.0.
[b] Significant at 5 percent level, 2-tailed t-test.

specific, and does not provide the "understanding" to respond appropriately to increased numbers of rivals (see Table 4), or to avoid the winner's curse in large group auctions.

B. *Effects of Public Information on Seller's Revenues*

Table 5 shows the actual effects of announcing x_L on average revenues and the predicted effects under both the RNNE and the strategic discounting models. As in Table 2, we have ordered the results by number of active bidders.

Averaging across the 3 auction series with small numbers of bidders, x_L raises revenues an average of \$2.75 per auction period. Pooling auction periods, a t-test shows this to be statistically significant ($t = 2.41$, $p < .02$, 1-tailed test), although well below the RNNE prediction of a \$6.30 increase in revenues. Public information reduced revenues in series 3, the auction series which came closest to the RNNE model's predictions under private information conditions. Nevertheless, this seems like an anomaly rather than the norm, since under all other conditions where the winner's curse was weak or nonexistent, as it was in series 6 and series 7 small and large, revealing the low information signal, x_L, raised seller's revenues (also see the discussion that follows).

Averaging across auctions with large numbers of bidders, public information *reduced* seller's revenues \$1.79 per auction period. A t-test based on pooled observations indicates that this decrease is statistically significant ($t = -1.48$, $p < .08$, 1-tailed test). While the reduced revenues are well below the predictions of the strategic discounting model, they are opposite in sign and magnitude to the RNNE model which calls for a \$1.78 *increase* in revenue.

A within-auction series analysis reinforces the importance of the winner's curse in determining whether public information raises or lowers revenues. The first two columns of Table 6 show the effects of announcing x_L conditional on the presence or absence of a winner's curse in large group auctions, for those auction periods where the RNNE model predicts an increase. A *chi*-square test shows the winner's curse to significantly affect the validity of the RNNE model's prediction ($\chi^2 = 4.25$, $p < .05$). The third

TABLE 6—EFFECTS OF THE WINNER'S CURSE ON REVENUE RAISING EFFECTS OF PUBLIC INFORMATION[a]

	Number of Periods in Auction		
	Large Numbers (6–7)		Small Numbers[b] (3–4)
Change in Seller's Revenues	Winner's Curse	No Winner's Curse	No Winner's Curse
Increase	6	12	29
Decrease	11	5	10

[a]Auction market periods where RNNE predicted an increase in seller's revenues. Winner's curse defined in terms of high bid in private information market in excess of $E[x_0|X_i = x_1]$.

[b]Winner's curse present in 3 auction periods where RNNE predicts increase in seller's revenues. Hence omitted.

column of the table shows the effects on revenue in the absence of a winner's curse in the small group auctions. The pattern here is much the same as found in auctions with 6–7 bidders in the absence of a winner's curse ($\chi^2 = .086$).[25]

In the two auction series where public information consisted of posting an additional, randomly drawn, private information signal, public information raised revenues $.27 per auction (an average increase of −$.80 in experiment 1 and $1.33 in experiment 2). Note that neither of these series exhibited significant traces of the winner's curse under private information conditions. In contrast, in an earlier series of experiments involving inexperienced subjects, revealing a random public information signal consistently *reduced* revenues, in this case by an average of $2.95 per auction (Kagel et al., 1984). In 2 of these 4 auction series, average profits were negative under private information conditions, while in 3 of the 4, the high bid exceeded $E[x_0|X_i = x_1]$ in 40 percent or more of the auctions. These results serve to reinforce the hypothesis that an absence of a winner's curse is a necessary condition for public information to raise average revenues.

[25]Results similar to these have been found in a companion series of 6 second-price common value auction experiments.

Table 7 reports market outcomes relative to the RNNE model's predictions with x_L announced. Average actual profits were positive in all experiments. While there is considerable variation in profits relative to the RNNE model's predictions across auction series (especially series 3 and 6), on average profits were only slightly less than predicted ($3.20 actual vs. $3.41 predicted). Further, unlike private information conditions, there were no systematic differences in realized profits relative to predictions as the number of active bidders varied. These results, at the market level at least, are consistent with our earlier suggestion that the RNNE model would provide a more accurate characterization of performance with x_L announced, compared with private information conditions.

More detailed analysis of the data, however, shows that more is at work here than simple strategic discounting with all bidders employing identical bid functions. With x_L announced, there is almost a complete breakdown of the prediction that the bidder with the highest private information signal wins the auction. In these experiments the high private information signal holder won only 29.5 percent of all auctions. This is only modestly above what one would expect if chance factors alone determined whether the high private signal holder won, an expected frequency of 21.8 percent.

TABLE 7—PROFITS AND BIDDING WITH PUBLIC INFORMATION (x_L)
(All profits in dollars)

Auction Series (No. of Periods)	No. of Bidders	Average Actual Profits (t-statistic)[a]	Average Profits Under RNNE (standard error of mean)	Profits as a Percentage of RNNE Prediction	Percent of Auctions Won by High Signal Holder
6 (23)	3–4	.15 (.08)	2.96 (1.60)	5.1	30.4
3 small (14)	4	10.24 (3.33)[c]	2.68 (2.03)	382.0	21.4
7 small (11)	4	2.07 (.86)	4.54 (2.00)	45.6	18.2
7 large (18)	6	1.67 (1.56)	3.06 (.62)	54.6	27.8
4 (18)	6–7	3.43 (2.24)[b]	4.14 (1.04)	82.9	44.4
5 (20)	7	1.64 (1.62)	3.06 (.86)	53.6	35.0

[a]Tests null hypothesis that mean is 0.0.
[b]Significant at 5 percent level, 2-tailed t-test.
[c]Significant at 1 percent level, 2-tailed t-test.

Detailed examination of the data shows a handful of bidders (20.0 percent) winning a disproportionately large number (57.7 percent) of the auctions with x_L announced. This handful of bidders did quite well as a group, earning average profits of \$2.79 per auction period won, as compared to \$2.89 for all other bidders. A distinguishing characteristic of these bidders is that they were relatively more aggressive than their rivals under private information conditions (ranking bids as a fraction of signal values consistently placed them in the top half of all bidders). The increased aggressiveness of this handful of bidders in the public information markets (they won only 15.1 percent of all private information auctions in which they did not have the highest private information signal, compared to 54.7 percent of the corresponding public information auctions) is directly attributable to the sharp reduction in beliefs about the underlying value of item inherent in announcing x_L. This reduction in the effective dispersion of information concerning x_0 permitted differences in risk attitudes and information processing capacities to play an increased role in the outcomes of auctions with public information.[26]

Table 8 reports the results of statistical estimates of individual bid functions with x_L announced. Recall from (8) that the parameters associated with the variables x_L and x_i are a function of the number of bidders present. The specifications in Table 8 employ different slope coefficients for these variables in small group ($N = 3$–4) and large group ($N = 6$–7) cases. With $N = 3$–4, the estimated slope coefficients for public and private information, are close to the theoretical bid function prediction (with $N = 4$, these are .67 and .33 for public and private information, respectively). With $N = 6$–7, more weight is attached to public rather than

[26]However, these bidders were unable to overcome the inherent disadvantage of holding only public information, as their average profits did not deviate significantly from zero in cases where they held the low private information signal.

TABLE 8—ERROR COMPONENTS ESTIMATES OF BID FUNCTION IN MARKETS WITH x_L ANNOUNCED

$b(x_i, x_L) = -\ .95 + .24x_i - .07x_i^* + .72x_L + .12x_L^* + .14\varepsilon + .08N$ (6.2) (.05) (.06) (.05) (.06) (.07) (.70)	$R^2 = .98$ $\sigma_\eta = 7.39$
$b(x_i, x_L) = .24x_i - .07x_i^* + .72x_L + .12x_L^* + .14\varepsilon$ (.05) (.05) (.05) (.06) (.06)	$R^2 = .98$ $\sigma_\eta = 7.37$

Note: $x_i^* = x_i$ if $N = 6$ or 7, $x_i^* = 0$ otherwise; $x_L^* = x_L$ if $N = 6$ or 7, $x_L^* = 0$ otherwise.

[a]Standard errors are shown in parentheses.

private information, in contrast to the theoretical bid function prediction (with $N = 7$, predicted weights are .58 and .42, respectively). Further, ε has a modest positive, statistically significant, effect on bids, contrary to the predictions of both the RNNE and strategic discounting models, in which x_L and x_i capture all the information necessary (recall equation (8)).

C. *Summary of Experimental Outcomes of Primary Interest*

The data permit us to reach clear conclusions regarding the research hypotheses of primary interest specified in Section II, subsection 3. With respect to Hypotheses 1 and 2, we reject the strong form of the RNNE bidding model, irrespective of the number of rivals in the market or whether the market involves private or public information. Bidding consistently exceeded the RNNE prediction in private information markets, was highly variable relative to the RNNE reference point in markets with public information, and x_L failed to raise revenues by the predicted amount, even in markets without a winner's curse. The weak form of the RNNE model consistently outperformed the winner's curse and the strategic discounting model in markets with small numbers of rivals, consistent with Hypotheses 3 and 4. However this ballpark characterization of the data failed on both counts in markets with large numbers of rivals, leading us to reject Hypothesis 5. Finally, bidders were sensitive to the strategic implications of the auctions, responding correctly to variations in ε and coming close, on average, to the RNNE model's prediction with x_L announced. This confirms Hypothesis 6, which in turn suggests that the rejection of Hypotheses 1–5, particularly the rejection of Hypothesis 5, follows from the judgmental errors underlying the winner's curse.

IV. Towards Generalizability: But Is This How the Real World Operates?

A common criticism of experimental research in economics is that behavior in the laboratory is unlikely to be representative of field behavior. This criticism increases, as well it should, with the degree to which laboratory behavior deviates from accepted economic theory and common understanding of what constitutes "rational" economic behavior. Critics argue that auction market subjects, MBA students and senior undergraduates, are inherently less sophisticated, and clearly less experienced, than executives in the relevant industry, that experimental subjects do not have as much time to think and respond to events as industry executives, and that they lack the assistance of expert advisors that many industries have, to cite some of the prominent criticisms we have encountered. One can rebut these arguments on grounds that the experimental designs drastically simplify the decision-making structure, thereby obviating the need for expert advisors and reducing time requirements to make sensible decisions. Further, experimental subjects receive substantially more feedback, with shorter delays, regarding the outcomes of their decisions, so that the feedback loops that promote learning and adjustment over time are substantially stronger for experimental subjects compared to industry executives. (This is particularly true in the case of OCS lease sales where executives know that returns on investment will only be revealed years after bids have been accepted, and the responsible parties might well be in different positions within the company, or moved to a rival firm.)

Logical arguments can only go so far in debates of this sort. The question posed here is, what do the relevant data outside the laboratory look like compared to laboratory-generated data? Is the same model capable of organizing behavior in both settings? Do the field data obviously contradict the laboratory data?

The remainder of this section examines these issues in the context of the U.S. government's outer continental shelf lease sales. Note that our objective here is not to definitively test between competing explanations using field data. If we thought the field data had this kind of potential, there would be no need to resort to laboratory experiments in the first place (see Vernon Smith, 1982, and Charles Plott, 1982, for general discussions of the problems involved in using field data to test between models of market behavior and the advantages of laboratory experiments). Rather, our objective is to show that a reasonable analysis of the available data does not falsify the hypothesis that similar economic processes are at work in both settings. If this can be done, the burden of proof rests on those who would argue that the results don't generalize to demonstrate that their arguments are correct.

The concept of a winner's curse arose from petroleum geologists analysis of OCS bidding patterns and industry based calculation of rates of return from winning lease sales (Capen et al.; Lorenz and Dougherty). In a more recent analysis, Walter Mead, Asbjorn Moseidjord, and Philip Sorensen (1983) found after-tax rates of return on all OCS leases in the Gulf of Mexico issued from 1954 to 1969 to be less than average returns on equity for U.S. manufacturing corporations. Mead et al. view lease purchases as high risk investments and conclude that "...they (lessees) have historically received no risk premium and may have paid too much for the right to explore for and produce oil and gas on federal offshore lands" (1983, pp. 42–43).[27] In light of the effects of public information on bidder's profits reported here, a second element of Mead et al.'s (1983) calculations, namely rate of return *differentials* between drainage and wildcat leases, provides important corroborating evidence for the argument that lessees probably paid "too much" in these early OCS lease sales. The remainder of this section details this argument.[28]

A wildcat lease involves a tract for which there are no drilling data available that would indicate potential productivity. When a hydrocarbon reservoir has been located on a wildcat tract that is expected to extend into adjacent unleased acreage, the adjacent tract is defined by the U.S. Geological Service (USGS) as a drainage tract. Considerably more information is available regarding the economic potential of drainage than wildcat tracts. This information has both public and private components. An important public information component is that drainage tracts are unlikely to be dry, thereby significantly reducing the uncertainty (relative to wildcat tracts) that hydrocarbons will be found. However, developers of the wildcat tract (called neighbors) are likely to have superior private information relative to non-neighbors regarding the quantity of oil likely

[27]There is some argument as to whether investors require risk premiums for investing in oil and gas leases. A number of writers suggest that risk-averse bidders would require a premium relative to investing in alternative activities. Others, one of our referees included, argue that large oil companies with access to capital markets and having a diversified portfolio of leases would not be expected to earn risk premiums.

[28]Our analysis is not concerned with absolute rates of return, or absolute present discounted value calculations, for OCS sales compared to other industries. Rather, we are concerned exclusively with *differences* in rate of return between drainage and wildcat leases. Differential rate calculations within an industry, by the same research team, should be relatively more robust to the empirical problems encountered in obtaining such measure than comparisons across industries by different research groups.

to be found, oil pressures, and other significant seismic information.[29]

If the information available on drainage leases were purely public, it should, according to Nash equilibrium bidding theory, raise average seller's revenues, hence reducing bidder's profits (recall Section II).[30] If the information were purely private, under Nash equilibrium bidding theory it would increase the rate of return for insiders (neighbors) relative to outsiders (nonneighbors), *and* reduce the average rate of return for nonneighbors below what would be earned in the absence of insider information (Wilson, 1975a, b; M. Weverbergh, 1979). If the added information on drainage leases contains both public and private information elements, rates of return for neighbors should be greater than for nonneighbors, but with nonneighbor returns definitely less than in the absence of the additional information (both the public and private information components push in this direction for nonneighbors).

What Mead et al. found were higher rates of return on drainage compared to wildcat leases for *both* neighbors (88.6 percent higher) *and* nonneighbors (56.2 percent higher). Further, nonneighbors won 43.2 percent of all drainage leases. While the higher rate of return for neighbors compared with nonneighbors can be explained by the presence of insider information (the explanation Mead et al. offer, 1983, 1984), the substantially higher rates of return for nonneighbors remains puzzling within the context of Nash equilibrium bidding theory. However, the higher rate of return for *both* neighbors and nonneighbors on drainage leases is perfectly consistent with our experimental findings, given the existence of a winner's curse in bidding on wildcat leases. According to this explanation, the additional information available from neighbor tracts served to correct for the overly optimistic estimate of lease value recorded in the average winning bids on wildcat tracts, thereby raising average profits for both neighbors and nonneighbors alike. In this respect, the OCS lease data parallel our experimental results with public information in the presence of a winner's curse.

What alternative explanations are available to explain *both* nonneighbors and neighbors rates of return being higher on drainage leases? Mead et al. suggest two alternatives. First, one might argue that the lower rate of return on wildcat leases reflects the option value of the private information consequent on discovering hydrocarbons. The higher rate of return of neighbors over nonneighbors on the drainage leases certainly suggests that neighbors had valuable proprietary information, the prospect of which would depress the value of the wildcat leases. However, returns to this proprietary information were far from certain to be realized, while the differential overall rate of return on leases in the Gulf, counting wildcats alone vs. counting wildcats plus drainage leases, was small, amounting to 7 percent of the wildcat rate of return (Mead et al., 1983). Thus the revealed value of the option is small and is unlikely to fully account for the depressed rate of return on wildcats relative to nonneighbors. Second, one can argue that the existence of insider information (and its common knowledge) scared off nonneighbors so that they did not bid, or bid very little, relative to lease value. Consequently, when nonneighbors won, since they bid quite low, they obtained higher rates of return as well. However, the frequency with which nonneighbors won drainage leases seems inconsistent with this argument.[31] To be sure,

[29] Only drainage leases have neighbors, namely those responsible for the development of the neighboring wildcat tract.

[30] All leases had the same royalty rate and were allocated on the basis of a first-price cash bonus bid. Drainage leases were spread throughout the Gulf so that each lease is likely to represent an independent pool of oil (Asbjorn Moseidjord, personal communication). The revenue-raising (profit-reducing) effects of public information in the RNNE model are expectations based on samples of independent observations (Milgrom and Weber). Hence, the drainage lease sample satisfies the assumptions of the model.

[31] Under Nash equilibrium bidding theory, it is not perfectly clear what ought to happen to the frequency

the average number of bids on drainage leases was less than on wildcats (2.88 vs. 3.33), but the data suggest only a modest 6.4 percent decline in the rate of return in going from leases with 2 bids to leases with 3–4 bids (Mead et al., 1983; 1984).[32]

Note that we do not dispute Mead et al.'s (1984) argument that neighbors had proprietary information leading to higher rates of return on drainage leases than wildcats, or on drainage leases relative to nonneighbors. What we are claiming is that this proprietary information does not fully account for the substantially higher rates of return on drainage leases over wildcat leases for *both* neighbors and nonneighbors alike. Rather this element of the data is more readily explained by the public information component of the drainage lease designation, in conjunction with a winner's curse on wildcat leases. This explanation has the virtue of parsimony and consistency with the experimental results reported here.[33]

Our analysis of field data has been limited to 1954–69, prior to the publication of Capen et al.'s article alerting the industry to the presence of a winner's curse, and suggesting ways to avoid it. Many would argue that adjustments in bidding in the 1970's, partly in response to Capen et al.'s article and related publications, has eliminated the winner's curse in OCS lease sales, although opinions are not unanimous on the subject (see Lorenz and Dougherty, for example). We know of no rate-of-return studies on drainage vs. wildcat leases for the 1970's similar to Mead et al.'s for the 1960's that might help resolve the issue. We do know that at times there are significant discrepancies between cognitive understanding of the "right" thing to do and actual behavior. For mineral rights auctions, this involves firms recognizing and admitting that their geologists' estimates of value (and their economists' estimates of future price) have a significant error component, and that in the absence of insider information are unlikely to be better (on average) than their rivals. Such an admission is no small matter when paying substantial salaries to these professionals. As such we reserve judgment for the moment on the issue of a continuing winner's curse in OCS sales. Even assuming elimination of a winner's curse in more recent OCS lease sales does not affect our argument here, however: the available data outside the laboratory are consistent with data inside it

with which the informationally disadvantaged will win auctions. We suspect that this depends critically on the underlying distributions of item value and private information signals, and the nature of the insider information. However, all formal Nash equilibrium bidding models developed to date have the less informed earning lower profits than under symmetric information conditions (Wilson, 1975a, b; Weverbergh).

[32] Numbers of bidders in field environments is endogenous, depending in part on perceived lease value, rather than exogenous, as commonly treated in the auction market literature (and as one can arrange for in the laboratory). As such it is far from clear why, in theory, rates of return should vary systematically with numbers of bidders in field environments, unless again we postulate the existence of a winner's curse that is exaggerated with increased numbers of bidders.

[33] Drainage tracts have sharply reduced exploration costs as there are substantially fewer dry holes drilled per lease than on wildcats. Further, there are reduced production costs as a consequence of existing investments on neighbor leases and possibilities of joint production. In efforts to reconcile Mead et al.'s (1983) estimates of higher rates of return on drainage leases with their own estimates that prior drilling raised seller's revenues in the Gulf, Jeffrey Leitzinger and Joseph Stiglitz (1984) argue that developers capture at least some of the rent associated with reduced production costs on drainage leases. No explanation is offered for how this can plausibly account for the full differential rate of return between wildcat and drainage leases. Nor why, since these savings are public knowledge and contain a strong common value element, traditional motions of rent capture in competitive markets should fail. (Reduced production costs are in large measure available to both neighbors and nonneighbors as a consequence of the federal government's ability to force unitization, and the strong effects of these enforcement powers on voluntary unitization of tracts; see Gary Liebcap and Steven Wiggins, 1985.) An alternative explanation is that Mead et al.'s rate of return estimates are incorrect. However, there are equally strong, if not stronger, reasons to suppose that Leitzinger and Stiglitz's estimates of information externalities, which are based on the size of the bonus bid on drainage compared with wildcat leases, are highly exaggerated, as the public information component associated with the drainage lease designation is systematically biased towards raising the expected value of these leases.

in the absence of extensive efforts to alert bidders to the presence of a winner's curse.

V. Conclusions

Our experiments provide an empirical example of a market where individual judgment errors significantly alter market outcomes. Bidders in common value auctions, as in other auctions, are sensitive to the strategic opportunities inherent in the auction process. However, when strategic considerations and adverse-selection forces resulting from uncertainty about the value of the item conflict, behavior fails to conform, in important ways, with the requirements of Nash equilibrium bidding strategies.

Although we reject the general applicability of Nash equilibrium bidding models, market outcomes come closer to the risk-neutral Nash equilibrium model's predictions than to the winner's curse in auctions with small numbers (3–4) of bidders. In addition, there is considerable adjustment to the adverse-selection problem with large numbers (6–7) of bidders. However, these adjustments are far from complete, as profit levels are consistently negative, in conformity with the winner's curse. The existence of a winner's curse in large groups, in conjunction with the positive effect of the number of bidders on the size of individual bids, indicates that avoidance of the winner's curse in small groups is specific to the situation, and does not carry over to auctions with larger numbers of bidders. Bidders have learned to avoid the winner's curse in small groups out of a trial and error survival process, as opposed to "understanding" the adverse-selection problem as it applies to new situations.

Accounting for judgmental errors in these markets has some practical policy implications in terms of whether sellers choose to obtain and release information narrowing down the value of the auctioned item. In the absence of judgmental errors, this information clearly enhances seller's revenues, as Nash equilibrium bidding theory predicts. In the presence of judgmental errors, however, such information will almost surely reduce average revenues, a factor ignored to date in the literature.

Given sufficient experience and feedback regarding the outcomes of their decisions, we have no doubt that our experimental subjects, as well as most bidders in "real world" settings, would eventually learn to avoid the winner's curse in any particular set of circumstances. The winner's curse is a disequilibrium phenomenon that will correct itself given sufficient time and the right kind of information feedback.[34] Clearly the attenuation of the feedback loop between a decision and determining the outcomes of that decision, as is commonly the case in outer continental shelf lease sales and a number of other settings, serves to perpetuate the phenomena. Further, comparative evaluations of management performance in terms of money "left on the table" (the difference between the high bid and the second high bid) can do little to arrest the problem since the winner's curse is ubiquitous and applies fairly uniformly across individuals at early stages of the learning process (Kagel et al., 1986). Finally, to the extent that market participants feel that they have an inside edge, and better judgmental abilities than their rivals, the winner's curse is bound to be difficult to eliminate.

Apart from the important task of replicating our experiments, a number of interesting research questions remain to be explored. Since avoidence of the winner's curse involves a learning process, exactly what mechanisms, if any, insure market memory of past mistakes? To what extent do new entrants learn from experience compared to learning from observation or formal education? Do inexperienced bidders learn more quickly in markets dominated by experienced bidders? What are the dynamics of markets characterized by continual entry of new "suckers" who must learn from personal experience, and do we observe these dynamics in field environments?

[34]Auction series 7 large clearly indicates this as it involved super-experienced subjects all of whom had been in at least two previous large group series.

INSTRUCTIONS

This is an experiment in the economics of market decision making. The National Science Foundation has provided funds for conducting this research. The instructions are simple, and if you follow them carefully and make good decisions you may earn a CONSIDERABLE AMOUNT OF MONEY which will be PAID TO YOU IN CASH at the end of the experiment.

1. In this experiment we will create a market in which you will act as buyers of a fictitious commodity in a sequence of trading periods. A single unit of the commodity will be auctioned off in each trading period. There will be several trading periods.

2. Your task is to submit written bids for the commodity in competition with other buyers. The precise value of the commodity at the time you make your bids will be unknown to you. Instead, each of you will receive information as to the value of the item which you should find useful in determining your bid. The process of determining the value of the commodity and the information you will receive will be described in Sections 6 and 7 below.

3. The high bidder gets the item and makes a profit equal to the difference between the value of the commodity and the amount they bid. That is,

(VALUE OF ITEM) − (HIGHEST BID) = PROFITS

for the high bidder. If this difference is negative, it represents a loss.

If you do not make the high bid on the item, you will earn zero profits. In this case, you neither gain nor lose money from bidding on the item.

4. You will be given a starting capital credit balance of $10.00. Any profit earned by you in the experiment will be added to this sum, and any losses incurred will be subtracted from this sum. The net balance of these transactions will be calculated and paid to you in CASH at the end of the experiment.

The starting capital credit balance, and whatever subsequent profits you earn, permit you to suffer losses in one auction to be recouped in part or in total in later auctions. However, should your net balance at any time during the experiment drop to zero (or less), you will no longer be permitted to participate. Instead we will give you your participation fee and you'll be free to leave the auction.

You *are* permitted to bid in excess of your capital credit balance in any given period.

5. During each trading period you will be bidding in a market in which *all* the other participants are also bidding. After all bids have been handed in they will be posted on the blackboard. We will circle the high bid and note the second high bid, and post the value of the item. We will also indicate whether a profit or loss was earned by the high bidder.

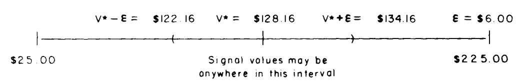
6. The value of the auctioned commodity (V^*) will be assigned randomly and will lie between $25.00 and $225.00 inclusively. For each auction, *any value* within this interval has an *equally likely chance* of being drawn. The value of the item can never be less than $25.00 or more than $225.00. The V^* values are determined randomly and independently from auction to auction. As such a high V^* in one period tells you nothing about the likely value in the next period—whether it will be high or low. It doesn't even preclude drawing the same V^* value in later periods.

7. Private Information Signals:

Although you do not know the precise value of the item in any particular trading period, you will receive information which will narrow down the range of possible values. This will consist of a private information signal which is selected randomly from an interval whose lower bound is V^* minus epsilon (ε), and whose upper bound is V^* plus epsilon. *Any value* within this interval has an *equally likely* chance of being drawn and being assigned to one of you as your private information signal. You will always know what the value of epsilon is.

For example, suppose that the value of the auctioned item is $128.16 and that epsilon is $6.00. Then each of you will receive a private information signal which will consist of a randomly drawn number that will be between $122.16 ($V^* - \varepsilon = \$128.16 - \$6.00$) and $134.16 ($V^* + \varepsilon = \$128.16 + \$6.00$). Any number in this interval has an equally likely chance of being drawn.

The line diagram below shows what's going on in this example.



The data below show the entire set of signals the computer generated for our sample bag. (Note we've ordered these signal values from lowest to highest.)

$V^* = \$128.16$; $\varepsilon = \$6.00$. Signal values: $122.57
124.14
124.68
126.76
128.84
129.51
129.96
129.98
132.07

You will note that some signal values were above the value of the auctioned item, and some were below the value of the item. Over a sufficiently long series of auctions, the differences between your private information signal and the value of the item will average out to zero (or very close to it). For any given auction, however, your private information signal can be above or below the value of the item. That's the nature of the random selection process generating the signals.

You will also note that V^* must always be greater than or equal to your signal value $-\ \varepsilon$. The computer calculates this for you and notes it. Further, V^* must always be less than or equal to your sample value $+\ \varepsilon$. The computer calculates this for you and notes it.

Finally, you may receive a signal value below $25.00 (or above $225.00). There is nothing strange about this, it just indicates V^* is close to $25.00 (or $225.00) relative to the size of epsilon.

8. Your signal values are strictly private information and are not to be revealed to anyone else prior to opening the bids.

You will be told the value of ε prior to bidding and it will be posted on the blackboard. However, you will not be told the value of V^* until after the bids have been posted. Finally we will post all of the signal values drawn along with the bids.

9. No one may bid less than \$0.00 for the item. Nor may anyone bid more than their signal value $+\varepsilon$. Any bid in between these two values is acceptable.

Bids must be rounded to the nearest penny to be accepted.

In case of ties for the high bid, we will flip a coin to determine who will earn the item.

10. You are not to reveal your bids, or profits, nor are you to speak to any other subject while the experiment is in progress.

11. As promised, everyone will receive \$4 irrespective of their earnings for participating in the experiment.

Let's summarize the main points: (1) High bidder earns the item and earns a profit = value of item − high bid price. (2) Profits will be added to your starting balance of \$10.00, losses subtracted from it. Your balance at the end of experiment will be paid in cash. If balance turns negative you're no longer allowed to bid. (3) Your private information signal is randomly drawn from the interval $V^* - \varepsilon, V^* + \varepsilon$. The value of the item can never be more than your signal value $+\varepsilon$, or less than your signal value $-\varepsilon$. (4) The value of the item will always be between \$25.00 and \$225.00.

Are there any questions?

ADDITIONAL INSTRUCTIONS:
PERIODS WITH PUBLIC INFORMATION

1. From now on bidding will be done twice during each trading period, once under each of two different information conditions. First, you will bid on the basis of your private information signals, just as you have been doing. After these bids have been made and collected, but before they are opened, you will be provided with additional information (to be described shortly) concerning the value of the item *and be asked to bid again on the commodity*. This additional information will be posted on the blackboard for everyone to see and will be referred to as a public information signal.

2. The public information signal will consist of posting on the blackboard the *lowest* of the private information signals any of you received. Note we will not reveal the bid of the player with the lowest information signal, just the signal value.

3. Note that V^* does *not* change between auctions. Your private information signals do *not* change between auctions either. However, what the public information signal does do is provide *everyone* with additional information about the possible value of V^*.

4. After both sets of bids have been collected they will be opened and the bids posted in each market and the high bid noted. We will also post the value of the item and compute profits and/or losses in the two markets as before:

PROFITS = (VALUE OF ITEM) − (HIGH BID PRICE).

Finally, to speed things up a bit we will no longer post all of the signal values drawn along with the bids.

5. However, we will only actually pay profits (or hold you accountable for losses) in one of the two markets. We will flip a coin to decide which market to pay off in. Heads we pay off in the market with private information values only, tails we pay off in the market with private and public information.

6. There is no obligation to make the same bid, or to bid differently in the two markets. This is strictly up to you to decide what to do in terms of what you think will generate the greatest profits.

Are there any questions?

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