Revenue Effects and Information Processing in English Common Value Auctions

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An experiment analyzing behavior in English common value auctions is reported. English auctions raise more revenue than first-price auctions only when bidders do not suffer from a strong winner's curse. Agents employ other bidders' drop-out prices along with their private information as Nash bidding theory predicts. However, a simple and natural signal-averaging rule, that does not require recognizing the adverse-selection effect of winning the auction, better characterizes the data than the Nash rule. Monte Carlo simulations using FIML estimates of the signal-averaging rule predict a number of data characteristics not directly employed in the estimation procedure. (*JEL* D44, C92.)

In a common value auction, the value of the item is the same to all bidders, but unknown at the time they bid. Rather, bidders have private information correlated with the unknown value. Mineral lease auctions are usually modeled as pure common value auctions, but there is a common value component to most auctions.

Economic theory predicts that the choice of institution for a common value auction will affect expected revenue. In particular, with symmetric, risk-neutral Nash equilibrium (RNNE) bidding, English auctions are predicted to raise more revenue than first-price, sealed bid auctions. This happens because both the pricing rule (the high bidder wins the item at the second highest bid price) and the "public" information disseminated during bidding (lower bidders' drop-out prices reveal their estimates of the value of the item) increase expected revenue (Paul R. Milgrom and Robert J. Weber, 1982).[1] Nash equilibrium bidding theory also makes precise predictions about how bidders combine this endogenously released and noisy public information with their private information in English auctions. This paper compares the information processing mechanism underlying the Nash model with an alternative, very sensible, signal-averaging rule that suggests itself.

The first part of the paper is concerned with the revenue-raising predictions of Nash equilibrium bidding theory. We find that, contrary to the theory, English auctions reduce rather than raise revenue for inexperienced bidders. These bidders suffer severely from the winner's curse in first-price auctions, bidding substantially above the Nash equilibrium prediction. They use the "public information" inherent in other bidders' drop-out prices to

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[1] These theoretical considerations played an important role in the design of recent U.S. government spectrum auctions (John McMillan, 1994; Peter C. Cramton, 1994). Although the underlying structure of the spectrum auctions is substantially more complicated than existing auction models, results from extant auction theory and related empirical work guided their design. The results of this paper are intended to add to this underlying knowledge.

(largely) overcome the winner's curse in English auctions. The net effect is a reduction in revenue. In contrast, more experienced bidders have learned to overcome the worst effects of the winner's curse in first-price auctions, so that there is scope for the public information inherent in bidders' drop-out prices to increase revenue, as the theory predicts.

The second part of the paper develops an econometric model to explore how bidders combine endogenously released and noisy public information with their private information in the English auctions. Two versions of the model are specified: one uses ordinary least squares (OLS) and observed drop-out prices to analyze bidding round by round. The other uses a full-information, censored bidding model which corrects for potential biases inherent in the OLS estimates and applies all the information at our disposal (including the drop-out prices implicit in continuing to bid when others have dropped out). Both specifications indicate that a rule in which bidders act as if they are averaging their own signal value and the signal values underlying the drop-out prices of all earlier bidders, characterizes behavior better than the Nash rule, irrespective of bidders' experience. Simulations using maximum likelihood estimates of the full-information signal-averaging model show that it can quantitatively account for a number of data characteristics not directly employed in the maximum likelihood estimates (most importantly, the frequency of "panic" dropouts). These simulations also show that the relatively low percentage (50–60 percent) of high signal holders winning the auctions is completely consistent with a symmetric bidding model, given the bidding errors actually observed.

With symmetry, under our design both the signal-averaging rule and the Nash rule provide unbiased estimates of the expected value of the item conditional on winning, and the same average prices and profits. In principle, the averaging model permits profitable, unilateral deviations by high-valued signal holders who employ a "signal-jamming" strategy. The averaging rule continues to be employed, however, since it is substantially more natural to apply than the Nash rule and profitable deviations are difficult to detect, given the complexity of the environment.

The paper is organized as follows: Section I outlines our experimental procedures. The theoretical underpinnings of the analysis are developed in Section II. Forces promoting as well as inhibiting revenue raising in English compared to first-price auctions are discussed, along with their observable implications. Section III reports the experimental results. Section IV briefly compares our results to the limited field data examining the revenue raising effects of English auctions. Section V concludes with a summary of the main results.

I. Structure of the Auctions

Each experimental session consisted of a series of auction periods in which a single unit of a commodity was awarded to the high bidder. The value of the item, x_o, was unknown at the time bids were submitted. In each auction period x_o was drawn randomly from a uniform distribution on $[\underline{x}, \bar{x}]$. Each bidder received his own private information signal, x, randomly drawn from a uniform distribution on $[x_o - \varepsilon, x_o + \varepsilon]$. The number of bidders (n), the value of ε, and the distributions underlying both x_o and x were common knowledge.

In first-price auctions each bidder submitted a single, sealed bid with the high bidder earning a profit equal to the value of the item less the price bid. The English auctions used an ascending clock to set price, with price starting at $\underline{x}$ and increasing continuously. Bidders decided when to drop out of the auction and could not reenter once they had left (an irrevocable exit auction).[2] The last bidder earned a profit equal to x_o less the price at which the next-to-last bidder dropped out. Posted on each bidder's screen was the current price of the item and the number of bidders remaining in the

[2] Prices started at $\underline{x}$ as any other price rule would have involved revealing information about x_o. Initially, the price increased every second with increments of \$1.00. Once the first bidder dropped out there was a brief pause after which prices increased every three seconds with smaller price increments as fewer bidders remained. With only 2 bidders remaining the price increments were \$0.05 with ε = \$6.00, \$0.10 with ε = \$12.00 and \$0.20 for ε > \$12.00. There were no additional pauses as more bidders dropped out. A single stroke on any key was required to drop out.

TABLE 1—TREATMENT CONDITIONS

Treatment condition	Experience	Number of bidders	Number of experimental sessions	Auction type
1	None	4	4	English
2	None	4	5	First-price
3	Experienced (from 1)	4	3	English and first-price
4	Experienced (from 2)	4	4	First-price
5	None	7	3	English
6[a]	None	7	3	First-price
7	Experienced (from 5)	7	2	English
8	Experienced (from 6)	7	2	First-price
9	Super experienced first-price	4	8	English and first-price
10[a]	Super experienced first-price (from 4 and 8)	7	7	English and first-price

[a] Includes a few periods with $n = 6$. Earlier work shows that pooling $n = 6$ and 7 is justified (Kagel and Levin, 1986; Kagel et al., 1995).

auction (with *no* information regarding bidders' identity). Bidders who did not win the item earned zero profit for that auction period.

At the end of each auction period, all bids were posted from highest to lowest along with the corresponding signal values (bidder identification numbers were suppressed) and the value of x_o. Profits (or losses) were calculated for the winning bidder and were reported to all bidders, and cash balances were updated.

To cover the possibility of losses bidders were given starting capital balances of at least \$10.00. Losses were subtracted from this balance and profits added to it. Subjects were told that if their balance went to zero or less they would no longer be allowed to bid. Bidders were paid their end of session balances in cash, along with a \$4 or \$5 participation fee.

Bidding was studied under two different values of n (4 and 7), five different values of ε (6, 12, 18, 24, and 30) and with three different levels of bidder experience (inexperienced, once experienced, and super-experienced). Super-experienced bidders are defined as having been in at least two previous first-price auction series. Experimental sessions using both first-price and English auctions had bidders first participate in a series of first-price (English) auctions, followed by bidding in a series of English (first-price) auctions, followed (sometimes) by an additional cross-over back to first-price (English) auctions.[3] Table 1 cross-classifies the experimental sessions by subjects' experience level, the number of active bidders, and by auction institution.

Subjects were primarily senior undergraduate economics majors and MBA students at the University of Houston (treatments 1–8 and 10) and the University of Pittsburgh (treatment 9). To cover the possibility of bankruptcies there were typically (up to three) extra bidders in each experimental session, with the active bidders in each auction period determined either randomly or through a rotation rule. For experienced subject sessions all bidders were invited back, with the exception of treatment 10 where the few bidders who went bankrupt early in both previous sessions were not invited back.[4] Each experimental session

[3] Detailed specification of treatment conditions along with the raw data from the experiment are available from the authors on request.

[4] Susan Garvin and Kagel (1994) provide evidence that in sealed-bid common value auctions returning bidders self-select with subjects who went bankrupt significantly less likely to return and with bidders who did not return bidding more aggressively than those who did return in the initial series of auctions.

lasted approximately two hours and had a minimum of 20 auction periods.

II. Theoretical Considerations

A. *Factors Promoting Revenue Raising in English Auctions*

With symmetric risk-neutral Nash equilibrium bidding (RNNE), English auctions are predicted to raise more revenue than first-price auctions. In what follows we apply the theory to our design. The basic theoretical results underlying this analysis are developed in Robert Wilson (1977), Milgrom (1979a, b), and Milgrom and Weber (1982).

1. *First-Price Auctions*.—For first-price auctions the RNNE bid function $\gamma(x)$ is given by

$$\text{(1a)}\quad \gamma(x) = \underline{x} + \frac{1}{n+1}(x - \underline{x} + \varepsilon),$$

$$\underline{x} - \varepsilon \leq x \leq \underline{x} + \varepsilon$$

$$\text{(1b)}\quad \gamma(x) = x - \varepsilon + h(x),$$

$$\underline{x} + \varepsilon \leq x \leq \bar{x} - \varepsilon \text{ where}$$

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

$$\text{(1c)}^{5}\quad (\bar{x} - 2\varepsilon) + \frac{n-1}{n}(x - \bar{x} + \varepsilon) \leq \gamma(x) \leq x - \varepsilon,$$

$$\bar{x} - \varepsilon \leq x \leq \bar{x} + \varepsilon.$$

Bidding in first-price auctions combines strategic considerations, similar to those involved in first-price private value auctions, and item valuation considerations. The latter involves recognizing that although x is an unbiased estimate of x_o, winning with it implies that it is the highest of the n signals and, therefore, must be used as a first-order statistic rather than an unbiased estimate of x_o. Failure to account for this adverse-selection effect is commonly referred to as the winner's curse. Both forces, strategic and item valuation, promote bidding below x, with the strategic forces reinforcing efforts to avoid the winner's curse.

Under (1a–c) expected profit for the high bidder is bounded from below and above as follows:

$$\text{(2a)}\quad E_F^L[\pi] = \frac{2\varepsilon}{n+1} - \left[\frac{4\varepsilon^2}{\bar{x} - \underline{x}}\right]\left[\frac{3n+2}{n(n+1)(n+2)}\right]$$

$$\text{(2b)}\quad E_F^u[\pi] = E_F^L[\pi] + \left[\frac{2\varepsilon^2}{\bar{x} - \underline{x}}\right]\left[\frac{1}{n+2}\right].$$

For the values of n (4 and 7), ε (6, 12, 18, 24, 30) and $[\underline{x}, \bar{x}]$ (50–250) employed, the lower bound of expected profit lies between −17 to −2 percent of $2\varepsilon/(n+1)$ and the upper bound lies between −5 to +2 percent of $2\varepsilon/(n+1)$.

2. *English Auctions*.—Milgrom and Weber (1982) offer a symmetric RNNE for the irrevocable exit English auction. When there are three or more bidders, however, the prices at which earlier bidders drop out of the auction convey information to those who continue to bid. The irrevocable exit English auction, with its continuous display of prices and number of active bidders makes this price information unambiguously clear to other bidders.[6]

[5] Assuming $h(\bar{x} - \varepsilon)$ is negligible, which it is for the parameter values employed. An appendix outlining the derivation of the bid functions along with the expected profit functions is available from the authors on request.

[6] Milgrom and Weber argue that the more loosely structured English auctions encountered in practice are best approximated by the irrevocable exit auction. Sushil Bikhchandani and John G. Riley (1991) disagree, arguing that they are better approximated by a second-price sealed bid auction as information revelation only occurs in English auctions despite the best efforts of the bidders. It's obviously beyond the scope of this paper to try and settle

Let $x_1 < x_2 < \cdots < x_n$ denote the ordered private signals and $d_1 < d_2 < \cdots < d_{n-1}$ the sequential drop-out prices (ties occur with zero probability, lower case letters represent actual values and, when appropriate, caps denote the corresponding random variables). Let I_j denote the auction conveyed information available to a bidder who is active in round j (the round advances when an additional bidder drops out), so that $I_1 = 0$ and $I_j = (d_1, \ldots, d_{j-1})$. Let $\gamma(x; I_j)$ denote the round j reservation bid of an active bidder with private information signal x. The γ_j's which are obtained below are strictly monotone in x, given I_j. It follows that $d_j = \gamma(x_j; I_j)$ and that there is a one-to-one (recursive) correspondence between I_j and $(x_1, \ldots, x_{j-1})$. Following Milgrom and Weber (1982), γ_j is given by

$$\gamma_j(x; I_j) = E[x_o \mid \xi_j(x; I_j)] \tag{3}$$

where $\xi_1(x; I_1)$ denotes the event $X_i = x$ for all i and for j: $2 \rightarrow n-1$; $\xi_j(x; I_j)$ represents the event $X_i = x_i$ for $i < j$ and $X_i = x$ for $i \geq j$. In other words, bidders form their reservation bids on the basis of earlier bidders' drop-out prices and their own signal value, assuming that all remaining bidders have the same signal value that they do. Active bidders infer whatever they can from the quitting prices of bidders who are no longer active. With affiliated signal values, the result is that each bidder remains active until the price rises to the point where the bidder is just indifferent between winning and losing at that price (Milgrom and Weber, 1982).[7]

Given the uniform distributions from which x_o and x are drawn, conditional on ξ_1, x_o is uniformly distributed on the interval $[a(x), b(x)]$ where $a(x) = \max(\underline{x}, x - \varepsilon)$ and $b(x) = \min(\bar{x}, x + \varepsilon)$; conditional on ξ_j, x_o is uniformly distributed on the interval $[a(x), b(x_1)]$. It follows that

$$d_j = \frac{a(x_j) + b(x_1)}{2}. \tag{4}$$

If $\underline{x} + \varepsilon < x_1 < x_n < \bar{x} - \varepsilon$ (referred to as region 2 in the following discussion) then

$$d_j = \frac{(x_1 + x_j)}{2}. \tag{5}$$

Note that in equilibrium, conditional on the event of winning, for bidder j the pair $[a(x_j), b(x_1)]$ is a sufficient statistic for x_o. That is, in the equilibrium of our design, the bidder with the lowest signal value determines his drop-out price strictly on the basis of his own signal value. Later bidders determine their drop-out prices based strictly on their own signal value and the first bidder's drop-out price; that is, bidders ignore the information contained in intermediate round drop-out prices.

The expected profit for the high bidder in the English auctions is

$$E_E[\pi] = \frac{\varepsilon}{n+1} - \left[\frac{4\varepsilon^2}{\bar{x} - \underline{x}}\right]\left[\frac{1}{(n+1)(n+2)}\right], \tag{6}$$

which is close to *half* the expected profit from winning in first-price sealed bid auctions. Lower profit, of course, translates into higher prices, so that with symmetry and risk neutrality, the English auction is within ± 10 percent of *doubling* expected revenue (after normalizing for the value of x_o) under our design.[8]

this issue (however, see Kagel et al. [1995] for an experimental investigation of bidding in second-price, common value auctions). The spectrum auctions contained an irrevocable exit element since, during the final stage, bidders generally had to remain active (be the current high bidder or put in a bid that exceeded the current high bid by the specified increment) on the number of licenses for which they wished to remain eligible.

[7] In equilibrium, lower-valued signal holders cannot profit from the information of higher valued signal holders since this information is only revealed after the latter have dropped out, at which point price is greater than the expected value of the item. The theory assumes a continuous price clock, which is not practical. With the discrete time clock employed, d_j is set at the nearest tick of the clock to (3).

[8] Bikhchandani and Riley (1991) show that the expected profit of the symmetric RNNE is unique even though the reservation price functions (4) are not unique for $j < n - 1$. The problem is this. Although the low-

B. *Forces Inhibiting Revenue Raising in English Auctions*

There are three principle reasons why English auctions may raise less revenue than first-price auctions or why the revenue increases might be smaller than predicted: the existence of asymmetric equilibria in English auctions (even with risk-neutral bidders), risk aversion, and the winner's curse. We consider each of these factors briefly.

1. *Asymmetric Equilibria.*—Bikhchandani and Riley (1991) prove that when $n \geq 3$ there exist a continuum of asymmetric equilibria in irrevocable exit English auctions. The idea underlying these asymmetric equilibria is as follows: there exist a continuum of asymmetric equilibria in second-price auctions with *two* bidders where one bidder bids higher and the second bidder bids lower than in the symmetric equilibrium (Milgrom, 1981). There does not exist a completely convincing way to rule out these "strange" equilibria, as Milgrom characterizes them (they are all perfect). These asymmetric equilibria apply to the irrevocable exit auction with $n \geq 3$ bidders since it reduces to a second-price auction with only two bidders, once $n - 2$ bidders have dropped out. Under certain regularity conditions, which are satisfied in our design, expected revenue in these asymmetric equilibria are lower than in the symmetric equilibrium (Bikhchandani and Riley, 1991 Proposition 3 and Corollary 1). Hence, the possibility for a revenue reversal relative to first-price auctions.[9]

2. *Risk Aversion.*—The effects of risk aversion in first-price common value auctions are, in general, ambiguous, as there are two opposing forces at work: with positive expected profit, strategic considerations promote bidding above the RNNE, just as in first-price, private value auctions (Milton Harris and Arthur Raviv, 1981; Charles A. Holt, 1980; Riley and William F. Samuelson, 1981). However, unlike private value auctions, in equilibrium there exists the possibility of negative profits which, other things equal, promotes lower bidding for risk averse bidders.

In contrast, there is no ambiguity about the role of risk aversion in English auctions, as average prices must be reduced in auctions with symmetric risk averse bidders. This results from the fact that the reservation bids (4) correspond to simple expectations, so that with risk aversion these are replaced by their certainty equivalents, which are less than the simple expectations. This may reduce bids sufficiently to offset the revenue raising possibilities of the English auction, although we would doubt that this could happen, given the size of the payoffs involved and the strong revenue raising possibilities inherent in our design. Nevertheless, to use risk aversion to help explain any revenue raising shortfalls, prices must be lower, hence average profits must be higher, than predicted under the symmetric RNNE in the English auctions.[10]

3. *The Winner's Curse.*—Failure to account for the adverse-selection effect associated with winning a common value auction is called the winner's curse. The winner's curse is likely to result in substantially higher bidding, relative to the RNNE, in first-price auctions, but much less overbidding in English auctions. The reason is that in English auctions drop-out prices of bidders reveal information regarding their signal values. If this information is not too distorted, it can alert higher

signal holder never wants to drop out above (4), in a symmetric RNNE he is indifferent between dropping out at (4) or below it (since he never wins in equilibrium). Thus, bidders other than the two highest-signal holders may use alternative drop-out rules. We do not consider these alternative symmetric equilibria for several reasons: (i) they are not robust to the possibility that other signal holders may err by dropping out sooner than predicted by (4), (ii) they involve an implausible degree of coordination between bidders, and (iii) there is no evidence that alternative equilibria of this sort are present in our data.

[9] Although, Bikhchandani and Riley (1991) note that symmetrically informed bidders are most likely to behave symmetrically, one might still see the emergence of such equilibria. No comparable asymmetric equilibria have been established for risk neutral bidders in first-price auctions.

[10] We do not consider risk loving as the evidence from the experimental literature indicates risk-neutral or risk-averse bidding (see Kagel [1995] for a review of the literature).

TABLE 2—INEXPERIENCED BIDDERS: ACTUAL VERSUS THEORETICAL REVENUE CHANGES AND PROFIT LEVELS

	n = 4							n = 7						
	Average change in revenue: English less first-price			Average profit				Average change in revenue: English less first-price			Average profit			
				First-price		English					First-price		English	
ε	Actual (1)	Theoretical (2)	Difference (3)	Actual (4)	Theoretical (5)	Actual (6)	Theoretical (7)	Actual (8)	Theoretical (9)	Difference (10)	Actual (11)	Theoretical (12)	Actual (13)	Theoretical (14)
\$6	−1.54	1.54	−3.08	−2.13	2.76	−0.58	1.23	−1.98	0.10	−2.08	−3.85	0.99	−1.87	0.89
	(0.72)*	(0.49)	(0.71)*	(0.52)*	(0.38)	(0.50)	(0.30)	(0.87)*	(0.34)	(0.78)*	(0.71)*	(0.19)	(0.51)*	(0.29)
				[29]		[28]					[18]		[18]	
\$12	−0.54	2.76	−3.30	−1.32	5.01	−0.78	2.25	−1.95	1.08	−3.03	−3.75	2.76	−1.80	1.68
	(1.25)	(0.92)	(0.84)*	(0.79)[a]	(0.60)	(0.95)	(0.69)	(1.19)[a]	(0.65)	(0.92)*	(0.89)*	(0.53)	(0.77)*	(0.40)
				[41]		[45]					[30]		[43]	
\$24	1.09	8.10	−7.01	1.20	9.83	0.11	1.73		ND			ND		
	(3.29)	(2.32)	(3.05)*	(1.93)	(1.25)	(2.64)	(2.14)							
				[25]		[13]								

Notes: All values are reported in dollars. Bracketed terms are the number of auction periods. Standard errors are given in parentheses. ND stands for no data.

* The null hypothesis that the value is greater than or equal to zero can be rejected at the 5-percent significance level.

[a] The null hypothesis that the value is greater than or equal to zero can be rejected at the 10-percent significance level.

valued signal holders to the fact that they have formed overly optimistic estimates of x_o, which will help attenuate overbidding. No such help is available in first-price auctions since they involve sealed bids. In this scenario, prices are substantially higher than predicted in first-price auctions and relatively closer to their predicted value in English auctions, hence the possibility for revenue reversals or reductions in revenue relative to those predicted.

There is precedent for this outcome from experimental studies of first- and second-price sealed bid auctions with public information (Kagel and Levin, 1986; Kagel et al., 1995). In these auctions, public information consisted of announcing x_1 (the lowest signal value). This is exactly the same information that is supposed to be revealed by the low signal holders' drop-out price in English auctions. In cases where bidders suffered from a clear winner's curse with only private information, announcing x_1 *lowered* revenue, *contrary* to the Nash prediction. It is another question entirely whether English auctions are capable of generating the same effect, as now information regarding x_1 is generated *endogenously* which (i) may degrade the quality of the information and (ii) may be more difficult for bidders to interpret, since they must now deduce that the low bidder's drop-out price is reflective of the underlying signal value.

III. Experimental Results

A. *Revenue Effects of English Auctions*

1. *Inexperienced Bidders*.—Table 2 shows average changes in the auctioneer's revenue between English and first-price auctions, as well as the winner's average profit in both types of auctions.[11] "Actual" figures are arithmetic means (and their standard deviations) obtained from the data while "theoretical" values are produced by computing equilibrium bids corresponding to actual signals and the realized value of x_0. The null hypothesis of interest is that the actual revenue changes reported in columns (1) and (8) are nonnegative. However, with the exception of $n = 4$ and $\varepsilon = \$24$, actual revenue changes are all negative and are significantly less than zero (at the 5-percent level) in two cases. Further, as

[11] Common value auctions involve pure surplus transfers so that revenue differences are calculated as: $[\pi_F - \pi_E]$ where π_E and π_F correspond to profits in English and first-price auctions, respectively. In this way we have effectively normalized for sampling variability in x_o by subtracting x_o from the price. For $x > \bar{x} - \varepsilon$ in first-price auctions we use the upper bound of the bid function in (1c) to compute predicted profit. Exact bid functions are used throughout in computing predicted profit for the English auctions.

TABLE 3—ONE-TIME-EXPERIENCED BIDDERS: ACTUAL VERSUS THEORETICAL REVENUE CHANGES AND PROFIT LEVELS

	Average change in revenue: English less first-price			Average profit			
				First-price		English	
	Actual (1)	Theoretical (2)	Difference (3)	Actual (4)	Theoretical (5)	Actual (6)	Theoretical (7)
$n = 4$	1.62	2.72	−1.10	1.37	4.32	−.25	1.60
$\varepsilon = \$12$	(0.89)	(0.65)	(0.63)[a]	(0.49)	(0.41)	(0.80)	(0.45)
				[89]		[49]	
$n = 7$	0.31	0.68	−0.37	−0.32	2.93	−0.63	2.25
$\varepsilon = \$12$	(1.02)	(0.69)	(0.96)	(0.56)	(0.54)	(0.71)	(0.43)
				[19]		[32]	

Notes: All values reported in dollars. Bracketed terms are the number of auction periods. Standard errors are given in parentheses.

[a] The null hypothesis that the value is greater than or equal to zero can be rejected at the 10-percent significance level.

indicated in columns (3) and (10), actual revenue changes are significantly lower than theoretical revenue changes in all five cases. Thus, for inexperienced bidders, in all cases there is less of a revenue increase than the theory predicts, and in 4 out of 5 cases average revenue is actually lower under English compared to first-price auctions, so that the theory does not even get the directional prediction right.

Average winner's profits are reported in columns (4) to (8) and (11) to (14) and provide the explanation for the "perverse" revenue effects just reported: inexperienced bidders suffer from a winner's curse in both English and first-price auctions, but the curse is relatively stronger in first-price auctions. The revenue results in Table 2 cannot be explained on the basis of risk aversion or the existence of asymmetric equilibria in the English auctions, since actual profits are always below predicted RNNE profits in the English auctions.[12]

This perverse revenue effect is, however, consistent with earlier experimental work in which revenue was *reduced* following the announcement of x_1 in first- and second-price sealed bid auctions when bidders suffered from a winner's curse (Kagel and Levin, 1986; Kagel et al., 1995). There is one important difference, however, between these earlier results and those reported here. With x_1 publicly announced, average profit was positive. In contrast, average profit here is negative for all n and ε (with the exception of $n = 4$ and $\varepsilon = \$24$). This suggests that information dissemination in the English auction is noisier relative to when x_1 is publicly announced.

2. *One-Time Experienced and Super-Experienced Bidders.*—Tables 3 and 4 report average changes in the auctioneer's revenue between English and first price auctions, as well as the winner's average profit in both types of auctions for one-time experienced and super-experienced bidders. In all cases English auctions fail to increase revenue as much as the theory predicts (column (3) in Table 3 and columns (3) and (10) in Table 4). However, the qualitative implications of the theory are generally correct, as the actual revenue changes are all essentially nonnegative, and are significantly greater than zero in two cases.

For the one-time experienced bidders, average revenue is higher under the English auction rules for both $n = 4$ and 7 (with the increased revenue being significantly greater than zero at the 10-percent level with $n = 4$). The increased revenue from the English

[12] Limited liability for losses establishes the possibility of more aggressive bidding than predicted under the one-shot Nash equilibrium as potential losses are truncated (Robert G. Hansen and John R. Lott, 1991). However, the use of sizable starting cash balances controls for limited-liability problems and has been shown, as a practical matter, to eliminate the problem in first-price auctions (Kagel and Levin, 1991; Barry Lind and Charles R. Plott, 1991).

TABLE 4—SUPER-EXPERIENCED BIDDERS: ACTUAL VERSUS THEORETICAL REVENUE CHANGES AND PROFIT LEVELS

	$n = 4$							$n = 7$						
	Average change in revenue: English less first-price			Average profit				Average change in revenue: English less first-price			Average profit			
				First-price		English					First-price		English	
ε	Actual (1)	Theoretical (2)	Difference (3)	Actual (4)	Theoretical (5)	Actual (6)	Theoretical (7)	Actual (8)	Theoretical (9)	Difference (10)	Actual (11)	Theoretical (12)	Actual (13)	Theoretical (14)
$18	2.21	3.96	−1.75	3.37	6.77	1.16	2.82	−0.25	2.85	−3.10	0.76	3.86	1.01	1.01
	(0.95)	(0.73)	(0.68)*	(0.50)	(0.48)	(0.88)	(0.53)	(0.86)	(0.61)	(0.59)*	(0.65)	(0.50)	(0.56)	(0.37)
					[163]		[107]					[75]		[96]
$30	1.20	2.98	−1.78	8.45	11.27	7.25	8.29							
	(3.10)	(2.30)	(2.19)	(1.28)	(1.34)	(2.76)	(1.93)		ND			ND		ND
					[31]		[33]							

Notes: All values reported in dollars. Bracketed terms are the number of auction periods. Standard errors are given in parentheses. ND stands for no data.

* The null hypothesis that the value is greater than or equal to zero can be rejected at the 5-percent significance level.

auctions is, in both cases, associated with considerably higher average profit in the first-price auctions than for completely inexperienced bidders (holding ε constant), as the worst effects of the winner's curse have been eliminated.

For super-experienced bidders, with $n = 4$, actual revenue is higher in the English auctions for both values of ε, with a statistically significant increase (at the 5-percent level) for ε = $18. However, for $n = 7$, there is essentially no difference in revenue between the first-price and English auctions. The significant increase in revenue in English auctions with $n = 4$ and ε = $18 is, once again, associated with elimination of the worst effects of the winner's curse in first-price auctions, as bidders earned a substantial share (more than 50 percent) of predicted profit. The importance of eliminating the winner's curse for the revenue raising prediction of the theory to hold is reinforced by the absence of any revenue increase with $n = 7$, in conjunction with the relatively low share (21 percent) of the profits that could have been earned in these first-price auctions.

The increased revenue in English auctions with experienced bidders who have largely overcome the winner's curse is consistent with earlier experimental work in which revenue was increased following the announcement of x_1 in first- and second-price sealed bid auctions when there was no winner's curse (as reported here, in these earlier experiments actual revenue increases were always lower than the theory predicts; Kagel and Levin [1986], Kagel et al. [1995]).[13] The important difference between the two sets of results is that in the English auctions the "public information" is generated endogenously so that (i) this information is noisier and (ii) bidders must figure out for themselves that lower bidders' drop-out prices have important informational content. Finally, since average actual profits are consistently at or below theoretical profits in the English auctions, the failure to raise as much revenue as the theory predicts cannot be attributed to risk aversion, but is more than likely due to residual traces of the winner's curse, which tends to be stronger in the sealed bid auctions.

[13] There is a potential artifactual explanation for the higher revenue in English auctions with super-experienced bidders. Since all of their experience was in first-price auctions it may be argued that the higher revenue in English auctions simply results from a lack of experience with English auctions, which results in larger errors and residual traces of the winner's curse than in the more familiar first-price auctions. However, as the data in Table 4 shows, realized profit as a percentage of predicted RNNE profit is roughly the same or greater in the English compared to first-price auctions. Further, comparing revenue effects over time for super-experienced bidders shows the same pattern as Table 4, albeit with some fluctuations in the size of the revenue differences (two auction sessions were conducted each week, for four weeks with $n = 4$ and for two weeks with $n = 7$, with subjects returning once a week in various combinations).

B. *Bidding Behavior in English Auctions*

This section explores the behavioral process underlying bidding in English auctions. We ask what kind of information do bidders rely on in the English auctions. Is it their own signal value and the first drop-out price as the theory predicts or is there some other behavioral process at work? If it is some other process, what is it and how does it work?

In developing an econometric model of the bidding process in English auctions we first introduce some notation. Three indices will be used: i for bidders (i: $1 \rightarrow n$); j for bidding rounds (j: $1 \rightarrow n-1$) and k for auctions (k: $1 \rightarrow K$). Without loss of generality, we can index bidders within each auction according to the order in which they drop out (so that the actual identity of bidder i varies across auctions). The relevant variables are:

γ_{ijk}: the reservation bid of bidder i in round j of auction k (with $i \geq j$, in line with our indexing rule);
d_{jk}: the drop out price in round j of auction k;
x_{ik}: the private signal of bidder i in auction k.

The information set available to bidder i in round j ($j \leq i$) of auction k consists of his private signal x_{ik} and, for $j > 1$, the drop-out prices of previous rounds $\{d_{sk}; s: 1 \rightarrow j-1\}$. Hence, under an overall linearity assumption, our baseline model for reservation bids is given by

$$\gamma_{i1k} = \alpha_1 + \beta_1 x_{ik} + \varepsilon_{i1k} \quad (i: 1 \rightarrow n, k: 1 \rightarrow K) \tag{7}$$

$$\gamma_{ijk} = \alpha_j + \beta_j x_{ik} + \sum_{s=1}^{j-1} \delta_{js} d_{sk} + \varepsilon_{ijk} \quad (i: j \rightarrow n; j: 2 \rightarrow n-1; k: 1 \rightarrow K). \tag{8}$$

We also assume that the ε_{ijk}'s are distributed independently of each other with zero means and variances $\sigma_j^2 = \text{var}(\varepsilon_{ijk})$. The assumption of mutual independence of the ε's could be relaxed in a number of ways that would not affect the consistency of our estimates, but only their efficiency. However, one assumption which is critical for the consistency of our estimates is independence of the ε's "across equations," that is, for different values of j. We will provide empirical verification of this assumption later.

In order to avoid technical complications, we only consider auctions with draws in region 2 ($\underline{x} + \varepsilon < x_1 < x_n < \bar{x} + \varepsilon$). It follows that the RNNE bidding model imposes the following restrictions on the parameters of the system of equations in (7) and (8)

$$\alpha_1 = 0 \quad \beta_1 = 1.0 \tag{9}$$

$$\alpha_j = 0, \quad \beta_j = \delta_{j1} = 0.5, \quad \delta_{js} = 0 \quad (j: 2 \rightarrow n-1; 1 < s < j). \tag{10}$$

Weaker versions of these restrictions, as well as alternative hypotheses, will be considered in the course of our analysis.

The econometric analysis is complicated by the fact that the sole observables are

$$\gamma_{ijk} = d_{jk} \quad (j: 1 \rightarrow n-1; k: 1 \rightarrow K). \tag{11}$$

All other γ's are "censored"; that is, for those bidders who do not drop out in round j we only have categorical information regarding γ_{ijk} (the censoring process is characterized in full in subsection B2 below). Our problem is complicated by the fact that a Full Information Maximum Likelihood (FIML) search on an unconstrained parameter set consisting of all the coefficients in equations (7) and (8)—in all $3n + (1/2)(n-1)(n-2)$ coefficients—is neither practical nor likely to be numerically reliable. Some form of simpler pretest analysis is required. Ordinary least squares (OLS) estimation based on the equalities in formula (11) are computationally attractive in this respect. But OLS estimates suffer from potential bias since conditional on γ_{ijk} being the lowest order statistic, the residuals ε_{jjk} have negative expectations and are potentially correlated with the x's. However, Monte Carlo (MC) simulations based on the FIML estimates show that the most significant biases are in the intercepts and variances (these are downward biased), which are essentially nuisance parameters, and the OLS estimates of the β's and the δ's (and of constrained versions thereof) provide a remarkably reliable picture of the salient features of the sampling process.[14]

1. *An OLS Pretest Analysis*.—Considering only the identities in formula (11) and substituting them into equations (7) and (8), we obtain the following system of equations for the observable drop-out bids

$$d_{1k} = \alpha_1 + \beta_1 x_{1k} + \varepsilon_{11k} \tag{12}$$

$$d_{jk} = \alpha_j + \beta_j x_{jk} + \sum_{s=1}^{j-1} \delta_{js} d_{sk} + \varepsilon_{ijk} \tag{13}$$

$$(j\colon 2 \rightarrow n - 1).$$

Note that this system is triangular in the drop-out bids. In particular, the covariance matrix of the residuals is diagonal since the ε's are assumed to be independent of each other for different j's. Hence, individual equation OLS estimators do not suffer from (additional) simultaneity biases.

Tables 5 and 6 report the results of these regressions, where we have pooled data from auctions with similar levels of bidder experience. Also shown are F test statistics for the null hypothesis that the restrictions implied by the symmetric RNNE model apply. The β's and the δ's being our primary coefficients of interest, we only report "conventional" F test statistics, whereby the constant α_j are left unconstrained.[15] Two forms of the Nash hypothesis are considered: (i) the *weak* Nash hypothesis which assumes that $\delta_{js} = 0$ for all $j > s > 1$; and (ii), the *strong* Nash hypothesis which assumes *in addition* that $\beta_j = \delta_{j1} = 0.50$.[16] The system of equations (12) and (13) being recursive, the F test statistics are evaluated for each equation individually.

We focus first on super-experienced bidders, those bidders who, according to the profit data reported, come closest to the symmetric RNNE model's predictions. For each round where a weak Nash test can be made (round 3 and higher), we overwhelmingly reject the Nash model's prediction that bidders ignore drop-out prices beyond the first round. In fact, looking at the coefficient estimates, from round 3 on, the lowest bidder's drop-out price is virtually ignored as the coefficient estimates for δ_1 are all essentially zero. Instead, bidders place weight on their own signal value and the drop-out price of the bidder who dropped out just before them (the drop-out price is round $j - 1$). Further, looking at auctions with $n = 7$, there is a general tendency for bidders who drop out later in the auction to put relatively less weight on their own signal value and more weight on the drop-out price in the preceding round. That is, for $j > 1$, bidders essentially appear to have adopted a (symmetric) rule of the form

$$\gamma_{ijk} = \lambda_j x_{ik} + \mu_j d_{j-1,k} \tag{14}$$

where the λ_j's decrease and the μ_j's increase as j increases. This same pattern characterizes the drop-out prices of inexperienced and once experienced bidders as well.

The obvious question is, what kind of information processing rule does (14) represent and is it sensible in the context of our English auctions? A little exploration immediately produces the following (quite plausible) scenario: assume bidders were not aware of all the subtleties of the RNNE model and, in particular, of the fact that the (joint) use of the sufficient statistic underlying the Nash formulation would protect them against the adverse selec-

[14] An appendix detailing the FIML estimates along with the MC simulations reported is available from the authors on request.

[15] MC simulations show that the OLS estimates of the α's are essentially uninterpretable: on the one hand they suffer from a downward censoring bias. On the other hand the existence of bidding "errors" biases downward bidders' own estimates of x_o. Bidders appear to *raise* their intercepts in (12) and (13) to compensate for this bias. Which effect dominates is likely to vary from one round to another.

[16] The weak Nash model tests are valid tests of the alternative symmetric RNNE described in footnote 8. The strong Nash model tests are not. Note, the F statistics reported have different degrees of freedom so that simply comparing F values between the weak and strong tests is not meaningful.

TABLE 5—EFFECT OF OWN SIGNAL AND OTHER BIDDERS' DROP-OUT PRICES ON BIDS (n = 4)

Bidder experienced	Dependent variable	Coefficient estimates[a] Intercept (α_j)	x_{ik} (β_j)	d_{1k} (δ_{j1})	d_{2k} (δ_{j2})	Nash test statistics[b] Weak[c]	Strong[d]	Signal-averaging test statistics[b] Weak[e]	Strong[f]	Adjusted R^2
Super experienced	d_{1k}	1.16 (3.60)	0.99 (0.03)**			NA	0.11	NA	0.11	0.915
	d_{2k}	2.81 (1.00)**	0.19 (0.03)**	0.80 (0.03)**		NA	62.1 (0.01)	NA	62.1 (0.01)	0.993
	d_{3k}	1.23 (0.94)	0.17 (0.03)**	0.07 (0.07)	0.76 (0.08)**	85.1 (0.01)	63.2 (0.01)	0.97	17.9 (0.01)	0.995
One-time experienced	d_{1k}	−0.62 (2.83)	1.01 (0.02)**			NA	0.19	NA	0.19	0.987
	d_{2k}	2.04 (1.06)	0.22 (0.06)**	0.77 (0.06)**		NA	12.1 (0.01)	NA	12.1 (0.01)	0.998
	d_{3k}	0.07 (1.11)	0.21 (0.04)**	−0.24 (0.13)	1.04 (0.13)**	60.4 (0.01)	29.1 (0.01)	3.43 (0.07)	4.56 (0.01)	0.998
Inexperienced	d_{1k}	0.66 (1.96)	1.00 (0.01)**			NA	0	NA	0	0.987
	d_{2k}	−0.11 (0.79)	0.19 (0.04)**	0.82 (0.04)**		NA	39.9 (0.01)	NA	39.9 (0.01)	0.998
	d_{3k}	0.37 (0.63)	0.25 (0.03)**	0.04 (0.08)	0.72 (0.08)**	71.5 (0.01)	38.4 (0.01)	0.22	3.34 (0.02)	0.999

Notes: Data analysis restricted to x_{1k} in the interval $\underline{x} + \varepsilon, \bar{x} - \varepsilon$. NA stands for not applicable.
** Significantly different from 0 at the 1-percent level.
[a] Standard errors are given in parentheses.
[b] Probability $F = 1$ in parentheses.
[c] Tests the null hypothesis that $\delta_{js} = 0$ for all $s > 1$.
[d] Tests the null hypothesis that $\beta_j = \delta_{j1} = 0.50$ and $\delta_{js} = 0$ for all $s > 1$.
[e] Tests the null hypothesis that $\delta_{js} = 0$ for all $s < j - 1$.
[f] Tests the null hypothesis that $\beta_j = 1/j$, $\delta_{j,j-1} = 1 - (1/j)$ and $\delta_{js} = 0$ for all $s < j - 1$.

tion problem which is inherent in common values auctions.[17] Consider the problem of choosing a reservation bid γ_{ijk} for bidder i who has reached round j (in auction k). If he or she knew the private signals of all the bidders who dropped out in earlier rounds, but was unaware of the adverse selection problem and the associated sufficient statistic underlying the uniform distribution, then it would be quite natural to average the signal values revealed to this point, along with their own signal value, and to use this to determine their reservation bid

$$(15) \quad \gamma_{ijk} = \frac{1}{j}\left(x_{ik} + \sum_{s=1}^{j-1} x_{sk}\right) \quad \text{for} \quad i \geq j > 1.$$

In fact, bidders do not know their rival's *individual* private signals. However, assuming symmetric behavior by all participants according to rule (15), they can infer by recursion that

$$(16) \quad d_{j-1,k} = \gamma_{j-1,j-1,k} = \frac{1}{j-1}\sum_{s=1}^{j-1} x_{sk} \quad \text{for} \quad j > 1.$$

Substitution of that partial sum in the right-hand side of equation (15) produces a rule of the form given in equation (14) where

$$(17) \quad \lambda_j = \frac{1}{j}, \quad \mu_j = \frac{j-1}{j} = 1 - \lambda_j$$

[17] There is an adverse selection problem: for super-experienced bidders the high signal holder won the auction 57.1 and 53.1 percent of the time with n = 4 and n = 6 or 7, respectively. Further, the high signal holder and the second-highest signal holder won the auction 85.0 and 70.8 percent of the time with n = 4 and n = 6 or 7, respectively. See subsection B3 below for more discussion of these apparent deviations from symmetric bidding.

TABLE 6—EFFECT OF OWN SIGNAL AND OTHER BIDDERS' DROP-OUT PRICES ON BIDS (n = 7)

Bidder experience	Dependent variable	Coefficient estimates[a] Intercept (α_j)	x_{jk} (β_j)	d_{1k} (δ_{j1})	d_{2k} (δ_{j2})	d_{3k} (δ_{j3})	d_{4k} (δ_{j4})	d_{5k} (δ_{j5})	Nash test statistics[b] Weak[c]	Nash test statistics[b] Strong[d]	Signal-averaging test statistics[b] Weak[e]	Signal-averaging test statistics[b] Strong[f]	Adjusted R^2
Super experienced	d_{1k}	−4.21	0.97						NA	2.84	NA	2.84	0.971
		(2.92)	(0.02)**							(0.10)		(0.10)	
	d_{2k}	−0.18	0.45	0.56					NA	0.51	NA	0.51	0.984
		(2.23)	(0.06)**	(0.07)**									
	d_{3k}	1.14	0.36	0.15	0.49				35.9	12.7	4.96	1.74	0.992
		(1.56)	(0.05)**	(0.07)*	(0.08)**				(0.01)	(0.01)	(0.03)	(0.17)	
	d_{4k}	0.26	0.18	0.01	0.09	0.73			195.0	103.3	1.54	2.71	0.997
		(1.08)	(0.03)**	(0.04)	(0.07)	(0.06)**			(0.01)	(0.01)	(0.22)	(0.04)	
	d_{5k}	1.99	0.10	0.04	0.03	−0.08	0.91		198.2	119.7	1.41	5.42	0.998
		(0.76)*	(0.02)**	(0.03)	(0.05)	(0.07)	(0.07)**		(0.01)	(0.01)	(0.25)	(0.01)	
	d_{6k}	1.43	0.19	−0.01	0.09	−0.02	0.00	0.75	105.4	70.8	0.77	0.78	0.998
		(0.98)	(0.03)**	(0.04)	(0.06)	(0.09)	(0.16)	(0.15)**	(0.01)	(0.01)			
One-time experienced	d_{1k}	−2.22	1.00						NA	0.0	NA	0.0	0.962
		(4.89)	(0.03)**										
	d_{2k}	0.89	0.16	0.85					NA	15.4	NA	15.4	0.992
		(2.30)	(0.06)*	(0.06)**						(0.01)		(0.01)	
	d_{3k}	3.08	0.19	0.09	0.71				13.0	7.01	0.26	1.16	0.999
		(2.85)	(0.08)*	(0.18)	(0.20)**				(0.01)	(0.01)		(0.34)	
	d_{4k}	−0.73	0.06	−0.01	−0.06	1.01			221.3	114.0	0.88	10.7	0.999
		(0.96)	(0.04)	(0.06)	(0.07)	(0.06)**			(0.01)	(0.01)		(0.01)	
	d_{5k}	2.95	0.20	0.18	−0.14	−0.37	1.12		42.9	28.3	1.69	1.47	0.997
		(1.43)*	(0.04)**	(0.09)	(0.12)	(0.29)	(0.26)**		(0.01)	(0.01)	(0.19)	(0.23)	
Inexperienced	d_{1k}	−3.39	1.03						NA	2.13	NA	2.13	0.979
		(3.10)	(0.02)**							(0.15)		(0.15)	
	d_{2k}	2.68	0.32	0.67					NA	5.18	NA	5.18	0.997
		(1.16)*	(0.06)**	(0.05)**						(0.01)		(0.01)	
	d_{3k}	1.62	0.15	0.04	0.81				48.4	18.5	0.20	4.42	0.998
		(1.00)	(0.05)**	(0.09)	(0.12)**				(0.01)	(0.01)		(0.01)	
	d_{4k}	1.37	0.08	0.03	−0.18	1.06			85.9	45.8	1.00	4.64	0.999
		(0.78)	(0.04)*	(0.07)	(0.13)	(0.12)**			(0.01)	(0.01)		(0.01)	
	d_{5k}	1.30	0.07	0.09	0.17	0.20	0.80		159.9	113.4	2.04	12.0	1.00
		(0.49)*	(0.02)**	(0.04)*	(0.08)	(0.13)	(0.10)**		(0.01)	(0.01)	(0.12)	(0.01)	
	d_{6k}	0.44	0.08	0.02	0.00	−0.01	−0.38	1.29	90.3	61.9	2.43	3.58	1.00
		(0.49)	(0.03)**	(0.04)	(0.08)	(0.11)	(0.15)*	(0.15)**	(0.01)	(0.01)	(0.06)	(0.01)	

Notes: Data analysis restricted to x_{1k} in the interval $\underline{x} + \varepsilon, \bar{x} - \varepsilon$. NA stands for not applicable.
* Significantly different from 0 at the 5-percent level.
** Significantly different from 0 at the 1-percent level.
[a] Standard errors are given in parentheses.
[b] Probability $F = 1$ in parentheses.
[c] Tests the null hypothesis that $\delta_{js} = 0$ for all $s > 1$.
[d] Tests the null hypothesis that $\beta_j = \delta_{j1} = 0.50$ and $\delta_{js} = 0$ for all $s > 1$.
[e] Tests the null hypothesis that $\delta_{js} = 0$ for all $s < j - 1$.
[f] Tests the null hypothesis that $\beta_j = 1/j$, $\delta_{j,j-1} = 1 - (1/j)$, and $\delta_{js} = 0$ for all $s < j - 1$.

which we will refer to as the (symmetric) signal averaging rule. The signal averaging rule offers a number of key advantages to the players. First and foremost, it helps them to overcome the winner's curse by processing the information offered by the bid sequence. Second, it does not actually require deducing signals from bids and averaging them along with one's own signal (a process that is neither transparent or easy to do given the rapidity with which prices increased in our auctions), since it strictly relies on readily observable data that is quite natural to employ (one's own private signal and the latest drop-out price). Third, it is efficient in that except for bidding errors, players are eliminated in ascending order of their private signals. Fourth, it provides the winning bidder with an unbiased and robust estimator of x_o. Finally, given the uniform distribution of signal values, within region 2 *average* profits and prices are the same under the signal averaging and Nash bidding rules, as is round by round bidding. As such, as discussed in Section V below, it would take an exceptionally sophisticated player to take advantage of signal-averaging opponents. In many ways the signal-averaging rule constitutes a very sensible (symmetric) rule of thumb and it is remarkable to find it emerging as a natural strategy for bidders at all levels of experience.

The F statistics reported in Tables 5 and 6 under the heading "averaging rule" test two versions of the averaging model: (i) a weak signal-averaging hypothesis which assumes that $\delta_{js} = 0$ for all $1 \leq s < j - 1$ in (14), and (ii) a strong signal-averaging hypothesis which assumes *in addition* that $\beta_j = 1/j$ and $\delta_{j,j-1} = 1 - \beta_j$.

Again, we start by focusing on super-experienced bidders, those who come closest to the predicted RNNE profits. With the exception of round 3 with $n = 6$ or 7, the weak signal-averaging test fails to be rejected at conventional significance levels for all $j > 2$. The strong test fails to be rejected at $p < 0.05$ in 6 of 10 rounds (when the strong hypothesis is rejected, particularly with $n = 4$, subjects put more weight on $d_{j-1,k}$ than (17) allows).[18] Looking at all the data, a similar pattern emerges. The weak signal-averaging hypothesis can be rejected at the 5-percent significance level in only 1 of 15 rounds in total. The strong hypothesis is consistently rejected in auctions with $n = 4$ and for inexperienced bidders with $n = 7$, but it fares considerably better, being rejected at a 5-percent significance level in 4 of 10 cases with $n = 7$ for super-experienced and one-time experienced bidders.[19]

The results reported in Tables 5 and 6 are robust to a number of alternative specifications. We obtain the same qualitative, and virtually the same quantitative, results using a fixed effects regression model specification, with subject dummy variables serving as the fixed effect. Interestingly, for super-experienced bidders the dummy variables are *not* significant at the 5-percent level in any auction round, although these dummy variables do achieve statistical significance in close to half the auction rounds for inexperienced and once experienced bidders. The results reported are also robust to controlling for different values of ε by restricting the analysis to auction periods with same value of ε.

In summary, our OLS pretest analysis appears to have produced a superior alternative to the Nash model. Bidders do not rely exclusively on their own signal value and the lowest bidder's drop-out price. Rather, behavior appears to be better characterized by a model in which bidders implicitly average their own signal value with the signal values implicit in all earlier bidder's drop-out prices.

One final point in concluding this section. Using the OLS estimators, we calculated the sample residual correlations across equations to test the assumption of independence of the residual ε's across equations (that is, for different j's). Among the 108 correlations that were computed, only one was significantly different from zero at the 10-percent level (with none significantly different from zero at the 5-percent level). This result strongly supports the assumption of independence across equations, which is essential to the consistency of the FIML censored estimators discussed next.

2. *Full Information Analysis.*—When a player continues to bid after someone has dropped out of an auction, this bidder reveals that his reservation value is greater then the observed drop-out price; that is, $\gamma_{ijk} > d_{jk}$. Further, in a model which permits bidding errors, there are times immediately after a bidder has dropped out that a remaining bidder, on reevaluating his drop-out price in light of the new information, may wish that he had dropped out at the same time or even earlier than the bidder who just dropped out. The obvious response of such a bidder is to drop out

[18] The FIML estimates show that the OLS estimates of the residual variances are downward biased (by as much as 50 percent in the first two rounds). Hence, actual p-levels are larger then those reported in Tables 5 and 6, to the effect that the signal-averaging hypothesis fares even better.

[19] There is a natural "semi-strong" test for the signal-averaging model: $\delta_{js} = 0$ for $1 < s < j - 1$ and $\beta_j + \delta_{j,j-1} = 1.0$ in (13). This semi-strong test does nearly as well as the weak test: with $n = 4$, it is rejected using a 5-percent significance level in only one round (in this case involving inexperienced bidders) and with $n = 6$ or 7 it fails to be rejected in any round for all three data sets. The biases inherent in the OLS estimates indicate that this is a more reliable test of the signal-averaging rule than the "strong" test reported.

immediately before the price has had a chance to increase.[20] We refer to such exits as panic drop outs. For these bidders, $\gamma_{ijk} \leq d_{j-1,k}$ is less than the observed d_{jk} for that round. A FIML censored bidding model incorporates the additional information about reservation bids associated with both these cases and corrects for the potential bias associated with our OLS estimates.

In developing these estimates we reformulate the decision problem as one of choosing among two rival point hypotheses—the Nash and the signal-averaging models. Estimation was done under two different assumptions regarding the error structure (ε_{ijk}) in equations (7) and (8): (1) The errors for individual i are independent across successive rounds (j) of each auction, and (2) The errors for individual i are perfectly correlated across rounds.[21] Under both specifications the signal-averaging model outperforms the Nash model over *all* six data sets having (i) smaller standard errors and (ii) larger maximum likelihood values.[22] Further, the variance dominance of the signal-averaging model is consistently greater in auctions with $n = 7$ than with $n = 4$, which is as it should be, since the difference between the two formulations increases with n.

[20] The computer program running the experiment had a built in delay of 10 seconds following the first dropout. After that the clock continued to increase rapidly at about 1 tick every 1–2 seconds. Bidders could tell immediately after someone had dropped out by the sound of that bidder hitting their terminal key and were able to respond before the clock could tick up. Our data files report these bidders as having dropped at the same price as the previous bidder while correctly ordering these ''simultaneous'' dropouts with respect to the order in which they dropped. Both our hardware and software were updated for the $n = 4$ auctions with super-experienced bidders. For these auctions we recorded these panic dropouts as having dropped out at the next programmed tick of the clock, so that for this data set we cannot distinguish between panic dropouts and bidders who chose to remain active for one more tick of the clock.

[21] Both specifications employ restrictions on the residual variance ratios (''weights'') across auction periods which were suggested on both theoretical and empirical grounds.

[22] For example, under the independent error specification, the log likelihood differences were 15.3 with $n = 4$ and 61.4 with $n = 7$ for super-experienced subjects (for which we have the most data).

3. *The Effect of Bidding Errors on Other Observable Quantities*.—Table 7 reports the percentage of auctions won for the highest and second highest signal holders, average profits of these bidders when they win, and the percentage of panic dropouts for all six data sets. Also shown are the results of MC simulations based on the censored FIML estimated bid functions, assuming independent error draws across successive rounds of bidding. The simulated profit data ''truncates'' drop-out bids so that in cases where the ε_{ijk} drawn results in a panic dropout, we treat this bidder as dropping out at the previous price. Table 7 provides a number of insights:

(i) In the MC simulations, the existence of *stochastic* bidding errors in conjunction with *independent* error draws implies that with signal averaging the high signal holders will win the auction around 55 percent when $n = 4$ and around 35 percent when $n = 7$. These are dramatically lower than the 100 percent winning percentage implied by homogeneous bidding without bidding errors. These predicted frequencies are remarkably accurate for $n = 4$ and, for $n = 7$, lie within the 95 percent confidence interval or just below it (super-experienced subjects).[23] Thus, what appears to be a breakdown in the symmetry assumption of the model is quite consistent with symmetry in conjunction with stochastic bidding errors.

(ii) The simulated frequencies of panic dropouts lie within the 95-percent confidence interval of the realized data for the signal-averaging model with independent errors in all cases. In contrast, the simulated frequency of panic dropouts assuming perfectly correlated error terms across successive rounds of each auction

[23] Part of the explanation for the super-experienced $n = 7$ case may have to do with our simulations assuming a normal distribution for the error term, whereas the actual error distribution in this case deviates significantly from the normal distribution, with a higher frequency of early dropouts than the normal distribution implies. In contrast, for the $n = 4$ cases, a null hypothesis of normal errors fails to be rejected at conventional significance levels in all cases.

TABLE 7—COMPARISON OF ACTUAL DATA WITH FULL INFORMATION SIGNAL-AVERAGING MODEL SIMULATIONS

		Actual data					Simulations				
		Percentage wins by signal rank		Average profit by signal rank			Percentage wins by signal rank		Average profit by signal rank		
	Experience	2nd high	High	2nd high	High	Percentage panic drops	2nd high	High	2nd high	High	Percentage panic drops
$n = 4$	Super experienced	28.4 (5.01)	56.8 (5.50)	−0.96 (1.95)	2.20 (1.28)	ND[a]	28.7 (0.04)	55.4 (0.05)	−2.75 (0.01)	−1.01 (0.01)	15.1 (0.04)
	One-time experienced	26.8 (6.92)	56.1 (7.75)	1.39 (1.16)	−0.28 (1.17)	15.5 (3.26)	28.6 (0.04)	56.3 (0.05)	−1.66 (0.01)	−0.46 (0.01)	14.8 (0.04)
	Inexperienced	27.5 (7.06)	60.0 (7.75)	−0.66 (1.60)	−0.12 (0.98)	10.8 (2.84)	28.4 (0.04)	57.2 (0.05)	−0.97 (0.01)	0.23 (0.01)	15.3 (0.04)
$n = 7$	Super experienced	17.4 (4.56)	57.9 (5.94)	−0.76 (1.25)	2.22 (0.48)	23.7 (2.09)	25.3 (0.04)	35.5 (0.05)	−1.61 (0.01)	−1.02 (0.01)	25.5 (0.04)
	One-time experienced	24.0 (8.54)	48.0 (9.99)	−0.62 (1.50)	−0.27 (1.49)	32.1 (3.67)	24.4 (0.04)	33.1 (0.05)	−1.63 (0.01)	−1.28 (0.01)	26.6 (0.04)
	Inexperienced	37.1 (8.17)	37.1 (8.17)	−3.14 (1.64)	−0.76 (0.92)	26.7 (3.05)	25.7 (0.04)	36.6 (0.05)	−3.34 (0.01)	−2.91 (0.01)	21.1 (0.04)

Notes: Standard errors reported in parentheses.
[a] ND stands for no data. See footnote 20.

are considerably smaller than the realized frequencies. For example, with super-experienced bidders and $n = 7$, the FIML estimates for the signal-averaging model yield a panic drop-out rate of 3.4 percent, which is far too low to provide a reasonable characterization of the data.

(iii) The simulated profit data for the signal-averaging model are well below the realized data for super-experienced bidders with both $n = 4$ and 7. The simulated profit data are quite sensitive, however, to the intercept value employed, and these coefficients are subject to reasonably large standard errors (see Table 1 of an appendix available from the authors). For example, for super-experienced bidders with $n = 7$, reducing the intercept value by one unit generates positive profits of $1.91 in the averaging model simulation when the high signal holder wins.

Accounting for the way in which constant terms accumulate across rounds within a given auction, expected profits would be significantly larger—by as much as $5 to $10—if the intercepts of the FIML bid functions were set to zero in the simulations. These are considerably larger than expected profits with error free bidding. This finding indicates that bidding errors, if unaccounted for, bias downward estimates of x_o and raise expected profits. However, the significant positive intercepts for the estimated bid functions suggest that bidders have become aware of this bias, and compensate for it by adjusting the intercepts of their bidding rules, thereby preserving their intrinsic "simplicity."

IV. Relationship to Field Data

Comparisons of revenue raising effects of English auctions using field data have been largely confined to U.S. government timber lease sales. Using OLS regressions, Walter J. Mead (1967) reports that first-price sealed bid auctions had significantly higher prices than English auctions; that is, English auctions resulted in significantly lower average revenue. Further study by Hansen (1985, 1986), who noted a selection bias caused by the way the forest service chose which auction to use, and corrected for it using a simultaneous equations model, found that although first-price auctions had slightly higher prices than English auctions, the difference was not statistically significant, so that revenue equivalence could not be rejected. The puzzling part about these results is that there are strong common value elements to timber lease sales which should, in theory, result in English auctions raising more revenue. R. Preston McAfee and McMillan (1987 p. 727) note this puzzle and go on to add, "The puzzle could be resolved by appealing to risk aversion of the bidders, but this remains an open empirical question."

Results from our common auction experiments offer an alternative resolution to this anomaly. In auctions with inexperienced bidders who clearly suffered from the winner's curse, English auctions consistently yield less revenue than first-price auctions (recall Table 2). Further, even in auctions where bidders earned positive profits, but still exhibited relatively strong traces of the winner's curse, as in auctions with one-time experienced and super-experienced bidders with $n = 7$, the two auctions yield roughly the same revenue. In other words, in auctions where bidders suffer from strong traces of the winner's curse, English auctions fail to raise more revenue. Of course, to use this mechanism to resolve the anomaly for the timber lease sales requires postulating that bidders suffer from a winner's curse, something many economists are loath to do. Nevertheless, this hypothesis is more consistent with the experimental data than the risk-aversion hypothesis.[24]

V. Summary and Conclusions

Irrevocable exit English auctions are capable of raising average revenue compared to first-price, sealed bid auctions as symmetric RNNE bidding theory suggests. A necessary condition for this outcome is for bidders to have largely overcome the winner's curse in sealed bid auctions. Otherwise average revenue in first-price auctions is substantially higher than predicted and the public information released in the English auctions serves primarily to correct for the winner's curse. These results replicate earlier experimental results concerning the release of public information in first- and second-price sealed bid auctions (Kagel and Levin, 1986; Kagel et al., 1995). The important difference between the two cases is that public information is endogenous and noisy in English auctions and exogenous and precise in the sealed bid auctions. Hence, there was no prior assurance that these earlier results would generalize.

In English auctions, later bidders employ earlier bidders' drop-out prices in determining what to bid, as Nash bidding theory suggests. However, the information processing mechanism is quite different from what Nash bidding theory predicts, involving a signal-averaging rule that, under our design, with symmetry, yields the same average prices and profits as the symmetric RNNE. We attribute the adoption of the signal-averaging rule to the fact that (i) it is easy and quite natural to use and (ii) it yields results quite similar to the Nash model without requiring that bidders explicitly recognize the adverse selection effect of winning the auction. The latter seems essential to explain the data since inexperienced and one-time experienced bidders use the same rule, while bidders with comparable experience in first-price, sealed bid auctions suffer from a strong winner's curse.

The econometric model used to test between the signal-averaging and Nash bidding models provides strong support for the averaging model. Both OLS estimates using only observed drop-out prices and censored FIML estimates show that the averaging model provides a remarkably accurate characterization of the data. MC simulations based on the censored estimates of the signal-averaging model accurately predict the frequency of panic dropouts and the frequency with which the highest and second-highest signal holders win the auction. These same simulations show that the relatively low percentage (50–60 percent) of high-signal holders winning the auctions is fully consistent with a symmetric bidding model, given the bidding errors actually observed.

Although the symmetric signal-averaging rule yields the same drop-out prices, on average, hence the same expected profit for the high bidder as the RNNE, it is not a Nash equilibrium. With $n \geq 4$, given that all other bid-

[24] See Michael H. Rothkopf and Richard Englebrecht-Wiggans (1993) for an alternative explanation of this anomaly.

ders follow the averaging rule, when the second-highest signal holder determines he has an above average signal value, he can unilaterally deviate by "hiding" his signal value and not dropping out. In doing so, he induces the highest-signal holder, who is forming his drop-out price according to the averaging rule, to drop out at an expected value that is *below* the true value. Thus, such a unilateral deviation will, on average, be profitable. In contrast, under the Nash rule, this "signal-jamming" strategy, except by the lowest-signal holder, will not affect the drop-out prices of the other bidders (and hiding by the lowest-signal holder only causes other bidders to drop out at an expected value that is *above* the true value, so that it does not constitute a profitable deviation).

One might ask, of course, why this signal-jamming strategy does not destroy the signal-averaging strategy, to which there are several possible answers. The most likely one is that the signal-jamming option (i) is not transparent and (ii) given the noise in applying the signal-averaging strategy and the noise inherent in the realizations of expected values, it is very unlikely to be discovered.

Arguably, there is no way that our subjects could hit on the Nash bidding strategy since they were not trained to recognize sufficient statistics. On the other hand, averaging the lowest drop-out price with one's own signal value seems simpler and easier to do then tracking all the signal values and implicitly averaging them. The key point, however, is that bidders do make use of the public information inherent in other bidders' drop-out prices, as Nash equilibrium bidding theory predicts. The results of both rules are quite similar, on average, under our design. This raises an interesting topic for future research: will the signal-averaging rule still have drawing power for distribution functions when it leads to markedly different outcomes relative to Nash equilibrium bidding.

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