The Economic Journal, **99** (*March* 1989), 108–115
Printed in Great Britain

A COMPARISON OF NAIVE AND EXPERIENCED BIDDERS IN COMMON VALUE OFFER AUCTIONS: A LABORATORY ANALYSIS*

Douglas Dyer, John H. Kagel and Dan Levin

Laboratory economics experiments typically use financially motivated students as subjects. An ongoing issue is whether this is an appropriate subject pool since the students are typically inexperienced in the types of decision-making required of them in the lab. This paper addresses this issue in the context of common value offer auctions as we compare the behaviour of experienced business executives in the construction contract industry ('experts') with that of ('naive') student subjects. Results of previous research of this sort have been equivocal; in some cases experts make the same errors as novices, in other cases they do not (Hogarth and Reder, 1987).

A series of sealed-bid, common value offer auctions in which bidders compete for the right to supply an item of unknown cost were conducted. Inherent to common value auctions (CVAs) is an adverse selection problem which may result in below normal or negative profits (the winner's curse). Experimental studies have documented the presence of the winner's curse with financially motivated student subjects in high price demand-side auctions (Kagel *et al.*, 1986; Kagel and Levin, 1986). The experiments reported here generalise these earlier studies from bid to offer auctions. Also, in employing offer auctions we establish a setting with which our 'experts' are familiar, thus allowing their experience the best chance to manifest itself.[1]

I. STRUCTURE OF THE AUCTIONS

Experiments 1–3 employed University of Houston upper-level economics majors with no prior laboratory experience. Experiment 4 used executives from local construction companies with an average of over 20 years experience in the construction industry. All but one of these individuals had many years experience in the actual bid preparation process.

Each experiment consisted of a series of auction periods in which the right

* Financial support was received from the Information Science and Technology Division and the Economics Division of the NSF, the Sloan Foundation, and the Energy Laboratory of the University of Houston. We would like to thank Ron Harstad and Susan Garvin for comments and assistance. The paper has benefited from comments of discussants at the Winter 1987 Econometric Society meetings and the referee and editor of this JOURNAL. This is a shortened version of Dyer *et al.* (1987) which contains a complete description of the experimental design, including instructions. Interested readers should contact Douglas Dyer, Department of Economics, Memphis State University.

[1] We do not claim that the laboratory setting we created is an exact replica of the commercial construction industry. However it captures many of the essential features and relevant economic considerations of that market. At the very least the executives are quite experienced in translating imprecise estimates into bids in competitive offer auctions.

to supply a single unit of a commodity was awarded to the low bidder using a first-price, sealed-bid institution. The actual cost of producing the item, C, was unknown at the time bids were submitted. The low bidder earned a profit equal to the difference between his bid and the actual cost of supplying the item; all other bidders earned zero profits.

C was drawn randomly from a uniform distribution on [\$50.00, \$250.00]. Each bidder received a private information signal, c_i, randomly drawn from a uniform distribution on $[C-\epsilon, C+\epsilon]$. The distributions underlying both C and the private information signals were common knowledge as was ϵ and the number of bidders, N.

To cover the possibility of losses subjects were given starting capital credit balances of at least \$10.00. Losses were subtracted from this balance and profits added to it. Subjects were told that if this balance went to zero or less that they would no longer be allowed to participate. After all bids were submitted they were posted along with the corresponding signal values, and the low bid noted. C was announced and profits (or losses) were calculated and balances updated. Each period the profit or loss earned was announced, but not the identity of the low bidder.

Experiments 1–3 employed 4 active bidders throughout. Experiment 4 began with 4 active bidders; after 24 periods bidding was done in markets with $N = 7$ both with and without public information which consisted of announcing the highest cost estimate (C_H) received by an active bidder.[2] Profits were paid in only one of the two markets. The market paid was determined randomly.

II. THEORETICAL CONSIDERATIONS

Wilson (1977) was the first to develop a Nash equilibrium solution for first-price sealed-bid CVAs. In the interval $[\$50+\epsilon < c_i < \$250-\epsilon]$ the symmetric risk neutral Nash equilibrium (SRNNE) bid function is

$$b(c_i) = c_i + \epsilon - Y \qquad (1)$$

where $Y = [2\epsilon/(N+1)] \exp[-(N/2\epsilon)(250-\epsilon-c_i)]$. The Y term contains a negative exponential and diminishes rapidly as c_i moves below \$250 $-\epsilon$. The SRNNE calls for signals to be 'marked-up' by an amount approximately equal to ϵ.[3]

The winner's curse arises as the result of bidders failing to properly account for the adverse selection process at work in CVAs. Consider two alternative expectations of the actual cost, based on a given estimate. In the interval $[\$50+\epsilon < c_i < \$250-\epsilon]$ an unbiased estimate of C is:

$$E(C \mid C_i) = c_i. \qquad (2)$$

However this expectation is naive in that it fails to account for the fact that the

[2] Two experienced student subjects were added to the five executives to create a market with $N = 7$.

[3] Unfortunately there is no clear cut prediction as to the effects of risk aversion on the equilibrium bid function. Depending on the nature and degree of the risk aversion, equilibrium bids could be greater than or less than the SRNNE.

low bidder tends to have the lowest, or one of the lowest, private information signals. An estimator which takes this information into account would be the expected cost, conditional on having the lowest signal:

$$E(C \mid C_i = c_1) = c_i + [(N-1)/(N+1)]\,\epsilon \tag{3}$$

where c_1 refers to the lowest signal. Given symmetry (or a high rank order correlation between bids and signals) in bidding, winning bids less than (3) will result in losses on average.

Note that there are two opposing forces at work when the number of bidders is increased in a CVA. There is a strategic force which tends to promote lower bidding as the number of bidders increases: With a greater number of rivals there is less room to markup bids relative to cost estimates and still win the auction. However item valuation considerations promote higher bidding: The adverse selection problem is greater the higher the number of bidders. Given the distributions in our design, the item valuation force dominates the strategic force, and the SRNNE requires that individual bids be constant or increasing as N increases (see (1)).

Milgrom and Weber (1982) extend the CVA model developed by Wilson. They show that in a high price auction, the release of public information regarding the true value of the item will raise seller's revenues on average. The analogous effect here is that the release of public information regarding the true cost of the item will lower the offer price, thus lowering bidder's profits.

Note that this is an equilibrium prediction. If the market is characterised by the winner's curse, i.e. below normal or negative profits, then the release of public information may have the effect of *increasing* the low bid, as bidders utilise the additional information to avoid the valuation errors which underlie the winner's curse.

III. EXPERIMENTAL RESULTS

A. *Experiments with $N = 4$*

Fig. 1 shows the market outcomes, by period, for experiment 4 (the executives). The actual profits earned along with the SRNNE predicted profits are shown for each period. Negative or near zero profits dominate; there appears to be little evidence of systematic learning over time within the experiment. A similar absence of within experiment learning is reported for the student subjects (Dyer, 1987).

Table 1 begins our comparison of subject populations. The second column reports the percentage of auction periods in which the low bid was submitted by the lower signal holder. Columns 3 and 4 report average actual profits earned and average profits predicted by the SRNNE, respectively. The fifth and sixth columns report the percentage of times the low bid was less than (3), the expected cost conditional on having received the lowest estimate and the percentage of all bids that were less than this conditional expectation.

Regarding the comparison across subject populations, both groups commit the winner's curse as average profits are negative in three of the four experiments and are not statistically different from zero in the other

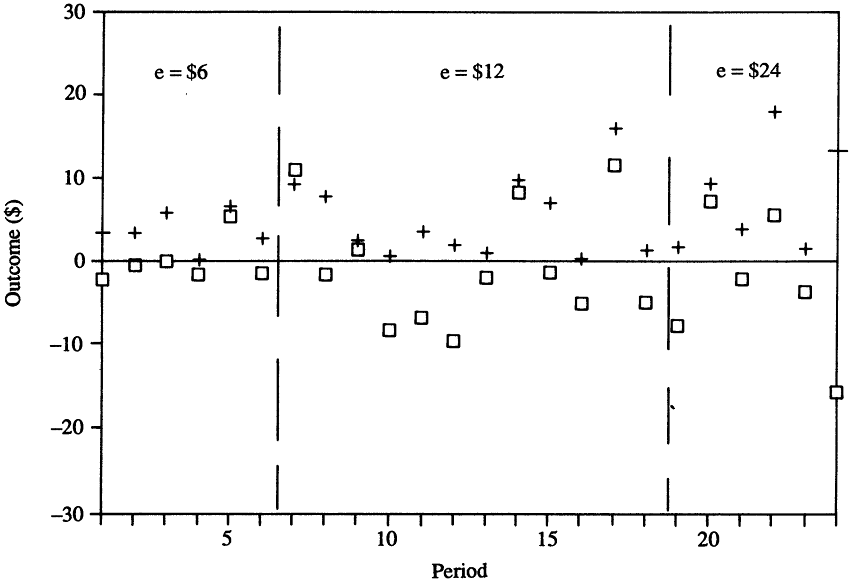

Fig. 1. Outcomes of experiment 4. □, Actual profits; +, SRNNE profits.

Table 1
Market Outcomes – N = 4

Exp	% of auctions won by the low signal holder (no times/no. per.)	Average actual profits (t-stat)	Average profits under SRNNE	% of low bids $b_i > E(C_0 \mid c_i = c_1)$ (no. times/no. per.)	% of all bids $b_i < E(C_0 \mid c_i = c_1)$ (no. times/no. per.)
1	70 (19/27)	−1·36 (−0·70)	6·03	85 (23/27)	67 (72/108)
2	65 (22/34)	0·18 (0·19)	4·43	53 (18/34)	45* (42/93)
3	77 (27/35)	−0·16 (−0·16)	4·83	66 (22/35)	52 (73/140)
Total (1–3)	71 (68/96)	−0·37	5·02	66 (63/96)	55 (187/341)
4 (execs)	79 (19/24)	−1·01 (0·74)	5·42	67 (16/24)	49 (47/96)

* All subjects had no prior laboratory experience except for two subjects in experiment 2 who had participated in experiment 1. Since there were 7 subjects present for experiment 2 we believe any effects of these subjects' prior experience to be negligible.

† Experiments 1 and 2 began with 2 dry runs, experiment 3 with 3 dry runs, and Experiment 4 with 1 dry run. These periods are deleted from the analysis.

‡ In Exp. 1 $\epsilon = 6$ in periods 1–6, $\epsilon = 12$ in 7–16 and 24–27, and $\epsilon = 24$ in 17–23.
In Exp. 2 $\epsilon = 6$ in periods 1–6, $\epsilon = 12$ in 7–16 and 25–34, and $\epsilon = 24$ in 17–24.
In Exp. 3 $\epsilon = 6$ in periods 1–7, $\epsilon = 12$ in 8–18 and 31–35, and $\epsilon = 24$ in 19–30.
In Exp. 4 $\epsilon = 6$ in periods 1–6, $\epsilon = 12$ in 7–18 and 25–36, and $\epsilon = 24$ in 19–24 and 37–40.

§ The starting capital balance was $10.00 in Exp. 1 and 2 and $20.00 in Exp. 3. Exp. 4 began with a capital balance of $20.00. When N was increased from 4 to 7 each subject was given a new capital balance of $25.00, with the understanding that the ending balances from part one of the experiment would be added to the ending balances from part two and paid in cash at the end of the experiment.

experiment. We find no significant differences, at the 10% level or better, across populations in any of the following measures of market performance: the percentage of times the low bid was submitted by the low signal holder, average actual profits and the percentage of times the low bid was less than (3). Finally, at an individual level we find no difference in the percentage of all bids less than (3).

More detailed analysis of the data reveals some differences however. The student subject experiments show a pattern of decreasing losses as ϵ increases from 6 to 12, with positive profits as ϵ increases from 12 to 24. When ϵ is returned to 12 losses again dominate. The executives show a different pattern, with modest losses at $\epsilon = 6$, which increases as ϵ increases.

Regression analysis on individual bid functions shows that the students employed a larger fixed markdown and were more responsive to changes in ϵ than the executives. We believe these different bidding rules may be reflective of underlying differences in risk attitudes between the two groups, with the students exhibiting risk aversion and the executives risk neutrality. The latter argument is supported by the fact that with increases in ϵ, cost estimates are less precise, which, other things equal, is likely to be reflected in proportionately greater markups in bids relative to signal values for risk averse bidders. Further, it seems reasonable to assume that the executives would be closer to risk neutrality, especially over the sums at stake in these auctions, than the student subjects. In either case, we see a somewhat different pattern of bidding with changing ϵ across the two subject populations (see Dyer, 1987, for a more complete discussion).

The different pattern of profits/losses with changes in ϵ, and the differences in estimated bid functions, lead us to reject the maintained hypothesis that there are *no* differences between the two subject pools; however, we feel that the similarities are much more striking than the differences.

B. Effects of Changing N and Public Information

Table 2 reports the results of changing N in experiment 4. Losses dominate with both $N = 4$ and $N = 7$ for both $\epsilon = 12$ and $\epsilon = 24$ and increase as N increases. Increasing losses with increased numbers of rivals implies that individual bidders are responding in the wrong direction, or are not responding sufficiently in the right direction, to overcome the increased adverse selection problem

Table 2

Market Data with Changing N Experiment 4

	$N = 4$		$N = 7$	
	Average actual profits	Average SRNNE profits	Average actual profits	Average SRNNE profits
$\epsilon = 12$	−0·57	5·08	−1·98	3·97
$\epsilon = 24$	−2·77	7·94	−3·22	4·11

inherent in more bidders. Regression analysis shows the executives do bid slightly higher with $N = 7$. This response is qualitatively in the direction predicted by the SRNNE; however, the magnitude of the response is less than that needed to avoid larger losses with increased N.

The response to changing N is qualitatively different from results reported with student subjects in both low and high price experiments (Dyer, 1987 and Kagel and Levin, 1986) and may well represent a difference between the two subject pools. However this conclusion is not without qualification. The student experiments involved experienced subjects who were making relatively large positive average profits in markets with $N \doteq 4$ when the number of bidders increased, while the executives were suffering losses when we increased market size from 4 to 7 bidders. Coming from the domain of positive profits, the students may have been more sensitive to the strategic pressures of changing N than the item valuation forces, which would lead them to bid more aggressively when the number of rivals increased. The executives however, coming from the domain of negative profits, may have been more responsive to the item valuation forces. Given that they were already suffering from the winner's curse, when N increased simple survival pressures dictated bidding less aggressively to avoid bankruptcy, and exit from the market. These differences in context provide an alternative explanation to the observed behavioural differences than any fundamental difference between the two subject pools.

Table 3 reports the results of announcing C_H, the highest private information signal received by an active bidder, on the offer price. Pooled over the 11 observations, public information *raised* the offer price by \$2.91 (t = 1.87 significant at the 5% level, 2-tailed test). This is contrary to the theoretical prediction of a *decrease* in the offer price of \$1.60 but is consistent with earlier findings with student subjects (Kagel and Levin, 1986). The perverse effects of public information relative to Nash equilibrium bidding theory generalise from students to the executives and from a bid to an offer auction institution.

IV. CONCLUSION AND DISCUSSION

Our experiments show that the judgmental failure known as the winner's curse, which has been documented in laboratory high price auction experiments, extends to an offer auction institution. Further, results with inexperienced bidders in large markets extend to small markets, as a strong and persistent winner's curse was found when bidding was done in markets with only four bidders. Finally similar results are reported almost without exception across students and business executives. We conclude that the winner's curse phenomenon is robust across auction form, market size and subject population.

The results for the executives seem most surprising given their experience bidding in a market presumed to have a strong common value component. In reporting these surprising results two recurring issues have been raised: (1) the executives may not have been taking the experiment seriously, with bidding done more or less at random, and/or (2) there may be institutional factors which protect overly aggressive low price bidders from suffering losses in the field. We now address these two issues.

Table 3

The Effects of Public Information on the Offer Price Experiment 4 N = 7

	Average change in offer price		Results from private information market		
ϵ (No. persons)	Actual (t-stat)	Predicted	Average profits	SRNNE profits	% of periods won by low signal holder
12 (7)	1·51 (1·60)	−3·34	−1·55	4·48	86 (6/7)
24 (4)	5·26 (1·35)	−0·52	−3·22	4·11	50 (2/4)
combined (11)	2·91 (1·87)	−1·60	−2·16	3·63	72 (8/11)

Regarding the attitude of the executives we emphatically reject the criticism that they did not take the experiment seriously. The group was attentive during the reading of the instructions, asked relevant questions, and in every way gave the impression of wanting to make as much money as possible. Although the amounts of money at stake were not large relative to their other earnings, predicted profits under the SRNNE approached $100.00 for the three hour experiment, not a trivial sum. Most important the data offer no support for the idea that the executives were not bidding seriously; regression analysis shows clearly that they were responsive to their private information signals, and that changes in N and ϵ had a statistically significant effect on behaviour in the 'right' direction.

The second criticism is more substantial. The executives *are* successful in their industry. If they made the same bidding errors consistently in the field, they could not remain in business. Instead recurring losses would necessitate a change in bidding strategy, or would result in bankruptcy and exit from the market. Why then are the executives successful in their field but suffer persistent losses in the lab? Several reasons suggest themselves. First, part of the dispersion of bids in the field reflects a strong private value component to bidding in the construction industry. This is reflected in one of the questions received following the reading of the instructions: 'What is my overhead at this time?' This indicates that at any given time different firms have different opportunity costs of committing to a new project; part of the dispersion of bids in the field undoubtedly reflects different opportunity costs rather than different valuations.

Clearly however this is not the whole story. Here we rely on discussions with people in the industry, including the executive subjects. The response is always fundamentally the same – it definitely *is possible* to suffer losses (and large losses) on a given project.[4] While there are processes which may mitigate such losses,

[4] Everyone we interviewed had stories of individual projects which resulted in large losses. These losses were attributed to a variety of factors, including poor take-offs, incorrect pricing formulas, and misforecast of such things as labour troubles, subcontractor reliability, and weather.

such as renegotiation or change orders, these losses are not eliminated altogether.

How then can we explain the divergence of behaviour in the field and in the lab? We believe that the executives have learned a set of situation specific rules of thumb which permit them to avoid the winner's curse in the field but which could not be applied in the lab.[5] Success in the field is in part a function of detailed knowledge about a particular market environment; when removed from this environment the executives' behaviour parallels that of 'naive' subjects. Success in the field thus derives not from conformity to a narrow notion of rationality, but from acquiring and utilising detailed knowledge of a particular market environment.

This analysis implies that the winner's curse is likely to be strongest in the start-up phase of a market, in those markets which experience the greatest turnover of participants and in markets where large numbers of agents come in and out sporadically so as not to acquire any strong learning from experience. Further it has fundamental implications for how learning occurs in economic environments in general: Not through understanding and absorbing 'the theory', but from rules of thumb that are likely to breakdown under extreme changes, or truly novel, economic conditions.

Memphis State University

University of Houston and University of Pittsburgh

University of Houston

Date of receipt of final typescript: May 1988

References

Dyer, D. (1987). 'An experimental analysis of auction theory.' PhD Dissertation, University of Houston.

—— Kagel, J. and Levin, D. (1987). 'Common value offer auctions: bidding behavior of student subjects and construction contractors.' University of Houston, September.

Hogarth, R. M. and Reder, M. W. (1987). 'Perspectives from economics and psychology.' in *Rational Choice*, Chicago: University of Chicago Press.

Kagel, J. H. and Dyer, D. (1988). 'Learning in common value auctions.' *Experimental Games and Markets*, (Reinhard Tietz, Wulf Albers and Reinhard Selten, eds.). Berlin: Springer-Verlag.

—— Levin, D., Battalio, R. C. and Meyer, D. J. (1989). 'First-price, sealed-bid, common value auctions: bidder behavior and the "winner's curse".' *Economic Inquiry*, (forthcoming).

—— and Levin, D. (1986). 'The winner's curse and public information in common value auctions.' *American Economic Review*, Vol. 77, pp. 894–920.

Milgrom, P. and Weber, R. (1982). 'A theory of auctions and competitive bidding.' *Econometrica*, Vol. 50, pp. 1089–122.

Wilson, R. (1977). 'A bidding model of perfect competition.' *Review of Economic Studies*, Vol. 44, pp. 511–8.

[5] This learning may be the result of trial and error which through information feedback results in the adoption of rules which 'work', or it may be the result of the market environment 'selecting for' those agents whose behaviour enables them to survive, with those agents using inappropriate rules not being viable (i.e. being forced out of the market). Kagel and Dyer (1987) and Kagel and Levin (1986) provide strong evidence that learning within the laboratory is situation specific as well.