THE LOSER'S CURSE

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If the value of a commodity is unknown, a prospective buyer must realize that a bid based on an overestimate of its value is likely to be accepted. In this situation, merely finding out that one's bid is accepted may cause one to reduce the estimate of a commodity's value, so winning an auction can bring a feeling of regret.[1] Acceptance of a bid is an informative event, and failure to incorporate this contingent information into the bidding strategy can lead to excessive bids and subsequent losses, a result widely known as the "winner's curse."[2] There is considerable anecdotal evidence that bidders for a prize of uncertain value fall prey to the winner's curse, and persistent overbidding has also been observed in laboratory experiments.[3]

There is a second factor that can also induce overbidding: the thrill of winning. This raises the possibility that overbidding is due to a "utility of winning" instead of being the result of an irrational failure to anticipate the informational content of a bid's acceptance. One way to distinguish these explanations is to examine a situation in which the winner's curse effect is neutralized, to see if bids are still too high. In order to neutralize the winner's curse, we identify an opposing bias: a situation in which a failure to anticipate the informational content of a bid's acceptance will cause one to bid *below* the optimal bid, resulting in a "loser's curse." Since the loser's curse produces underbidding, its effect is the opposite of that arising from the winner's curse.

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1 This regret is captured in the title of Max H. Bazerman and William F. Samuelson's (1983) paper: "I Won the Auction But Don't Want the Prize."

2 The winner's curse phenomenon is first mentioned in Capen, Clapp, and Campbell (1971) in the context of bidding for oil leases. When multiple bidders obtain independent estimates of the lease value, then the bidder with the highest estimate is likely to have overestimated the value. Bids are correlated with value estimates, so the high bidder is also likely to have overestimated the value, and failure to correct for this bias can produce large losses. For an introductory discussion of the winner's curse, see Richard H. Thaler (1992, chapter 5) and Paul Milgrom (1989).

3 Kagel and Dan Levin (1986) report that losses due to overbidding are more common in auctions with larger numbers of bidders, and that losses are not eliminated by using subjects with previous experience in such auctions. For a review of more recent experimental studies, see Kagel (1994) and Douglas D. Davis and Holt (1993, chapter 5).

In a laboratory experiment, it is possible to select parameter values so that the winner's curse bias dominates the loser's curse bias, and vice versa. It is also possible to choose parameters so that these two effects exactly balance each other, for a "no-curse" treatment, where any residual tendency to overbid may be interpreted as evidence of a thrill of winning. To summarize, the well documented winner's curse suggested a way to model the information-processing errors which, in turn, led to a prediction that a loser's curse would be observed under some treatment conditions and that no bias would be observed under others. The advantage of experimental methods is that these conditions can be implemented for empirical study.

The next section shows how both overbidding and underbidding biases can arise. Section II contains a parametric bargaining model that will be used to generate parameter values for the experiment. The laboratory procedures are summarized in section III, and the results are analyzed in section IV. The final section contains a conclusion.

I. Winner's and Loser's Curses

Consider a bilateral bargaining problem with asymmetric information and valuations. Following the theoretical work of Samuelson (1984) and Samuelson and Bazerman (1985), the current owner of an object knows its true current value, while the potential buyer knows only the distribution of possible current values. For example, suppose that the seller value, v, is uniformly distributed on [0, 1.00], as shown by the rectangular density function in figure 1. The randomly determined seller value is observed by the seller, but not by the buyer. This informational disadvantage is offset by an assumption that the buyer's value will be $1.5v$. The buyer makes a single bid on a take-it-or-leave-it basis, so the bid will be accepted only if $B > v$.

The optimal bid in this context is sensitive to the fact that acceptance is an informative event that should be anticipated. Given that a bid B is accepted, the conditional distribution of seller values is uniform on $[0, B]$. If the bid is 0.5, for example, the conditional density is represented by the dotted-line density function in figure 1. The expected value of an accepted bid to the seller is $B/2 = 0.25$, and the expected value to the buyer is $1.5(B/2) = 0.75B = 0.375$. Thus if the bid is accepted, the buyer pays B for an object that has a conditional expected value of only $0.75B$, which generates an expected loss. This analysis applies for any positive value of

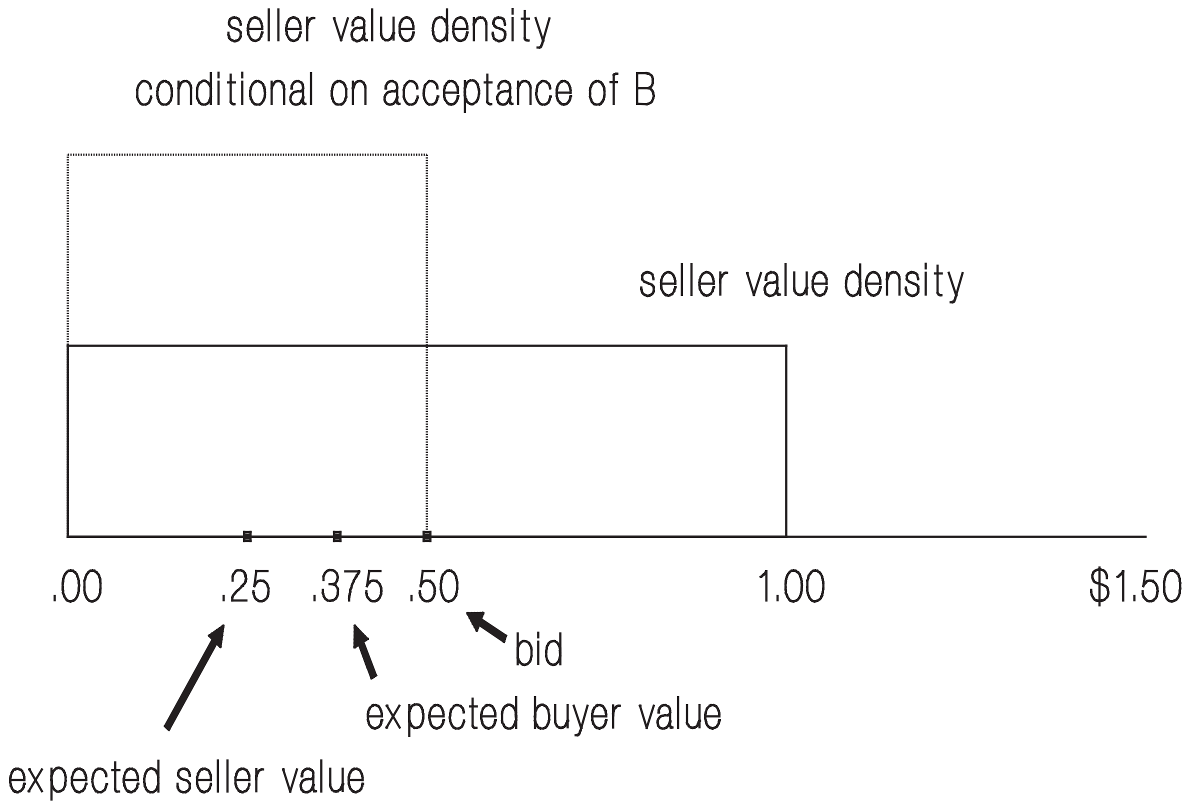

Figure 1. A Winner's Curse

B, so the optimal bid is zero.

Sheryl B. Ball, Bazerman, and John S. Carroll (1990) report an experiment with this parametric structure, and bidders without previous experience tended to bid at about 0.5 over 20 rounds. In their experiment 3, for example, only 6 percent of the subjects learned to bid 0, and the mean for the others was 0.50. When the same group was brought back a second day, the percentage of learners did not increase significantly, but the mean bid for non-learners dropped to 0.34. Fewer than 10 percent of these bidders learned to select bids of 0.[4]

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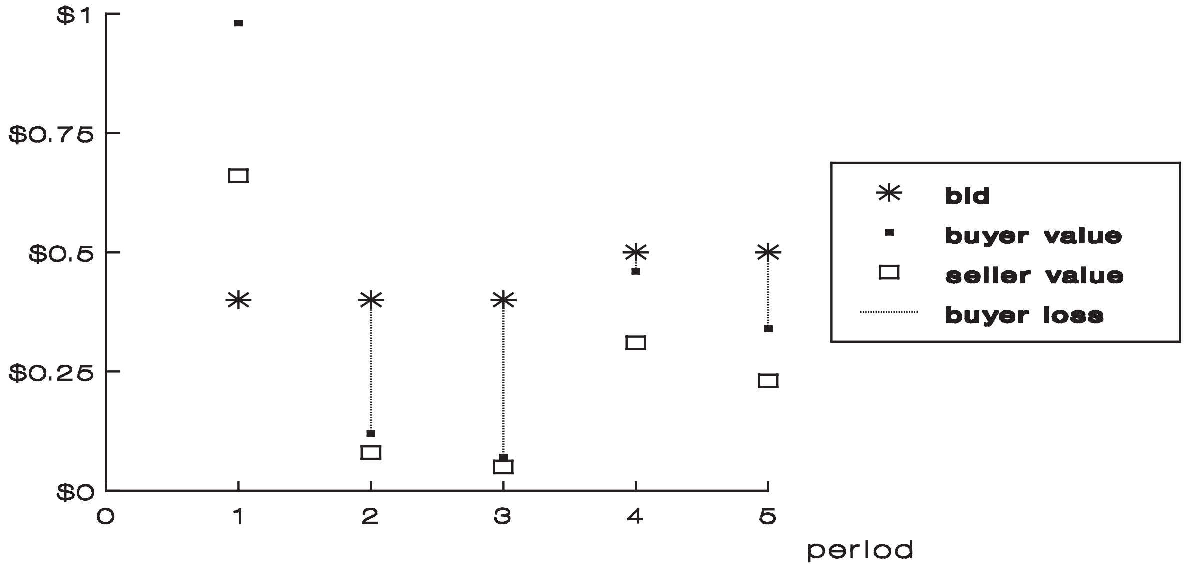
[4] Similar results were obtained by Samuelson and Bazerman (1985), who drew seller values from a discrete uniform distribution on [0, 20, 40, 60, 80, 100]. Edward Horkan (1990) also observed little learning in this situation.



The nature of the decision errors is instructive. A typical pattern of behavior is presented in figure 2, which shows the first 5 rounds of data for a representative subject.[5] The seller value is drawn from a uniform distribution on [0, 1.00]. In round 1, the seller value of 0.66 is shown by a small box, the buyer value of 0.99 is shown by a dot, and the bid of 0.50 is shown by an asterisk. The bid was rejected, and there was no gain or loss for the bidder. The seller values were below the bids for the next 4 rounds, but the sales resulted in losses for the bidder. In round 5, for example, the bid of 0.5 was accepted, and the seller value of 0.23 was quite close to the expected seller value conditional on the bid's acceptance. The buyer value was 1.5(0.23) = 0.34, which is less than the purchase price of 0.50. Buyer losses are indicated by the dotted lines in figure 2. This pattern more or less continued for 30 rounds, with an average bid of 0.48, and with more losses than gains.

A failure to perceive the correct conditional expected value of an accepted bid does not necessarily cause the bid to be too high. An intuitive explanation is suggested by figure 3, where the lower bound of the range of possible values to the current owner is greater than zero. The

[5] The subject was recruited at the University of Virginia, and was given an initial cash balance of $9.00, which fell to $7.77 by the end of round 30. The procedures for this trial are described in section III below.

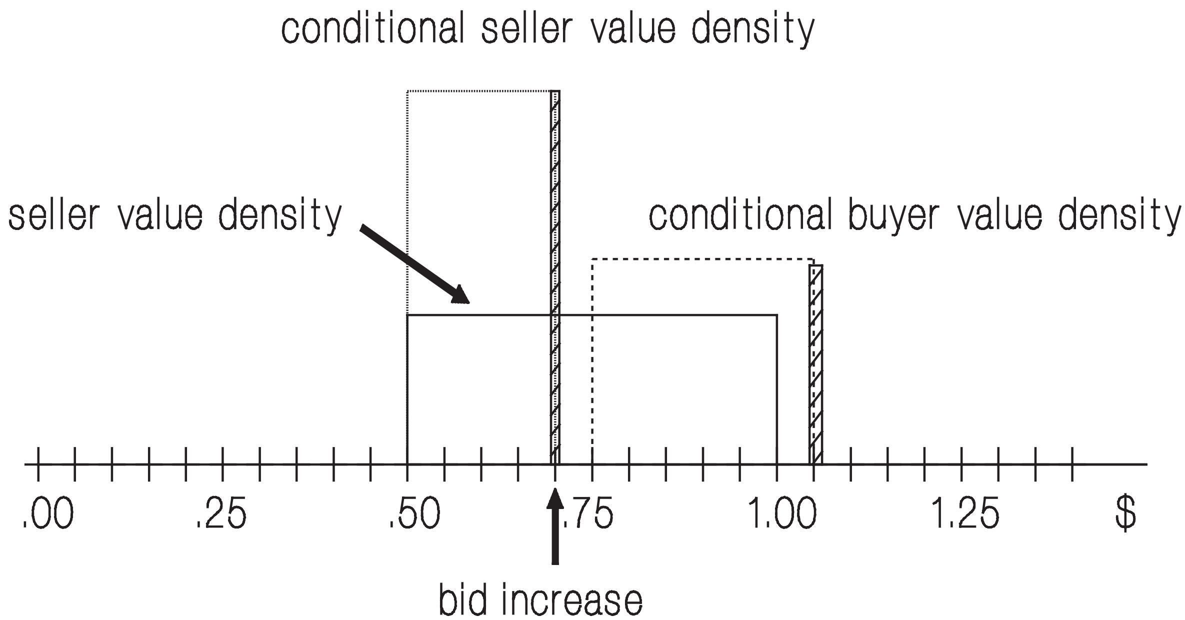


Figure 3. The Effect of an Increase in the Bid on Value Distributions

value distribution is represented by the solid-line uniform density on [0.5, 1.00], which allows the potential value to the bidder to be larger relative to the range of values the seller might accept. Consider a bid of 0.7, for example. The distribution of seller values conditional on this bid's acceptance is uniform on [0.5, 0.7], as indicated by the dotted-line, conditional-seller-value density. The conditional distribution of the object's value to the buyer is uniform on a range of values 1.5 times larger, or [.75, 1.05], as indicated by the dashed-line, conditional-buyer-value density. Notice that a bid of 0.7, if accepted, will always earn a profit for the buyer. In addition, an increase in the bid from $0.7+\Delta$ will only be relevant if the seller value is between 0.7 and $0.7+\Delta$, which is higher than the seller values on [0.5, 0.7] that would have resulted in a sale before the increase. In this example, a bid increase at the margin picks up relatively high-value units, as shown by the shaded vertical bands in figure 3. A bidder who ignores this information will tend to bid too low and to make purchases too infrequently. This is the loser's curse, which will be explained in more detail in the next section.

II. Models of Bidding and Biases

Suppose the value of a firm to its current owner is v, where v is uniformly distributed in the range from X to $X+R$. When a bid, B, is greater than v, and so is accepted, the value to the bidder is Mv, where $M>1$. The expected gain to a bidder will be the value of the item less the amount bid for it, all times the probability of having the bid accepted. It is easy to see that $(B-X)/R$ represents the probability of having a bid B accepted, since it is the probability that v is less than B. The optimal bid will take into account the current owner's decision rule in order to use the added information that would be revealed by the fact of winning. If the bidder wins, for instance, the value of the firm to the current owner cannot exceed B. Indeed, its expected value must be $X + (B-X)/2$, which is the average value that would lie between X and B if bid B is accepted. For a risk-neutral bidder, the optimal bid maximizes the integral of $Mv - B$ over the interval from $v = X$ to $v = B$. It is straightforward to express this expected-earnings integral as the product of the acceptance probability and the expected earnings conditional on acceptance, as shown in the top part of equation (1).

$$\text{(1)} \quad \begin{aligned} &\left(\frac{B - X}{R}\right)\cdot\left[M\left(X + \frac{B-X}{2}\right) - B\right] \qquad (\textit{rational objective}) \\ &\left(\frac{B - X}{R}\right)\cdot\left[M\left(X + \frac{R}{2}\right) - B\right] \qquad (\textit{naive objective}). \end{aligned}$$

Suppose that a naive bidder, in contrast, does not condition the value of a purchase on the level of the accepted bid but, rather, assumes that the value is $M(X + R/2)$, because $X + R/2$ is the expected value of v. This yields the naive objective in the bottom part of (1). Both objectives are concave in the choice variable B.

Differentiation of the alternative objectives in (1) with respect to B yields alternative first-order conditions for rational and naive bidding:

$$(2)\quad \begin{aligned} &M\left(X + \frac{B-X}{2}\right) - B + (B-X)\frac{M}{2} - (B-X) = 0 \qquad (\textit{rational bidding}) \\ &M\left(X + \frac{R}{2}\right) - B + \ast\ast\ast - (B-X) = 0 \qquad (\textit{naive bidding}), \end{aligned}$$

where the "***" indicates a missing term to be discussed below. The intuition behind the winner's and loser's curse can be found from a comparison of these two conditions. By the concavity of the objective functions in *B*, any factor that makes the left side of a first order condition in (2) larger will result in higher bids, and vice versa.

First, note that it is never optimal to bid above the range of seller values, because a bid of $X+R$ will always be accepted. Since $B-X \le R$, the 1st term on the left side of (2) is lower for rational bidding. This is the winner's curse effect; the far left-hand terms in (2) are the buyer expected values, conditional on a bid's acceptance, and the lower conditional valuation for the rational bidder will lead to lower bids.

Next consider the term, $(B-X)M/2$, which is present in the top part of (2) but is missing from the bottom part where the *** appears. This term represents the rational observation that *B* is the upper limit of seller values that will result in a purchase, so increasing the bid by 1 at the margin will raise the expected seller value of a purchased unit by 1/2, which is multiplied by *M* to get the buyer value. In the rational bidding condition in (2), this product of 1/2 and *M* is multiplied by $(B-X)$, which is proportional to the probability of making a purchase. The result is a positive term that tends to raise the rational bid determined by (2), as compared with the naive bid. The failure of a naive bidder to raise *B* in this manner generates the loser's curse effect.

The rational and naive bids, denoted by B_R and B_N respectively, are obtained directly from (2):

$$(3)\quad \begin{aligned} B_R &= \left(\frac{1}{2-M}\right)X \\ B_N &= \left(\frac{M+1}{2}\right)X + \left(\frac{M}{4}\right)R. \end{aligned}$$

The bidding functions in (3) are linear and provide a basis for several null hypotheses. In particular, if X and R are varied across several treatments, the coefficient for R in a linear bid regression should be zero for a rational bidder and should be positive for a naive bidder.

III. Experimental Design

Using the bid functions in (3), it is straightforward to choose parameters so that the rational bid is below the naive bid (a winner's curse treatment), so that the rational bid is above the naive bid (a loser's curse treatment) and so that these two bid predictions are equal (a no-curse treatment). Table 1 shows some values of R, X, and M that will give rise to these three different situations.

TABLE 1. MODEL PARAMETERS, BIDS, AND EXPECTED GAINS

Treatment	Parameters			Bids		Expected Gains	
	R	X	M	B_R	B_N	for B_R	for B_N
Winner's Curse	4.50	1.50	1.5	3.00	3.56	0.25	0.21
No Curse	2.00	1.00	1.5	2.00	2.00	0.25	0.25
Loser's Curse	0.50	0.50	1.5	1.00	0.81	0.25	0.21

Many factors that do not affect the bid functions may, nevertheless, affect behavior in a laboratory setting. If earnings are extremely low, for example, erratic behavior can result. Therefore, we decided to hold constant the expected earnings under rational bidding as the treatment is varied. For the parameters in table 1, the expected earnings for rational bidding are \$0.25 per trial, as shown in the appropriate "expected gains" column of table 1.[6] In the no-curse treatment, rational and naive bidding coincide, so earnings equal 0.25 for both bidding rules in this treatment. In both the winner's curse and loser's curse treatments, however, expected earnings will be lower for a naive bidder than for a rational bidder, and we chose parameters so

[6] Strictly speaking, the parameters in table 1 yield expected earnings of \$0.125 per trial. To ensure adequate motivation, all earnings were doubled, and table 1 shows those doubled earnings to represent the gains that were actually paid. Scaling up the earnings even further would have reduced the chances of observing an upward bias in all treatments due to the thrill of winning.

that the earnings reduction for naive bidding was the same in both of these treatments.[7] This comparable effect on earnings of departures from rationally is desirable for a study of bidding biases, since the extent of the bias may be affected by the cost of the nonoptimal behavior. Choosing parameters to balance earnings in this manner requires that the bidding biases differ between the winner's and loser's curse treatments. The difference between rational and naive bids covers 37.5 percent of the possible bidding range in the case of the loser's curse, while the difference in these bids extends over only 12.5 percent of the nine-times-larger bidding range in the case of the winner's curse.

By having the same subjects make decisions under the three different treatment conditions, variations across subjects can be controlled and sharper contrasts are possible. Of course the disadvantage of such a design is that experience in one of the conditions may systematically affect a subject's choices in the ensuing conditions. Alternating the treatment order provides balance and does not preclude tests for an order effect. This multiple-treatment design is an improvement on obtaining separate subject samples for every condition, since original effects can be achieved in subjects' first encounters and more can be observed from other conditions. Moreover, it turns out that there is not a very severe time constraint in this experiment, so exposure of subjects to multiple treatments conditions is relatively easy to accomplish. If the carry-over effect is not too serious, some advantage may also be gained through subject experience.

With three treatment conditions, there are six possible orders. Since our main interest is in the winner's and loser's curses, we used two orders: no-curse/winner's/loser's and no-curse/loser's/winner's. These orders also allow us to isolate any general bidding bias in the initial no-curse treatment when rational and naive bidding coincide. Subjects made 10 choices in each condition, to allow for learning.[8]

Several types of hypotheses will be considered. First, is there a motive to win that will cause bids to be greater than the rational level, even when there is no curse? And, second, are

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[7] The four-cent reduction in earnings from naive bidding is admittedly small. Larger earnings reductions can be obtained by using larger values of R, which has the disadvantage of increasing the chance of large losses by making earnings more variable in the winner's curse treatment.

[8] In fact, we initially allowed some of the subjects to go through each set of 10-trial treatments twice, but the second "round" was discontinued since it seemed to be no different from the first round.

the alternative curse conditions accompanied by the expected biases in bidding? That is, will bids be higher than optimal under the winner's curse treatment and lower than optimal under the loser's curse treatment? If these biases are observed, we should also ask whether they are equal. If there is a sheer thrill of winning, there will be an added bias in the same direction as the winner's curse, but in the opposite direction as the loser's curse. Finally, we consider whether bidding generally is rational.

Bid and earnings data can be used to test these hypotheses. For the first type of hypothesis, we can test whether bids are rational with no curse. For the second type, the difference between observed and optimal bids can be calculated and a test of means can be used to see whether the difference is positive when there is a winner's curse and negative when there is a loser's curse. It is difficult to carry out a simpler test of whether observed deviations from rational bidding are greater under the winner's curse than under the loser's curse, because of scale differences; the optimal bid in the winner's curse case is nearly three times that in the loser's curse case. Earnings, unlike bids, are perfectly symmetric across loser's and winner's curses. For the second type of hypothesis, it is possible to use earnings, since a greater bias will lead to poorer earnings. The overall rationality of bidding can be evaluated by estimating the linear bidding equation implied by (3).

Subjects were recruited from undergraduate economics classes at the University of Virginia. None of the 50 subjects had participated previously in this particular experiment, but some had participated in market and game experiments. Upon arrival in the laboratory, subjects were seated at visually isolated personal computers and they followed along on their screens as the instructions were read aloud.[9] After the instructions were read, cumulative earnings were set to the initial level ($6.00 for 6 subjects, $8.00 for 8 subjects, and $12.00 for the remainder). Each subject then made bidding decisions for 10 trials with the no-curse treatment and for 10 trials in the other two treatments, with half of the subjects in each treatment order.

Subjects were always in the role of the bidder, with the seller behavior being simulated. In each trial, the subject would enter a bid on the keyboard and confirm it with the "c" key. A seller value would then be drawn from the uniform distribution over the range of values for the

[9] The software for this experiment was written by Lisa Anderson and Charles Holt, and is available at Charles Holt's homepage: http://www.people.virginia.edu/~cah2k/teaching. The program records the treatment parameters, and the value, bidding, and earnings data. A printout of the instructions is provided in the Appendix.

treatment being used. If the bid was less than that seller value, there was no purchase and earnings were zero for the trial. If the bid was greater than or equal to the random seller value, the earnings would be calculated (buyer value minus bid), multiplied by 2, and added to the cumulative earnings. Subjects were told that they would be paid and released from the experiment if their cumulative earnings fell to $4.00, and this happened for 4 participants. Cumulative earnings for the other subjects ranged from $4.00 to $33.94, with typical earnings of about $16 for a session that normally would last about an hour and a half.

IV. Results

The bid data are summarized in table 2, where the rational and naive bid predictions are reproduced in the first two rows. The data used in the calculations are the individuals' 10-period averages under each of the treatment conditions. First, consider the no-curse treatment column on the left. The average bid data closely match the rational and naive prediction of 2.00. The observed difference from this prediction is positive, as implied by a desire to win, but it is very small relative to the standard deviations shown in parentheses. For the other two treatments, overall results show that average bids are closer to the predicted naive bids than to rational bids, as can be seen from a comparison of the first three rows of table 2. Bids under the loser's curse are significantly below the rational level; bids under the winner's curse are higher than the rational bid but not significantly higher (due to a large standard error). The two bottom rows of table 2 indicate that the treatment-order effect is not significant.

Table 3 summarizes average per-trial gains for decisions made(omitting stakes). Average gains are below the rational and naive prediction in the no-curse treatment, and below the naive predictions in the other two treatments. In the no-curse treatment, although the average bid was close to the rational prediction, departures from that bid across subjects kept earnings from reaching the rational prediction on average. Since the average bid was above the naive bid in the winner's curse, and below the naive bid in the loser's curse, it is not surprising that average gains were less than the naive predictions in those two treatments. There is considerable dispersion of individuals' earnings, and there is no evidence from earnings data that the winner's curse bias is more severe than the loser's curse bias.

Naive and rational bid predictions may be obtained by letting $M = 1.5$ in the linear bid functions in (3):

$$
B_R = 0.0 + 2.00X + 0.0R \qquad (4)
$$

$$
B_N = 0.0 + 1.25X + 0.375R
$$

TABLE 2. SUMMARY BID DATA BY TREATMENT

	Average Bid (Standard Deviation)		
	No Curse	Winner's Curse	Loser's Curse
Theoretical Prediction: Rational	2.00	3.00	1.00
Theoretical Prediction: Naive	2.00	3.56	0.81
Data: Aggregate, Both Orders	2.03	3.78	0.74
n = 50	(0.21)	(0.58)	(0.08)
Data: No-curse/Winner's/Loser's	2.03	3.64	0.74
n = 25	(0.18)	(0.33)	(0.08)
Data: No-curse/Loser's/Winner's	2.03	3.92	0.75
n = 25	(0.32)	(0.56)	(0.08)

he bid equation was estimated by regressing averages of the individual subjects' 10 actual bids in each treatment condition on the corresponding *X* and *R* values for the treatment. The dependent variable, *B*, is the average of 10 bids in a treatment for a given subject, so there are 150 observations (3 treatments × 50 subjects). The three observations for each subject may not be independent, so individual effects were controlled by adding a dummy variable for each subject. Omitting the individual-effects coefficients, the relevant portion of the estimated equation is:

$$
\underset{}{B} = \underset{(0.47)}{1.19X} + \underset{(0.12)}{0.46R} \qquad R^2_{adj.} = .93, \quad d.f. = 98 \qquad (5)
$$

The estimation results in (5) are inconsistent with the rational bidding equation in (4) because the coefficients on *R* and *X* are each significantly different from the values of 0.0 and 2.0 that are implied by rational bidding (significance levels of 0.001 and 0.05 respectively).

TABLE 3. SUMMARY GAINS DATA BY TREATMENT

	Average Gains per Trial (Standard Deviation)		
	No Curse	Winner's Curse	Loser's Curse
Theoretical Prediction: Ratio	0.25	0.25	0.25
Theoretical Prediction: Naive	0.25	0.21	0.21
Data: Aggregate, Both Orders	0.22	0.18	0.18
n = 50	(0.23)	(0.53)	(0.08)
Data: No-curse/Winner's/Loser's	0.22	0.17	0.17
n = 25	(0.21)	(0.51)	(0.07)
Data: No-curse/Loser's/Winner's	0.23	0.19	0.20
n = 25	(0.24)	(0.53)	(0.09)

Results are not inconsistent with naive bidding, however. The estimated coefficient on *R* is 0.46, which is not significantly different from the coefficient of 0.375 for the naive bidding rule. The estimated coefficient on *X* of 1.19 is below both the rational-bid coefficient (2.00) and the naive-bid coefficient (1.25), but significantly different only from the rational bid coefficient.[10] Thus, the regression results, like the overall averages, provide more support for the naive bidding model than for the rational bidding model.

V. Conclusion

This paper began with a theoretical analysis of the nature of the information processing bias that might explain the previously observed overbidding and losses in a bilateral bidding game with asymmetric information. The bias arises because bidders fail to recognize that winning an auction is an informative event, and a bid will only be accepted if the seller value

[10] The possibility of bankruptcy depends on the size of the initial stake, and has been claimed as an influence on winner‘s curse behavior (Robert G. Hansen and John R. Lott, 1991). The empirical significance of this effect is discounted by Kagel and Levine (1991) and Barry Lind and Charles R. Plott (1991). We did run an alternative version of (5) with dummy variables for the initial stakes ($6, $8, or $12), and the coefficients for these dummy variables were insignificant. We also constructed an order-of-treatment dummy (= 1 for observations under the winner's and loser's curse treatments when the subject faces them in that (winner's/loser's) order), and its coefficient was insignificant. The inclusion of these dummy variables changes the estimated coefficients of *X* and *R*, perhaps because of multicolinearity, but the primary results are unaffected. In particular, the coefficients on *X* and *R* are significantly different from the values implied by the rational bidding model.

is less than the bid. Failure to condition expected seller values on the bid in this manner can lead to excessively high bids and consequent losses (the winner's curse). This same information-processing bias can also produce underbidding. The intuition behind this possible underbidding is that an increase in the bid at the margin, from B to $B+\Delta$, will only matter if the seller value is between B and $B+\Delta$, i.e. if the seller value is high relative to the range of seller values below B. Failure to adjust for the fact that a bid increase picks up the sale of relatively valuable units will cause a naive bidder to bid too low. So the winner's curse tendency that causes a naive bidder to overbid is countered by the loser's curse tendency to underbid.

It is possible to choose parameters in a bilateral bidding model for which these two tendencies are just balanced, so that a naive bidder will choose a bid that just happens to maximize expected earnings. Subjects' bids in this "no curse" treatment were quite close to the prediction of both rational and naive bidding, indicating that there is no inherent bias in the procedural setup; there is no strong evidence for a "utility of winning" that would bias bids upwards. When the parameters are set so that the tendency for a naive bidder to overbid dominates (the winner's curse treatment), high bids and low earnings are observed, as was the case for previous experimental studies of bilateral bidding games. But when the parameters were set so that the naive bidder's tendency to underbid dominates (the loser's curse treatment), bids were below the optimal level by about the amount predicted by the naive bidding rule. Thus a loser's curse can result from naive bidding and it is analogous, but in the opposite direction from the winner's curse. And a naive bidding rule predicts bidding under the loser's curse quite well.

APPENDIX: INSTRUCTIONS[11]

This experiment deals with the economics of decision making under uncertainty. Various agencies have provided funds for the experiment. If you follow these instructions and make good decisions, you can earn a significant amount of money, which you will receive in cash privately at the end of the experiment.

You are to act as a potential buyer in this experiment. You will be asked to choose an amount to bid on a product, without knowing the exact value of the product.

The current owner of the product, who is the potential seller, knows more about the product's basic value than you know as the potential buyer. On the other hand, the product will be worth more to you than it is to the current owner. The potential transactions can be described in the following way.

During each period, you may bid on a product. The product's value to its current owner will lie in a "Range" of values between a "Lower Limit" and an "Upper Limit." All penny values within this range will be equally likely. For example, if the Lower Limit is $1.00 and the Range is $2.00, the product will be worth between $1.00 and $3.00 to its current owner. Every value in that range, such as $1.00, $1.01, .. $2.99, will be equally likely.

The product's value to you, should you acquire it, will be 1.5 times as much as the value for its current owner. The product's value to you, should you acquire it, will be calculated:

value to you = 1.5 times the value to current owner.

For example, if the product is worth $1.00 to its current owner, it will be worth $1.50 to you should you acquire it; if the product is worth $2.00 to its current owner, it will be worth $3.00 to you if you acquire it.

Your decisions will be recorded on a decision sheet that is attached. Note that there are 8 numbered columns. Column (1) contains the period number. Column (2) contains the Lower Limit of the range of values for the seller, and column (3) contains the Upper Limit of the range of possible seller values.

There will be space on the sheet for 10 periods, and in each one you must decide what you wish to bid. Once you have entered a bid, it will be recorded in column (4), labeled "your bid" on the decision sheet.

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[11] The electronic version of this game can be downloaded from Charles Holt's homepage: http://www.people.virginia.edu/~cah2k. Each paragraph in the text of these instructions is followed by the message "Press ENTER to continue." The instructions that follow do not include passages that prompt subjects for their decisions and remind them of the Upper and Lower Limit parameters at the beginning of each 10 period sequence.

In each period, you will make a single bid, which must be either accepted or rejected by the current owner. After you have entered your bid, the product's value for its current owner will be determined by a random number between the upper and lower limits. The value of the Lower Limit will initially be $1.00, and the Range of seller values will initially be 2.00, so the random number will be between 1.00 and 3.00. Each number 1.00, 1.01, ... 3.00 will have an equal chance of being selected.

Please look at the decision sheet again. After you make a bid, the value to the seller will be recorded in column (5). Then the value to you will be calculated by multiplying the seller value by 1.5. The resulting figure is entered in column (6), labeled "value to you." (This figure will be rounded off to the nearest integer number of pennies. This figure is, of course, your value for the product if you acquire it.)

If your bid is greater than or equal to the product's value to its current owner, you will acquire the product. In this case, your gain or loss will be the product's value to you, which is 1.5 times the value to its current owner, minus your bid.

If your bid is less than the product's value to its current owner, you will not acquire the product and will neither gain nor lose anything. Your earnings are zero in a period in which you do not acquire the product.

VALUE to current owner = random number between Lower Limit and Upper Limit

(1) If BID >= VALUE to current owner,
EARNINGS = 1.5 x VALUE to current owner - BID

(2) If BID < VALUE to current owner, EARNINGS = 0

Please look at the decision sheet again. At the end of each period, your gain or loss will be recorded in column (7) on the decision sheet. The cumulative total, calculated by adding this period's earnings to all previous earnings, will be recorded in column (8). You will begin the experiment with an initial earnings balance of $6.00. When you gain money during a period, your earnings will increase by the amount that you gain. When you lose money during a period, your earnings will decrease by the amount you lose. Your gain or loss will be recorded in column (7) for each period, and your cumulative earnings will be recorded in column (8), labeled "cumulative earnings" on the decision sheet. At the beginning of the experiment, your cumulative earnings equals the initial balance of $6.00 as shown at the top of column (8).

At the end of the experiment, YOUR CUMULATIVE EARNINGS WILL BE MULTIPLIED BY A FACTOR OF 2.0, and the result will be paid to you privately in cash. If this product of 2.0 and your total earnings falls below $4.00, then the experiment will end and we will pay you the amount $4.00.

Some common questions: How is the random value to the seller generated? The computer will first generate a random fraction between 0.00 and 0.99. The seller value is calculated by 1) multiplying the random fraction times the difference between the Upper and Lower Limits, and 2) adding this product to the Lower Limit. To summarize: Seller Value = Lower Limit + [Random Fraction]x[Upper Limit - Lower Limit]
Since any fraction from 0.00 to 0.99 is just as likely as any other, it follows that any seller value in the range between the lower and upper limits is equally likely.

Another common question: What does "equally likely" mean? Suppose that there is a roulette wheel with 100 equally spaced stopping points, which are labeled: 0.00, 0.01, 0.02, ... 0.99. Then a hard spin would make the chance of stopping on any one point exactly the same as the chance of stopping on any other, so all values are "equally likely." The computerized randomization routine makes any fraction from 0.00 to 0.99 equally likely in this sense. Are there any questions? (Two practice periods followed.)
Table 4. Decision Sheet

Decision Sheet for Sequence 1

(1) period number	(2) lower limit	(3) upper limit	(4) your bid	(5) value to current owner	(6) value to you	(7) your gain or loss	(8) cumulative earnings $6.00
1	1.00	3.00					
2	1.00	3.00					

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