Common Value Auctions with Voluntary Entry*

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Abstract

In a lab experiment, we assess the role of voluntary entry on the incidence of severe overbidding and bankruptcies, which are widespread in common value auctions. We show that voluntary entry amplifies overbidding and reduces auction profits. Less experienced, male and more risk averse subjects tend to enter the common value auctions.

Keywords: Experiments; self-selection; winner’s curse; procurement; company takeover.

JEL Classification: D44; D03

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1. Introduction

In the field, auction participants self-select into bidding and are not a random sample of the population. We know little about the bidding behavior of those who seek to enter auctions compared to the population at large. This study investigates in the laboratory the implications of sampling biases due to self-selection on the performance of common-value auctions. We consider a benchmark situation where bidders are randomly assigned to a given auction and compare it with a situation where entry into auctions is voluntary.

In common value auctions, bidders compete for an item that has the same value for everyone. Typically, in auction models and in the field, the item value is uncertain and bidders base their decisions on estimates of the true value, which is generally observed only after the auction is over. Canonical examples of this type of auction include procurement of public construction and public works projects, and leases and sales of government assets such as mineral extraction rights and the radio spectrum. Reverse auctions for private procurement of inputs or services also have a strong common value component. Persistent overbidding is a robust empirical finding for these types of auctions, both in naturally-occurring data and in data from controlled experiments (Wilson, 1992; Kagel and Levin, 2002). The winning bidder often incurs in systematic losses, a phenomenon known as the “Winner’s Curse.”

Almost all auction experiments do not disclose the nature of the experiment when recruiting subjects and require everyone to participate in auction bidding. The only selection that takes place in the laboratory is generally through an eventual bankruptcy, which leads the subject to drop out of the auction. Moreover, very few auction experiments have considered endogenous entry. Nearly all of those consider the independent private values setting (Ivanova-Stenzel and Salmon, 2004; Palfrey and Pevnitskaya, 2008; Ertaç et al., 2011), where the winner’s curse does not occur since bidders know their own value with certainty, but bidders tend to enter the auction too often in these experiments. Cox et al. (2001) is the only previous experiment that studies endogenous entry in common value auctions. Subjects’ alternative to auction bidding was to collect a known “safe haven” payment. Cox et al. (2001) study market size given that entry is endogenous. In our paper market size is fixed and we study the selection of bidders in markets.

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1 Theoretical models considering endogenous entry include Harstad (1990), Hausch and Li (1993), Levin and Smith (1994), and McAfee and McMillan (1987).
We also allow subjects to choose between different bidding activities rather than simply collecting a fixed payment when opting out of the auction.

We report that voluntary entry into common value actions does not reduce the winner’s curse, as the fraction of overbidders and amount of auction losses are higher when participants self-select into auctions than in the case of random assignment. Less experienced, male and more risk averse subjects tend to enter the common value auctions.

2. Theoretical Considerations

In each session all subjects placed bids in one of three activities: a high-stake, a medium-stake and a low-stake activity. There were \( n = 5 \) subjects in each activity, except for brief periods following bidder bankruptcies. The high-stake and medium-stake activities were common value auctions with identical rules, except for the conversion rate of points into dollars. The low-stake activity was a company takeover game. The high-stake activity yielded equilibrium earnings more than five times as large as the low-stake activity. Activities differed in their potential rewards as well as their relative riskiness. In particular, the low-stake activity involved no competition with other subjects, and hence no strategic risk. Below we describe each activity, beginning with the common value auctions.

The high- and medium-stake activities were common value auctions where, in each period the item value \( x_o \) was randomly drawn from a uniform distribution with upper and lower bounds \([50, 950]\). In each auction each bidder received a private information estimate, \( x \), drawn from a uniform distribution on an interval centered on the actual item value \([x_o - 15, x_o + 15]\). Using a first price sealed-bid auction procedure, bids were ranked from highest to lowest with the high bidder paying the amount bid and earning profits equal to \( x_o - b_1 \), where \( b_1 \) is the high bid.

The Nash equilibrium solution will be discussed only in reference to estimates in the interval \( 65 \leq x \leq 935 \) (called region 2), where by design about 97 percent of the observations lie (Wilson 1977, Milgrom and Weber, 1982). Within region 2, bidders have no end point information to help in calculating the expected value of the item. For risk neutral bidders the symmetric risk neutral Nash equilibrium (RNNE) bid function \( f(x) \) is given by (Kagel and Richard, 2001):

\[
f(x) = x - 15 + h(x), \quad \text{where}
\]

\( h(x) \) is determined.
and $n$ is the number of active bidders in the auction. This equilibrium bid function combines strategic considerations similar to those involved in first-price private-value auctions, and item valuation considerations resulting from the bias in the estimate value conditional on the event of winning. We deal with the latter first.

In common-value auctions bidders usually win the item when they have the highest, or one of the highest estimates of value. Define $E[x_o|X = x_{1n}]$ to be the expected value of the item conditional on having $x_{1n}$, the highest among $n$ estimate values. For estimates in region 2,

$$E[x_o|X = x_{1n}] = x - [(n-1)/(n+1)] 15.$$  \hspace{1cm} (3)

This provides a convenient measure of the extent to which bidders suffer from the winner's curse since in auctions in which the high estimate holder always wins the item, bidding above $E[x_o|X = x_{1n}]$ results in negative expected profit.\(^2\)

Recall that within region 2, $(x - 15)$ is the smallest possible value for $x_o$, and that $x$ is the unconditional expected value of $x_o$ (the expected value, *independent* of winning the item), so that the expected value, conditional on winning, must be between $(x - 15)$ and $x$. Thus, from equation (3) it is clear that the “bid factor,” the amount bids need to be reduced relative to the signal in order to correct for the adverse selection effect from winning the auction, is quite large relative to the range of sensible corrections. With $n = 5$ the bid factor required to generate zero expected profits is 10.00, or approximately 67% of the total bid factor in the RNNE.\(^3\) Strategic considerations account for the rest of the bid factor. The strategic element results from the fact that by only correcting for the adverse selection effect, the winner would earn zero expected profit. As such, a bidder would find it profitable to lower her bid from this hypothetical benchmark (equation 3) since zero expected gains are lost by doing so even if this causes her not to win the item, and strictly positive expected gains are obtained should she win the item with the lower price.

The **low-stake activity** was a **company takeover game** where there was a buyer and a seller who moved sequentially (e.g. Samuelson, 1984). We used this auction environment to

\(^2\) This design mostly followed Casari et al. (2007). Even with zero correlation between bids and estimate values, if everyone else bids above $E[x_o|X = x_{1n}]$, bidding above $E[x_o|X = x_{1n}]$ results in negative expected profit as well. As such, if the high estimate holder frequently wins the auction, or a reasonably large number of rivals are bidding above $E[x_o|X = x_{1n}]$, bidding above $E[x_o|X = x_{1n}]$ is likely to earn negative expected profit.

\(^3\) This approximation is based on the fact that within region 2 the RNNE bid function is well approximated by $f(x) = x - 15$, because the negative exponential term $h(x)$ in equation 1, approaches zero rapidly as $x$ moves beyond 65.
provide a bidding activity for bankrupt subjects and those who wished to avoid bidding in the interactive common value auctions. The buyer made a take-it-or-leave-it offer \( b \in [0, 36] \) to a computer seller whose company’s value was \( s \). The seller either rejected or accepted the bid. The payoff for the seller was \( s \) if she rejected and \( b \) if she accepted. The payoffs for the buyer were 0 if the seller rejected and \((1.5s - b)\) if she accepted. The company could have possible values between 6 and 24, \( s \in \{6.00, 6.01, \ldots, 23.99, 24.00\} \). When making a decision, the seller had private information about \( s \), while the buyer only knew that each realization of \( s \) had equal probability. The computer seller accepted all bids greater or equal to the seller’s company value.

Hence, the task was a bilateral bargaining problem against a computer with asymmetric information and valuations. The informational disadvantage of the buyer was offset by an assumption that the buyer's value was 1.5 times the seller value, \( s \). A bid of 12 is optimal for the risk-neutral rational buyer who accounts for the selection effect arising from the fact that sellers only accept bids that exceed their valuation \( s \). This bid yields an expected profit of 0.5.

3. Experimental Procedures

The experiment involved two treatments, which differed in the way subjects were allocated into activities: random assignment and voluntary entry.

Each session had 15 subjects and comprised 34 paid periods, divided between a training part and main part. The training was identical across treatments and aimed at familiarizing subjects with the various activities: low-stake, medium-stake and high-stake auctions. For each activity there was a dry run (unpaid) period followed by 3 periods for profit. Each subject began the session with a starting balance of $10 and accrued period earnings according to activity-specific rules. Training began for everyone with the low-stake auction, where subjects received $1 for every 4 points acquired. Subjects received full feedback after each period: their computer screens displayed the realized company value for the buyer, their period earnings in points, and their cumulative balance in dollars.

The training continued with the medium-stake auction, where subjects received $1 for every 4 points acquired from winning auctions. For this activity, the participants were randomly divided into three independent markets with five bidders each. Subjects stayed in the same market across periods 4-6, except in case of bankruptcy, which occurred if a subject had a negative US dollar cumulative balance. Bankrupt bidders are no longer liable for losses and for
this reason are placed in the low-stake auction to prevent the possibility of irresponsibly high bidding. Each auction involved new random draws for the true item value \( (x_o) \) and for item private estimates \( (x) \). The instructions informed the subjects about the underlying distribution of \( x_o \) and estimate values. An admissible bid was any number between 0.00 and \( x + 22.50 \).

Subjects received full feedback at the end of each auction: all bids were posted from highest to lowest along with the corresponding estimate values (bidder identification numbers were suppressed) and the value of \( x_o \). Profits (or losses) were calculated for the high bidder and reported to all bidders as well. These implementation details are fairly standard in experimental common value auction research. The training phase ended with the high-stake auction. This activity was identical to the medium-stake auction described above, except for a more favorable conversion rate: subjects received $1 for every 2 points earned. To make them financially more attractive, every subject also received $0.25 per period for participation in the medium-stake and high-stake auctions, regardless of the auction outcome.

The main part of the session comprised 25 periods. Subjects in the same session were allocated into three different activities: five subjects bid in low-stake auctions, five in the medium-stake auction, and five in the high-stake auction. In every period each subject placed a bid in just one activity. The rule to allocate subjects to activities varied by treatment and was explained in the final set of instructions.

The allocation into activities remained fixed for a block of five periods. At the start of every block subjects observed the list of all individual U.S. dollar profits earned in the previous block sorted by activity and without identities. At that point, subjects were reallocated into the three activities. Bankrupt bidders were automatically assigned to the low-stake auction.

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4 Notice that Cox et al. (2001) finds no evidence that limited liability increases the winner’s curse. Some markets occasionally had fewer than five bidders. The number of bidders in the subject’s market was always posted at the top of bidders’ computer screens.

5 This upper restriction on allowable bids was intended to prevent bankruptcies resulting from typing errors, while still permitting substantial overbidding. Bids could be specified in up to two decimal places. A copy of the instructions are included in the appendix.

6 Before each activity of the training phase, an experimenter read aloud the instructions while subjects followed along on their own copy. At the conclusion of these initial instructions subjects answered five computerized quiz questions to test their instruction comprehension for that activity, and were paid $1 for each correct answer. Besides providing incentives for subjects to consider the instructions carefully, this quiz also provided reinforcement of the key points and generated immediate clarifying feedback along with explanations for any wrong answers.

7 In one of the 8 sessions, more than five bidders were bankrupt during six of the final periods. In that case, we reduced the market size of the low-stake auction to four bidders, with the number of bidders always posted on subjects’ computer screens.
In the **Random Assignment treatment**, subjects were reassigned to activities *randomly* at the start of every 5-period block.\(^8\)

In the **Voluntary Entry treatment**, subjects stated their first, second and third choice for which activity they wanted to bid in for the upcoming 5-period block. Bankrupt subjects were not offered an opportunity to rank the activities, but were automatically placed into the low-stake auction. The allocation algorithm provided subjects with the incentive to truthfully reveal their preferences over activities without interference from strategic considerations about over- or under-subscription of activities. The algorithm first placed five subjects into the high-stake auction. Subjects obtained their first choice whenever possible. Since the capacity was 5 bidders in each auction activity, sometimes an activity was over-subscribed. In such cases the assignment to the high-demand activities was randomly determined among those who ranked that activity highest. When an activity was under-subscribed, we next allocated those subjects who ranked that activity as second choice. Subjects who did not get their first choice were placed into their second choice whenever possible. If there were still slots available, we then considered also those who ranked it third choice.\(^9\) The algorithm then placed five subjects into the medium-stake auction following the same rules as above. (Before proceeding to assign subjects to the medium-stake auction, the algorithm removed their preferences for the high-stake auction from their rankings since this auction was already filled.)

Our design required subjects to choose between three similar bidding activities, which differ most substantially in their payoff scale and risk. This (approximately) holds constant the level of challenge and inherent interest across activities so that selection and entry into the high-stake auction is based on economic opportunities. A simplified alternative design could have provided subjects who did not enter the common value auctions with some constant payment, but this could have led subjects to enter the auctions to avoid the boredom of merely collecting a small and uninteresting payment each period. This could be one reason for the over-entry into

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\(^8\) Since all random draws were independent, in principle it was possible for a subject to be assigned to the same activity in all periods. In practice this never occurred, except for one subject who was bankrupt in all periods due to large losses during the training periods. This subject thus always bid in the low-stake auction.

\(^9\) Bidders were placed into a common value auction that they least preferred in only 2 times (out of 261 non-bankrupt activity rankings). If a subject who could not get their first choice specified a common value auction as their second choice, then they were assigned this second choice when space was available. If a subject who could not receive their first choice instead indicated that the low-stake auction was their second choice, then they were placed in the low-stake auction unless the common value auctions did not yet have 5 bidders each.
independent private value auctions observed in previous experiments that feature a simple known payment for non-entry (Palfrey and Pevnitskya, 2008; Ertaç et al., 2011).

Additionally, at the start of each session everyone chose an amount up to $5 to place into a risky investment that yielded 0 or three times the invested amount with equal probability. This simple task followed the design of Gneezy and Potters (1997) to measure subjects’ preferences toward risk. Subjects could allocate $0.00, $0.50, ..., $4.50, or $5.00. The outcome of this risky investment decision was determined at the end of the session.

We recruited 120 subjects by email using ORSEE (Greiner, 2004), drawn from the diverse student population at Purdue University. Each treatment involved 60 subjects divided into 4 sessions. The experiment was programmed and conducted with the software z-Tree (Fischbacher, 2007). No eye contact was possible among subjects during the experiment due to visual dividers between computer stations. Average earnings were $20.08 per subject (standard deviation $7.20). Sessions lasted less than two hours, including instruction reading, quizzes, and a post-experiment questionnaire.

4. Results

Here we report three main results. Assigning people to activities according to their revealed preferences made them worse off on average, despite preferences being elicited in an incentive-compatible way.

**Result 1:** The pooled profits from all activities were lower when subjects could voluntarily choose where to bid compared to the random assignment treatment.

Table 1 reports the total profits earned by bidders. Subjects in the Voluntary Entry treatment on average earned negative profit on average, compared to the positive profit earned with random assignment. A cross-sectional regression shown in the appendix (with robust variance estimates clustering to account for intra-session correlation) indicate that these profits are marginally significantly lower than the Random Assignment control treatment ($p$-value=0.075).

Many participants randomly assigned to a common value auction often placed bids with negative expected profits. The data are thus consistent with the literature documenting the winner’s curse (Kagel and Levin, 2002). Our novel finding is that the frequency of these winner’s curse bids increased in the Voluntary Entry treatment.
Result 2: When bidders voluntarily enter into the common value auctions, they suffered from the winner’s curse more frequently than in the random assignment treatment.

Support: Table 2 and Figure 1 provide support for Result 2. Table 2 summarizes the profits and frequency of winner’s curse bids in the common value auctions (col. 1, 2 and 4, 5, respectively) based on the 25 periods following the initial training periods.

The winner’s curse frequency in the Voluntary Entry treatment is nearly one-half of the bids, compared to about one-third of the bids in the other two treatments (Table 2). In order to compare the bidding performance of the auctions across treatments, we focus on the propensity to submit winner’s curse bids using standard panel data econometrics. In particular, we estimate probit models to compare overbidding across treatments, using robust variance estimates that allow for intra-subject and intra-session correlation. Treatment differences are assessed through dummy variables. These estimates are reported in the appendix, and they indicate that the winner’s curse frequency is marginally significantly higher in the Voluntary Entry treatment compared to the Random Assignment control treatment ($p$-value=0.056).10

With experience, subjects learn to avoid in part the winner’s curse but learning appears retarded in the Voluntary Entry treatment (Figure 1). By the end of the session, 8 out of 60 bidders were bankrupt with Random Assignment and 11 out of 60 were bankrupt with Voluntary Entry. Similarly, average cumulative payoffs favored Random Assignment ($12.30$ vs. $9.70$).

In the Voluntary Entry treatment, every 5 periods the non-bankrupt subjects ranked the three activities and were placed into their most preferred activity whenever possible. When ranking activities, subjects’ decision screens displayed the historical profit performance of individual bidders (shown anonymously) in each activity during the preceding block of periods. This information revealed that the high-stake auction exhibited the lowest average profit and the highest (variance) risk (Table 1), and therefore a subject who believes he would achieve typical earnings should avoid it. Nevertheless, the high-stake auction was the first choice in 40% of bidders’ rankings, the medium-stake auction was first choice in 32%, and the low-stake auction was the first choice the remaining 27%. This suggests that subjects focused on factors other than the mean and variance returns of the alternative bidding activities when choosing which auction

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10 Small differences across treatments exist in the training periods, but these bids occur before any treatment manipulations are introduced. The same statistical tests applied to these training periods never reveal any significant differences across treatments. This indicates that the random assignment of subjects to treatments worked properly.
to enter.

**Result 3:** Subjects who seek to enter the high-stake auction are more frequently male, have no previous experience in field auctions, have high cumulative earnings, and have avoided losses more frequently in previous common value auctions. Subjects who display a greater tolerance for risk are less likely to enter.

**Support:** Support for Result 3 comes from Table 3, which presents two probit models of bidders’ choice to rank the high-stake auction as their top choice. Model (1) includes as regressors the frequency of experienced losses and highest private estimates in earlier periods, and model (2) employs instead the subject’s accumulated earning balance up to the period of entry choice. Since these earnings are endogenous, we use an instrumental variable approach that employs the frequency of receiving the high estimate in previous common value auctions and the period number as instruments for this variable. The results are consistent across both specifications.  

The increased entry likelihood for male subjects is consistent with research documenting men’s greater willingness to enter competitions (e.g., Croson and Gneezy, 2009). Confusion does not appear to play a significant role. Table 3 includes variables to capture subject comprehension and confidence, but none of these variables are significantly associated with high-stake auction entry. The high-stake auction does not attract bidders that have more auction experience in the field; in fact, it is more likely to attract naïve bidders, which may be an important reason for the high rates of the winner’s curse and bankruptcy in this Voluntary Entry treatment. A possible interpretation is that high risk aversion is associated to low cognitive ability (Dohmen et al., 2010), which is relevant for bidding in a complex setting such as common-value auctions. Indeed we see that subjects who are most willing to take on risk according to our separate risk assessment task, investing at least $4 out of their $5 stake in an attractive but risky investment, are significantly less likely to want to enter the high-stake auction.

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11 These models exclude some other factors that are never correlated with auction preference, such as self-reported grade point average, class standing, and major field of study. We also include a dummy for only the final block of periods, since all other period block dummy variables were never statistically significant.

12 To measure confidence, after reading the instructions for the allocation rules after the training periods were over, we asked subjects “How do you think you will rank in terms of earnings among all participants?” There were five possible options, ranging from being among the three highest earners to be among the lowest three earners out of group of fifteen. This “confidence” question was not incentivized.
5. Conclusion

In naturally occurring settings firms and individuals voluntarily enter when deciding to bid in auctions. We report a laboratory experiment on common value auctions that studies entry decisions and their impact on bidding behavior, profits, the winner’s curse, and bankruptcies.

We report that letting auction participants self-select into the activities has null or negative consequences on performance. Voluntary entry actually increases the fraction of overbidders in common value auctions compared to the benchmark of random allocation of subjects to auctions. Voluntary entry reduces profits and does not lower bankruptcy rates. This result is not due to more people entering into the auction, as we kept market size constant. Thus, voluntary entry does not improve auction performance over random allocation of bidders. This study provides empirical evidence showing a net detrimental effect of self-selection in common-value auctions.
REFERENCES


Table 1: Mean Period Earnings (US Dollars)

<table>
<thead>
<tr>
<th>Treatment</th>
<th>Low-stake auction</th>
<th>Medium-stake Auction</th>
<th>High-stake Auction</th>
<th>Sum of earnings</th>
</tr>
</thead>
<tbody>
<tr>
<td>Random Assignment</td>
<td>0.148</td>
<td>0.033</td>
<td>0.055</td>
<td>+0.236</td>
</tr>
<tr>
<td></td>
<td>(0.856)</td>
<td>(0.998)</td>
<td>(1.694)</td>
<td></td>
</tr>
<tr>
<td>Voluntary Entry</td>
<td>0.052</td>
<td>-0.017</td>
<td>-0.061</td>
<td>-0.026</td>
</tr>
<tr>
<td></td>
<td>(0.844)</td>
<td>(1.021)</td>
<td>(1.796)</td>
<td></td>
</tr>
</tbody>
</table>

Note: Standard deviations shown in parentheses
Table 2: Summary Statistics for Common Value Auction by Treatment

|                  | (1) Average Profits (in tokens) | (2) RNNE Bid Average Profits (in tokens) | (3) Percent of Winner’s Curse Bids, $b > E[x_0 | X = X_{1n}]$ | (4) All Bidders | (5) High Bidders |
|------------------|---------------------------------|------------------------------------------|-------------------------------------------------------------|-----------------|------------------|
| Random Assignment| -1.64 (0.51)                    | 4.91 (0.31)                              | 57.8                                                        | 35.8            | 66.5             |
| Voluntary Entry  | -2.61 (0.58)                    | 5.27 (0.36)                              | 61.9                                                        | 48.8            | 75.6             |

Notes: $b =$ bid, $x_0 =$ item value, $X_{1n}$ = highest private estimate, RNNE = Risk Neutral Nash Equilibrium. Only periods with 5 bidders, pooling medium-stake and high-stake auctions, and value draws in region 2 are included. (1) reports the average period profits of the winner in each treatment (including relevant participation points), with standard errors in parentheses; (2) displays the average profits that would be earned at the RNNE for the realized value and estimate draws, with standard errors in parentheses; (3) indicates the percent of auctions in which the bidder with the highest estimate won the auction; (4) and (5) show the percentage of bids that are winner’s curse bids, which are defined as bids that exceed the item’s expected value conditional on being the highest estimate.
Table 3: Probit Models of Preference for High-stake Auction

(Voluntary Entry Treatment Only)

<table>
<thead>
<tr>
<th>Dependent Variable:</th>
<th>Model (1)</th>
<th>Model (2)</th>
</tr>
</thead>
<tbody>
<tr>
<td>1 = top preference for high-stake auction</td>
<td></td>
<td></td>
</tr>
<tr>
<td>0 = otherwise</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Frequency of Losses in Previous Common Value Auctions</td>
<td>-1.00**</td>
<td></td>
</tr>
<tr>
<td>(0.311)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Frequency Received highest Value Estimate in Previous Common Value Auctions</td>
<td>-0.32</td>
<td></td>
</tr>
<tr>
<td>(0.215)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>USD Earnings Balance at Time of Ranking (Instrumental Variable)</td>
<td>0.17*</td>
<td>0.17*</td>
</tr>
<tr>
<td>(0.074)</td>
<td>(0.074)</td>
<td></td>
</tr>
<tr>
<td>High tolerance for risk (Investing $4 or more out of $5 in Risk Task)</td>
<td>-0.90**</td>
<td>-1.01**</td>
</tr>
<tr>
<td>(0.349)</td>
<td>(0.329)</td>
<td></td>
</tr>
<tr>
<td>Perfect Score on Instructions</td>
<td>-0.17</td>
<td>-0.22</td>
</tr>
<tr>
<td>Comprehension Quiz (0.320)</td>
<td></td>
<td>(0.324)</td>
</tr>
<tr>
<td>Poor Score on Instructions</td>
<td>-0.54</td>
<td>-0.04</td>
</tr>
<tr>
<td>Comprehension Quiz (below 80%)</td>
<td>(0.388)</td>
<td>(0.560)</td>
</tr>
<tr>
<td>Confident to be high Earner in Session (top 40%)</td>
<td>0.38</td>
<td>0.67</td>
</tr>
<tr>
<td>(0.416)</td>
<td>(0.534)</td>
<td></td>
</tr>
<tr>
<td>Confident to be low Earner in Session (bottom 20%)</td>
<td>0.25</td>
<td>0.71</td>
</tr>
<tr>
<td>(0.592)</td>
<td>(0.538)</td>
<td></td>
</tr>
<tr>
<td>Male</td>
<td>0.63*</td>
<td>0.56*</td>
</tr>
<tr>
<td>(0.286)</td>
<td>(0.278)</td>
<td></td>
</tr>
<tr>
<td>No Field Auction Experience Reported (e.g., eBay)</td>
<td>0.70*</td>
<td>0.88**</td>
</tr>
<tr>
<td>(0.315)</td>
<td>(0.304)</td>
<td></td>
</tr>
<tr>
<td>Final Block of Periods</td>
<td>0.38*</td>
<td>0.06</td>
</tr>
<tr>
<td>(0.151)</td>
<td>(0.226)</td>
<td></td>
</tr>
<tr>
<td>Constant</td>
<td>0.32</td>
<td>-2.30**</td>
</tr>
<tr>
<td>(0.437)</td>
<td>(0.775)</td>
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<tr>
<td>Observations</td>
<td>261</td>
<td>261</td>
</tr>
<tr>
<td>Number of Subjects Included</td>
<td>57</td>
<td>57</td>
</tr>
<tr>
<td>Pseudo R-squared</td>
<td>0.154</td>
<td></td>
</tr>
</tbody>
</table>

Notes: Standard errors robust to clustering on subjects are shown in parentheses.

** p<0.01, * p<0.05 (two-tailed tests)
Figure 1: Frequency of winner’s curse bids
Appendix: Pairwise Treatment Comparisons for Results Summarized in Text

Treatment Comparisons of per-Bidder Profits Earned (Result 1)

Dependent Variable = subject earnings

<table>
<thead>
<tr>
<th>Treatment Dummy</th>
<th>Coefficient</th>
<th>Standard Error</th>
</tr>
</thead>
<tbody>
<tr>
<td>Random Assignment</td>
<td>2.60&lt;sup&gt;+&lt;/sup&gt;</td>
<td>1.25</td>
</tr>
<tr>
<td>Qualified Entry</td>
<td>9.70&lt;sup&gt;**&lt;/sup&gt;</td>
<td>0.67</td>
</tr>
<tr>
<td>Constant</td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

Observations: 120
R-squared: 0.021

Notes: Omitted treatment is the Voluntary Entry treatment. Standard errors robust to clustering on sessions are shown in parentheses. ** p<0.01, * p<0.05, + p<0.10.

Probit Models of Winner’s Curse Bid Frequency (Result 2)

Dependent Variable = 1 iff submitted bid is a winner’s curse bid

<table>
<thead>
<tr>
<th>Treatment Dummy</th>
<th>Coefficient</th>
<th>Standard Error</th>
</tr>
</thead>
<tbody>
<tr>
<td>Random Assignment</td>
<td>-0.33&lt;sup&gt;+&lt;/sup&gt;</td>
<td>0.17</td>
</tr>
<tr>
<td>Qualified Entry</td>
<td>-0.03</td>
<td>0.12</td>
</tr>
<tr>
<td>Constant</td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

Observations: 1595
Pseudo R-squared: 0.013

Notes: Omitted treatment is the Voluntary Entry treatment. Standard errors robust to clustering on subjects are shown in parentheses. ** p<0.01, * p<0.05, + p<0.10.