Are Experimental Auctions Demand Revealing when Values are Affiliated?

Jay R. Corrigan and Matthew C. Rousu

The theoretical properties of purely private and purely common value auctions are well understood (Krishna 2002), and these properties have been extensively tested in the lab (Kagel 1995). Empirical researchers, however, have paid much less attention to the arguably more realistic scenario where a good’s value is “affiliated” or determined by a combination of private and common value components.

Milgrom and Weber (1982) show that when a good’s value is affiliated, the second-price sealed bid auction (Vickrey 1961) is no longer incentive compatible. This is because rational agents must adjust their bidding strategies to take into account that the winning bidder’s common value signal likely exceeds the good’s true common value. Auction participants’ bids then no longer reflect their best guess of a good’s value, but instead are adjusted downward to avoid the winner’s curse. In this environment, second-price auctions may also lead to an inefficient allocation if the bidder with the highest private value receives a relatively low common value signal and, as a result, is outbid by a competitor with a lower private value.

Corrigan is associate professor, Department of Economics, Kenyon College, Gambier, OH. Rousu is associate professor, Department of Economics, Susquehanna University, Selinsgrove, PA. The authors thank Greg Colson and Jayson Lusk for helpful comments. Corrigan and Rousu share lead authorship.
While these theoretical predictions are well understood, economists have only recently begun to test them empirically. Work in this area has focused primarily on allocative efficiency and revenue maximization (e.g., Kirchkamp and Moldovanu 2004). These issues are of primary importance, for example, to policy makers designing a radio spectrum auction where firms with heterogeneous costs compete to buy one common value good. But efficiency and revenue are less important in the experimental auction valuation literature (e.g., Lusk and Shogren 2007). What is important here is the extent to which bids provide an accurate and unbiased reflection of auction participants’ underlying value signals.

Value affiliation could arise in an experimental auction environment in a number of ways. For example, participants may be certain of the value they place on the good up for auction but uncertain of the price the good sells for in the field. Recognizing that auction bids should not exceed the field price (Harrison, Harstad, and Rutström 2004), censored values become affiliated if participants believe their competitors possess additional information about the true field price.

Alternatively, auction participants may “mark down” the value of any good sold in an experimental auction because of concerns about whether the good will actually be delivered at the end of the auction or about the quality of that good relative to field substitutes. Marked down values become affiliated if participants believe their competitors possess additional information about the auction market’s credibility.

Still another possibility is that while auction participants may be certain of the value they would derive from a conventional good, they may be uncertain of the value
they would derive from a similar good endowed with some novel trait. One example would be a comparison of conventional fresh produce with locally grown fresh produce. The “locally grown” designation could take on common value characteristics if participants believe that their competitors have additional knowledge about whether local produce tastes better than conventional produce or the extent to which local agriculture has a smaller impact on the environment. In either case, competitive auction mechanisms like the second-price auction lose their incentive compatibility.

We present the results of an auction experiment designed specifically to test whether value affiliation leads to a breakdown of the incentive compatibility of the second-price auction, one of the auctions most frequently used in experimental auction valuation. Our design mirrors the current state of the art in experimental auction valuation as closely as possible, except that homegrown value goods are replaced with induced values constructed so that each participant’s value includes both private and common value components. Comparing the results of a second-price auction with those from a noncompetitive Becker-DeGroot-Marschak (1964) mechanism, we find modest evidence that second-price auction participants adjust their bids downward as predicted by theory. However, we also find that repeated second-price auction rounds with price feedback lead to “overheating” with participants submitting bids in later rounds well in excess of their induced value. No such underbidding in early rounds or overheating in later rounds is observed with the BDM mechanism.
Theoretical Background

In their classic study on auction theory, Milgrom and Weber (1982) observe that auction participants’ valuations are affiliated if a high value estimate for one participant increases the likelihood that other participants also have high value estimates. Klemperer (1999) considers the case where participant $i$’s value $v_i$ is defined as

$$v_i = \alpha t_i + \beta \sum_{j \neq i} t_j,$$  \hspace{1cm} (1)

where $\alpha$ and $\beta$ are the weights participants put on their own signal and those of their competitors. More specifically, $\beta = 0$ in the purely private value case, $\alpha = \beta$ in the purely common value case, and $\alpha > \beta > 0$ in the affiliated value case considered in our study. Klemperer goes on to show that when auction participants are risk neutral and their value signals $t$ are independently and uniformly distributed over $[0, \bar{t}]$, participant $i$’s optimal bid $b_i^*$ equals her expected value conditional on having tied for submitting the highest bid. In that case, participant $i$ assumes that the $(n-2)$ lowest bids are uniformly distributed over $[0, t_i]$, therefore

$$b_i^* = \alpha t_i + \beta t_i + \beta (n-2) \frac{t_i}{2} = (\alpha + n\beta/2) t_i.$$  \hspace{1cm} (2)

Goeree and Offerman (2002, 2003) present an alternative model of affiliated values where an auction participant’s value is equal to the sum of discrete private and common value components. Participant $i$’s private value is simply equal to her private value signal. Her common value, on the other hand, is equal to the average of all $n$ participants’ common value signals. More formally, participant $i$’s value $v_i$ is
where both the private value signal \( p_i \) and the common value signal \( c_i \) are drawn from known uniform distributions. As in Klemperer (1999), risk-neutral second-price auction participants are willing to bid as much as their expected value conditional on having tied for submitting the highest bid. That is,

\[
(4) \quad b_{i}^{sp}(p_i, c_i) = s_i + \frac{1}{n} E(C \mid s = s_i) + \frac{n-2}{n} E(C \mid s \leq s_i),
\]

where \( C = \sum c_i / n \) and \( s_i = p_i + c_i / n \) or that portion of participant \( i \)'s value \( v_i \) that is determined by her own signals.

Under either model of affiliated values, rational bidders in a second-price auction must take into account the information provided by winning the auction. Namely, they must recognize that if they submitted the winning bid, they likely received a higher-than-average common value signal, and if common value signals are on average an unbiased estimate of the good’s underlying common value, the highest bidder’s signal is likely an overestimate. Because rational bidders should not submit bids equal to what they think the good up for auction is worth but instead should adjust their bids downward to avoid the winner’s curse, the second-price auction is not incentive compatible when values are affiliated.

The noncompetitive BDM mechanism, on the other hand, remains incentive compatible when values are affiliated. With the BDM mechanism, participants first submit sealed bids, then the monitor randomly selects a price from a known distribution.
Participants who submitted bids greater than or equal to this price buy the good at the randomly selected price. Others buy nothing. Under Goeree and Offerman’s affiliation framework, winning in the BDM mechanism provides no information about the relative size of a bidder’s common value signal because the bidder did not need to outbid her competitors in order to win. Here, risk-neutral participants are willing to bid as much as their expected value. That is,

\[ b_{ij}^{BDM} \left( p_i, c_i \right) = p_i + \frac{c_i}{n} + E \left[ \sum_{j \neq i} \frac{c_j}{n-1} \right]. \]

The next section introduces the design of an experimental study that takes advantage of the fact that \( b_{ij}^{BDM} \left( \cdot \right) > b_{ij}^{SP} \left( \cdot \right) \) in order to test whether the incentive compatibility of the second-price auction breaks down in practice when values are affiliated.

**Experimental Design**

Forty-eight introductory economics students at Susquehanna University took part in an induced value experiment, with three groups of eight students taking part in the second-price treatment, and three groups of eight students taking part in the BDM treatment. The experimental auction had five steps:

*Step one.* Participants received written and oral instructions on the nature of the induced value good they would be bidding on and the details of the auction they would take part in. These instructions closely followed Goeree and Offerman (2002) and
included a numerical example, a short quiz, and a practice auction. The instructions are presented in the supplementary appendix (Corrigan and Rousu 2010).

**Step two.** Participants received both private and common induced value signals. Following Goeree and Offerman (2002), participants’ induced value $v_i$ was

$$v_i = p_i + \frac{1}{n} \sum_{j=1}^{n} c_j,$$

with $n$ equal to eight in all auctions.

**Step three.** Participants submitted bids in the first of ten auction rounds with the understanding that only the transactions from one of these rounds would be carried out, and that that round would be randomly determined at the end of the experiment. In the second-price treatment, the monitor posted the highest bidder’s ID number and the second highest bid submitted on a blackboard at the front of the room. In the BDM treatment, the monitor posted the randomly selected market price. While Corrigan and Rousu (2006) present evidence suggesting that posting prices may influence bidding in later rounds, our goal was to mirror the current state of the art as closely as possible, so we followed Lusk and Shogren’s (2007) recommendation to post prices.

**Step four.** Participants took part in nine more potentially binding auction rounds.

**Step five.** The monitor announced the average of participants’ common value signals and randomly determined the binding auction round. Participants then completed a post-auction questionnaire, carried out any transactions they had agreed to, and received $5 for taking part in the study.
It is worth noting that while participants in most induced value studies receive different induced values in each auction round and every auction round is binding, we did not vary $v_i$ across rounds in this study and only the transactions from one of our ten auction rounds were carried out. Our aim was to parallel the experimental auctions used in the agricultural valuation literature as closely as possible. Participants in these auction experiments typically bid on the same good in a series of potentially binding auction rounds (e.g., Depositario et al. 2009). With this in mind, we chose to deviate from standard practice in the induced value literature in order to hue more closely to standard practice in the agricultural valuation literature.

Results

None of the demographic characteristics we collected differed across treatments at conventional levels of statistical significance.

Table 1 presents summary bids and “underbids” from both treatments across rounds. We define “underbid” as the difference between the unconditional expected value presented in equation (5) and the bid submitted, or

$$\text{underbid}_i = p_i + \frac{c_i}{8} + E\left(\sum_{j \neq i} \frac{c_j}{8}\right) - \text{bid}_i,$$

Figure 1 depicts mean underbids across rounds. In the BDM treatment an underbid of zero is the Nash-equilibrium bidding strategy. In the second-price treatment an underbid of zero fails to account for the information that winning the auction provides. Consistent with the predictions of theory, we cannot reject the null hypothesis that the mean BDM
underbid in round 1 equals zero \((t = 1.31)\), while the mean second-price underbid in round 1 is positive and highly statistically significant \((t = 2.92)\). However, a two-sample \(t\)-test assuming equal variance cannot reject the null hypothesis that mean underbids from the two treatments are equal \((t = 1.25)\).

Table 1 and figure 1 also show that the mean underbid falls across rounds in both treatments, and that this decrease is more dramatic in the second-price treatment. Mean second-price underbids decreased relatively rapidly across rounds because mean second-price bids increased relatively rapidly.

Taking advantage of the panel nature of our data, we estimate the following random-effects regression:

\[
\text{underbid}_{it} = \beta_0 + \beta_1 BDM_i + \sum_{j=2}^{10} \gamma_j Round_j + \sum_{j=2}^{10} \lambda_j BDM_i \times Round_j + u_i + \varepsilon_{it},
\]

where \(BDM_i\) is a dummy variable equal to 1 if participant \(i\) took part in a BDM treatment, the \(Round_j\) terms are dummy variables indexing rounds 2 through 10, \(u_i\) is an individual-specific effect, and \(\varepsilon_{it}\) is a zero-mean error term.

Table 2 presents the results of this regression analysis. The intercept is positive and statistically significant, which is consistent with second-price auction participants initially adjusting for the winner’s curse. The \(BDM_i\) coefficient is not different from zero at conventional significance levels, thus our results provide no evidence that BDM participants submit initial bids different from second-price auction participants. The \(Round_j\) coefficients are negative and monotonically decreasing, and all but the \(Round_2\) coefficient are highly statistically significant. This is consistent with the widely reported
tendency for experimental auction bids to increase across rounds regardless of the specifics of the auction mechanism (e.g., Corrigan and Rousu 2006). The $BDM_i \times \text{Round}_j$ coefficients are positive and show an increasing trend. The coefficients associated with rounds 4 through 10 are statistically significant. The random effects regression results support the unconditional results and suggest that underbids in the BDM treatment decreased less quickly than in the second-price treatment. Taken as a whole, our results provide limited evidence that second-price auction participants’ values are initially affiliated in the manner Milgrom and Weber (1982), Klemperer (1999), and others describe. In other words, our results suggest that second-price auction participants may lower their initial bids in an effort to avoid the winner’s curse. This is consistent with empirical studies focusing on common value goods. Lind and Plott (1991), for example, find that while the winner of a second-price auction typically incurs a loss, bids overall are best described by the risk-neutral Nash equilibrium strategy of adjusting for the information winning provides.

However, our results also show that second-price auction participants quickly abandon their conservative bidding strategy. Mean bids in the second-price treatment increase so rapidly that they exceed mean bids in the BDM treatment by an average of more than a dollar in the last five rounds. While results from later rounds are at odds with the predictions of auction theory detailed earlier in this paper, they are consistent with empirical studies suggesting that repeated second-price auctions with price feedback may overheat (e.g., Knetsch, Tang, and Thaler 2001; Corrigan and Rousu 2006). That is, participants driven by a behavioral anchoring effect or a desire to win for winning’s sake
may submit bids in later rounds that substantially overstate the innate value of the good up for auction.

**Conclusions**

Though the auction literature is vast, most theoretical and empirical investigations have focused on auctions for goods with either purely private or purely common value. However, most real world auctions are for goods with both private and common value components (Goeree and Offerman 2003). Values could become affiliated in an experimental auction environment for a number of reasons. For instance, while auction participants may be certain of the value they would derive from a conventional good, they may be uncertain of the value they would derive from a similar good endowed with some novel trait, and they may believe that other auction participants possess better information about the novel trait’s value.

Unfortunately for the experimental auction practitioner, the theoretical incentive compatibility of the popular second-price auction breaks down when values are affiliated. When a good’s value has a common value component, theory predicts that rational second-price auction participants will adjust their bids downward in order to avoid the winner’s curse. In this environment, second-price auction bids systematically underestimate participants’ actual expected values.

Researchers have only recently conducted empirical studies for goods with both common and private value (e.g., Goeree and Offerman 2002), but these studies have focused on efficiency and revenue. Far more important for the experimental auction
valuation literature is the extent to which auction participants’ bids provide an accurate and unbiased reflection of their underlying value signals.

In this article we test whether second-price auction participants understate their unconditional expected value in practice when values are affiliated. We do this by comparing results from a second-price auction with those from a BDM mechanism. Because the BDM mechanism is noncompetitive, winning provides no information about the relative value of a bidder’s common value signal so she has no incentive to adjust her bid to account for the winner’s curse.

Our results are mixed. While we find that second-price auction participants submit initial bids that significantly understate their unconditional expected value, these bids are not significantly different from initial bids in the BDM treatment. Perhaps more interestingly, we also find that because bids in second-price auctions increase relatively quickly across rounds, second-price auction participants submit bids in later rounds that significantly overstate their unconditional expected value. Taken together, our results suggest that researchers who use competitive auctions in experimental valuation studies should be less concerned about affiliation than about specific auction design considerations such as whether participants in repeated potentially binding auction rounds should receive price feedback.

Corrigan et al. (2010) recommend repeated second-price auctions without price feedback as a way to provide market experience while mitigating overheating. Future research should investigate whether auction participants in this setting continue to understate their unconditional expected value across rounds.
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Table 1. Summary Statistics for Bids and Underbids Across Rounds

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* (**) Statistically significant at the 0.05 (0.01) level.
Figure 1. Mean underbids in second-price and BDM treatments