Knowing Your Opponent: An Experiment on Auction Design with Asymmetries

Andrew McClellan

June 21, 2017

Abstract

Economists, when faced with undesirable bidder behavior in an auction, have often studied how changing the auction format can be beneficial. We study instead how changing the information available to bidders can change bidder behavior and increase the revenue an auction generates. We study common-value second-price auctions where bidders differ in the precision of their information (i.e., are experts or non-experts) and compare two auction designs, Disclosure and Non-Disclosure, in which bidders are told if their opponents are experts or not, providing a test of the effectiveness of information design in auctions. Theory predicts that bidders should decrease their bids when facing an expert and that non-disclosure should generate higher revenue. Despite the presence of the winner’s curse, we find experimental evidence that non-disclosure does generate higher revenue and achieves roughly 50% of the theoretical gains. Looking at individual bidding behavior, the higher revenue generated by non-disclosure appears to be due bidder behavior similar to that of the theory. Additionally, we derive a measure of sophistication and find that it predicts bidding behavior closer to theoretical predictions.

1 Introduction

In many auctions, bidders differ in how accurate their information is about the good being auctioned. In oil lease auctions, some bidders may have drilled on nearby leases and thereby have access to better estimates of the leases value; in corporate auctions, there may be bidders with insider knowledge about the value of the company or asset being sold.

We would especially like to thank Andrew Schotter for his support and guidance throughout this project. I would also like to thank Guillaume Frechette and participants at the NYU-Wharton-Columbia Graduate Student Experimental Economics Conference for helpful suggestions.
These asymmetries are an important determinant of bidding behavior and can lead to large decreases in the revenue an auction generates. Understanding the role of asymmetries and how auctions can be designed to dampen the negative impact of asymmetries is an important but overlooked aspect of auction design.

This question was looked at in a theoretical framework in McClellan (2017). We looked at a model in which bidder’s possess different precisions of their information about the good being auctioned. Rather than looking at how to change the underlying auction to dampen the effects of asymmetry, we looked how the design of the information bidders have about other bidders could dampen the effect of asymmetry. More specifically, we asked whether or not the auctioneer can raise expected revenue by disclosing to bidder’s whether their opponents have precise information or not. We show that the auctioneer interesting in maximizing revenue should not disclose information about a bidder’s opponents. This auction design recommendation is both easily implementable and can have large theoretical impact on the expected revenue an auction generates. However, many papers have shown significant deviations in experimental auctions from the theoretical predictions. Additionally, by introducing uncertainty about other bidder’s informational precision as well as about the good, the auction can be potentially cognitively difficult. Therefore, it is important to test whether the theory is a good road map for reality before implementing the design recommendation. In this paper we run an experimental auction which will allow us to study how disclosure changes bidder’s behavior and what the effect is on auction revenue.

Our results provide evidence in favor of the theoretical prediction that non-disclosure generates higher revenue than disclosure. Although subjects do not use Nash equilibrium bidding functions and are subject to the winner’s curse, we find that the theory works as a good road map of the forces at play in subject’s behavior. The factors driving the revenue ranking are changes in individual behavior (predicted by the theory) across the different auction designs which are predicted by the theory. We also find these revenue differences to be largest where theory predicts they would be. The data also suggests that subjects do understand that they should bid differently when they or their opponents have more precise information. When subjects are informed that they are facing an expert, they decrease their bids as theory would predict. Additionally, we find that subjects bid differently as experts and non-experts.

Our experimental design also gives us the ability to test whether subjects who are “sophisticated” are able to translate that sophistication to other environments. By using a cluster analysis over their bids as experts (where they have a dominant strategy), we can classify subjects as sophisticated or unsophisticated by how far their bid function as experts
differs from the dominant strategy. Since subjects are classified based on their actions as experts, we compare the bids of the two clusters as non-experts to see whether sophistication as experts implies sophistication as non-experts. We find that in the sophisticated subjects behave closer to theoretical predictions than unsophisticated subjects when bidding as non-experts. We interpret this as evidence that sophistication in bidding as experts and non-experts was closely linked.

Our findings show that information design has a relevant role in the design of auctions. Whereas most of the literature has focused on changing the auction format to deal with undesirable features of auctions, our theoretical and experimental results illustrate that a realistic form of information design (disclosure or non-disclosure) can have a significant impact on the revenue an auction generates. Our experimental findings show that subjects do react to the effect of information in the way the theory predicts, providing evidence for the ability of information design to work even when subjects depart from Nash equilibrium.

2 Literature

This paper is a test of the theory of McClellan (2017), which looked at how different informational environments affect bidding behavior and expected revenue. A special case of the model is presented in the next section.

We also contribute to the experimental auction literature. A much broader review of the field can be found in Kagel (1995) and Kagel and Levin (2011), so instead we highlight several papers asking questions close to our own.

Kagel and Levin (1999) also examines the question of how an insider bidder affects the first-price auction. Like us, they consider the effect of having an better informed bidder in a common-value auction. In their experiment, bidders know if their opponent is an expert (which corresponds to our disclosure environment) and they find that the presence of an expert can actually increase revenue. This finding differs from our own due to the choice of auction format; the negative effect of the expert is particularly strong in the second-price auction.

Choi et al. (2017) also study, both theoretically and experimentally, auctions with insiders and outsiders. Formally, their definition of insider and outsiders is different (our paper consider a common-value model whereas they consider an interdependent-value model with common- and private-value components in the bidder’s utility function). They examine the efficiency properties of the English and second-price auctions whereas we examine changes in the information given to bidders about other bidders.

Avery and Kagel (1997) look at the case of almost-common value auctions. In the
model they test, theory predicts that slight asymmetries can create a large change in bidder behavior (and expected revenue) when compared to the case of symmetric bidders. They find that this explosive effect of small asymmetries fails to materialize experimentally.

Brocas et al. (2016) look at a second-price auction where bidders may have access to different amounts of information. They find that subjects do not perceive a much of a difference between information with is private and information which is public as they should. Like our results, they find consistent overbidding and departure from Nash predictions. Unlike our paper, their theoretical model yields very different predictions when one player is more informed and they do not study the effect of letting bidders see how informed their opponents are.

3 Theory

We will study the design of a common-value second-price auction with \( N \) bidders without a reserve price.\(^1\) The value of the good being auctioned is \( V \sim U[V, \bar{V}] \). Each bidder \( i \) receives a type \( \theta_i \) at the beginning of the game. These types are iid and binary: \( \theta_i \in \{\theta_\ell, \theta_h\} \) with \( \mu = \text{prob}(\theta_i = \theta_\ell) \) and \( \theta_\ell < \theta_h \). These types will determine the accuracy of their signals. We will call \( \theta_\ell \) types experts and \( \theta_h \) types non-experts.

The signal of bidder \( i \) is \( s_i = V + \epsilon_i \) where \( \epsilon_i \sim U[-\theta_i, \theta_i] \).\(^2\) When \( \theta_\ell = 0 \), experts’ signal is equal to value of the good. In this case, we will say that experts are perfectly informed and when \( \theta_\ell \in (0, \theta_h) \), we will say that experts are imperfectly informed. Our main focus will be on the case of perfectly informed experts, but the same intuition applies to the case of imperfectly informed experts.

In many situations, a bidder’s type may be known to the auctioneer. In the example of the oil lease, the auctioneer can look up whether or not a bidder has drilled on nearby leases. Since the auctioneer is designing the auction, he can also choose how much information to disclose to bidders about their opponents. The auctioneer could ask bidders to mail in their bids (so that they are not able to see who their opponents are) or they could bring all the bidders to the same room to bid (so that who is participating in the auction is common-knowledge). Our goal will be to understand how these two different informational environments affect bidding behavior and auction revenue.

More formally, the non-disclosure environment means that each bidder’s type is private information (they know their own type) and the exact realization of other bidder’s types are unknown. Under disclosure, each bidder knows the types of all other bidders and

---

\(^1\)Since the value is the same for all bidders and the good is always allocated, the auction is efficient.

\(^2\)This is a special case of McClellan (2017).
(a) Non-Disclosure with $N = 2$: Each player knows his own type before the auction begins, but has an information set over his opponent’s type. The dotted lines mark $P_2$’s information set and the dashed lines mark $P_1$’s information set.

(b) Disclosure with $N = 2$: The types of all players are common-knowledge and known before the auction begins.

Figure 1: The two auction designs we consider.
knowledge of other bidder’s types is common-knowledge.

Let us briefly present the intuition of the model. In our model, as in all common-value auctions, bidder \( i \) must condition their bids on the information implied about other’s signals in the event that bidder \( i \) wins. A key observation is that the effect of this conditioning affects bidders with different precisions differently. In the extreme case of an expert who is perfectly informed, he has no conditioning to do since he already has all relevant information. In the case of a non-expert though, the presence of an expert exacerbates the “winner’s curse” in that winning against an expert is worse news than winning against a non-expert. This exacerbated winner’s curse leads to large drops in the non-experts bidding and function (and thereby expected revenue) when an expert is present. Disclosure, by letting non-expert’s know for sure that they are facing an expert, leads a large decrease in revenue when experts are present. On the other hand, in non-disclosure, the potential presence of an expert leads non-experts to shade their bid more, but not to the level that they do in disclosure when an expert is present. Understanding which effect (some shading all of the time in non-disclosure or extreme shading some of the time in disclosure) is larger is the goal of the rest of the section.

The first result of McClellan (2016) is to show some conditions under which an equilibrium \(^3\) exists under non-disclosure. Because each bidder is characterized by a type and a signal (which are not iid), equilibrium existence doesn’t follow from previous results in the literature. However, by assuming that signals are iid conditional on \( V \) and satisfy a reverse hazard rate dominance condition (which is satisfied here), we can ensure that an equilibrium exists.

**Theorem 1.** When experts are perfectly informed, an equilibrium exists under non-disclosure. For \( x \in [V + \theta, \bar{V} - \theta] \), we have that the bidding functions for non-experts is \( \beta^{ND}(x; \mu) = x + C(\mu) \) where \( C(\mu) < 0 \) and \( C'(\mu) < 0 \). Experts always bid \( \beta(x; \mu) = x \).

The above theorem implies that bid shading for non-experts should increase when the probability of an expert increases. As the non-expert believes that it is more likely that he is facing an expert, the information implied by winning the auction becomes more negative, leading to less aggressive bidding. Meanwhile, the expert, since he knows the value of the good, has a dominant strategy to bid the value of the good, regardless of \( \mu \) (or whether or not we are in disclosure or non-disclosure).\(^4\) This gives us our first two hypothesis:

**Hypothesis 1.** Non-expert’s bidding functions will decrease when \( \mu \) increases.

---

\(^3\)We focus on the case of symmetric equilibrium in which all bidders of the same type use the same bidding function.

\(^4\)This follows directly from the private-value second-price auction argument for bidding the value of the good.
Figure 2: Bid Shading: The non-experts bid lower as $\mu$ increases-i.e., as it becomes more likely that at least one of their opponents is an expert, non-experts must shade their bid more.
Hypothesis 2. All perfectly-informed experts bid their signal and all non-experts bid below their signal.

Next we turn our attention to the case of disclosure (we will consider perfectly informed experts unless otherwise stated). Since bidding functions will depend on what bidder types are realized, we will need to analyze the equilibrium for each possible number of realized experts. We will let $\beta_{D,n}$ be the bidding function of the non-expert when there are $n$ experts. Note that since the realized types are known, the bidding function will not depend on $\mu$.

Let us begin when all bidder’s are of the same type (i.e., all experts or all non-experts). Since all bidders are of the same type, we can apply Milgrom-Weber (1982) to explicitly calculate the equilibrium bidding function. For $x \in [V + \theta, \bar{V} - \theta]$, it takes a particularly simple form of $\beta_{D,0}(x) = x - \frac{\theta}{2}$.

When there is at least one expert present, Milgrom-Weber’s result doesn’t apply. In fact, we run into the issue of multiple equilibrium. In general, all second-price auctions face the issue of multiple equilibria (e.g., Bidder 1 bids $\bar{V}$ always and all other bidders bid 0). The usual strategy of restricting attention to symmetric equilibria doesn’t have the same bite when bidders are of multiple types. For example, when there are three bidders, then at least one bidder is the only one of his type. For this bidder, restricting attention to symmetric equilibrium doesn’t add much restriction for him. Fortunately, in our set-up, the perfectly informed experts’ have a dominant strategy to bid the true value of the good (since they are not subject to the winner’s curse, the same logic from private value second-price auctions applies). This will greatly help us pin down the set of equilibrium.

Let’s consider the case when there are two non-experts and one expert. Imagine that a non-expert wins the good. He knows then that the expert bid lower than he did and hence the value of the good is lower than his bid. If the second-highest bid comes from the expert, then the non-expert makes a profit of zero (since the price he pays is equal to the value of the good). However, when the second-highest bid comes from a non-expert, the winner is making a strict loss since the expert’s bid (and hence the value of the good) must have been less than the second-highest bid. Therefore, the non-expert would have been better off losing the auction. This argument implies that in any equilibrium in which non-experts use symmetric bidding strategies, the non-expert must win with zero probability. If we restrict attention to undominated bidding functions, then the non-expert must bid $\beta_{D,1}(x) = x - \theta_h$. Intuitively, the presence of the experts creates an exacerbated winner’s curse phenomenon: the information that one won the auction conveys very negative information about the value of the good.

Finally, we consider the case in which there are two experts and one non-expert. Notice that regardless of what the non-expert does, the experts will both bid the value of the
Figure 3: Non-expert’s Bidding Functions: We can see that non-expert’s bid highest when they know for sure that all their opponents are non-experts. When at least one-expert is present, the significantly decrease their bids, much more so than they do under non-disclosure.

good. Therefore, the second-highest bid (and hence revenue) will be equal to the value of the good with probability one. Therefore, the bid of the non-expert is immaterial for the revenue of the auction. If we want to pin down his bidding function, we can appeal to the equilibrium refinement of Abrahmn et al. (2016), which perturbs the auction by adding, with probability $\epsilon$, an additional bidder who bids randomly and look at the equilibrium set as $\epsilon \to 0$. With this refinement, we can establish that the non-expert will bid as he did in the previous case: $\beta^{D,2}(x) = x - \theta_h$. Additionally, we can establish in our uniform-uniform setup that this will be the limiting bidding function as the expert’s precision becomes perfect.

**Theorem 2.** The equilibrium bidding functions of the non-expert under disclosure are given by

$$\beta^{D,1}(x) = \beta^{D,2}(x) = x - \theta_h \quad \text{or} \quad x - \frac{\theta_h}{3} = \beta^{D,0}(x)$$

The theory gives us a number of predictions which will be useful for testing in the theory. We formally state these predictions below:
Hypothesis 3. Let us define bid shading to be $\alpha^2(x) = x - \beta^2(x)$.

$$
a^{D,2}(x) = a^{D,1}(x) > a^{ND}(x) > a^{D,0}(x)
$$

The equilibrium results so far have looked at the case of a perfectly informed expert. With our specific uniform-uniform value-signal structure, we can derive equilibrium when expert’s are not perfectly informed and $N = 3$. Intuitively, we would expect the same exacerbated winner’s curse to cause a decrease in non-expert’s bidding function when an expert is present, albeit not to the same degree. Additionally, because experts are no longer perfectly informed, they too must condition on the information implied in the event that they win the auction. Since their private signal is more precise, this new information doesn’t change their expectation of the value of the good as much as it does for non-experts. This leads to our next hypothesis:

Hypothesis 4. Non-Experts bid higher when facing non-perfectly informed experts and experts decrease their bids when their information is less precise.

Finally, we look at the expected revenue generated by the auction. For $N > 2$, it is not ex-ante clear whether or not disclosure will generate less revenue than non-disclosure. Remember, when no experts are present disclosure does better while when at lease one expert is present, disclosure does worse. McClellan (2017) shows that if non-experts are informed enough, then non-disclosure generates higher revenue. Because we can calculate the bid functions in our set-up, we can verify that indeed revenue is higher in non-disclosure than disclosure with the parameter values we use (see next section). This leads to our final hypothesis:

Hypothesis 5. Non-disclosure yields lower revenue than disclosure.

4 Experimental Design

The experiment was conducted using a between-subject design at NYU over 5 sessions using 99 undergraduates. Subjects participated in auctions of size $N = 3$ and were randomly rematched after each round. They participated in 5 or 10 practice rounds and either 35 or 40 regular rounds. Each session was either a non-disclosure or disclosure session. Across the non-disclosure sessions, we varied the probability that each bidder was an expert (2 session with $\mu = 0.7$, 1 with $\mu = 0.3$) and in the disclosure treatment we varied the precision of the experts $\theta_e$ (1 session with $\theta_e = 0$ and 1 session with $\theta_e = 50$). In all sessions the non-expert’s precision was fixed at $\theta_n = 150$. The values were drawn uniformly between
200 and 1200. Each subject knew the distribution of signals and the precisions of the signals of different types.

We used a dual-market procedure in order to elicit subjects bids: at the beginning of each round, subjects were given a signal but not told their type. In disclosure sessions, subjects were told how many of their opponents were experts; in non-disclosure sessions, they were only told that each of their opponents had a $\mu$ probability of being an expert. Subjects were then asked to submit two bids: one to be used if they were an expert and one to be used if they were a non-expert. The were told that only bid that corresponded to their true type would be used (and so they had an incentive to choose their bid for each type as if they were sure they were that type). After submitting all bids, subjects were told which type they were and, if they won the auction, what the value of the good was and what price they paid. Bidders that lost were only told that they lost the auction, whether they were an expert or not and what the winning bid was. We decided on this feedback in order to best fit real-world auctions, where the actual bids are all participants may not be announced.

Other than the information conveyed to subjects and the parameters $\mu, \theta, \ell$, the auction environment was the same across all sessions. There was no reserve price for the good, although subjects were restricted from bidding below 0 and above 1500.

5 Results

5.1 Revenue Comparison

We begin by looking at the results on realized revenue to test Hypothesis 5. The dual market procedure design gives us twice as much data on subjects bidding functions than was actually used to calculate profits in the session. To make full use of the available data, we calculate expected revenue using a simulation method. We draw values and signals randomly and select subject's bids corresponding to the signals and bidder types. To test the significance of the data, we construct confidence intervals using a bootstrapping technique. In each bootstrap sample, we draw samples (with replacement) of signal and bid pairs from the data randomly and then use the simulation method described above to calculate the expected revenue from this bootstrap sample. By observing the quantiles of the expected revenue of the bootstrap samples, we can construct a confidence interval around the true sample which we have.

The table below reports the results comparing the theoretical and simulated difference between disclosure and non-disclosure with perfectly informed experts at both $\mu = 0.7$ and $\mu = 0.3$. We see that non-disclosure always outperforms disclosure, with the greatest difference at $\mu = 0.3$ as the theory predicts. We see that revenue is significantly greater
than zero for $\mu = 0.3$ but not for $\mu = 0.7$. However, the difference between theoretical and actual is only significant for $\mu = 0.3$ and we find that the actual revenue difference is lower than the theoretical difference. In both cases, the average simulated revenue difference is roughly half of the theoretical gains.

<table>
<thead>
<tr>
<th>Revenue Difference: Non-Disclosure - Disclosure</th>
<th>Theoretical</th>
<th>Actual</th>
<th>Difference</th>
</tr>
</thead>
<tbody>
<tr>
<td>$\mu = 0.3$</td>
<td>23.69</td>
<td>12.48**</td>
<td>11.21*</td>
</tr>
<tr>
<td>$\mu = 0.7$</td>
<td>6.51</td>
<td>3.345</td>
<td>3.165</td>
</tr>
</tbody>
</table>

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

The above simulation averages across realizations of types, which hides heterogeneity in the expected revenue differences across different realizations of bidder's types. The theory gives us strong predictions about when non-disclosure will generate higher revenue than disclosure and when it will not. To truly test whether the theory is correct, we need to look at the case-by-case realizations of types and see when non-disclosure does better than disclosure.

Figures 4 and 5 show the predicted and simulated difference in revenue between non-disclosure and disclosure for different numbers of experts. The white bar gives the theoretical prediction while the shaded bar gives the simulated difference. Theory predicts that disclosure should do better when there are no experts (i.e., a negative difference), should do worse when there is only one expert (i.e., a positive difference) and should do just as well as non-disclosure when there is more than one expert (i.e., no difference).

As we see in the above charts, the actual revenue differences are smaller than predicted and non-disclosure always does better than disclosure, even when there are no experts present. However, we do see that the hump-shaped revenue differences is observed in our data. In the table below, we see that the biggest difference between disclosure and non-disclosure occurs when there is one or two experts, as the theory would predict. This offers some support for the theoretical prediction that disclosing bidders types will lead to large loses compared to not disclosing types when there is one expert present. This suggests that subjects do appreciate the disadvantage they have as a non-expert facing an expert but do not internalize this disadvantage as much as would be theoretically optimal. The table below gives the exact values of the revenue differences (along with their significance) as well as the theoretical predictions.
Figure 4: The difference between Non-Disclosure and Disclosure when $\mu = 0.3$

Figure 5: The difference between Non-Disclosure and Disclosure when $\mu = 0.7$
5.2 Individual Bidding Behavior

While the revenue findings offer some support the theoretical predictions, we need to dive deeper so as to understand if predicted individual behavior is what drives our results. Are subjects reacting the presence of experts as theory predicts? Does non-disclosure somehow drive bids up? To answer these questions, we look at individual bids. First, we look at disclosure. The following graph gives a scatter plot of bids and signals of experts and non-experts.

We see that bid functions appear to be monotonic but with a large degree of noise and that there is a large degree of overbidding (contradicting Hypothesis 2). Visual inspection also tells us that experts bid much closer to Nash equilibrium and the degree of overbidding is much higher for non-experts. This is comforting in that it seems to indicate that subjects understood the difference between bidding as experts and bidding as non-experts. The presence of overbidding is not surprising; the winner’s curse is well and alive in our results (given the prevalence and persistence of the winner’s curse in previous papers, any other result would be extremely surprising). The table below illustrates that almost all types of bidders experienced losses on average. We can also see that experts, even though they still took losses, on average performed better than non-experts did (so having the more precise information was useful).
Figure 6: In the top graph we see bids for perfectly informed experts under disclosure. While we do see over- and under-bidding, subjects' bids are reasonably close to the red line which gives the Nash equilibrium of bid = signal. In the bottom graph we see bids for non-experts under disclosure. The lower line gives the theoretical bid function when an expert is present and the upper line gives the 45 degree line of bid = signal. Clearly we see a large degree of overbidding.
Figure 7: In the top graph we see bids for perfectly informed experts under non-disclosure with $\mu = 0.3$. While there is a high degree of overbidding, we see that bids are tightly clustered around the 45 degree line, which is the dominant strategy. In the bottom graph we see bids for non-experts under non-disclosure when $\mu = 0.3$. The top line marks the 45 degree line and the bottom line marks the Nash equilibrium bidding function. Like the experts, we see a high degree of overbidding and we see that bids are much more dispersed than expert’s bids.
Figure 8: In the top graph we see bids for perfectly informed experts under non-disclosure with $\mu = 0.7$ and in the bottom graph we see bids for non-experts under non-disclosure when $\mu = 0.3$. The graphs (and analysis) is similar to that of Figure 7.
While the theory clearly fails at a first pass, we need to see whether the theory correctly predicts the “direction” of bids—e.g., do bids decrease when bidders learn there is a non-expert? We compare the amount of bid shading that they did by performing some t-tests to see how bid shading compares in the different informational environments of interest.

To test Hypothesis 1, we see whether the amount of bid shading in the non-disclosure treatments differed when we changed the value of $\mu$. In line with the theory, we find that bid shading is higher when the probability of an expert is higher, indicating that subjects were more cautious when it was more likely their opponent was better informed.

\textbf{Non-Expert Bid Shading: Difference between $\mu = 0.7$ and $\mu = 0.3$}

\begin{align*}
\alpha(0.7) - \alpha(0.3) &= 13.25^* \\
&\quad (7.57)
\end{align*}

When making the comparison between non-expert’s bid shading in non-disclosure and disclosure, we find significant evidence that non-disclosure leads to less bid shading than disclosure and that this difference is larger when experts are present.
Next, we want to see if subjects are reacting being informed that their opponent is an expert. For the case of disclosure, we make comparisons across the bid shading of experts and non-experts when different numbers of experts are present. In the case of non-experts, we find that the directions are all as theory would predict i.e., bid shading is larger when experts are present and bid shading doesn't change between one and two experts. However, none of the differences are significant.

### Non-Expert Bid Shading: Non-Disc. – Disc

<table>
<thead>
<tr>
<th></th>
<th>$\mu = 0.7$</th>
<th>$\mu = 0.3$</th>
</tr>
</thead>
<tbody>
<tr>
<td>0 Exp.</td>
<td>$-4.84$</td>
<td>$-18.09$</td>
</tr>
<tr>
<td>1 Exp.</td>
<td>$-17.08$</td>
<td>$-30.33^{***}$</td>
</tr>
<tr>
<td>2 Exp.</td>
<td>$-18.64$</td>
<td>$-31.89^{**}$</td>
</tr>
</tbody>
</table>

Standard deviation in parentheses
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

In Figure 9 we see that there are a small number of subjects who engage in extreme bid shading (e.g., bidding zero even with a high signal). In order to see if these are driving the results, we drop the observations above 95th percentile of the absolute value of their bid shading (this turned out to be bid shades greater (in absolute terms) than 300, which correspond to bids which were strictly dominated). We rerun the same significance tests.

### Bid Shading: Disclosure Difference Across Number of Experts

<table>
<thead>
<tr>
<th>Other Experts</th>
<th>Non-Experts</th>
<th>Experts</th>
</tr>
</thead>
<tbody>
<tr>
<td>0 Exp. - 1 Exp.</td>
<td>$-12.24$</td>
<td>$-0.070$</td>
</tr>
<tr>
<td>0 Exp. - 2 Exp.</td>
<td>$-13.80$</td>
<td>$10.60$</td>
</tr>
<tr>
<td>1 Exp. - 2 Exp.</td>
<td>$-1.55$</td>
<td>$10.68$</td>
</tr>
</tbody>
</table>

Standard deviation in parentheses
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$
Figure 9: The absolute value of shading. We can see that the tail is extremely long and there is a small number of extreme values of bid shading.

and find that the ordering predicted by the theory is present and is highly significant. Moreover, we find that the predicted ranking of bid shading from the theory holds.\(^5\)

<table>
<thead>
<tr>
<th>Non-Expert Bid Shading: Non-Disc. – Disc</th>
<th>(\mu = 0.7)</th>
<th>(\mu = 0.3)</th>
</tr>
</thead>
<tbody>
<tr>
<td>0 Exp.</td>
<td>1.02</td>
<td>3.38</td>
</tr>
<tr>
<td></td>
<td>(7.52)</td>
<td>(7.64)</td>
</tr>
<tr>
<td>1 Exp.</td>
<td>–15.23**</td>
<td>–12.87**</td>
</tr>
<tr>
<td></td>
<td>(5.90)</td>
<td>(6.26)</td>
</tr>
<tr>
<td>2 Exp.</td>
<td>–18.14**</td>
<td>–15.78**</td>
</tr>
<tr>
<td></td>
<td>(8.55)</td>
<td>(8.73)</td>
</tr>
</tbody>
</table>

Standard deviation in parentheses

\(^5\)We re-run our revenue simulations with the extreme bids dropped and we get roughly the same results as we did originally, indicating that the bid-shading we find here (and not a small number of extreme bids) is the driving force behind our revenue results.
Bid Shading: Disclosure Difference Across Number of Experts

<table>
<thead>
<tr>
<th>Other Experts</th>
<th>Non-Experts</th>
<th>Experts</th>
</tr>
</thead>
<tbody>
<tr>
<td>0 Exp. - 1 Exp.</td>
<td>-16.25**</td>
<td>-7.57</td>
</tr>
<tr>
<td></td>
<td>(9.80)</td>
<td>(5.76)</td>
</tr>
<tr>
<td>0 Exp. - 2 Exp.</td>
<td>-19.16*</td>
<td>-5.22</td>
</tr>
<tr>
<td></td>
<td>(9.82)</td>
<td>(8.06)</td>
</tr>
<tr>
<td>1 Exp. - 2 Exp.</td>
<td>-2.90</td>
<td>2.35</td>
</tr>
<tr>
<td></td>
<td>(11.20)</td>
<td>(6.60)</td>
</tr>
</tbody>
</table>

Standard deviation in parentheses
* p < 0.1, ** p < 0.05, *** p < 0.01

We can also test Hypothesis 4 at whether non-experts and experts bid more or less aggressive when experts were not perfectly informed. We perform t-tests on the difference between non-experts bid shading when experts are perfectly informed and when experts are perfectly informed. As experts become less informed, the negative information implied by winning against an expert becomes milder. We should expect that non-experts and experts will shade their bids more when experts are more informed. As we see in the table below, we see strong evidence for Hypothesis 4 in the data for non-experts and not for experts.

Bid Shading: Difference between Perfectly and Imperfectly Informed Experts

<table>
<thead>
<tr>
<th>Other Experts</th>
<th>Non-Experts</th>
<th>Experts</th>
</tr>
</thead>
<tbody>
<tr>
<td>0 Exp.</td>
<td>40.03*</td>
<td>7.65</td>
</tr>
<tr>
<td></td>
<td>(26.06)</td>
<td>(24.18)</td>
</tr>
<tr>
<td>1 Exp.</td>
<td>44.09***</td>
<td>1.92</td>
</tr>
<tr>
<td></td>
<td>(15.65)</td>
<td>(14.67)</td>
</tr>
<tr>
<td>2 Exp.</td>
<td>59.64***</td>
<td>-1.56</td>
</tr>
<tr>
<td></td>
<td>(24.48)</td>
<td>(19.81)</td>
</tr>
</tbody>
</table>

Standard deviation in parentheses
* p < 0.1, ** p < 0.05, *** p < 0.01

Thus we see consistent evidence that non-experts bid more aggressively when they are at less of an informational disadvantage. This shows that subjects seem to react to the quality of the experts information as theory predict. It is not ex-ante obvious that this theoretical
prediction would appear in the data: we could imagine other stories which would lead to non-experts to bid less aggressively when experts are better informed (e.g., non-experts feel they are disadvantaged against perfectly informed experts and bid aggressively to “compensate” for the perceived disadvantage).

When we look at the case of how non-experts react to an expert when experts are not perfectly informed, we find that bids are not significantly different. It may be that learning about the winner’s curse (and the disadvantage of facing an expert as a non-expert) is more difficult when experts are not perfectly informed. Losses will be less severe when facing an imperfectly informed expert.

In line with the previous literature, we also want to check to see if subjects fall prey to the winner’s curse. From visual inspection of the observed bids in Figures 6-8, we can already see that there is rampant over bidding in all environments. As the following graphs show, we see a high incidence of the winner’s curse for non-experts for disclosure and non-disclosure. We see in the table below that all non-experts earned negative profits on average and many experts earned negative profits on average (although losses for experts with less than those for non-experts). While this does imply some failure of the theory, it is unsurprising given the well-noted prevalence and persistence of the winner’s curse. It would be somewhat troubling if we didn’t find a persistent winner’s curse, as it might imply that the dual-market set-up added an extra effect absent from previous auction experiments.

A natural question about the over-bidding is whether is driven by an extremely clueless few or a more mildly confused multitude. To test this, we need a metric in order to split subjects based on a notion of sophistication. For this end, the dual market procedure gives us data which is particularly well-suited to answer this question. Since perfectly informed experts have a dominant strategy to bid the value of the good. Therefore, all bidders should use the same expert bidding function regardless of what beliefs they have about other bidders. We use the mean squared-difference of each subject’s expert bids from the Nash equilibrium as a measure of their sophistication. We then use a cluster analysis to group subjects into two clusters, one of which we call sophisticated and the other which we call non-sophisticated. The graphs below give the resulting division of expert bids into the two clusters. We can see that the clusters do a reasonably good of grouping the subjects: many of the more extreme bids come from the unsophisticated cluster while the sophisticated bids are close to the dominant strategy. This tells us that the extreme deviations from the dominant strategy are caused by the same subset of people, and not random errors among the general subject pool.

We then use these groupings of subjects to see how well their non-expert bids do. If the
Figure 10: Expert’s Bids: x’s mark the unsophisticated bidders and dots mark the sophisticated bidders. We see that most of the extreme deviations from optimal bidding are caused by unsophisticated types.
Figure 11: Non-Experts Bids: x’s mark the unsophisticated bidders and dots mark the sophisticated bidders. We see than many of the extreme bids are from the unsophisticated types, albeit not to the same degree as among the expert’s bids.
sophisticated experts truly are sophisticated, then we should expect to see a lower incidence of the winner’s curse among them. The Figure 11 illustrates that while the cluster analysis doesn’t separate the bids quite as nicely for non-experts, most of the extreme deviations from the theoretical predictions are caused by these unsophisticated types.

Interestingly, when we calculate the average losses as non-experts from the two clusters, we see that the sophisticated cluster always does better (although the difference is only significant under disclosure). As for the winner’s curse among experts, we see that our cluster analysis did a good job separating the types, as sophisticated experts do significantly better than unsophisticated experts.

Additionally, we see that the difference is bid shading among non-experts are significant for subjects in the sophisticated cluster while they are no significantly different for subjects in the unsophisticated cluster.

If we go back to our non-expert bid shading tests, we see that sophisticated have bid shading directions which correspond to the theory and are significant (even without dropping the extreme bids) whereas the unsophisticated subjects experience much noisier bid shading. By classifying people over their behavior over their expert bids, we get a metric which performs well in the test of classifying the sophistication of their bids as non-experts. We find that the classification only translates into non-expert bids well for disclosure and non-disclosure The first table below give the bid-shading results separating out the sophisticated types ($S$) and the unsophisticated types ($U$) for disclosure. Sophisticated types shade their bids when at least one expert is present, but do not change their bid shading much between one and two experts. For the unsophisticated types, we see much larger standard errors and that they bid higher when there are more experts (although not significantly). The second table gives the difference between clusters among non-experts in non-disclosure We see that the sophisticated types have significantly lower over-bidding and are closer (thought not equal to) the theoretical predictions.
### Bid Shading: Disclosure Across Clusters

<table>
<thead>
<tr>
<th>Other Experts</th>
<th>Non-Experts (S)</th>
<th>Non-Experts (U)</th>
</tr>
</thead>
<tbody>
<tr>
<td>0 Exp. - 1 Exp.</td>
<td>−25.62***</td>
<td>25.69*</td>
</tr>
<tr>
<td></td>
<td>(10.91)</td>
<td>(63.83)</td>
</tr>
<tr>
<td>0 Exp. - 2 Exp.</td>
<td>−37.93**</td>
<td>59.08</td>
</tr>
<tr>
<td></td>
<td>(19.25)</td>
<td>(70.57)</td>
</tr>
<tr>
<td>1 Exp. - 2 Exp.</td>
<td>−2.31</td>
<td>33.39*</td>
</tr>
<tr>
<td></td>
<td>(14.76)</td>
<td>(64.15)</td>
</tr>
</tbody>
</table>

Standard deviation in parentheses
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

### Bid Shading: Non-Disclosure Across Clusters

<table>
<thead>
<tr>
<th></th>
<th>Non-Experts (S)</th>
<th>Non-Experts (U)</th>
<th>Difference</th>
</tr>
</thead>
<tbody>
<tr>
<td>$\mu = 0.3$</td>
<td>−9.21*</td>
<td>−50.02</td>
<td>−40.81***</td>
</tr>
<tr>
<td></td>
<td>(4.72)</td>
<td>(10.95)</td>
<td>(10.55)</td>
</tr>
<tr>
<td>$\mu = 0.7$</td>
<td>−3.16</td>
<td>−31.85***</td>
<td>−28.69***</td>
</tr>
<tr>
<td></td>
<td>(5.44)</td>
<td>(11.27)</td>
<td>(11.10)</td>
</tr>
</tbody>
</table>

Standard deviation in parentheses
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

### 6 Conclusion

While much work has looked at how much information to release about a good being auctioned, less work has looked at the auction design implications of changing how much information bidders can see about their opponents. We provide an experimental test of McClellan (2016), which shows theoretically that non-disclosure will yield higher revenue. Our results provide some support for the theory: while observed bids differ from the theoretical predictions, the theoretical comparative statics of changing the information structure appear in our data and appear to drive the higher revenue generated by non-disclosure.

As noted in the literature on information design, there are two ways to change bidder’s behavior: to change their payoffs (mechanism design) or to changes their beliefs (infor-
Our experiment tests a version of information design by changing the information bidders have about their opponents rather than changing the underlying mechanism. We think this has many features which are useful in real-world implementation—e.g., many theoretically optimal mechanisms are complicated and take a long time for subjects to even learn how they work. Our experimental results provide evidence that information design can be useful in the design of auctions.

References


