

Naturally Occurring Markets and Exogenous Laboratory Experiments: A Case Study of the Winner's Curse

by

Glenn W. Harrison & John A. List †

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ABSTRACT

There has been a dramatic increase in the use of experimental methods in the past two decades. An oft-cited reason for this rise in popularity is that experimental methods provide the necessary control to estimate treatment effects in isolation of other confounding factors. We question the relevance of experimental findings from laboratory settings that abstract from the field context of the task that theory purports to explain. Using common value auction theory as our guide, we identify naturally occurring settings in which one can test the theory. In our treatments the subjects are not picked at random, as in lab experiments with student subjects, but are deliberately identified by their trading roles in the natural field setting. We find that experienced agents bidding in familiar roles do not fall prey to the winner's curse. Yet, when experienced agents are observed bidding in an unfamiliar role, we find that they frequently fall prey to the winner's curse. We conclude that the theory predicts field behavior well when one is able to identify naturally occurring field counterparts to the key theoretical conditions.

† Department of Economics, College of Business Administration, University of Central Florida (Harrison), and National Bureau of Economic Research, Council of Economic Advisors, and University of Maryland (List). E-mail contacts: GHARRISON@BUS.UCF.EDU and JLIST@AREC.UMD.EDU. We are grateful to Lisa Rutström for helpful comments.

One of the main attractions of experimental methods is the control that it provides over factors that could influence behavior. The ability to control the environment allows the researcher to study the effects of treatments in isolation, and hence makes it easier to draw inferences as to what is influencing behavior. In most cases we are interested in making inferences about existing or possible field behavior. We hypothesize that there is a risk that the imposition of an exogenous laboratory control might make it harder, in some settings, to make reliable inferences about field behavior. The reason is that the experimenter might not understand something about the factor being controlled, and might impose it in a way that is inconsistent with the way it arises naturally in the field, and that affects behavior.

We take as a case study the effect of “insiders” on the market phenomenon known as the “winner’s curse.” For now we define an insider as anyone that has better information than other market participants. The winner’s curse (WC) refers to a situation in which the winner of an auction regrets having won the auction.¹ The WC arises because individuals fail to correctly process the information about the auction setting. Specifically, they do not take into account the fact that *if they win* then they may have over-estimated the value of the object, and correct their bids for that fact.

If insiders are present in a market, then one might expect that the prevailing prices in the market will reflect their better information. This leads to two general questions about market performance.² First, do insiders fall prey to the WC? Second, does the presence of insiders mitigate the WC for the market as a whole?

Our approach is to *undertake experiments in naturally occurring settings in which the factors that are at*

¹ We will define later a related concept which is more widely used in the experimental literature. Our initial definition of the WC views it as an *ex post facto* condition, whereas the alternative is *ex ante*.

² Formal game-theoretic models of bidding in first-price auctions with common values lead to certain specific testable predictions about the effects of insiders. These predictions depend on the precise informational structure of the institution, as one would expect. We review those predictions in section 1.

the heart of the theory are identifiable and arise endogenously, and then to impose the remaining controls needed to implement a clean experiment. In other words, rather than impose all controls exogenously on a convenience sample of college students, we find a population in the field in which one of the factors of interest arises naturally, where it can be identified easily, and then add the necessary controls.³ To test our methodological hypotheses, we also implement a fully controlled laboratory experiment with subjects drawn from the same field population.

The relevance of field subjects and field environments for tests of the WC is evident from Dyer and Kagel [1996; p.1464], who review how executives in the commercial construction industry appear to avoid it in the field:

Two broad conclusions are reached. One is that the executives have learned a set of situation-specific rules of thumb which help them to avoid the winner's curse in the field, but which could not be applied in the laboratory markets. The second is that the bidding environment created in the laboratory and the theory underlying it are not fully representative of the field environment. Rather, the latter has developed escape mechanisms for avoiding the winner's curse that are mutually beneficial to both buyers and sellers and which have not been incorporated into the standard one-shot auction theory literature.

These general insights motivated our design. We study the behavior of insiders in their field context, while controlling the “rules of the game” to make their bidding behavior fall into the domain of existing auction theory. In this instance, the term “field context” means the commodity and institution for which they are familiar as well as the type of bidders they normally encounter.

Our design allows us to tease apart the two hypotheses implicit in the conclusions of Dyer and Kagel [1996]. It is plausible to assume that survival in the industry as a dealer provides

³ Bohm and Lind [1993] make some of the same methodological points in the context of an examination of the relevance of the “preference reversal” anomaly in the field. They find that the anomaly was significantly reduced when using field subjects in a field setting. They do not, however, supplement their analysis by conducting laboratory experiments with subjects drawn from the same field population, as we do. Lichtenstein and Slovic [1973] also undertook experiments with field subjects who had some field experience with gambles, but the objects of study in their experiments were designed to be artificial. Ortmann and Gigerenzer [1997] identify numerous instances in classic psychology experiments where context matters, and explain why they should matter for economics experiments.

sufficient evidence that they do not make persistent losses in their natural market setting. Hence, if our insiders fall prey to the WC in our field experiment, then it must be that they avoid it by using market mechanisms other than those we study. We find evidence that is consistent with the conclusion that *dealers in the field do not fall prey to the winner's curse in the field experiment, providing tentative support for the hypothesis that naturally occurring markets are efficient because certain traders use heuristics to avoid the inferential black hole that underlies the winner's curse.* That is, we conclude that the dealers employ heuristics that enable them to avoid the winner's curse, rather than rely *exclusively* on extra-market adjustments in contracts such as those identified by Dyer and Kagel [1996].⁴

This support is only tentative, however, because it could be that these dealers have developed heuristics that protect them from the WC only in their specialized corner of the economy. That would still be valuable to know, but it would mean that the type of heuristics they learn in their corner are not general, and do not transfer to other settings. Hence, we also conducted laboratory experiments, using induced valuations as in the laboratory experiments that Kagel and Levin [1999] conducted with college students, but with field subjects. These laboratory experiments were designed to examine if the heuristic that field dealers apparently use in the field setting transfers to a laboratory setting. Thus we retain our focus on field subjects with experience in the general type of valuation task, but add the controls of a laboratory experiment. We find that their apparent use of a heuristic does indeed transfer when they are acting in familiar roles, adding further support to the claim that *these insiders have developed a "heuristic that travels" from problem domain to problem domain.*

Furthermore, when dealers are exogenously provided with less information than their

⁴ In the sportscard market environment, *some* auctioneers allow a full money-back return within a set number of days. This policy applies to dealers and non-dealers, and is usually written. Unwritten conventions exist in trades between dealers, and punishments are relatively easy to effect in future shows or trading opportunities. Price discrimination is widely employed when dealers trade with amateurs, but the degree of discrimination is somewhat limited to avoid the amateurs leaving the market altogether.

bidding counterparts, a role that is rarely played by dealers, we find that they frequently fall prey to the WC. We therefore conclude that *the theory predicts field behavior well when one is able to identify naturally occurring field counterparts to the key theoretical conditions.*

In section 1 we review the relevant theoretical predictions, in section 2 we review previous experimental findings, in section 3 we discuss our experimental procedures and design, in section 4 we present our results, and in section 5 we draw conclusions.

1. Theoretical Predictions

Economic theory provides game-theoretic predictions of behavior in first price common value actions with certain features. The most important feature for us is the information structure:

- In a Symmetric Information Structure (SIS) auction, each bidder is given a private signal as to the true value of the object.
- In an Asymmetric Information Structure (AIS), the insider knows the value with certainty, and the outsider either gets a private signal (AISpr) or a public signal (AISpu).

Theoretical bidding behavior in these structures has been studied by Wilson [1967], Weverbergh [1979], Milgrom and Weber [1982], Engelbrecht-Wiggans, Milgrom and Weber [1983], Kagel and Levin [1986][1999][2002] and Hausch [1987], amongst others.

Kagel and Levin [1999] provided theoretical predictions for SIS and AISpr, and implicitly for AISpu.⁵ For the parameters employed here, they provide five general predictions when bidders employ symmetric Nash equilibrium strategies:

⁵ The AISpu case corresponds to what they refer to (p.1219ff.) as the “double informational advantage model.” Their reference correctly suggests that the insider has two informational advantages in the AISpu case compared to the SIS case – apart from knowing the value of the good perfectly (a precision advantage), they know something that others do not (a privacy advantage). Kagel and Levin [1999; p.1219] note that the AISpu model has been extensively studied in the earlier auction literature, but does not provide as direct a laboratory counterpart to SIS as the AISpr model. Hence they introduced the AISpr model, which does provide that tighter link to previous experiments. Our design complements theirs, by providing treatments that are close to both previous experiments and previous theory.

1. *Expected Seller Revenue.* Expected seller revenue in the AISpr setting *exceeds* expected seller revenue in comparable SIS settings, even though it is known to be *lower* in the AISpu setting compared to SIS. Thus, privacy of the outsider's information makes a difference from the perspective of the seller.
2. *Informational Rents to Outsiders.* Outsiders earn *positive* informational rents in the AISpr setting, albeit *less* than they would earn in the SIS setting.⁶ Outsiders should earn *zero* informational rents in the AISpu setting.⁷
3. *Effects of the Number of Bidders.* Increases in the number of outsiders increases bids by insiders in the AISpr setting, even though it should have no effect in the AISpu setting.
4. *Relative Profitability of Inside Information.* Expected profits of insiders exceed those of outsiders in both AIS settings.
5. *Insider Profits.* Expected profits of insiders are larger in both AIS settings than their expected profits in comparable SIS settings.

We empirically evaluate each of these sets of predictions.

Important as predictions about seller revenue and profits are, the main focus of attention in common value settings has been the propensity of different institutions to generate instances of the WC. In standard theoretical models, the WC is not predicted since these models presume that individual bidders take into account the inferential implications of winning the auction. In symmetric settings, where all bidders employ the same bid function, winning the auction implies that you received the highest signal. To the extent that signals can exceed true values, this implies that there is some chance that you have over-estimated the value of the object. Thus, conditional on winning, the

⁶ Unless otherwise noted, all claims about expected rents or expected profits are conditional on winning. Expected profit is zero, by design, conditional on not winning.

⁷ This result is proven in Engelbrecht-Wiggans, Milgrom and Weber [1983; Theorem 2], who note that it is more general than the specific assumptions normally used in the auction literature.

rational bidder should “shave” his bid to allow for this additional information.

Insiders might be expected to change the possibility of a WC emerging. As a general matter, the fact that one or more bidders has better information should lead to more informationally-efficient outcomes, which would imply less evidence of a WC when insiders with perfect information are added. Alternatively, the fact that some bidders are known to have better information might lead outsiders to bid more aggressively, in the belief that they have to overcome the informational dis-advantage they face. Neither prediction follows from traditional auction theory, but each can be evaluated using a controlled experiment.⁸

Kagel and Levin [1999; p.1223ff.] define a number of WC thresholds, which are bid levels that signal that the bidder faces a certain or expected WC outcome. For SIS auctions, the natural definition is where the bid exceeds the expected value of the object conditional on the signal received being the highest. Bids in excess of this threshold ensure negative expected profits to the bidders.⁹ We use this WC threshold for SIS auctions.

For AISpr auctions, two bidding thresholds are offered by Kagel and Levin [1999; p. 1223, 1225]. The first threshold is obtained by assuming insiders do not best-respond to bids of outsiders; this threshold is similar to the WC threshold for SIS auctions and ensures that outsiders in an AIS auction, bidding in excess of it, would earn negative expected profits.¹⁰ However, it is conservative in the sense that it does not allow for insiders adopting best responses to the bidding rules adopted by outsiders. If outsiders bid *at* this conservative WC threshold, then they would be expected to earn

⁸ The informational role of insiders has been studied extensively in the older experimental asset market literature (e.g., Plott and Sunder [1982] and Friedman, Harrison and Salmon [1984]).

⁹ This threshold equals the signal received by the bidder minus $\gamma \epsilon$, where ϵ is the amount by which the signal could be under or over the true value and γ equals $(N-1)/(N+1)$ for N bidders. Hence when $N=4$, $\gamma=0.6$, and when $N=7$, $\gamma=0.75$. This expression presumes the auction structure employed in our experiments (e.g., the use of uniform distributions to generate the true value and the signal value).

¹⁰ This threshold is the same as the WC threshold for the SIS auction, but with N defined as the number of outsiders bidding in the auction.

negative expected profits; in this sense it is a conservative threshold. If one posits a model in which outsiders are boundedly rational in the sense of using a simple linear bid function defined over their signal and the amount by which their signal could over-estimate the true value, and allow insiders to best-respond to this bidding rule, it is possible to derive a tighter WC threshold for outsiders such that bids equal to it earn zero expected profits. Hence bids in excess of this WC threshold earn negative expected profits for outsiders, but it is not conservative in the same sense as the previous threshold.¹¹ The approximations underlying this threshold are generally excellent ones for the parameter space considered here.¹² Unless otherwise noted, we use the tighter WC threshold for the AISpr auctions.

For AISpu auctions, it is more difficult to derive precise WC thresholds without imposing artificial restrictions on the nature of the public information signal.¹³ However, there is a robust relationship between the AISpr and AISpu environments, due to the generic “domino” or “linkage” effect of providing public information in auctions with affiliated values.¹⁴ Public information works, on average, to cause all bidders except the bidder with the highest signal to increase their expected value for the good since there is some affiliation in values. Of course, for bidders with signals *just* below the highest signal, the effect may not be strong; but, on average, the effect will be to raise expected values. The crucial linkage effect then comes when the bidder with the highest signal recognizes that everyone else will be bidding more aggressively because of the public information;

¹¹ This threshold equals the signal value minus $\lambda \epsilon$, where $\lambda=0.690$ when $N=4$ and $\lambda=0.825$ when $N=7$. Thus $\gamma < \lambda$ for each case of N , so this WC threshold is tighter than the conservative WC threshold as expected logically.

¹² See Kagel and Levin [1999; p.1224/5] and Laskowski and Slonim [2000].

¹³ Kagel and Levin [1986; p.902] deliberately use the lowest private signal as the public signal to simplify their calculations of the WC threshold in the SISpu model. Kagel, Harstad and Levin [1987; p.1283] essentially provided subjects with complete information on the range of private signals in one of their public information treatments, collapsing the model to an independent private values model. Their other treatment is like ours, and involves the public release of a random signal; they do not offer models of bidding in that case.

¹⁴ Kagel and Levin [2002; p.12] introduce the term “domino effect,” which is the same as the “linkage effect” of Milgrom and Weber [1982; p.1110].

even though this bidder does not revise his expected value, he does bid more aggressively in relation to it. This second effect also works for bidders whose signal is close to the highest. The upshot is that AISpu auctions can be viewed as simply “more aggressive” variants of the AISpr auction, just as the SISpu auction is a more aggressive variant of the SISpr auction. It is more aggressive due to informational effects (the first path) as well as strategic effects (the second path). Behaviorally, it would not be surprising to see these forces interacting with the WC to provide marked differences in bidding behavior and *ex post* losses.

We could assume the same WC thresholds for the AISpu and AISpr cases, since the subjects in the public information setting could have viewed their signals as if they were private. However, we undertake specific hypothesis tests just with the AISpr thresholds.

2. Previous Experimental Evidence

Previous laboratory experiments have shown that the WC is robust, particularly with inexperienced bidders. They have also shown that the WC results in several key comparative static predictions being violated in observed behavior with inexperienced bidders. Kagel and Levin [1986] demonstrated that the provision of public information in SIS auctions did *not* raise seller revenue with inexperienced bidders, as theory would predict. Again in a SIS environment and with inexperienced bidders, Levin, Kagel and Richard [1996] demonstrated that the English and first-price auctions yielded similar revenues, which is inconsistent with theoretical predictions. Only with intense experience does the WC decline in SIS laboratory auctions, as demonstrated most thoroughly by Dyer, Kagel and Levin [1989]. Thus the laboratory experiments with SIS auctions points to the importance of understanding the extent of “experience” in field settings to which one might apply the theory.

Turning to AIS auctions, Kagel and Levin [1999] find that inexperienced bidders continue to fall prey to the WC, and that virtually none of the theoretical comparative static predictions comparing AIS and SIS hold. Thus, adding an “insider” with better information about the true value of the object does not lead to a large enough reduction in the incidence of the WC such that the predictions of theory are confirmed. Behavior is substantially more consistent with “super-experienced” bidders, who exhibit far less WC bidding behavior, and for these bidder types virtually all of the predictions of theory are supported. In their laboratory settings, super-experienced means that the subject had participated in at least two previous experiments with first-price common value auctions and the same number of bidders.¹⁵ Furthermore, no bidder that went bankrupt in early trading in the prior experiments was recruited into the super-experienced pool. Nor would one expect traders that made tiny profits to volunteer to return.

Our experiment is designed to focus on the differences identified by Kagel and Levin [1999] between “inexperienced” and “super-experienced” bidder behavior, particularly when “insiders” are added to the mix. Our field setting provides an opportunity to define these terms that is more natural and role-specific than normally encountered in a lab environment.

3. Experimental Procedures

We recruit subjects from a well-functioning marketplace, the floor of a sportscard show, using essentially the same general procedures explained in List and Lucking-Reilly [2000] and List [2001]. All experiments were run in Tucson, Arizona, in the Spring and Summer of 2001. The advantage of this field sample is that we can readily identify individuals who are “dealers” and those who are “non-dealers.” The former make a living out of trading in these settings, and have self-

¹⁵ It is not clear if the previous experiments used the same SIS or AIS treatment that the super-experienced subjects participated in.

selected this occupation.

We run two types of experiments. One type is a traditional laboratory experiment with induced values defined over an abstract commodity, but using field subjects. The other type is a field experiment with homegrown values that the field subjects are familiar with.

A. Laboratory Experiment With Field Subjects

Each participant's experience in the laboratory experiment followed two steps: considering the invitation to participate in an experiment that would take about 1 hour, and participation in the experiment.

In the first step the experimenter (List) approached potential subjects entering the trading card show and inquired about their interest in participating in an experiment that would take about 1 hour. If the individual agreed to participate, we briefly explained that in return the subject would have the chance to earn a considerable amount of money. The administrator explained that at a pre-specified time on the Saturday or Sunday of the show, the subject should enter an adjacent room to take part in the experiment. Directions to the room were provided and the subject was informed that she would receive instructions for the experiment when she arrived. Unlike the field experiments discussed below, these treatments should not be considered field experiments in the strict sense. Rather, they should be considered a laboratory experiment with a field subject pool.

The second step began when subjects entered the room and signed a consent form in which they acknowledged their voluntary participation in the experiment and agreed to abide by the rules of the experiment. Subjects were randomly allocated into treatments based on the time that they participated, and each subject participated in only one treatment. Of course, we knew who was a dealer and who was not.

In these experiments we generally followed the procedures and instructions typically used in previous experiments with common value first-price auctions (e.g., Kagel and Levin [1999]). Appendix A lists the written instructions provided to subjects. First, we chose a range of commodity values, in this case between \$40 and \$200. Second, we randomly selected the common value. This was \$94.33, and for simplicity and control was used for all treatments. Third, we computed the subject's signal via a random number generator using $\epsilon=6$ or $\epsilon=12$, depending on the treatment. Fourth, subjects were randomly assigned to a treatment with either $N=4$ or $N=7$ bidders. Variations in ϵ or N should have predictable effects on bidding behavior. Fifth, several dry practice runs were carried out in each treatment to familiarize subjects with the rules of the auction. The experiment was not begun until everyone knew the rules and understood every example. Finally, to ensure that subjects went home with gains, we ran a second experiment that was not announced until after the first experiment was complete.

B. The Field Experiment

In the field experiment subjects drawn from the field are asked to bid on a commodity that is familiar in this field setting. Each participant's participation in the field experiment followed four steps: (1) inspection of the good, (2) learning the rules, (3) bidding, and (4) conclusion of the transaction.

In step 1 a potential subject approached the experimenter's table and inquired about the sale of the 1990 unopened pack of *Leaf* Series 1 wax baseball cards displayed on the table. An unopened pack of 1990 *Leaf* baseball cards retailed for about \$10 at the time of the experiment, although it could be obtained on the web for \$9 (or even \$8 if purchased in bulk).¹⁶ Each pack could contain

¹⁶ See [HTTP://WWW.BBCKID.COM](http://www.BBCKID.COM) for a popular web site that trades in unopened cards.

thousands of dollars of sportscards. The pack is sealed by the factory, and has not been opened. This characteristic, coupled with the fact that subjects planned to open the pack and sell its contents if they were deemed winners, provides our field auctions with a common value component. The company producing the pack, *Donruss*, goes to great lengths to ensure that the “collation” of cards is random.¹⁷ There were 264 cards in the 1990 *Leaf* set, and 10 cards per pack; each “set” refers to a list of baseball players included in the production run for that year. Thus, since Sammy Sosa’s rookie card is in the *Leaf* set, there is a $10/264 = 0.038$ probability of getting a Sosa card in the auctioned pack. A Sosa card in Gem-Mint condition retails for more than \$350.

As mentioned above, all participants stated that if they won the auction they planned to open the pack. Thus they each have their own private signals about the various probabilities of any given card being included in the pack and the total value of the cards in the pack. The experimenter then invited the potential subject to take about five minutes to participate in an auction. If the individual agreed to participate, he could pick up and visually examine the unopened pack. The experimenter worked one-on-one with the participant, and imposed no time limit on his inspection of the cards.

In step 2 the administrator gave the participant an instruction sheet that consisted of the auction rules for a standard first price auction. This instruction sheet is reproduced in Appendix B. Several examples of the auction were carried out to ensure that a wide range of subjects would understand the auction rules. No decisions were made until the subject fully understood the rules and her task.

After having her questions answered, in step 3 the participant placed her bid on the sheet provided. Finally, in step 4 the experimenter explained that the subject should return at a specified time to find out the results of the auction. Transactions took place at 6p.m. on Saturday and

¹⁷ In fact, the collation is so good that each pack is effectively a random sample without replacement in our experience.

Sunday. If a subject did not return for the specified transaction time, she would be notified; after we had received her payment, she would receive her unopened pack of cards within three days via standard postal service, with postage paid by the experimenter.

Again, no subject participated in more than one treatment. Subjects were randomized into treatments by changing the treatment every hour. Hence subjects' treatment type was determined based on the time they visited the table at the card show.

C. Treatments

In our laboratory experiment conducted with the field sample, two general treatments were examined. To re-define the key acronyms, the first was a Symmetric Information Structure (SIS) auction in which each person is given a signal. The second was an Asymmetric Information Structure (AIS) auction in which the insider knows the value with certainty, and the outsider either gets a private signal (AISpr) or a public signal (AISpu). Kagel and Levin [1999] implemented the SIS treatment and the AISpr treatment in laboratory experiments with student samples. To ensure comparability with traditional laboratory experiments, our experiment includes treatments with $N=4$ or $N=7$ bidders.

Moreover, to examine bidding behavior across subjects who are placed in both familiar and unfamiliar roles, in the AIS treatments we randomly allocate dealers and nondealers into the insider and outsider roles. This characteristic of our experimental design permits us to get a sense of the influence of exogenously placing a subject in the opposite role of the one they typically fill in the field.

In our field treatments we examined the natural counterparts of the SIS and AIS conditions. Specifically, in the field SIS condition dealers are paired with dealers and non-dealers are paired with

non-dealers, and everyone is informed of this composition. In the field AIS condition we matched three non-dealers with one dealer, and again everyone is informed of this fact. The signal in the field treatments is *a list of the potential cards in the pack and their associated, estimated probabilities*. For example, in the AISpu treatment we provided a list of the cards potentially in the *Leaf* pack to each bidder, the associated probabilities of obtaining one, two, three, etc. of any one given card, and the most recent book values of each card. All of the field treatments used $N=4$.

All treatments were one-shot, since that is the context typically encountered in the field. Figure 1 reports the samples collected in each treatment. Data were collected on 504 bids in the $N=4$ treatments, with 184 of these in the field experiments and 320 in the lab experiments. In each case roughly one-third were in the AIS treatment. In addition, 245 bids were collected in the $N=7$ treatments, all in the laboratory experiment.

4. Results

A. Laboratory Experiment

Bidding Behavior

The most straightforward metric to evaluate bidding behavior is the bid itself, and then the difference between the bid and the WC thresholds defined earlier. Figure 2 summarizes bids across SIS and AIS treatments (left and right panels, respectively), and for dealers and non-dealers (top and bottom panels, respectively). Figure 3 presents the difference between bids and this threshold. The results are sharp. In summary, we see that *in both SIS and AIS settings, dealers provide lower bids than non-dealers, leading to non-dealers falling prey to the WC much more often than dealers*. This general result is discussed more fully below.

Simple regression analysis of the observed bid functions reveals the difference in dealer and

non-dealer behavior.¹⁸ Consider bidding patterns in the SIS treatments first, since these are the auctions which have the richest set of experimental evidence from student samples. In the N=4 treatments, dealers bid on average \$2.23 less than non-dealers, and this was almost entirely due to their processing of the information about the signal uncertainty (ϵ). In both ϵ cases, bids were equal to the signal received minus some fraction of the signal uncertainty. Non-dealers reduced their bids by only 40% of this uncertainty, whereas dealers reduced their bids by 93% of the signal uncertainty. In the N=7 treatments, dealers bid nearly \$2.40 lower, again due to differential shading of the signal uncertainty (by 88% versus 82%). We conclude that dealers appear to be paying more attention to the signal uncertainty than non-dealers, which suggests that they are less likely to fall prey to the WC.

Turning to the AIS bidding patterns, in the N=4 treatment, dealers bid \$3.16 lower than non-dealers, again due to differential shading of the signal uncertainty (by 72% versus 50%). In the N=7 treatments, dealers bid \$3.92 lower than non-dealers due to differential shading of the signal uncertainty (by 91% versus 22%). Indeed, in the N=7 treatment signal uncertainty was not a statistically significant determinant of bids for non-dealers, with the 95% confidence interval being between negative 51% and plus 9%. Thus we observe the same general pattern in SIS and AIS settings in terms of the differences in bidding patterns by dealers and non-dealers.

Changes in the number of bidders, and hence outsiders, did not affect bids by insiders in either AIS setting. Theory predicts an increase in bids, but our results show no significant change in either direction. This result applies whether we consider the bids of dealers or all bids by insiders.

¹⁸ The detailed regression results are of little interest apart from the effects we discuss in the text, and can be obtained from the software and data documented in Appendix C.

Winner's Curse

These observed bidding patterns map directly into the incidence of the WC, which is summarized in Figure 4 for the laboratory treatments that have a WC threshold defined theoretically. Figure 3 shows the average difference between the bid and the WC threshold, to provide some sense of the monetary significance of the violations underlying Figure 4.

The first result from Figure 4 is that the *WC incidence is much higher in the AIS auctions compared to the SIS auctions.*¹⁹ This difference is not affected by the signal uncertainty, as bidding data across $\epsilon=6$ and $\epsilon=12$ are statistically indistinguishable. Similarly, the number of bidders does not make a considerable difference. Employing comparable WC thresholds, these findings are consistent with those reported by Kagel and Levin [1999; Table II, p. 1227] for inexperienced subjects.

The second result is that the *WC incidence is significantly lower for dealers compared to non-dealers.* This holds whether one is looking at symmetric or asymmetric information environments.

The third result is that *when dealers are placed in a role that they are unfamiliar with, they perform relatively poorly.* The WC incidence for dealers increases as we compare SIS auctions to AISpr auctions, and this is a statistically significant difference. In the SIS environment the dealers know that they are not at an informational disadvantage, and that no other trader knows more than them. But in the AISpr (and AISpu) environment they know that they are the “informational underdog” when they are not the insider.²⁰ Controlling for the number of bidders and signal uncertainty, being a dealer is generally associated with an incidence of the WC which is roughly 50% lower than for non-dealers. However, moving from the AISpr to the SIS environment is associated with a reduction in

¹⁹ Unless otherwise stated, all claims are supported by statistical tests at the 1% level. For unconditional comparisons, we employ a two-sample *t*-test, assuming unequal variances, and a two-sample Wilcoxon rank-sum test. Conditional comparisons of regression coefficients employ an *F*-test. Specific numerical results are provided in the statistical output referenced in Appendix C.

²⁰ The WC incidence is evaluated only for outsiders, since it is meaningless for insiders because they know the true value. Thus the dealers underlying the WC incidence in the right panel of Figure 4 are all outsiders.

the WC incidence for dealers of 40% compared to non-dealers.²¹ This difference is statistically significant at the 8.7% level.

Seller Revenue

Turning to the general comparative static hypotheses, we find that the seller revenue predictions are borne out in the data. Table 1 displays a regression of seller revenue in the 115 distinct laboratory auctions, with various controls added.

Consider the top panel of Table 1, which reports results for the full sample. The relevant variables for the hypothesis test are AISpu and AISpr, which represent interactions between the AIS information condition and the provision of public or private information. Theory predicts that seller revenue will be higher in the AISpr setting compared to the SIS, and that it will be lower in the AISpu setting compared to the SIS. Since SIS is the omitted information category in this regression, these estimation results can be used to directly test these hypotheses. We find strong support for the hypothesis regarding the positive effect on revenue of private information, and weak support for the hypothesis regarding the negative effect on revenue of public information.

The remaining panels of Table 1 examine possible interaction effects between the number of bidders and the effect of public information, and the signal size and the effect of public information. The qualitative conclusion remains intact, but the positive effects of private information on revenue are particularly strong with a smaller numbers of bidders and/or smaller signal uncertainty. Conversely, the negative effects of public information on revenue are enhanced with larger numbers of bidders and/or greater signal uncertainty.

²¹ These are marginal effects from a probit regression model.

Bidder Profits

Economic theory also organizes the observations on individual bidder profits well. Simple t -tests allow us to examine the theoretical predictions for the profits of winners, defined here as those that submitted the highest bid in any group.²² We cannot reject any of the hypotheses stated earlier, with one exception. Insiders do earn much more than outsiders as a general matter, and particularly in AISpu settings. Similarly, insiders in AIS settings earn much more than bidders in comparable SIS settings. Outsiders earn less in AISpr settings than bidders in SIS settings, and earn zero in AISpu settings.

B. Field Experiments

Since we are using home-grown values, there is no WC threshold that can be defined for our field treatments. However, we can examine patterns of bidding levels to gain insights into whether the various theoretical predictions are met. Figure 5 displays the distribution of bids in the SIS and AIS treatments, split into dealer and non-dealer bids. Again one sees from a vertical comparison of the bid distributions that *dealers generate lower bids than non-dealers in the same setting*. This result holds true in each of the SIS and AIS treatments. Moreover, from the horizontal comparison of the bid distributions we see that non-dealers bid more aggressively when an insider is added, and that there is *some* evidence that dealers might as well.

These conclusions are supported by regressions reported in Table 2. Dealers in the SIS auctions bid \$1.21 lower on average, although this is only a significant difference at the 11.4% level. In the AIS auctions, dealers bid \$1.82 lower and this is statistically significant. However, as panels C

²² In cases where two or more bidders tied with the highest bid, the actual winner in each auction was selected at random from amongst those that submitted the highest bid. This fact was explained to all participants through one of the examples.

and D in Table 2 show, this overall result is due primarily to the significantly lower bidding in the AISpr auctions. We also display results separately for the AISpu and AISpr auctions, since they were quite different in the lab setting. The effect of public information in these field experiments is to mitigate the informational advantage dealers have from being insiders, as one would expect.

Figure 6 displays the average seller revenue across the four types of field treatments. Seller revenue in the AISpr treatment is higher than in the AISpu treatment, as predicted by theory, but not significantly at conventional levels. There is a large and significant increase in seller revenue in the AIS treatments compared to the SIS auctions with dealers, but not with respect to the SIS auctions with non-dealers. This result is consistent with the evidence from the lab experiments that dealers shave their bids significantly more than non-dealers in common value settings.

No precise tests of the profitability hypotheses are possible in the field setting, since we do not know the true value of the object. However, if we take the current market price of \$9 as a measure of the current value of the object, or alternatively as the informationally efficient estimate of the actuarial value, then we can derive some tests of the profit hypotheses conditional on that assumption.

We find that outsiders do *not* earn positive profits in the AISpr auctions, and actually earn *less* than their SIS counterparts. Although both results contradict the theoretical predictions, neither is statistically significant at conventional levels. Outsiders in the AISpu auctions earn positive profits on average, but at very small levels (\$0.93).

Although insiders tend to earn less than outsiders in the field experiments, our data reveal *very* few insiders (dealers) winning these auctions when there is a mix of insiders and outsiders in the same auction. In fact, 10 outsiders win for every 1 insider that wins in the field AIS auctions. This is a corollary of them being able to avoid the WC, by bidding lower than outsiders (non-dealers). We

are unable to report any statistical tests of this hypothesis, since the data provide so few realizations of dealers winning these auctions. Moreover, it is possible that dealers know that one could obtain such packs at a bulk price of \$8, rather than the single pack price of \$9; as it happens, if we assume a true market value of \$9 the average loss for the 3 dealers that were winners is exactly \$1.

5. Conclusion

Auction theory provides a rich set of predictions concerning bidders' behavior. One particularly salient finding in a plethora of laboratory experiments that is not predicted in first price common value auction theory is that bidders commonly fall prey to the winner's curse. Only "super-experienced" subjects, who are in fact recruited on the basis of not having lost money in previous experiments, avoid it regularly. This would seem to suggest that experience is a sufficient condition for an individual bidder to avoid the winner's curse. We show that this implication is supported when one considers a natural setting in which it is relatively easy to identify traders that are more or less experienced at the task. In our experiments their experience is either tied to the commodity, the valuation task and the use of auctions (in the field experiments with sportscards) or simply to the use of auctions (in the laboratory experiments with induced values). In all tasks, experience is generated in the field and not the lab. Thus we provide support for the notion that context-specific experience does appear to carry over to comparable settings, at least with respect to these types of auctions.

Our experimental design emphasizes the identification of a naturally occurring setting in which one can control for experience in the way that it is accumulated in the field. Experienced traders gain experience over time by observing and surviving a relatively wide range of trading circumstances. In some settings this might be proxied by the manner in which experienced or super-experienced subjects are defined in the lab, but we doubt if the standard lab settings will reliably

capture the full extent of the field counterpart of experience. This is not a criticism of lab experiments, just their domain of applicability.

The methodological lesson we draw is that one should be careful to generalize from the evidence of a winner's curse by student subjects that have no experience at all with the field context. Our results do not imply that *every* field context has experienced subjects, like our dealers, that avoid the winner's curse. Instead, they point to a more fundamental need to consider the field context of experiments before drawing general conclusions. *It is not the case that abstract, context-free experiments provide more general findings if the context itself is relevant to the performance of subjects.* In fact, one would generally expect such context-free experiments to be unusually tough tests of economic theory, since there is *no control for the context that subjects might themselves impose on the abstract experimental task.*

The main result is that if one wants to draw conclusions about the validity of theory in the field, then one must pay attention to the myriad ways in which field context can affect behavior. We believe that conventional lab experiments, in which roles are exogenously assigned and defined in an abstract manner, cannot ubiquitously provide reliable insights into field behavior. One might be able to modify the lab experimental design to mimic those field contexts more reliably, and that would make for a more robust application of the experimental method in general.

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Figure 1: Sample Sizes by Experimental Treatment

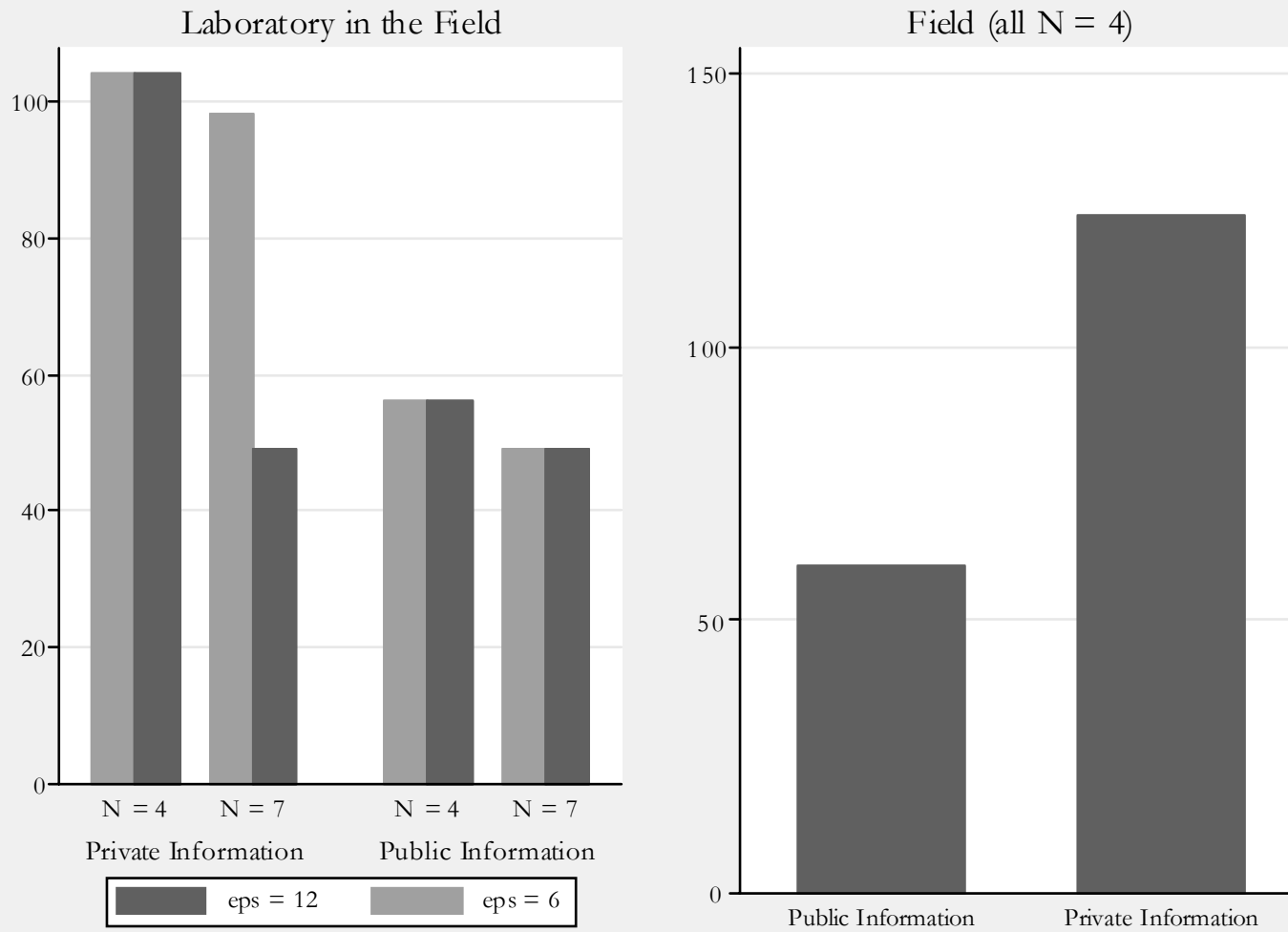


Figure 2: Bids in Laboratory Experiments

True Common Value = \$94.33

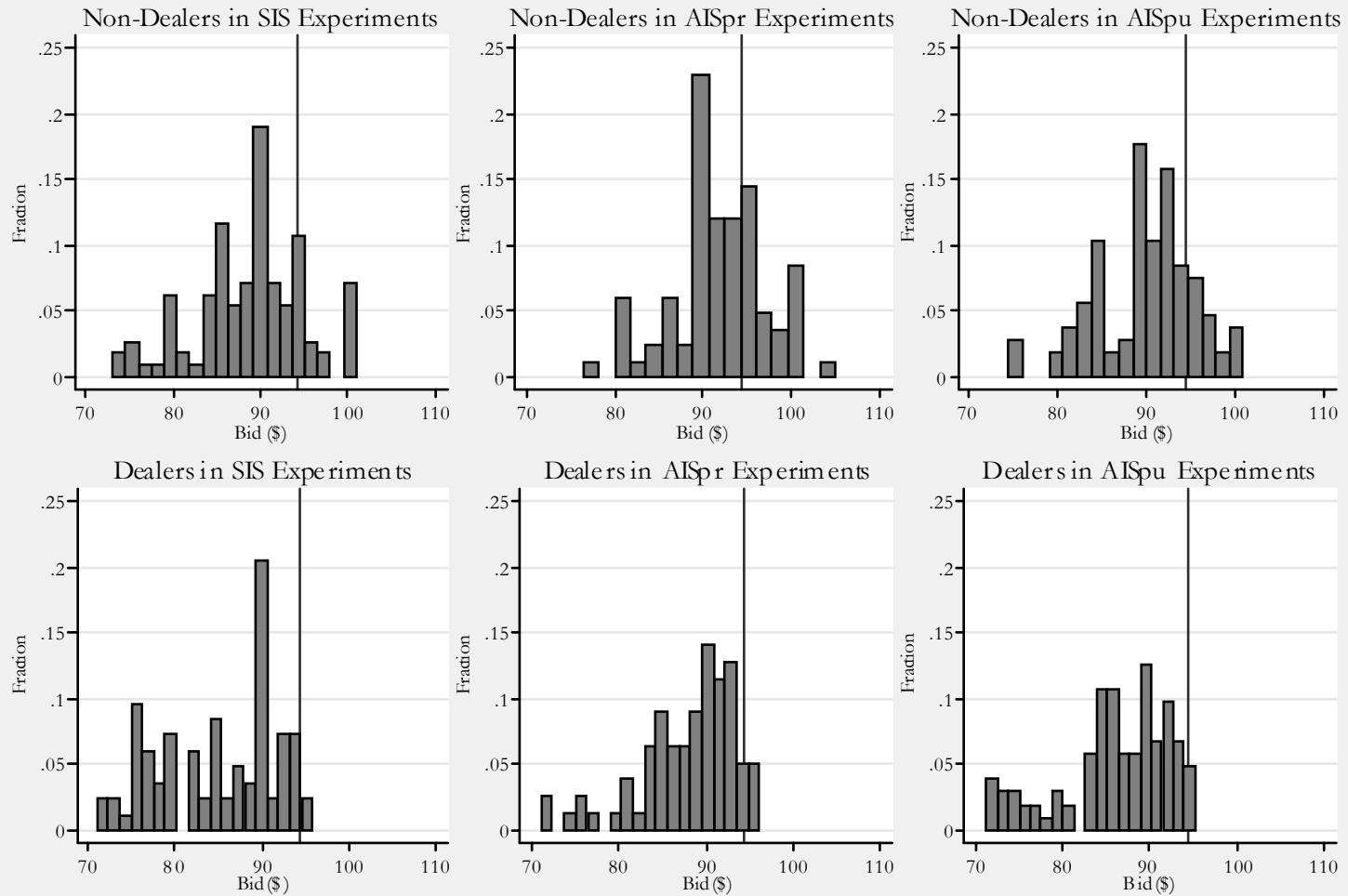


Figure 3: Excess Bids in Laboratory Experiments
 Bids in Excess of the Winner's Curse Threshold

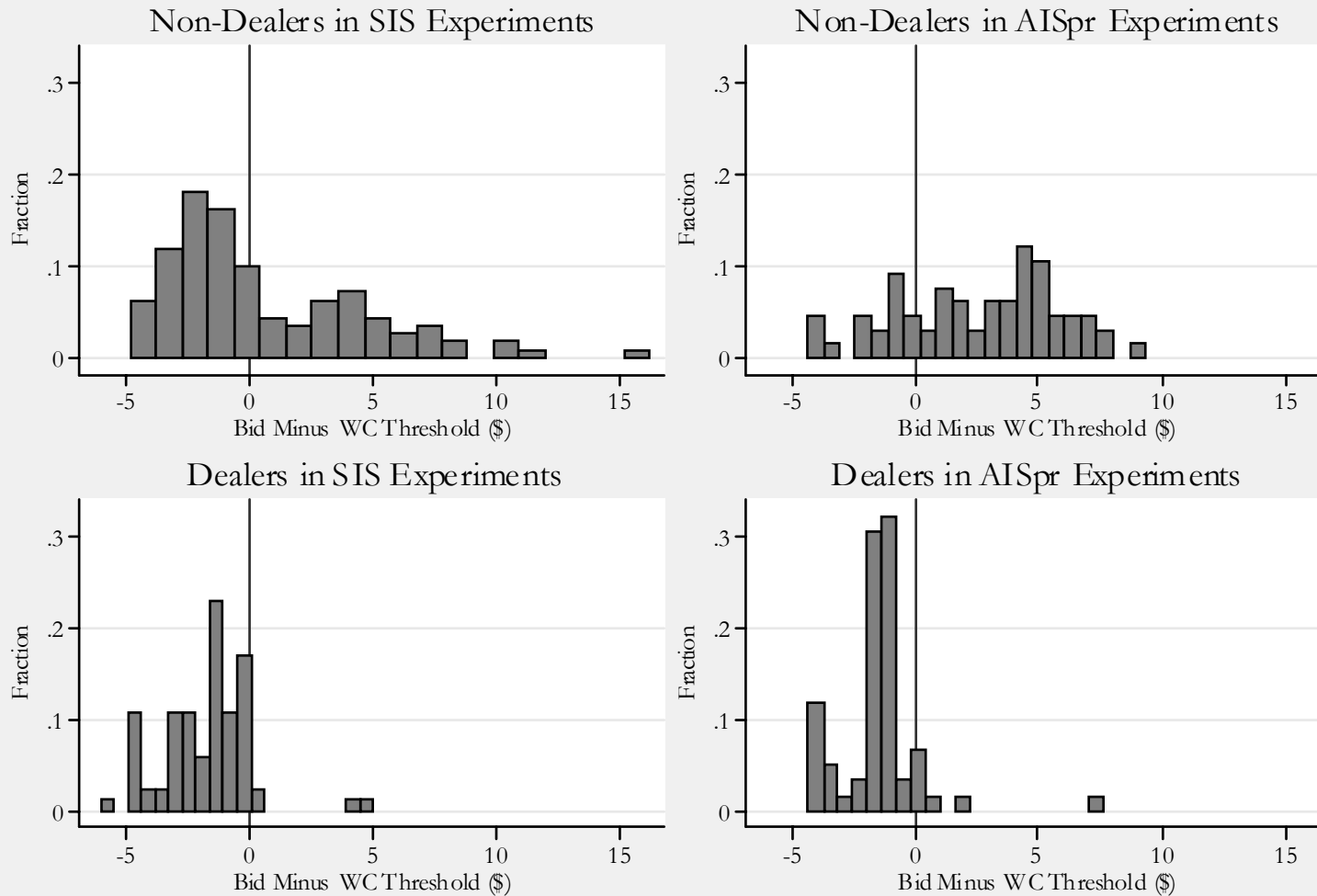


Figure 4: Incidence of Winner's Curse in Laboratory Experiments

Fraction of Bids Exceeding WC Threshold

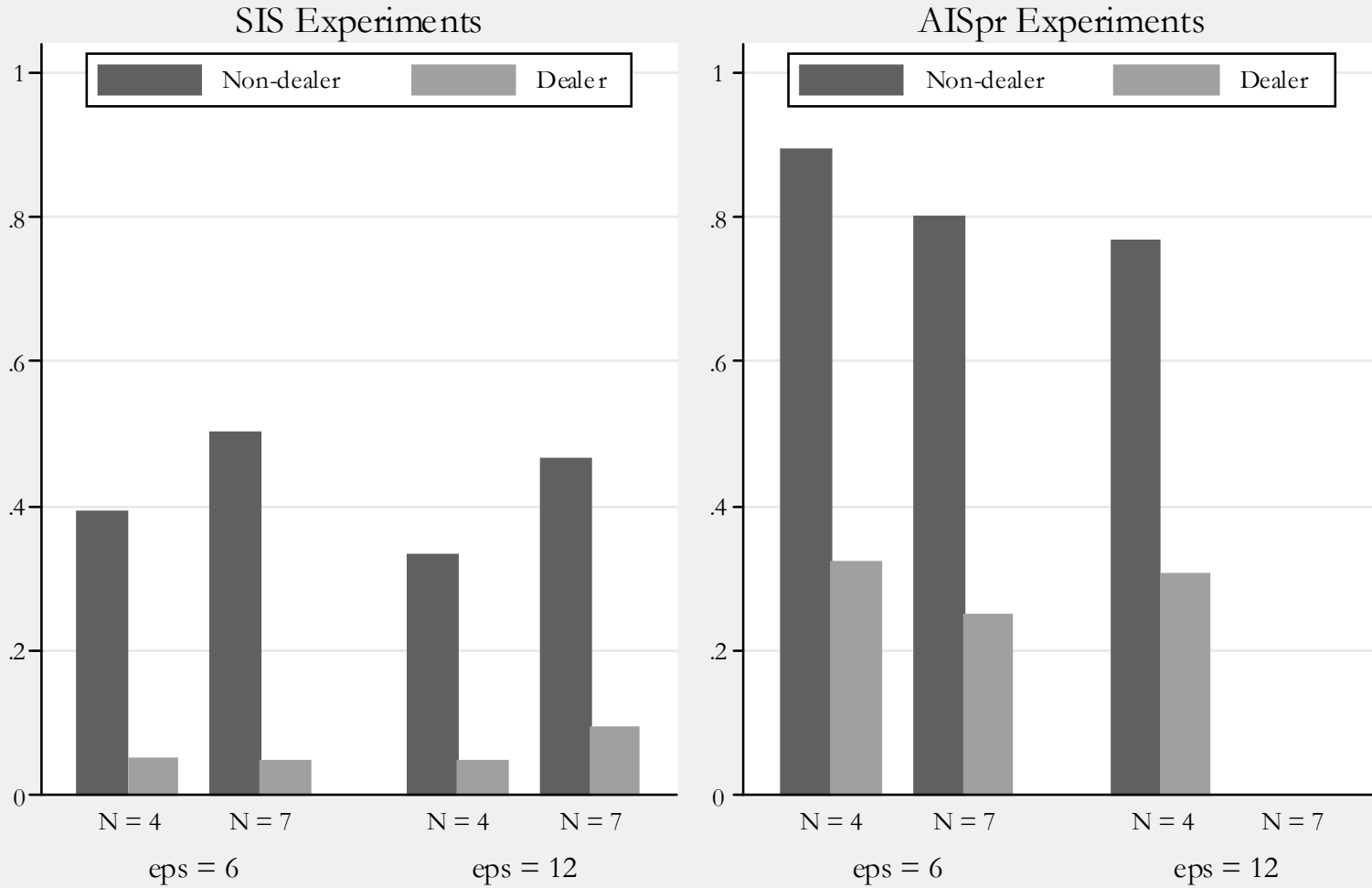


Table 1: Seller Revenue Regressions

Regression with robust standard errors

Number of obs = 115
 F(5, 109) = 10.99
 Prob > F = 0.0000
 R-squared = 0.3202

revenue	Coef.	Robust Std. Err.	t	P> t	[95% Conf. Interval]	
<u>A. Full Sample</u>						
Constant	94.18004	1.835957	51.30	0.000	90.54124	97.81885
n	.7020527	.2547746	2.76	0.007	.1970977	1.207008
eps	-.2046453	.1284622	-1.59	0.114	-.4592532	.0499627
Dealer	-5.315766	1.046445	-5.08	0.000	-7.389787	-3.241746
AISpr	1.932915	.9264832	2.09	0.039	.0966553	3.769174
AISpu	-1.414148	.9807252	-1.44	0.152	-3.357914	.529617
<u>B. N=4 sub-sample</u>						
Constant	96.8252	1.32069	73.31	0.000	94.19425	99.45615
eps	-.2487593	.157464	-1.58	0.118	-.5624436	.064925
Dealer	-5.162228	1.231388	-4.19	0.000	-7.615279	-2.709176
AISpr	2.670063	1.224608	2.18	0.032	.2305191	5.109607
AISpu	-.7567025	1.298516	-0.58	0.562	-3.34348	1.830075
<u>C. N=7 sub-sample</u>						
Constant	99.81281	2.629987	37.95	0.000	94.44166	105.184
eps	-.1604761	.2491226	-0.64	0.524	-.6692524	.3483001
Dealer	-5.941563	1.700654	-3.49	0.002	-9.414762	-2.468364
AISpr	.2516258	1.271338	0.20	0.844	-2.344793	2.848045
AISpu	-2.569088	1.473081	-1.74	0.091	-5.57752	.4393449
<u>D. eps=6 sub-sample</u>						
Constant	91.49899	1.399123	65.40	0.000	88.69621	94.30177
n	.5921308	.2482342	2.39	0.020	.0948579	1.089404
Dealer	-2.032195	.7412545	-2.74	0.008	-3.517106	-.5472836
AISpr	2.357157	.7348775	3.21	0.002	.8850206	3.829294
AISpu	-.5615069	.9157389	-0.61	0.542	-2.395952	1.272939
<u>E. eps=12 sub-sample</u>						
Constant	92.83889	3.238964	28.66	0.000	86.32995	99.34783
n	.8795562	.5163571	1.70	0.095	-.1581022	1.917215
Dealer	-8.514655	1.813151	-4.70	0.000	-12.15832	-4.870991
AISpr	1.515401	1.918649	0.79	0.433	-2.340268	5.37107
AISpu	-2.423418	1.627238	-1.49	0.143	-5.693475	.8466392

Note: n is the number of bidders (4 or 7), eps is the signal uncertainty (6 or 12), Dealer indicates a dealer, AISpr is an interaction between the AIS condition and private information, AISpu is an interaction between the AIS condition and public information, and the omitted information condition is SIS.

Figure 5: Bids in Field Experiments

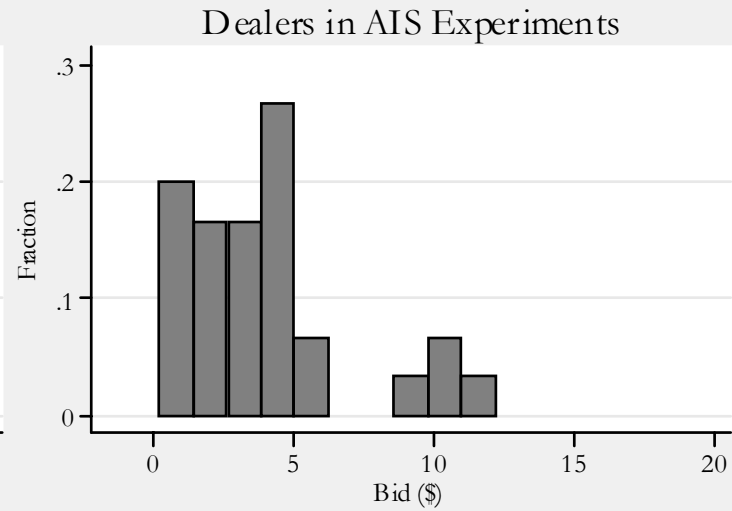
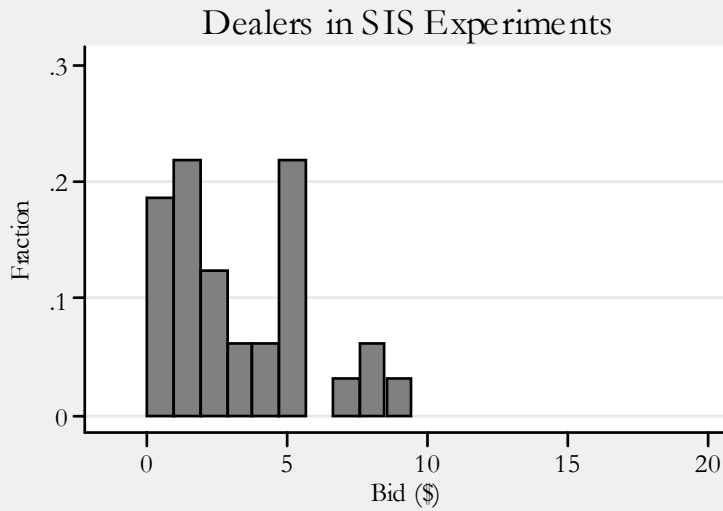
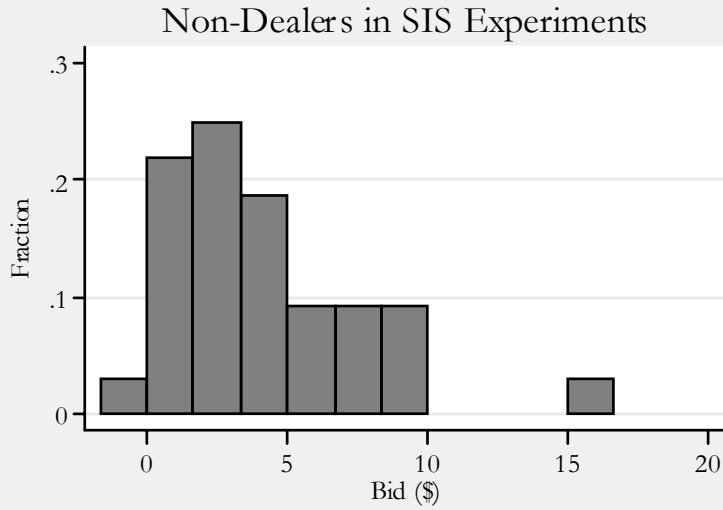


Table 2: Bids in Field Experiment

A. SIS Auctions

Regression with robust standard errors						Number of obs = 64	
						F(1, 62) = 2.56	
						Prob > F = 0.1144	
						R-squared = 0.0397	
	bid	Coef.	Robust Std. Err.	t	P> t	[95% Conf. Interval]	

	Dealer	-1.210937	.756182	-1.60	0.114	-2.722524	.3006487
	Constant	4.314375	.6112634	7.06	0.000	3.092477	5.536273

B. All AIS Auctions

Regression with robust standard errors						Number of obs = 120	
						F(2, 117) = 4.21	
						Prob > F = 0.0171	
						R-squared = 0.0626	
	bid	Coef.	Robust Std. Err.	t	P> t	[95% Conf. Interval]	

	Dealer	-1.820229	.627177	-2.90	0.004	-3.06232	-.5781376
	public	-.17433	.5675363	-0.31	0.759	-1.298306	.9496459
	Constant	5.864387	.4858607	12.07	0.000	4.902166	6.826609

C. AIS Auctions With Private Information

Regression with robust standard errors						Number of obs = 60	
						F(1, 58) = 6.28	
						Prob > F = 0.0151	
						R-squared = 0.0814	
	bid	Coef.	Robust Std. Err.	t	P> t	[95% Conf. Interval]	

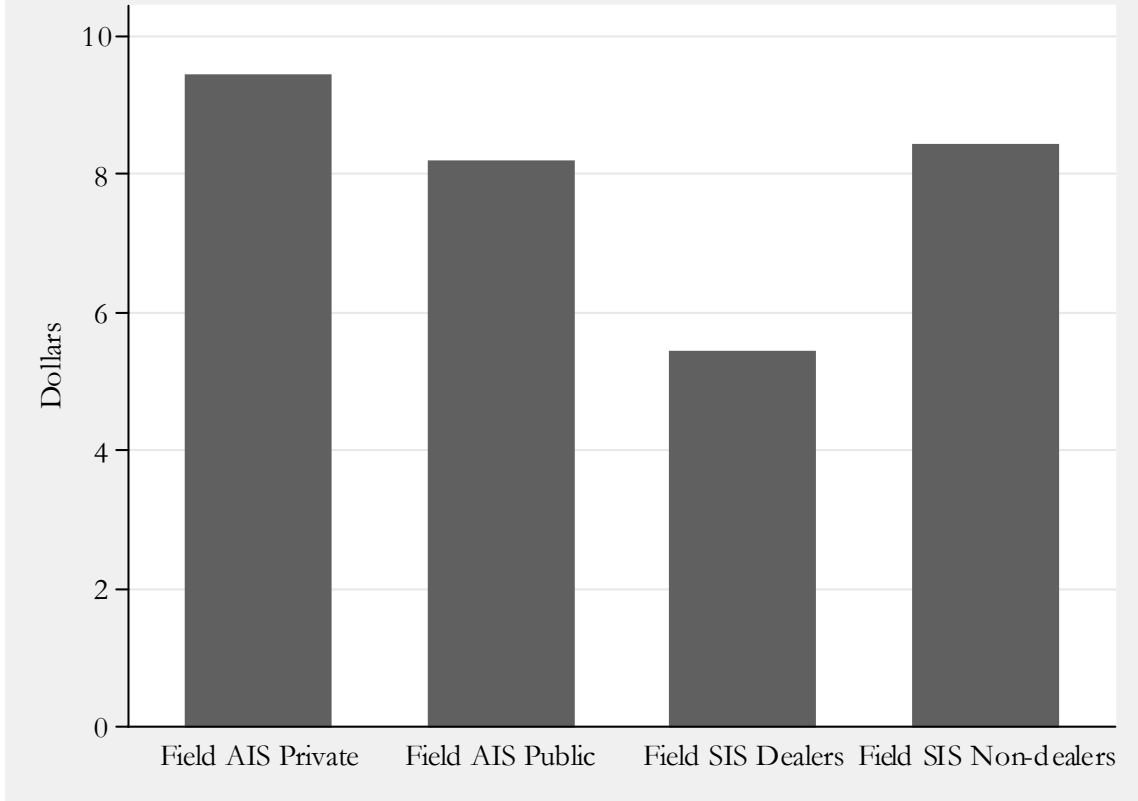
	Dealer	-2.313791	.9236524	-2.51	0.015	-4.162682	-.4648999
	Constant	5.987778	.5329625	11.23	0.000	4.920937	7.054618

D. AIS Auctions With Public Information

Regression with robust standard errors						Number of obs = 60	
						F(1, 58) = 2.46	
						Prob > F = 0.1219	
						R-squared = 0.0426	
	bid	Coef.	Robust Std. Err.	t	P> t	[95% Conf. Interval]	

	Dealer	-1.326667	.8451236	-1.57	0.122	-3.018365	.365032
	Constant	5.566667	.4082014	13.64	0.000	4.749563	6.38377

Figure 6: Average Seller Revenue in Field Experiments



Appendix A. Subject Instructions in the Laboratory Auctions

[These instructions are for the \$6 symmetric lab auctions with 4 participants.]

This is an experiment in the economics of decision making. The instructions below should be carefully read and understood before we proceed to the actual auction. If you follow the instructions carefully, and make a good decision, you may earn a considerable amount of money-which I will personally pay you in cash at the end of the experiment.

In this experiment I will auction off a fictitious commodity in a first price auction.

Your task is simple: to submit a written bid for the commodity. But, the value of the commodity at the time you make your bid will be unknown to you. Instead of knowing the true value, each of you will receive a private signal as to the value of the item, which you should find useful in determining your bid (more on this below).

The value of the auctioned commodity (denoted V^*) will lie between \$40 and \$200 inclusively. In the auction, any value within this interval has an equally likely chance of being drawn. Hence, each person has the same value (V^*) for the commodity.

Although you do not know V^* precisely, you will receive information which will narrow down the range of possible V^* values. The information will come via your private signal: the signal is selected randomly from an interval: $V^* - \$6$ and $V^* + 6$. Any value within this interval has an equally likely chance of being drawn and being assigned to one of you as your private information signal (note that each of you will receive your own individual signal).

An example will help illustrate the value of such a signal. Lets suppose that $V^* = \$150$ (the value of the commodity is \$150). Then each of you will receive a private signal that will be a randomly determined number between \$144 and \$156 (these two numbers come from $(\$150 - \$6)$ and $(\$150 + \$6)$). Consider four such signals for $V^* = \$150$: \$145.07; \$149.59; \$152.89; and \$154.96.

You can see that some of the signals in this example are below the true value of the auctioned item and some are above the true value. But, you will note that V^* must always be greater than or equal to your signal value - \$6. Likewise, V^* must always be less or equal to your signal value + \$6. In the actual auction, these upper and lower bound estimates for V^* and your signal value will be provided on your bidding sheet.

As you can see, a bid above $V^* + \$6$ makes little sense because you are guaranteed to lose money if you are the high bidder; thus I will restrict bids to not exceed $V^* + \$6$ in the auction.

In this first price auction, you will be competing with 3 other bidders, who also receive a private signal. The rules of the first price auction are straightforward-the high bidder wins the item and makes a profit (or loss) equal to the difference between the value of the commodity and the amount he/she bid:

$$V^* - \text{Highest bid} = \text{profit (or loss)}$$

Of course, a loss results if the winner bids more for the item than it is actually worth. If you do not make the high bid in the auction, you will earn zero profits.

You are not to reveal your bid or private signal to any other subject during this experiment. Also, please do not speak to anyone except the monitors. After all bids are received, we will post V^* and compute everyone's profits and/or losses.

Lets now proceed through a few practice auctions to assure that everyone understands the auction and payoff rules before we proceed to the actual auction.

ARE THERE ANY QUESTIONS?

Appendix B: Subject Instructions in the Field Auctions

[These instructions are for the symmetric field auctions with 4 participants.]

Welcome to Lister's Auctions! You have been invited to participate in an auction for the unopened pack of 1990 *Leaf* cards displayed on the table. I guarantee to sell the unopened pack to the highest bidder, no matter how low the price. You will be bidding against 3 other bidders in this auction, but you will not know their identities (nor will they know yours); the other bidders will be randomly chosen from other participants at today's card show. If you are a card dealer you will be paired randomly with three other card dealers. If you are not a dealer, you will be paired with three other non-dealers.

This is a first-price sealed-bid auction. In a first-price auction, the person with the highest bid wins the good and pays the amount of his or her bid. For example, I will order the four bids from highest to lowest in order to determine the winner.

Example 1: if the bids are ranked highest to lowest as follows:

\$A (from bidder 3)
\$B (from bidder 4)
\$C (from bidder 1)
\$D (from bidder 2)

Bidder 3 wins the unopened pack and pays \$A. Would you like to proceed through another example? {If "yes", then show another example}

There is no secret "reserve price." The pack will be sold to the highest bidder, no matter how low the price.

Your bid represents a binding commitment to pay for the pack according to the rules of this auction. I will determine the winner at 5PM today. After the winner pays me (cash or check) for the pack, the pack will be awarded to the winner. If you win the pack in this auction and are not in attendance at 5PM, it will be sent to you via first-class mail upon the receipt of your payment. There is no charge for shipping.

Please provide your name, mailing address, and phone number below:

Name_____

Address_____

Phone#_____

Email_____

Signature_____

Good luck - please write your bid on the sheet provided. Thanks for participating.

Appendix C: Data, Code and Statistical Output

All data and statistical software are available from

<http://www.bus.ucf.edu/gharrison/data/ee/Wcourse/>

in the form of ASCII data sets and *Stata* code to execute all statistical analyses. Statistical output is in the form of LOG files. This web page also contains an Appendix D documenting the specific extract from the statistical output that supports each claim in the text.

Variables in the statistical output are defined as follows: bid is the bid in dollars, signal is the signal in dollars, eps is the value of the signal uncertainty (ϵ in the text), dealer identifies sportscard dealers if =1, epsD is an interaction between eps and dealer, n is the number of bidders, symm identifies the SIS auctions if =1, and field identifies the field experiments if =1 and the lab experiments if =0.

Appendix D: Documentation of Statistical Tests

In this appendix we reproduce the section of the paper presenting results, and intersperse the numerical output from the log file generated by the data and code documented in Appendix C. The goal is to facilitate readers seeing where we get specific numerical support for each claim. We appreciate that a full understanding of each statistical test will require examination of the documentation of the variables involved, but this is best provided in the complete log file; our goal here is just to document the specific test result referred to.

A. Laboratory Experiment

Bidding Behavior

The most straightforward metric to evaluate bidding behavior is the bid itself, and then the difference between the bid and the WC thresholds defined earlier. Figure 2 summarizes bids across SIS and AIS treatments (left and right panels, respectively), and for dealer and non-dealers (top and bottom panels, respectively). Figure 3 presents the difference between bids and this threshold. The results are sharp. In summary, we see that *in both SIS and AIS settings, dealers provide lower bids than non-dealers, leading to non-dealers falling prey to the WC much more often than dealers.* This general result is discussed more fully below.

Simple regression analysis of the observed bid functions reveals the difference in dealer and non-dealer behavior. Consider bidding patterns in the SIS treatments first, since these are the auctions which have the richest set of experimental evidence from student samples. In the N=4 treatments, dealers bid on average \$2.23 less than non-dealers, and this was almost entirely due to their processing of the information about the signal uncertainty (ϵ). In both ϵ cases, bids were equal to the signal received minus some fraction of the signal uncertainty. Non-dealers reduced their bids by only 40% of this uncertainty, whereas dealers reduced their bids by 93% of the signal uncertainty. In the N=7 treatments, dealers bid nearly \$2.40 lower, again due to differential shading of the signal uncertainty (by 88% versus 82%). We conclude that dealers appear to be paying more attention to the signal uncertainty than non-dealers, which suggests that they are less likely to fall prey to the WC.

```
. global N "4"

. regress bid signal eps Dealer          if n==$N & symm==1 & field==0, robust
noconstant

Regression with robust standard errors          Number of obs =      96
                                                F(   3,   93) =45302.02
                                                Prob > F      =  0.0000
                                                R-squared     =  0.9984
                                                Root MSE     =  3.5647

-----+-----
      bid |          Coef.   Robust
           |          Std. Err.   t   P>|t|   [95% Conf. Interval]
-----+-----
      signal |  1.002082   .0084845  118.11  0.000   .9852339   1.018931
           eps | -.6221896   .1222069   -5.09  0.000  -1.8648683  -.379511
      Dealer | -2.233927   .6746906   -3.31  0.001  -3.573729  -.8941254
-----+-----

. for num 0 1: regress bid signal eps          if n==$N & symm==1 & field==0 & Dealer==X,
robust noconstant

-> regress bid signal eps if n==4 & symm==1 & field==0 & Dealer==0, robust noconstant
```

Regression with robust standard errors

Number of obs = 55
F(2, 53) =27847.74
Prob > F = 0.0000
R-squared = 0.9977
Root MSE = 4.349

bid	Coef.	Robust Std. Err.	t	P> t	[95% Conf. Interval]	
signal	.980463	.0148521	66.01	0.000	.9506734	1.010253
eps	-.3962919	.1987754	-1.99	0.051	-.7949848	.0024009

-> regress bid signal eps if n==4 & symm==1 & field==0 & Dealer==1, robust noconstant

Regression with robust standard errors

Number of obs = 41
F(2, 39) =57968.65
Prob > F = 0.0000
R-squared = 0.9996
Root MSE = 1.7156

bid	Coef.	Robust Std. Err.	t	P> t	[95% Conf. Interval]	
signal	1.008273	.0074778	134.84	0.000	.9931477	1.023398
eps	-.9316795	.0802094	-11.62	0.000	-1.093918	-.7694407

. regress bid signal eps epsD if n==\$N & symm==1 & field==0, robust noconstant

Regression with robust standard errors

Number of obs = 96
F(3, 93) =51642.87
Prob > F = 0.0000
R-squared = 0.9984
Root MSE = 3.4933

bid	Coef.	Robust Std. Err.	t	P> t	[95% Conf. Interval]	
signal	.9923211	.0092358	107.44	0.000	.9739805	1.010662
eps	-.5071471	.1463954	-3.46	0.001	-.7978593	-.2164349
epsD	-.2791513	.0824386	-3.39	0.001	-.442858	-.1154446

. global N "7"

. regress bid signal eps Dealer if n==\$N & symm==1 & field==0, robust noconstant

Regression with robust standard errors

Number of obs = 98
F(3, 95) =68817.54
Prob > F = 0.0000
R-squared = 0.9989
Root MSE = 2.9278

bid	Coef.	Robust Std. Err.	t	P> t	[95% Conf. Interval]	
signal	1.019502	.0085557	119.16	0.000	1.002516	1.036487
eps	-.8374721	.0984416	-8.51	0.000	-1.032903	-.6420407
Dealer	-2.396396	.5322088	-4.50	0.000	-3.452964	-1.339828

. for num 0 1: regress bid signal eps Dealer if n==\$N & symm==1 & field==0 & Dealer==X, robust noconstant

-> regress bid signal eps if n==7 & symm==1 & field==0 & Dealer==0, robust noconstant

Regression with robust standard errors

Number of obs = 56

```

F( 2, 54) =20557.58
Prob > F = 0.0000
R-squared = 0.9984
Root MSE = 3.6994

```

bid	Coef.	Robust Std. Err.	t	P> t	[95% Conf. Interval]	
signal	1.017902	.0152414	66.79	0.000	.9873454	1.04846
eps	-.8180777	.1757808	-4.65	0.000	-1.170497	-.4656584

```
-> regress bid signal eps if n==7 & symm==1 & field==0 & Dealer==1, robust noconstant
```

```

Regression with robust standard errors
Number of obs = 42
F( 2, 40) =94486.35
Prob > F = 0.0000
R-squared = 0.9998
Root MSE = 1.3153

```

bid	Coef.	Robust Std. Err.	t	P> t	[95% Conf. Interval]	
signal	.997195	.0063204	157.77	0.000	.984421	1.009969
eps	-.8751565	.0601698	-14.54	0.000	-.9967642	-.7535489

```

. regress bid signal eps epsD if n==$N & symm==1 & field==0, robust
noconstant

```

```

Regression with robust standard errors
Number of obs = 98
F( 3, 95) =72074.20
Prob > F = 0.0000
R-squared = 0.9989
Root MSE = 2.9336

```

bid	Coef.	Robust Std. Err.	t	P> t	[95% Conf. Interval]	
signal	1.008428	.0088121	114.44	0.000	.9909342	1.025923
eps	-.7274169	.1174474	-6.19	0.000	-.9605794	-.4942545
epsD	-.2521897	.0624198	-4.04	0.000	-.3761088	-.1282707

Turning to the AIS bidding patterns, in the N=4 treatment dealers bid \$3.16 lower than non-dealers, again due to differential shading of the signal uncertainty (by 72% versus 50%). In the N=7 treatments, dealers bid \$3.92 lower than non-dealers due to differential shading of the signal uncertainty (by 91% versus 22%). Indeed, in the N=7 treatment signal uncertainty was not a statistically significant determinant of bids for non-dealers, with the 95% confidence interval being between negative 51% and plus 9%. Thus we observe the same general pattern in SIS and AIS settings in terms of the differences in bidding patterns by dealers and non-dealers.

Changes in the number of bidders, and hence outsiders, did not affect bids by insiders in either AIS setting. Theory predicts an increase in bids, but our results show no significant change in either direction. This result applies whether we consider the bids of dealers or all bids by insiders.

```

. global N "4"
. regress bid signal eps Dealer if n==$N & symm==0 & field==0, robust

```

noconstant

Regression with robust standard errors

Number of obs = 224
F(3, 221) =93086.85
Prob > F = 0.0000
R-squared = 0.9988
Root MSE = 3.0881

bid	Coef.	Robust Std. Err.	t	P> t	[95% Conf. Interval]	
signal	1.01741	.0062502	162.78	0.000	1.005092	1.029727
eps	-.6037541	.0694189	-8.70	0.000	-.7405619	-.4669463
Dealer	-3.163961	.4088098	-7.74	0.000	-3.969625	-2.358296

. for num 0 1: regress bid signal eps if n==\$N & symm==0 & field==0 & Dealer==X,
robust noconstant

-> regress bid signal eps if n==4 & symm==0 & field==0 & Dealer==0, robust noconstant

Regression with robust standard errors

Number of obs = 115
F(2, 113) =54659.64
Prob > F = 0.0000
R-squared = 0.9986
Root MSE = 3.422

bid	Coef.	Robust Std. Err.	t	P> t	[95% Conf. Interval]	
signal	1.007227	.0092129	109.33	0.000	.9889744	1.025479
eps	-.4980335	.107197	-4.65	0.000	-.7104102	-.2856569

-> regress bid signal eps if n==4 & symm==0 & field==0 & Dealer==1, robust noconstant

Regression with robust standard errors

Number of obs = 109
F(2, 107) =95174.07
Prob > F = 0.0000
R-squared = 0.9991
Root MSE = 2.656

bid	Coef.	Robust Std. Err.	t	P> t	[95% Conf. Interval]	
signal	.9952141	.0069578	143.03	0.000	.981421	1.009007
eps	-.7258983	.0870838	-8.34	0.000	-.8985317	-.5532649

. regress bid signal eps epsD if n==\$N & symm==0 & field==0, robust
noconstant

Regression with robust standard errors

Number of obs = 224
F(3, 221) =93373.40
Prob > F = 0.0000
R-squared = 0.9988
Root MSE = 3.0719

bid	Coef.	Robust Std. Err.	t	P> t	[95% Conf. Interval]	
signal	1.001099	.0057463	174.22	0.000	.9897741	1.012423
eps	-.4411292	.0748393	-5.89	0.000	-.5886193	-.293639
epsD	-.3406197	.049145	-6.93	0.000	-.4374725	-.2437668

. global N "7"

```
. regress bid signal eps Dealer if n==$N & symm==0 & field==0, robust
noconstant
```

```
Regression with robust standard errors      Number of obs = 147
F( 3, 144) = .
Prob > F = 0.0000
R-squared = 0.9991
Root MSE = 2.7248
```

bid	Coef.	Robust Std. Err.	t	P> t	[95% Conf. Interval]	
signal	1.012484	.0067762	149.42	0.000	.9990904	1.025878
eps	-.5502557	.0902383	-6.10	0.000	-.7286185	-.3718929
Dealer	-3.915897	.4425955	-8.85	0.000	-4.79072	-3.041074

```
. for num 0 1: regress bid signal eps if n==$N & symm==0 & field==0 & Dealer==X,
robust noconstant
```

```
-> regress bid signal eps if n==7 & symm==0 & field==0 & Dealer==0, robust noconstant
```

```
Regression with robust standard errors      Number of obs = 75
F( 2, 73) = 36489.00
Prob > F = 0.0000
R-squared = 0.9987
Root MSE = 3.3426
```

bid	Coef.	Robust Std. Err.	t	P> t	[95% Conf. Interval]	
signal	.9844816	.0118198	83.29	0.000	.9609249	1.008038
eps	-.219949	.1564279	-1.41	0.164	-.5317094	.0918114

```
-> regress bid signal eps if n==7 & symm==0 & field==0 & Dealer==1, robust noconstant
```

```
Regression with robust standard errors      Number of obs = 72
F( 2, 70) = .
Prob > F = 0.0000
R-squared = 0.9998
Root MSE = 1.274
```

bid	Coef.	Robust Std. Err.	t	P> t	[95% Conf. Interval]	
signal	1.00118	.0043315	231.14	0.000	.9925415	1.009819
eps	-.9076325	.0531048	-17.09	0.000	-1.013547	-.8017184

```
. regress bid signal eps epsD if n==$N & symm==0 & field==0, robust
noconstant
```

```
Regression with robust standard errors      Number of obs = 147
F( 3, 144) = .
Prob > F = 0.0000
R-squared = 0.9992
Root MSE = 2.5555
```

bid	Coef.	Robust Std. Err.	t	P> t	[95% Conf. Interval]	
signal	.9928304	.0063374	156.66	0.000	.980304	1.005357
eps	-.3073521	.1021891	-3.01	0.003	-.5093366	-.1053676
epsD	-.5142797	.0577754	-8.90	0.000	-.6284772	-.4000823

Winner's Curse

These observed bidding patterns map directly into the incidence of the WC, which is summarized in Figure 4 for the laboratory treatments that have a WC threshold defined theoretically. Figure 3 shows the average difference between the bid and the WC threshold, to provide some sense of the monetary significance of the violations underlying Figure 4.

The first result from Figure 4 is that the *WC incidence is much higher in the AIS auctions compared to the SIS auctions.*²³ This difference is not affected by the signal uncertainty, as bidding data across $\epsilon=6$ and $\epsilon=12$ are statistically indistinguishable. Similarly, the number of bidders does not make a considerable difference.

The second result is that the *WC incidence is significantly lower for dealers compared to non-dealers.* This hold whether one is looking at symmetric or asymmetric information environments.

```
. ttest WC if Eps~="None", by(symm) unequal
Two-sample t test with unequal variances
```

Group	Obs	Mean	Std. Err.	Std. Dev.	[95% Conf. Interval]	
AIS	371	.5552561	.0258345	.4976085	.5044551	.606057
SIS	194	.2680412	.0318835	.4440852	.2051565	.330926
combined	565	.4566372	.0209745	.4985575	.4154396	.4978348
diff		.2872148	.0410363		.2065594	.3678703

```
Satterthwaite's degrees of freedom: 432.399

Ho: mean(AIS) - mean(SIS) = diff = 0

Ha: diff < 0          Ha: diff != 0          Ha: diff > 0
t = 6.9990             t = 6.9990             t = 6.9990
P < t = 1.0000        P > |t| = 0.0000        P > t = 0.0000

. ranksum WC if Eps~="None", by(symm) porder
Two-sample Wilcoxon rank-sum (Mann-Whitney) test
```

symm	obs	rank sum	expected
AIS	371	115329	104993
SIS	194	44566	54902
combined	565	159895	159895

```
unadjusted variance 3394773.67
adjustment for ties -867835.44
adjusted variance 2526938.23

Ho: WC(symm==AIS) = WC(symm==SIS)
z = 6.502
Prob > |z| = 0.0000

P{WC(symm==AIS) > WC(symm==SIS)} = 0.644
```

²³ Unless otherwise stated, all claims are supported by statistical tests at the 1% level. For unconditional comparisons, we employ a two-sample *t*-test, assuming unequal variances, and a two-sample Wilcoxon rank-sum test. Conditional comparisons of regression coefficients employ an *F*-test. Specific numerical results are provided in the statistical output referenced in Appendix C.

. ttest WC if Eps=="6", by(symm) unequal

Two-sample t test with unequal variances

Group	Obs	Mean	Std. Err.	Std. Dev.	[95% Conf. Interval]	
AIS	210	.5571429	.0343591	.4979109	.489408	.6248777
SIS	97	.2783505	.0457429	.4505152	.1875516	.3691494
combined	307	.4690554	.0285283	.4998563	.4129189	.5251919
diff		.2787923	.0572098		.1659971	.3915876

Satterthwaite's degrees of freedom: 204.923

Ho: mean(AIS) - mean(SIS) = diff = 0

Ha: diff < 0	Ha: diff != 0	Ha: diff > 0
t = 4.8732	t = 4.8732	t = 4.8732
P < t = 1.0000	P > t = 0.0000	P > t = 0.0000

. ranksum WC if Eps=="6", by(symm) porder

Two-sample Wilcoxon rank-sum (Mann-Whitney) test

symm	obs	rank sum	expected
AIS	210	35179.5	32340
SIS	97	12098.5	14938
combined	307	47278	47278

unadjusted variance 522830.00
 adjustment for ties -132205.29

 adjusted variance 390624.71

Ho: WC(symm==AIS) = WC(symm==SIS)
 z = 4.543
 Prob > |z| = 0.0000

P{WC(symm==AIS) > WC(symm==SIS)} = 0.639

. ttest WC if Eps=="12", by(symm) unequal

Two-sample t test with unequal variances

Group	Obs	Mean	Std. Err.	Std. Dev.	[95% Conf. Interval]	
AIS	161	.552795	.0393075	.4987562	.4751666	.6304235
SIS	97	.257732	.0446405	.4396578	.1691213	.3463426
combined	258	.4418605	.0309776	.4975735	.3808583	.5028627
diff		.2950631	.0594798		.1778468	.4122794

Satterthwaite's degrees of freedom: 222.369

Ho: mean(AIS) - mean(SIS) = diff = 0

Ha: diff < 0	Ha: diff != 0	Ha: diff > 0
t = 4.9607	t = 4.9607	t = 4.9607
P < t = 1.0000	P > t = 0.0000	P > t = 0.0000

. ranksum WC if Eps=="12", by(symm) porder

Two-sample Wilcoxon rank-sum (Mann-Whitney) test

symm	obs	rank sum	expected
AIS	161	23153.5	20849.5

```

      SIS |      97      10257.5      12561.5
-----+-----
combined |      258      33411      33411

```

```

unadjusted variance  337066.92
adjustment for ties  -87681.05
-----
adjusted variance    249385.87

```

```

Ho: WC(symm==AIS) = WC(symm==SIS)
      z = 4.614
      Prob > |z| = 0.0000

```

P{WC(symm==AIS) > WC(symm==SIS)} = 0.648

```
. ttest WC if Eps~="None" & Dealer==0, by(symm) unequal
```

Two-sample t test with unequal variances

```

-----+-----
Group |      Obs      Mean      Std. Err.      Std. Dev.      [95% Conf. Interval]
-----+-----
AIS |      190      .7947368      .029379      .4049609      .7367841      .8526896
SIS |      111      .4234234      .0471107      .4963421      .3300611      .5167858
-----+-----
combined |      301      .6578073      .027392      .4752338      .6039025      .7117121
-----+-----
diff |              .3713134      .0555206              .2618155      .4808113
-----+-----

```

Satterthwaite's degrees of freedom: 195.027

Ho: mean(AIS) - mean(SIS) = diff = 0

```

Ha: diff < 0              Ha: diff != 0              Ha: diff > 0
      t = 6.6878              t = 6.6878              t = 6.6878
P < t = 1.0000              P > |t| = 0.0000              P > t = 0.0000

```

```
. ranksum WC if Eps~="None" & Dealer==0, by(symm) porder
```

Two-sample Wilcoxon rank-sum (Mann-Whitney) test

```

-----+-----
symm |      obs      rank sum      expected
-----+-----
AIS |      190      32605.5      28690
SIS |      111      12845.5      16761
-----+-----
combined |      301      45451      45451

```

```

unadjusted variance  530765.00
adjustment for ties  -172340.45
-----
adjusted variance    358424.55

```

```

Ho: WC(symm==AIS) = WC(symm==SIS)
      z = 6.540
      Prob > |z| = 0.0000

```

P{WC(symm==AIS) > WC(symm==SIS)} = 0.686

```
. ttest WC if Eps~="None" & Dealer==1, by(symm) unequal
```

Two-sample t test with unequal variances

```

-----+-----
Group |      Obs      Mean      Std. Err.      Std. Dev.      [95% Conf. Interval]
-----+-----
AIS |      181      .3038674      .0342809      .4612019      .2362233      .3715115
SIS |      83      .060241      .0262753      .2393792      .0079711      .1125109
-----+-----
combined |      264      .2272727      .025841      .4198662      .1763912      .2781543
-----+-----
diff |              .2436264      .0431922              .1585724      .3286805
-----+-----

```

Satterthwaite's degrees of freedom: 258.088

Ho: mean(AIS) - mean(SIS) = diff = 0

Ha: diff < 0	Ha: diff != 0	Ha: diff > 0
t = 5.6405	t = 5.6405	t = 5.6405
P < t = 1.0000	P > t = 0.0000	P > t = 0.0000

. ranksum WC if Eps~="None" & Dealer==1, by(symm) porder

Two-sample Wilcoxon rank-sum (Mann-Whitney) test

symm	obs	rank sum	expected
-----+-----			
AIS	181	25812.5	23982.5
SIS	83	9167.5	10997.5
-----+-----			
combined	264	34980	34980

unadjusted variance 331757.92

adjustment for ties -156965.60

adjusted variance 174792.32

Ho: WC(symm==AIS) = WC(symm==SIS)

z = 4.377

Prob > |z| = 0.0000

P{WC(symm==AIS) > WC(symm==SIS)} = 0.622

. ttest WC if Eps~="None" & Dealer==1 & public==0, by(symm) unequal

Two-sample t test with unequal variances

Group	Obs	Mean	Std. Err.	Std. Dev.	[95% Conf. Interval]
-----+-----					
AIS	78	.2948718	.0519643	.4589365	.1913976 .398346
SIS	83	.060241	.0262753	.2393792	.0079711 .1125109
-----+-----					
combined	161	.173913	.0299653	.3802173	.1147345 .2330916
-----+-----					
diff		.2346308	.0582296		.1192827 .349979

Satterthwaite's degrees of freedom: 114.386

Ho: mean(AIS) - mean(SIS) = diff = 0

Ha: diff < 0	Ha: diff != 0	Ha: diff > 0
t = 4.0294	t = 4.0294	t = 4.0294
P < t = 0.9999	P > t = 0.0001	P > t = 0.0001

. ranksum WC if Eps~="None" & Dealer==1 & public==0, by(symm) porder

Two-sample Wilcoxon rank-sum (Mann-Whitney) test

symm	obs	rank sum	expected
-----+-----			
AIS	78	7077.5	6318
SIS	83	5963.5	6723
-----+-----			
combined	161	13041	13041

unadjusted variance 87399.00

adjustment for ties -49728.41

adjusted variance 37670.59

Ho: WC(symm==AIS) = WC(symm==SIS)

z = 3.913

Prob > |z| = 0.0001

P{WC(symm==AIS) > WC(symm==SIS)} = 0.617

. ttest WC if Eps~="None" & symm==1, by(Dealer) unequal

Two-sample t test with unequal variances

Group	Obs	Mean	Std. Err.	Std. Dev.	[95% Conf. Interval]	
Non-deal	111	.4234234	.0471107	.4963421	.3300611	.5167858
Dealer	83	.060241	.0262753	.2393792	.0079711	.1125109
combined	194	.2680412	.0318835	.4440852	.2051565	.330926
diff		.3631825	.0539426		.2566867	.4696782

Satterthwaite's degrees of freedom: 167.355

Ho: mean(Non-deal) - mean(Dealer) = diff = 0

Ha: diff < 0	Ha: diff != 0	Ha: diff > 0
t = 6.7328	t = 6.7328	t = 6.7328
P < t = 1.0000	P > t = 0.0000	P > t = 0.0000

. ranksum WC if Eps~="None" & symm==1, by(Dealer) porder

Two-sample Wilcoxon rank-sum (Mann-Whitney) test

Dealer	obs	rank sum	expected
Non-dealer	111	12495.5	10822.5
Dealer	83	6419.5	8092.5
combined	194	18915	18915

unadjusted variance 149711.25
adjustment for ties -61591.05
adjusted variance 88120.20

Ho: WC(Dealer==Non-dealer) = WC(Dealer==Dealer)
z = 5.636
Prob > |z| = 0.0000

P{WC(Dealer==Non-dealer) > WC(Dealer==Dealer)} = 0.682

. ttest WC if Eps~="None" & symm==0, by(Dealer) unequal

Two-sample t test with unequal variances

Group	Obs	Mean	Std. Err.	Std. Dev.	[95% Conf. Interval]	
Non-deal	190	.7947368	.029379	.4049609	.7367841	.8526896
Dealer	181	.3038674	.0342809	.4612019	.2362233	.3715115
combined	371	.5552561	.0258345	.4976085	.5044551	.606057
diff		.4908694	.0451475		.4020815	.5796574

Satterthwaite's degrees of freedom: 357.725

Ho: mean(Non-deal) - mean(Dealer) = diff = 0

Ha: diff < 0	Ha: diff != 0	Ha: diff > 0
t = 10.8726	t = 10.8726	t = 10.8726
P < t = 1.0000	P > t = 0.0000	P > t = 0.0000

. ranksum WC if Eps~="None" & symm==0, by(Dealer) porder

Two-sample Wilcoxon rank-sum (Mann-Whitney) test

Dealer	obs	rank sum	expected
Non-dealer	190	43780.5	35340
Dealer	181	25225.5	33666
combined	371	69006	69006

unadjusted variance 1066090.00
 adjustment for ties -276281.82

 adjusted variance 789808.18

Ho: WC(Dealer==Non-dealer) = WC(Dealer==Dealer)
 z = 9.497
 Prob > |z| = 0.0000

The third result is that *when dealers are placed in a role that they are unfamiliar with, they perform relatively poorly*. The WC incidence for dealers increases as we compare SIS auctions to AISpr auctions, and this is a statistically significant difference. In the SIS environment the dealers know that they are not at an informational disadvantage, and that no other trader knows more than them. But in the AISpr (and AISpu) environment they know that they are the “informational underdog” when they are not the insider.²⁴ Controlling for the number of bidders and signal uncertainty, being a dealer is associated with a reduction in the incidence of the WC by roughly 50%, whereas moving from the AISpr to the SIS environment is associated with a reduction of 40%.²⁵ This difference is statistically significant at the 8.7% level.

```

. probit WC n eps Dealer symm if Eps~="None" & public==0, robust

Iteration 0:  log pseudo-likelihood = -239.31874
Iteration 1:  log pseudo-likelihood = -183.09776
Iteration 2:  log pseudo-likelihood = -180.85944
Iteration 3:  log pseudo-likelihood = -180.84267
Iteration 4:  log pseudo-likelihood = -180.84267

Probit estimates                               Number of obs   =       355
                                                Wald chi2(4)    =       88.26
                                                Prob > chi2     =       0.0000
Log pseudo-likelihood = -180.84267             Pseudo R2      =       0.2443

```

	WC	Coef.	Robust Std. Err.	z	P> z	[95% Conf. Interval]
n		.0256448	.0541291	0.47	0.636	-.0804464 .1317359
eps		-.010375	.0267499	-0.39	0.698	-.0628037 .0420538
Dealer		-1.414095	.1672798	-8.45	0.000	-1.741958 -1.086233
symm		-1.080544	.1669466	-6.47	0.000	-1.407753 -.7533346
_cons		.8509092	.4007749	2.12	0.034	.0654048 1.636414

```

. test Dealer=symm

( 1)  Dealer - symm = 0

      chi2( 1) =    2.93
      Prob > chi2 =    0.0870

```

²⁴ The WC incidence is evaluated only for outsiders, since it is meaningless for insiders because they know the true value. Thus the dealers underlying the WC incidence in the right panel of Figure 4 are all outsiders.

²⁵ These are marginal effects from a probit regression model.

Seller Revenue

Turning to the general comparative static hypotheses, we find that the seller revenue predictions are borne out. Table 1 displays a regression of seller revenue in the 115 distinct laboratory auctions, with various controls added.

Consider the top panel of Table 1, which reports results for the full sample. The relevant variables for the hypothesis test are AISpu and AISpr, which represent interactions between the AIS information condition and the provision of public or private information. Theory predicts that seller revenue will be higher in the AISpr setting compared to the SIS, and that it will be lower in the AISpu setting compared to the SIS. Since SIS is the omitted information category in this regression, these estimation results can be used to directly test these hypotheses. We find strong support for the hypothesis regarding the positive effect on revenue of private information, and weak support for the hypothesis regarding the negative effect on revenue of public information.

The remaining panels of Table 1 examine possible interaction effects between the number of bidders and the effect of public information, and the signal size and the effect of public information. The qualitative conclusion remains intact, but the positive effects of private information on revenue are particularly strong with smaller numbers of bidders and/or smaller signal uncertainty. Conversely, the negative effects of public information on revenue are enhanced with larger numbers of bidders and/or greater signal uncertainty.

Bidder Profits

Economic theory also organizes the observations on individual bidder profits well. Simple *t*-tests allow us to examine the theoretical predictions for the profits of winners, defined here as those that submitted the highest bid in any group.²⁶ We cannot reject any of the hypotheses stated earlier, with one exception. Insiders do earn much more than outsiders as a general matter, and particularly in AISpu settings. Similarly, insiders in AIS settings earn much more than bidders in comparable SIS settings. Outsiders earn less in AISpr settings than bidders in SIS settings, and earn zero in AISpu settings.

```
. * buyer expected profits
. generate profit=(94.33-bid)*Winner if field==0
(184 missing values generated)

. replace profit=(9.00-bid)*Winner if field==1
(184 real changes made)

. summ profit, detail
```

		profit			
Percentiles		Smallest			
1%	-5.835	-10.67			
5%	-2.090001	-10.67			
10%	0	-8		Obs	800
25%	0	-6.67		Sum of Wgt.	800

²⁶ In cases where two or more bidders tied with the highest bid, the actual winner in each auction was selected at random from amongst those that submitted the highest bid. This fact was explained to all participants through one of the examples.

```

50%          0          Largest      Mean          .1545625
75%          0          9.33        Std. Dev.     1.981824
90%    1.324999      10.33      Variance      3.927626
95%          3.33      10.33      Skewness      1.283434
99%          8.83      17.06      Kurtosis      18.40733

```

. summ profit if field==0 & Winner>0, detail

```

-----
                    profit
-----
Percentiles      Smallest
1%              -10.67      -10.67
5%              -5.67       -10.67
10%             -5.67       -6.67   Obs          132
25%             -2.335      -6.65003 Sum of Wgt. 132

50%             .3850003      Mean          .6443939
75%              3.33        Largest      Std. Dev.     4.505938
90%              6.33        9.33        Variance      20.30348
95%              9.33        10.33      Skewness      .384261
99%             10.33        17.06      Kurtosis      3.755565

```

```

.
. * tests for lab experiments
. ttest profit=0 if field==0 & Winner>0 & symm==0 & insider==0 & public==0 /*
test hypothesis 2 -- first part */

```

One-sample t test

```

-----
Variable |      Obs      Mean      Std. Err.      Std. Dev.      [95% Conf. Interval]
-----+-----
profit |         32    -1.353854    .5444893      3.080097    -2.464347    -.2433607
-----+-----

```

Degrees of freedom: 31

Ho: mean(profit) = 0

```

Ha: mean < 0          Ha: mean != 0          Ha: mean > 0
t = -2.4865          t = -2.4865          t = -2.4865
P < t = 0.0092      P > |t| = 0.0185      P > t = 0.9908

```

```

. ttest profit=0 if field==0 & Winner>0 & symm==0 & insider==0 & public==0 & Dealer==0 /*
test hypothesis 2 -- first part FOR NON-DEALERS ONLY */

```

One-sample t test

```

-----
Variable |      Obs      Mean      Std. Err.      Std. Dev.      [95% Conf. Interval]
-----+-----
profit |         22    -2.25106    .6741648      3.162113    -3.653063    -.8490581
-----+-----

```

Degrees of freedom: 21

Ho: mean(profit) = 0

```

Ha: mean < 0          Ha: mean != 0          Ha: mean > 0
t = -3.3390          t = -3.3390          t = -3.3390
P < t = 0.0016      P > |t| = 0.0031      P > t = 0.9984

```

```

. ttest profit=0 if field==0 & Winner>0 & symm==0 & insider==0 & public==0 & Dealer==1 /*
test hypothesis 2 -- first part FOR DEALERS ONLY */

```

One-sample t test

```

-----
Variable |      Obs      Mean      Std. Err.      Std. Dev.      [95% Conf. Interval]
-----+-----
profit |         10    .6200002    .5522497      1.746367    -.6292755    1.869276
-----+-----

```

Degrees of freedom: 9


```

Ho: mean(profit) = 0

Ha: mean < 0          Ha: mean != 0          Ha: mean > 0
t = 1.1227            t = 1.1227            t = 1.1227
P < t = 0.8547      P > |t| = 0.2906      P > t = 0.1453

. replace insider=0 if insider==.
treat all bidders in SIS as outsiders */
(378 real changes made)

. ttest profit if field==0 & Winner>0 & insider==0 & public==0, by(symm) unequal
test hypothesis 2 -- second part */

Two-sample t test with unequal variances

-----+-----
Group |      Obs      Mean   Std. Err.   Std. Dev.   [95% Conf. Interval]
-----+-----
AIS |      32  -1.353854   .5444893    3.080097   -2.464347   -.2433607
SIS |      41   .6309756   .7331234    4.69428    -0.8507219   2.112673
-----+-----
combined |      73  -.2390867   .4869592    4.160581   -1.209822    .7316487
diff |              -1.98483   .9132023              -3.806548   -.1631115
-----+-----
Satterthwaite's degrees of freedom: 69.1503

Ho: mean(AIS) - mean(SIS) = diff = 0

Ha: diff < 0          Ha: diff != 0          Ha: diff > 0
t = -2.1735          t = -2.1735          t = -2.1735
P < t = 0.0166      P > |t| = 0.0332      P > t = 0.9834

. ranksum profit if field==0 & Winner>0 & insider==0 & public==0, by(symm)
test hypothesis 2 -- second part NON-PARAMETRIC */

Two-sample Wilcoxon rank-sum (Mann-Whitney) test

symm |      obs      rank sum      expected
-----+-----
AIS |      32          997          1184
SIS |      41         1704          1517
-----+-----
combined |      73         2701          2701

unadjusted variance      8090.67
adjustment for ties      -26.58
-----
adjusted variance      8064.08

Ho: profit(symm==AIS) = profit(symm==SIS)
z = -2.082
Prob > |z| = 0.0373

. ttest profit=0 if field==0 & Winner>0 & symm==0 & insider==0 & public==1
test hypothesis 2 -- third part */

One-sample t test

-----+-----
Variable |      Obs      Mean   Std. Err.   Std. Dev.   [95% Conf. Interval]
-----+-----
profit |      25  -.1120003   .7777334    3.888667   -1.717163    1.493162
-----+-----
Degrees of freedom: 24

Ho: mean(profit) = 0

Ha: mean < 0          Ha: mean != 0          Ha: mean > 0
t = -0.1440          t = -0.1440          t = -0.1440
P < t = 0.4433      P > |t| = 0.8867      P > t = 0.5567

. ttest profit=0 if field==0 & Winner>0 & symm==0 & insider==0 & public==1 & Dealer==0

```

test hypothesis 2 -- third part FOR NON-DEALERS ONLY */

One-sample t test

Variable	Obs	Mean	Std. Err.	Std. Dev.	[95% Conf. Interval]	
profit	23	-.2852177	.8224737	3.944445	-1.990924	1.420488

Degrees of freedom: 22

Ho: mean(profit) = 0

Ha: mean < 0	Ha: mean != 0	Ha: mean > 0
t = -0.3468	t = -0.3468	t = -0.3468
P < t = 0.3660	P > t = 0.7321	P > t = 0.6340

. ttest profit=0 if field==0 & Winner>0 & symm==0 & insider==0 & public==1 & Dealer==1 /*
test hypothesis 2 -- third part FOR DEALERS ONLY */

One-sample t test

Variable	Obs	Mean	Std. Err.	Std. Dev.	[95% Conf. Interval]	
profit	2	1.879999	2.450001	3.464824	-29.25021	33.01021

Degrees of freedom: 1

Ho: mean(profit) = 0

Ha: mean < 0	Ha: mean != 0	Ha: mean > 0
t = 0.7673	t = 0.7673	t = 0.7673
P < t = 0.7083	P > t = 0.5833	P > t = 0.2917

. ttest profit if field==0 & Winner>0 & symm==0, by(insider) unequal /*
test hypothesis 4 for all AIS auctions */

Two-sample t test with unequal variances

Group	Obs	Mean	Std. Err.	Std. Dev.	[95% Conf. Interval]	
0	64	-1.043958	.4620567	3.696454	-1.967305	-.1206118
1	27	4.66679	.6517506	3.386595	3.327098	6.006483
combined	91	.6504395	.465972	4.44509	-.2752952	1.576174
diff		-5.710749	.7989213		-7.313068	-4.108429

Satterthwaite's degrees of freedom: 53.1612

Ho: mean(0) - mean(1) = diff = 0

Ha: diff < 0	Ha: diff != 0	Ha: diff > 0
t = -7.1481	t = -7.1481	t = -7.1481
P < t = 0.0000	P > t = 0.0000	P > t = 1.0000

. ranksum profit if field==0 & Winner>0 & symm==0, by(insider) /*
test hypothesis 4 for all AIS auctions NON-PARAMETRIC */

Two-sample Wilcoxon rank-sum (Mann-Whitney) test

insider	obs	rank sum	expected
0	64	2283.5	2944
1	27	1902.5	1242
combined	91	4186	4186

unadjusted variance 13248.00
 adjustment for ties -16.46

adjusted variance 13231.54

Ho: profit(insider==0) = profit(insider==1)
z = -5.742
Prob > |z| = 0.0000

. ttest profit if field==0 & Winner>0 & symm==0 & public==0, by(insider) unequal /*
test hypothesis 4 for private AIS auctions */

Two-sample t test with unequal variances

Group	Obs	Mean	Std. Err.	Std. Dev.	[95% Conf. Interval]	
0	32	-1.353854	.5444893	3.080097	-2.464347	-.2433607
1	8	2.255417	1.252248	3.541892	-.7056792	5.216513
combined	40	-.6319999	.5461307	3.454034	-1.736653	.4726537
diff		-3.609271	1.365501		-6.659468	-.5590732

Satterthwaite's degrees of freedom: 9.81779

Ho: mean(0) - mean(1) = diff = 0

Ha: diff < 0	Ha: diff != 0	Ha: diff > 0
t = -2.6432	t = -2.6432	t = -2.6432
P < t = 0.0125	P > t = 0.0250	P > t = 0.9875

. ranksum profit if field==0 & Winner>0 & symm==0 & public==0, by(insider) /*
test hypothesis 4 for private AIS auctions NON-PARAMETRIC */

Two-sample Wilcoxon rank-sum (Mann-Whitney) test

insider	obs	rank sum	expected
0	32	587	656
1	8	233	164
combined	40	820	820

unadjusted variance 874.67
adjustment for ties -1.97
adjusted variance 872.70

Ho: profit(insider==0) = profit(insider==1)
z = -2.336
Prob > |z| = 0.0195

. ttest profit if field==0 & Winner>0 & symm==0 & public==1, by(insider) unequal /*
test hypothesis 4 for public AIS auctions */

Two-sample t test with unequal variances

Group	Obs	Mean	Std. Err.	Std. Dev.	[95% Conf. Interval]	
0	25	-.1120003	.7777334	3.888667	-1.717163	1.493162
1	19	5.682105	.6495061	2.831132	4.317544	7.046667
combined	44	2.39	.6779596	4.497075	1.022764	3.757236
diff		-5.794106	1.013276		-7.839056	-3.749155

Satterthwaite's degrees of freedom: 41.9464

Ho: mean(0) - mean(1) = diff = 0

Ha: diff < 0	Ha: diff != 0	Ha: diff > 0
t = -5.7182	t = -5.7182	t = -5.7182
P < t = 0.0000	P > t = 0.0000	P > t = 1.0000

```
. ranksum profit if field==0 & Winner>0 & symm==0 & public==1, by(insider) /*
test hypothesis 4 for public AIS auctions NON-PARAMETRIC */
```

Two-sample Wilcoxon rank-sum (Mann-Whitney) test

insider	obs	rank sum	expected
0	25	375	562.5
1	19	615	427.5
combined	44	990	990

```
unadjusted variance    1781.25
adjustment for ties    -2.89
-----
adjusted variance      1778.36
```

```
Ho: profit(insider==0) = profit(insider==1)
      z = -4.446
      Prob > |z| = 0.0000
```

```
. replace insider=1 if symm==1 /*
treat all bidders in SIS as insiders ONLY FOR THE NEXT TEST */
(258 real changes made)
```

```
. ttest profit if field==0 & Winner>0 & insider==1, by(symm) unequal /*
test hypothesis 5 */
```

Two-sample t test with unequal variances

Group	Obs	Mean	Std. Err.	Std. Dev.	[95% Conf. Interval]	
AIS	27	4.66679	.6517506	3.386595	3.327098	6.006483
SIS	41	.6309756	.7331234	4.69428	-.8507219	2.112673
combined	68	2.233431	.5631345	4.643726	1.10941	3.357453
diff		4.035815	.9809427		2.076954	5.994676

Satterthwaite's degrees of freedom: 65.382

Ho: mean(AIS) - mean(SIS) = diff = 0

Ha: diff < 0	Ha: diff != 0	Ha: diff > 0
t = 4.1142	t = 4.1142	t = 4.1142
P < t = 0.9999	P > t = 0.0001	P > t = 0.0001

```
. ranksum profit if field==0 & Winner>0 & insider==1, by(symm) /*
test hypothesis 5 NON-PARAMETRIC */
```

Two-sample Wilcoxon rank-sum (Mann-Whitney) test

symm	obs	rank sum	expected
AIS	27	1240	931.5
SIS	41	1106	1414.5
combined	68	2346	2346

```
unadjusted variance    6365.25
adjustment for ties    -13.00
-----
adjusted variance      6352.25
```

```
Ho: profit(symm==AIS) = profit(symm==SIS)
      z = 3.871
      Prob > |z| = 0.0001
```

B. Field Experiments

Since we are using home-grown values, there is no WC threshold that can be defined for our field treatments. However, we can examine patterns of bidding levels to gain insights into whether the various theoretical predictions are met. Figure 5 displays the distribution of bids in the SIS and AIS treatments, split into dealer and non-dealer bids. Again one sees from a vertical comparison of the bid distributions that *dealers generate lower bids than non-dealers in the same setting*. This result holds true in each of the SIS and AIS treatments. Moreover, from the horizontal comparison of the bid distributions we see that non-dealers bid more aggressively when an insider is added, and that there is *some* evidence that dealers might as well.

These conclusions are supported by regressions reported in Table 2. Dealers in the SIS auctions bid \$1.21 lower on average, although this is only a significant difference only at the 11.4% level. In the AIS auctions, dealers bid \$1.82 lower and this is significant. However, as panels C and D in Table 2 show, this overall result is due primarily to the significantly lower bidding in the AISpr auctions. We also display results separately for the AISpu and AISpr auctions, since they were so different in the lab setting. The effect of public information in these field experiments is to mitigate the informational advantage dealers have from being insiders, as one would expect.

Figure 6 displays the average seller revenue across the four types of field treatments. Seller revenue in the AISpr treatment is higher than in the AISpu treatment, as predicted by theory, but not significantly at conventional levels. There is a large and significant increase in seller revenue in the AIS treatments compared to the SIS auctions with dealers, but not with respect to the SIS auctions with non-dealers. This result is consistent with the evidence from the lab experiments that dealers shave their bids significantly more than non-dealers in common value settings.

No precise tests of the profitability hypotheses are possible in the field setting, since we do not know the true value of the object. However, if we take the current market price of \$9 as a measure of the current value of the object, or alternatively as the informationally efficient estimate of the actuarial value, then we can derive some tests of the profit hypotheses conditional on that assumption.

We find that outsiders do *not* earn positive profits in the AISpr auctions, and actually earn *less* than their SIS counterparts. Although both results contradict the theoretical predictions, neither is statistically significant at conventional levels. Outsiders in the AISpu auctions earn positive profits on average, but at very small levels (\$0.93).

Although insiders tend to earn less than outsiders in the field experiments, our data reveal *very* few insiders (dealers) winning these auctions when there is a mix of insiders and outsiders in the same auction. In fact, 10 outsiders win for every 1 insider that wins in the field AIS auctions. This is a corollary of them being able to avoid the WC, by bidding lower than outsiders (non-dealers). We are unable to report any statistical tests of this hypothesis, since the data provide so few realizations of dealers winning these auctions. Moreover, it is possible that dealers know that one could obtain such packs at a bulk price of \$8, rather than the single pack price of \$9; as it happens, if we assume a true market value of \$9 the average loss for the 3 dealers that were winners is exactly \$1.

```
. replace insider=0 if symm==1                                     /*
treat all bidders in SIS as outsiders */
(258 real changes made)

.
. * tests for field experiments
. replace insider=1 if Dealer==1 & field==1                       /* in
the field experiments only, dealers ARE the insiders */
(62 real changes made)
```

```
. tabulate insider symm if field==1 & Winner>0
```

insider	Information		Total
	AIS	SIS	
0	30	8	38
1	3	11	14
Total	33	19	52

```
. ttest profit=0 if field==1 & Winner>0 & symm==0 & insider==0 & public==0
test hypothesis 2 -- first part */
```

```
/*
```

One-sample t test

Variable	Obs	Mean	Std. Err.	Std. Dev.	[95% Conf. Interval]	
profit	15	-.36	.8583656	3.324436	-2.201011	1.481011

Degrees of freedom: 14

Ho: mean(profit) = 0

Ha: mean < 0	Ha: mean != 0	Ha: mean > 0
t = -0.4194	t = -0.4194	t = -0.4194
P < t = 0.3406	P > t = 0.6813	P > t = 0.6594

```
. replace insider=0 if insider==.
treat all bidders in SIS as outsiders */
(0 real changes made)
```

```
/*
```

```
. ttest profit if field==1 & Winner>0 & insider==0 & public==0, by(symm) unequal
test hypothesis 2 -- second part */
```

```
/*
```

Two-sample t test with unequal variances

Group	Obs	Mean	Std. Err.	Std. Dev.	[95% Conf. Interval]	
AIS	15	-.36	.8583656	3.324436	-2.201011	1.481011
SIS	8	.5625	1.178064	3.332068	-2.223179	3.348179
combined	23	-.0391304	.6842164	3.281387	-1.458108	1.379848
diff		-.9225	1.45761		-4.041047	2.196048

Satterthwaite's degrees of freedom: 14.3791

Ho: mean(AIS) - mean(SIS) = diff = 0

Ha: diff < 0	Ha: diff != 0	Ha: diff > 0
t = -0.6329	t = -0.6329	t = -0.6329
P < t = 0.2684	P > t = 0.5367	P > t = 0.7316

```
. ranksum profit if field==1 & Winner>0 & insider==0 & public==0, by(symm)
test hypothesis 2 -- second part NON-PARAMETRIC */
```

```
/*
```

Two-sample Wilcoxon rank-sum (Mann-Whitney) test

symm	obs	rank sum	expected
AIS	15	171	180
SIS	8	105	96
combined	23	276	276

unadjusted variance 240.00
adjustment for ties -1.54

adjusted variance 238.46

```

Ho: profit(symm==AIS) = profit(symm==SIS)
      z = -0.583
      Prob > |z| = 0.5600

. ttest profit=0 if field==1 & Winner>0 & symm==0 & insider==0 & public==1 /*
test hypothesis 2 -- third part */

```

One-sample t test

Variable	Obs	Mean	Std. Err.	Std. Dev.	[95% Conf. Interval]	
profit	15	.9333333	.6182412	2.394438	-.3926622	2.259329

Degrees of freedom: 14

Ho: mean(profit) = 0

Ha: mean < 0	Ha: mean != 0	Ha: mean > 0
t = 1.5097	t = 1.5097	t = 1.5097
P < t = 0.9233	P > t = 0.1534	P > t = 0.0767

```

. ttest profit if field==1 & Winner>0 & symm==0, by(insider) unequal /*
test hypothesis 4 for all AIS auctions */

```

Two-sample t test with unequal variances

Group	Obs	Mean	Std. Err.	Std. Dev.	[95% Conf. Interval]	
0	30	.2866667	.5334104	2.921609	-.8042801	1.377613
1	3	-1	.5773503	1	-3.484138	1.484138
combined	33	.169697	.4904903	2.817652	-.829399	1.168793
diff		1.286667	.7860407		-.5986835	3.172017

Satterthwaite's degrees of freedom: 6.54276

Ho: mean(0) - mean(1) = diff = 0

Ha: diff < 0	Ha: diff != 0	Ha: diff > 0
t = 1.6369	t = 1.6369	t = 1.6369
P < t = 0.9257	P > t = 0.1487	P > t = 0.0743

```

. ranksum profit if field==1 & Winner>0 & symm==0, by(insider) /*
test hypothesis 4 for all AIS auctions NON-PARAMETRIC */

```

Two-sample Wilcoxon rank-sum (Mann-Whitney) test

insider	obs	rank sum	expected
0	30	535.5	510
1	3	25.5	51
combined	33	561	561

unadjusted variance 255.00
adjustment for ties -2.22

adjusted variance 252.78

```

Ho: profit(insider==0) = profit(insider==1)
      z = 1.604
      Prob > |z| = 0.1087

```

```

. ttest profit if field==1 & Winner>0 & symm==0 & public==0, by(insider) unequal /*
test hypothesis 4 for private AIS auctions */

```

Two-sample t test with unequal variances

Group	Obs	Mean	Std. Err.	Std. Dev.	[95% Conf. Interval]
-------	-----	------	-----------	-----------	----------------------

0	15	-.36	.8583656	3.324436	-2.201011	1.481011
1	1	-1
combined	16	-.4
diff		.64

Satterthwaite's degrees of freedom: .

Ho: mean(0) - mean(1) = diff = 0

Ha: diff < 0	Ha: diff != 0	Ha: diff > 0
t = .	t = .	t = .
P < t = .	P > t = .	P > t = .

. ranksum profit if field==1 & Winner>0 & symm==0 & public==0, by(insider) /*
test hypothesis 4 for private AIS auctions NON-PARAMETRIC */

Two-sample Wilcoxon rank-sum (Mann-Whitney) test

insider	obs	rank sum	expected
0	15	130	127.5
1	1	6	8.5
combined	16	136	136

unadjusted variance 21.25
adjustment for ties -0.09

adjusted variance 21.16

Ho: profit(insider==0) = profit(insider==1)
z = 0.544
Prob > |z| = 0.5868

. ttest profit if field==1 & Winner>0 & symm==0 & public==1, by(insider) unequal /*
test hypothesis 4 for public AIS auctions */

Two-sample t test with unequal variances

Group	Obs	Mean	Std. Err.	Std. Dev.	[95% Conf. Interval]	
0	15	.9333333	.6182412	2.394438	-.3926622	2.259329
1	2	-1	1	1.414214	-13.7062	11.7062
combined	17	.7058824	.5715779	2.356676	-.5058086	1.917573
diff		1.933333	1.175679		-3.415726	7.282393

Satterthwaite's degrees of freedom: 1.89081

Ho: mean(0) - mean(1) = diff = 0

Ha: diff < 0	Ha: diff != 0	Ha: diff > 0
t = 1.6444	t = 1.6444	t = 1.6444
P < t = 0.8756	P > t = 0.2489	P > t = 0.1244

. ranksum profit if field==1 & Winner>0 & symm==0 & public==1, by(insider) /*
test hypothesis 4 for public AIS auctions NON-PARAMETRIC */

Two-sample Wilcoxon rank-sum (Mann-Whitney) test

insider	obs	rank sum	expected
0	15	146	135
1	2	7	18
combined	17	153	153

unadjusted variance 45.00


```

adjustment for ties      -1.43
-----
adjusted variance      43.57

```

```

Ho: profit(insider==0) = profit(insider==1)
      z = 1.667
      Prob > |z| = 0.0956

```

```

. replace insider=1 if symm==1
treat all bidders in SIS as insiders ONLY FOR THE NEXT TEST */
(226 real changes made)

```

```

. ttest profit if field==1 & Winner>0 & insider==1, by(symm) unequal
test hypothesis 5 */

```

Two-sample t test with unequal variances

Group	Obs	Mean	Std. Err.	Std. Dev.	[95% Conf. Interval]	
AIS	3	-1	.5773503	1	-3.484138	1.484138
SIS	19	1.736316	.6175607	2.691885	.4388689	3.033763
combined	22	1.363182	.5732712	2.68888	.1709991	2.555364
diff		-2.736316	.8454079		-4.684683	-.7879485

Satterthwaite's degrees of freedom: 8.02714

Ho: mean(AIS) - mean(SIS) = diff = 0

Ha: diff < 0	Ha: diff != 0	Ha: diff > 0
t = -3.2367	t = -3.2367	t = -3.2367
P < t = 0.0059	P > t = 0.0119	P > t = 0.9941

```

. ranksum profit if field==1 & Winner>0 & insider==1, by(symm)
test hypothesis 5 NON-PARAMETRIC */

```

Two-sample Wilcoxon rank-sum (Mann-Whitney) test

symm	obs	rank sum	expected
AIS	3	12	34.5
SIS	19	241	218.5
combined	22	253	253

```

unadjusted variance      109.25
adjustment for ties      -1.30
-----
adjusted variance      107.95

```

```

Ho: profit(symm==AIS) = profit(symm==SIS)
      z = -2.166
      Prob > |z| = 0.0303

```

```

. replace insider=0 if symm==1
treat all bidders in SIS as outsiders */
(258 real changes made)

```