Impact of Valuation Ranking Information on Bidding in First-Price Auctions: A Laboratory Study

by

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Abstract

Landsberger *et al.* (2001) identified optimal bidder behavior in first-price private-value auctions when the ranking of valuations is common knowledge, and derived comparative-statics predictions regarding the auctioneer's expected revenue and the efficiency of the allocation. The experiment reported here tests the behavioral components of these comparative-statics predictions. The results support the prediction that buyers are inclined to bid more aggressively when they learn they have the low value. Contrary to the theory, buyers are inclined to bid less when they learn they have the high value. Consistent with theory, the overall proportion of efficient allocations is lower than in the first-price auction before information is revealed. But as a result of high-value bidders decreasing their bids, the expected revenue does not increase on a regular basis, contrary to the theory's predictions.

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1 Introduction

Traditional auction models assume that agents do not know how their valuations stand relative to those of their rivals, with knowledge limited to the underlying distribution from which values are drawn. In real-life situations, agents usually know more than this. Such would be the case in procurement auctions, where due to accumulated experience, bidders might learn who the strongest bidder is. There is also a general perception that, in privatizations, firms already in the market or, in takeovers, firms with related activities have a greater valuation than potential entrants or competing firms. For instance, in the recent privatization of airwaves in the US, there was a general perception that the Pacific Telephone Company had a greater valuation for the Los Angeles area than did the other similar potential bidders. Another example would be the auctioning of the third generation mobile phone licenses in the UK, where firms already in the market were believed to have greater valuations for the new licenses being sold than similar potential entrants.[1] The relevance of information revelation on bidding behavior is a common factor to all of these examples, some of them using different auction formats. Thus, there is a need to determine the impact of information revelation on bidding behavior in auction markets, on seller's revenue, and on the efficiency of the auction outcome.[2]

Early theoretical contributions in auction theory considered a single unit auction under the assumptions of bidders' risk neutrality, *independence* of bidders' reservation values and *symmetry* of bidders' beliefs (Vickrey, 1961; Myerson, 1982; Riley and Samuelson, 1981). Relaxing simultaneously the last two assumptions, Landsberger,

[1]Further examples include art auctions, where bidders might revise their bidding strategies based on the participation of a wealthy art collector who is known to have a high valuation. In the selling process of Wellcome, a drug company, it was commonly known that Wellcome and Glaxo had particular synergies that made Wellcome worth more to Glaxo than to any other competing firms (Klemperer, 2003). Fang and Morris (2003) quote situations where bidders can obtain some information about similar opponents' estimates via insider rumors and industrial espionage. From the seller's perspective, Kaplan and Zamir (2002) cite situations in which a seller knows the object's worth to each buyer, which provides him valuable information to obtain additional rents.

[2]For a description of the importance of information revelation in auction markets, see Kagel (1995), Klemperer (2003), Krishna (2002), and Wolfstetter (1996, 1999).

Rubinstein, Wolfstetter and Zamir (2001) − hereafter referred to as LRWZ − developed a theoretical model in which two bidders draw their values from the same distribution, but the ranking of these valuations is common knowledge. The auction is ex-ante symmetric since bidders' valuations are drawn independently from a single density distribution. However, the revelation of the ranking makes it *affiliated* and *asymmetric* since the subsequent conditional distributions differ.[3,4]

In this paper, I report the results of an auction experiment in which two bidders are required to bid for a single item following a first-price sealed-bid allocation rule and under two different information conditions. While each bidder knows the value of the item to herself, the revelation of the valuation ranking induces a particular asymmetry in bidding behavior. This experiment evaluates the comparative-statics predictions of LRWZ's model regarding the auctioneer's expected revenue and the efficiency of the first-price auction in cases when the ranking of valuations is common knowledge to two bidders: (i) The bidder with the lower reservation value will bid more aggressively than the high-value bidder. Thus, the proportion of efficient allocations should be lower than when the bidders lack information about the ranking of valuations. (ii) For a number of distributions, including the uniform distribution studied here, bidders are expected to bid more aggressively than in the standard first-price auction model, in which information regarding the ranking of valuations is not available. Thus, the seller's expected revenue should be higher when rankings are known than when they are unknown.

These comparative-statics predictions are founded on two behavioral components:

[3] In auctions with *affiliated* private-values, values might remain private for bidders, but the higher (lower) the value is for one bidder, the more likely the value will be higher (lower) for other bidders as well (Milgrom and Weber, 1982).

[4] Kaplan and Zamir (2000) study the strategic use of seller information using LRWZ as a baseline. The seller can increase his expected revenue by committing to a signaling strategy to both bidders. Fang and Morris (2003) consider a parametric examples of two bidder private value auctions in which valuations are drawn from the same distribution and each bidder observe a noisy signal about her opponent's private valuation. They show that for the first price auction inefficiency increases as the signal becomes more informative. For more on the relevance of information in asymmetric auctions see Kim and Che (2004) and McAdams (2004).

For the low-value bidder, the more aggressive bidding behavior is an immediate consequence of knowing her position. Meanwhile, for the high-value bidder, the more aggressive bidding behavior is a consequence of incorporating her expectations about the low-value bidder response to her strategy.

The current paper is closely related to previous auction experiments where bidders can use information strategically. In the context of affiliated private-values, Kagel, Harstad and Levin (1987) tested the effects of public information about rivals' valuations on the seller's expected revenue (Milgrom and Weber, 1982). In that paper, bidders are required to bid for a single item following a first-price sealed-bid allocation rule and under two different information conditions. While each bidder knows the value of the item to herself, the revelation of a public signal induces a particular *symmetric affiliation* between bidders' valuations.[5] As a consequence, the low-value bidder should raise her bid in an effort to win the item once she has realized she has a lower valuation than she had assumed prior to the announcement of the public signal. In turn, this should put pressure on the high-value bidder to raise her bid, resulting in more expected revenue for the seller. Kagel *et al.* (1987) showed that the revelation of a public signal increases average bidding and market prices. However, the increase in prices is closer to the predictions of the risk-averse Nash equilibrium (RANE) model, which permits some increase in revenue lower than the predicted by the risk-neutral Nash equilibrium (RNNE) model.

In the context of independent private-values, but with values drawn from different distributions, Pezanis-Christou (2000) and Güth, Ivanova-Stenzel and Wolfstetter (2004) concentrated on testing predictions derived respectively by Maskin and Riley (2000) and Plum (1992).[6] In those papers, one strong-bidder and one weak-bidder are required to bid for a single item following a first-price sealed-bid allocation rule,

[5] While for Milgrom and Weber (1982) the affiliation is among *symmetric* distributions of signals, LRWZ (2001) consider a model in which the affiliation is among *asymmetric* distribution of signals.

[6] Maskin and Riley (2000) and Plum (1992) assume that bidders' valuations are drawn independently from *asymmetric* distributions, which are common knowledge among them. LRWZ (2001) consider another kind of asymmetry among bidders that *cannot* be encompassed under the approach of the aforementioned papers, since values are not independent.

where the weak-bidder is more likely to draw values lower than the strong-bidder.[7] In both cases, the strong bidder has an incentive to *low-ball*; that is, to submit low bids. They showed that although the strong-bidder is willing to low-ball, the reduction in the average bidding and market prices is not as significant as expected when compared to a second-price auction.

In a more recent experimental paper, Andreoni, Che and Kim (2005) tested some comparative-statics predictions established by Kim and Che (2004) about how bidders' knowledge of their rivals' exact valuations affect their behavior in standard auctions. In their experiment, subjects play a sequence of auctions with increasingly more information about their rivals' valuations. They showed that the revelation of information about other bidders valuations affect bidding behavior as expected. As in Kagel *et al.* (1987), changes in behavior look closer to the predictions of the RANE model.

The experimental results reported here support the prediction that low-value bidders are inclined to bid more aggressively once information about the ranking of valuations has been revealed. Contrary to the predictions of the theory, high-value bidders are inclined to bid less aggressively. Thus, consistent with the theory, the overall proportion of efficient allocations is lower than in the first-price auction before information is revealed. But as a result of high-value bidders decreasing their bids, the expected revenue does not increase consistently. Although both kinds of bidders improve their average monetary payoff per auction by moving toward the asymmetric RNNE after information is revealed, high-value bidders continue to bid above it. Therefore, I consider a modify version of LRWZ's auction model with risk-averse bidders as an alternative way to explain why high-value bidders may keep bidding above the RNNE (Cox, Smith and Walker, 1988).

This paper is organized as follows. Section 2 describes the experimental design. Section 3 specifies the RNNE bidding strategies for the auction models and states

[7] While in Pezanis-Christou (2000) the weak-bidder has a positive probability of not bidding at all, in Güth *et al.* (2004) the upper bound of the distribution for the weak-bidder is smaller than for the strong-bidder.

the comparative-statics predictions for the first-price auction when the information about the ranking of valuations is revealed. Section 4 evaluates the experimental results regarding these auctions settings. Section 5 summarizes the research results.

2 Experimental Design

The experimental design used directly measures the information impact of the ranking of valuations on bidding behavior in first-price private-values auctions. The particulars of the experimental design follow.

2.1 Structure of the Auction

Subjects in this experiment are required to bid for a single item following a first-price sealed-bid allocation rule under two different information conditions. In the first-price sealed-bid auction, the high bidder earns a payoff equal to her value of the item less the high bid, while the other subject earns nothing. In one information condition (hereafter referred to as *symmetric condition*), two private values, one for each bidder, are independently drawn from a commonly known uniform distribution. In the symmetric condition bidders have no information about the rank order of valuations. In the second information condition (hereafter referred to as *asymmetric condition*), both bidders are informed about the rank order of their valuations before bidding, whether they have the highest or lowest valuation (but not informed about the size of the differences in valuations.)

2.2 Dual-Market Bidding Procedure

A dual-market bidding was employed. In the dual-market, bidders just submit a bid under the symmetric condition. Then, once these bids are collected, but before they are posted, information about the ranking of valuations is released and subjects are asked to then submit a second bid. The winner in each market is determined after the second bid is submitted. Payoffs are determined based on just one of the two markets

Table 1: Experimental Design

Experimental Treatment	Sessions	Auction Periods	Markets	Information Condition
Asym. Condition and Dual-Market Bidding	1 & 2	1 to 10	Single-Auction	Asymmetric
		11 to 30	Dual-Auction	Sym./Asym.
Sym. Condition and Dual-Market Bidding	3 & 4	1 to 10	Single-Auction	Symmetric
		11 to 30	Dual-Auction	Sym./Asym.

Note: In session 1, during the dual-auction markets, only 18 trading periods (out of 20) were actually run since the network system broke down at that stage.

(chosen with equal probability). Participants' positions as high-value or low-value bidder are determined randomly in each period.

The dual-market bidding procedure, involving the same two bidders bidding for the same item under two different information conditions, has the advantage of directly controlling for between-subject variability in bidding.[8] The rule of flipping a fair coin to determine which market to pay in ensures that, under the expected utility hypothesis, the optimal strategy in the private information market should be unaffected by bids made after the ranking is revealed, and vice-versa.

In order to determine whether the dual-market bidding procedure actually affects the way bidders bid, and to familiarize subjects with the auction conditions so as to make it easier for them to bid in dual-auction markets, each session began with bidding in single-auction markets. For the single-auction markets, each bidder submitted one bid in each period. Table 1 briefly summarizes the experimental treatments. Sessions 1 and 2 began with ten periods of single-auction markets with the asymmetric condition followed by twenty periods of dual-auction markets. During these ten initial periods, each bidder maintained her role as a high-value or low-value bidder.[9] Sessions

[8] A similar procedure has been used in previous auction experiments by Kagel and Levin (1986) and Kagel *et al.* (1987). Andreoni *et al.* (2005) use a triple-market bidding procedure.

[9] There is the possibility of randomizing the roles of being low-value and high-value bidders in the asymmetric auctions, favoring learning in the bidding procedure once roles change. However, I kept subjects in fixed positions in order to maximize the prospect that rivalrous elements will come into play, allowing me to make a stronger comparison against the situation when players did not know the ranking.

3 and 4 began with ten periods of single-auction markets with the symmetric condition followed by twenty periods of dual-auction markets.

2.3 Design Parameters

This section characterizes the basic parameters and the general procedure of the experiment.

Valuation Distribution. All bidders were informed that their valuations were drawn randomly from the interval \$0.00 to \$6.00 and that any value in this interval has an equally likely chance of being draw. Valuations were any penny amount from 0.01 up to 6.00.[10]

Payoff Mechanism and Participation Fee. Each group of players received an initial cash balance of zero. Players were paid in cash the total earnings obtained from each auction period, plus a participation fee, at the end of the experiment. Since bidders' roles were not changed during the initial ten auction periods of sessions 1 and 2, the low-value bidders received an additional \$5 at the end of each session. Players were informed at the beginning about this additional payment. This was a fixed amount that was not expected to impact behavior.

Matching Procedure. Bidders were informed that participants would be randomly matched in every period, but that no pair of bidders would be matched twice in two consecutive periods. Bidders were also informed that, in the dual-auction markets section, each of them would face the same opponent (with the same valuation) in both markets.

Information Feedback. At the end of every period each player obtained the following information. For the single-auction markets with the asymmetric condition, each subject received feedback about her earnings and the competing bidder's valuation and bid. For the single-auction markets with the symmetric condition, additional information about the ex-post ranking of valuations was posted on the computer screens.

[10] Actually, the valuations mean for low-value and high-value bidders were 2.00 and 4.00, respectively, while the standard error was 0.05 for both cases.

For the dual-auction markets, each subject received complete feedback about who the high bidder was in each market, as well as her earnings in each market, what the other bidder's value and bids were in each market, and which market was randomly selected to pay off in. Subjects' identifications were not revealed.

Dry Runs. In order to familiarize subjects with the auction procedures, two practice periods occurred at the beginning of the single-auction markets, and one practice period occurred just before the dual-auction markets began.

Subjects. For each session, subjects were drawn from a wide cross-section of students (mostly undergrads) at the University of Pittsburgh and Carnegie Mellon University. There were 18 subjects for session 1 and 20 subjects for sessions 2, 3 and 4. Subjects participated in only one session. The experiment was run in the economics lab at the University of Pittsburgh using computers.

3 Theoretical Predictions

LRWZ consider the specific situation where a single object is auctioned between two bidders. Both bidders have risk-neutral utility functions and independently drawn private valuations. These valuations are ex-ante identically distributed according to a distribution function, which is common knowledge to bidders. Each bidder knows whether she has the higher or the lower valuation but does *not* know her opponent's exact valuation. Under the assumption that the underlying distribution of valuations is uniform with the support $[0, 6]$, both agents maximization problems can be reduced to the following differential equation system by the first order necessary conditions:

$$l'(b)\,(h(b) - b) = l(b)$$

$$h'(b)\,(l(b) - b) = h(b) - l(b)$$

$$h(0) = l(0) = 0$$

$$\exists b^* \in [0, 6] \text{ such that } h(b^*) = l(b^*) = 6$$

where $l(\cdot)$ and $h(\cdot)$ are the inverse bid functions of b_L and b_H, respectively. By l'Hôpital's Rule, $h'(0) = 2$ and $l'(0) = \frac{4}{3}$. For a numerical approximation of the above system of equations with two boundary conditions, I follow a general method implemented by Elbittar and Ünver (2001).[11]

The bidding response for the symmetric and independent private-values first-price auction model, b_S, can be derived analytically. For the case of n risk-neutral bidders with a uniform distribution, the unique symmetric Nash Equilibrium bid function is $b_S(v) = \frac{(n-1)}{n}v$ (Vickrey, 1961).

The equilibrium bidding response for the low-value bidder and for the high-value bidder are represented in Figure 1 by b_L and b_H, respectively. In the same graphic, the equilibrium bidding response for the symmetric and independent private-values model when $n = 2$ is represented by b_S.[12]

3.1 Comparative-Statics Predictions

The comparative-statics predictions of these two auction models define the theoretical benchmark for measuring the possible impact of valuation ranking revelation on bidding behavior. These predictions also provide us with precise statements about the changes in the seller's revenue and the proportion of optimal allocations. First, the high-value bidder should bid less aggressively than the low-value bidder for any given value ($b_L(v) > b_H(v)$, $\forall v \in (0, 6)$). Since the low-value bidder can obtain the item with positive probability, the proportion of efficient allocations should decrease. Second, for a number of different distributions, including the case of uniform distribution studied here, revealing the ranking should induce the low-value bidder to bid strictly higher than when this information is not known ($b_L(v) > b_S(v)$, $\forall v \in (0, 6]$). It should also induce the high-value bidder to bid the same for valuations below or equal to

[11] The intuition behind the second boundary condition is the following: If the bids are not equal to each other at equilibrium, when the valuations are equal to the upper bound of the distribution, the owner of the higher bid can lower her bid slightly and still win the object.

[12] The discreteness of the strategy space introduced in the experimental design should not have an effect on the equilibrium bid functions and the resulting predictions (Athey, 2001).

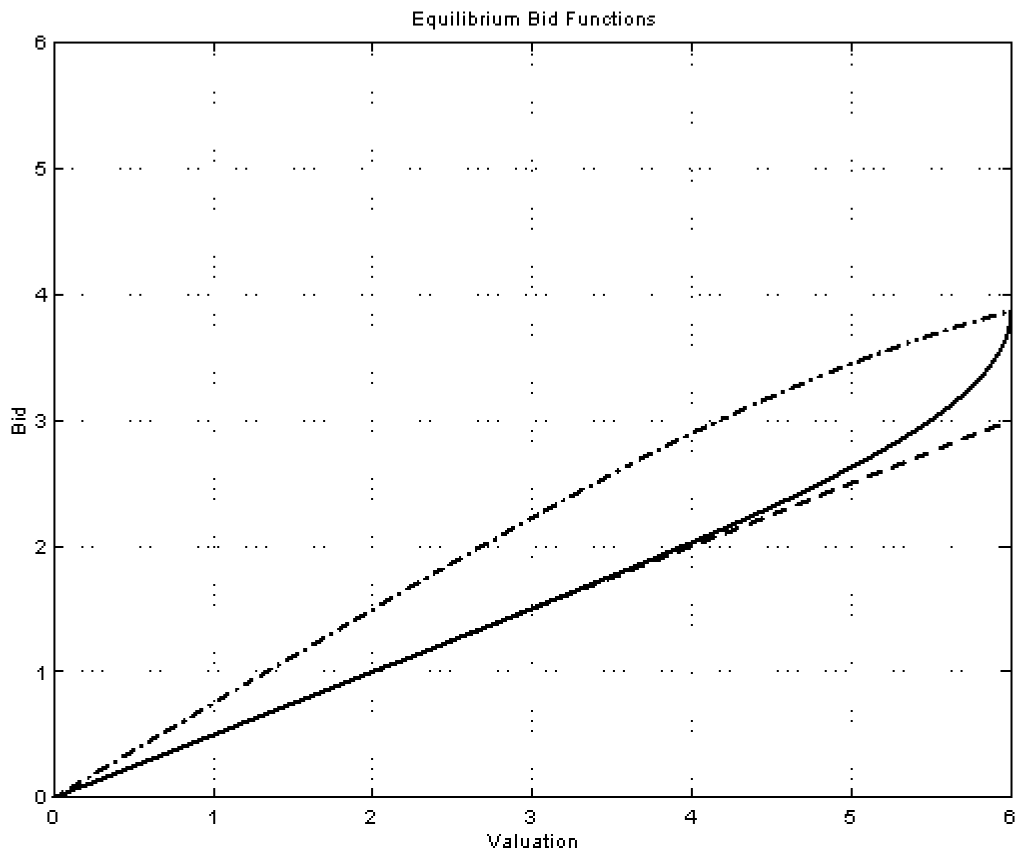

Figure 1: Equilibrium Bid Functions: $b_L(v)$ [$-\cdot$], $b_H(v)$ [—] and $b_S(v)$ [$- -$]

Table 2: Numerical Results from the Equilibrium Bid Functions

Auction Model	Sellers Revenue	Regular Buyer		High-Value		Low-Value		Proportion	
		Payoff	Pr[Win]	Payoff	Pr[Win]	Payoff	Pr[Win]	of POA[a]	ME[b]
Symmetric*	2.000	1.000	0.500	(–)	(–)	(–)	(–)	1.000	1.000
Asymmetric	2.219	(–)	(–)	1.361	0.710	0.263	0.290	0.710	0.957

Note: Valuations are drawn from the uniform interval [0,6]. Mean is computed by Monte Carlo using 10,000 samples of 1,000 drawings.

*: Calculations are made analytically.

[a]: Pareto-Optimal Allocations: POA

[b]: Mean Efficiency: $ME = \frac{v_{win}}{v_h}$

4 and strictly higher for valuations above 4 ($b_H(v) = b_S(v)$, whenever $v \in (0, 4]$ and $b_H(v) > b_S(v)$, whenever $v \in (4, 6]$). Therefore, the seller's expected revenue should increase.[13]

These changes are associated with two components, both producing positive effects on the seller's expected revenue (Maskin and Riley, 2000). One behavioral component is the "sure thing effect": The high-value bidder must take into consideration that the low-value bidder is willing to increase her bid in order to increase her probability of winning the object. Note that the high-value bidder must think more deeply to formulate the right response compared to the low-value bidder. However, if the high-value bidder does not take the low-value bidder's more aggressive bidding into consideration, she could be tempted to bid less in a misguided attempt to take advantage of her higher valuation. The statistical component would be the "weight effect": The low-value bidder must bid more aggressively once she is informed about her position. Therefore, since the low-value bidder is expected to bid more aggressively than the high-value bidder, the higher bid is weighted more in the expected revenue due to the higher probability of winning.

[13]This will always be true for the low-value bidder. However, for the high-value bidder, LRWZ showed that there exist probability distributions for which $b_S(v) > b_H(v)$ for some values of v.

Table 2 summarizes some important theoretical predictions for both auction models using the equilibrium bid functions. The seller's expected revenue, the proportion of Pareto-Optimal Allocations (POA), the proportion of the maximal payoff − or Mean Efficiency (ME) −, and each type of bidder's conditional expected payoff and probability of winning the item are numerically estimated, drawing valuations from the uniform distribution in the interval [0,6]. The values used in these results indicate that the theoretical impact of the valuation ranking revelation would increase the seller's expected revenue from \$2.00 to around \$2.22, with the percentages of POA and of ME decreasing from 100.0% to 71.0% and 95.7%, respectively.[14]

4 Experimental Results

This section compares the experimental results for the dual-auction markets in order to directly measure how revealing the ranking of valuations affects bidding behavior.[15,16]

4.1 Bidding Behavior

Table 3 reports the observed bid factor, $\delta_i^j(v)$, for each type of bidder, and each information condition. The bid factor, or relative difference between subjects' valuations and bids, tells us how much a bidder shaves off her own reserve value when bidding for an item.

LRWZ predict that both types of bidders bid more aggressively under the asymmetric condition than under the symmetric condition ($\delta_i^S(v) > \delta_i^A(v)$, $i =$L,H). Analysis of the actual bid factors in Table 3 indicates that, contrary to expectations,

[14] A level below 100 characterizes unrealized gains from trade.

[15] As we will see in each of the following sections, the results of single-auction markets are consistent with the results for the dual-auction markets and indicate that the dual-market bidding procedure does not to affect the bidding behavior.

[16] The total number of bids from the dual-market is 1524. However, some observations were excluded from the statistical analysis: Either because the subject's bidding was above her own valuation (18 observations), or the subject's valuation was less than two cents, so the corresponding symmetric RNNE was less than a cent (10 observations). The final number of observations over which I concentrate the analysis is 1496.

Table 3: Observed Bid Factors

	Bid Factor* Symmetric Condition			Bid Factor Asymmetric Condition	
Statistics	$\delta_L^S(v)$	$\delta_H^S(v)$	$\delta^S(v)$	$\delta_L^A(v)$	$\delta_H^A(v)$
Median	0.303	0.342	0.326	0.180	0.393
Mean	[0.333]	[0.356]	[0.344]	[0.243]	[0.400]
s.e.	(0.007)	(0.006)	(0.005)	(0.008)	(0.006)

Note: δ^S is the aggregation of δ_L^S and δ_H^S.
*: Bid Factor: $\delta_i^j = \frac{v-b(v)}{v}$, $i =$L,H and $j =$S,A.

$\delta_H^S(v) < \delta_H^A(v)$. For the pooled data, the high-value bidders shave off in average 4.4 percentage points more after information is released, which is about 15 cents per auction. Although bids according to Figure 1 do not begin to increase measurably until valuations exceed 4, bidding reduction happen in the whole range of valuations. Bidders with valuations less than 4 shave off in average 6.4 percentage points in average more after information is released, which is about 16 cents per auction. Meanwhile, bidders with valuations greater than 4 shave off 2.9 percentage points in average, which is about 15 cents per auction. Thus, *high-value bidders tend to bid lower under the asymmetric condition.* By contrast, low-value bidders tend to discount less after information about the ranking of valuations is released. For the pooled data, the same bidders shave off 9.0 percentage points less after information is released, which is about 23 cents per auction. As expected, *low-value bidders tend to bid higher under the asymmetric condition.*[17] Table 4 displays, for every auction period, a one-tailed Matched Pairs Wilcoxon (W_i) test statistic for each group of

[17]For the single-auction markets, the results are similar to those for the dual-auction markets – i.e., low (high) value bidders under the asymmetric condition tend to bid more (less) aggressively than bidders under the symmetric condition. For the pooled data, the low-value bidders shave off 11.1 percentage points less in the asymmetric auctions than in the symmetric auctions. The high-value bidders shave off 4.0 percentage points more in the asymmetric auctions than in the symmetric auctions. Using a one-tailed Rank-Order test statistic, the null hypothesis that the bid factor for the low-value bidders under the symmetric condition is lower than or equal to this factor under the asymmetric condition is rejected for every period. However, for the high-value bidders, the same null hypothesis is not rejected for every period.

Table 4: Matched Pairs Wilcoxon Test Statistic for Comparison of Bid Factors

Auction Period	$^{a}W_L$	W_H	Auction Period	W_L	W_H
11	2.724**	-0.560	21	3.907***	-1.988
12	1.666*	-2.183	22	3.256***	-1.154
13	2.607**	-1.609	23	4.411***	-2.886
14	3.391***	-2.198	24	3.743***	-2.986
15	2.621**	-2.812	25	3.021**	-1.512
16	4.223***	-1.406	26	4.413***	-3.464
17	2.326**	-3.151	27	3.406***	-1.669
18	3.067**	-3.431	28	4.460***	-2.707
19	1.972*	-1.476	29	2.977**	-0.446
20	3.464***	-2.707	30	3.275***	-3.036

[a]: $H_0 : \delta_i^S \leq \delta_i^A$ against $H_1 : \delta_i^S > \delta_i^A$.

Reject H_0 for *: $p < 0.05$, **: $p < 0.01$ or ***: $p < 0.001$

players type i. The null hypothesis that the bid factor for low-value bidders under the symmetric condition is lower than or equal to that under the asymmetric condition is rejected in all auction periods. For high-value bidders, however, the same null hypothesis holds for all auction periods.

Using the pooled data, Table 5 reports how individual subjects alter their bids following the announcement of the valuation ranking. For the upper part of this table, each entry is the percentage of values drawn in a particular range, as in the row heading, for which high-value bidders respond as in the column heading. The

Table 5: Effects of Valuation Ranking Information on Bidders' Bids

	Bids		
Valuation Range	$b_H(v) < b_S(v)$	$b_H(v) = b_S(v)$	$b_H(v) > b_S(v)$
$6 \geq v > 4$	52.5%	19.9%	27.6%
$4 \geq v > 0$	57.9%	21.2%	20.9%
$6 \geq v > 0$	54.9%	20.5%	24.6%
Valuation Range	$b_L(v) < b_S(v)$	$b_L(v) = b_S(v)$	$b_L(v) > b_S(v)$
$6 \geq v > 0$	13.7%	22.2%	64.1%

same information is shown for low-value bidders. As said, LRWZ predict that high-value bidders will raise their bids for valuations above 4 and keep them the same for valuations below or equal to 4. As shown in Table 5, a sizable proportion of high-value bidders (54.9%) decrease their bids over the whole support. Meanwhile, the other 45.1% split their decision between bidding the same and increasing their bids. A similar kind of behavior is observed for valuations above and below four. The same model predicts that low-value bidders will raise their bids. As shown in the same table, low-value bidders increase their bid in 64.1% of the observations, with 22.2% involving no change in bids.[18,19]

In conclusion, *there is an indication of a larger variation in the response of high-value bidders than in that of low-value bidders.*[20] This result could be attributed to the greater complexity of bidding strategies for high-value bidders once information is released.[21] For low-value bidders, the obvious response to such information is to increase their bids in order to increase the probability of obtaining the object. For high-value bidders, the response is less obvious: Once high-value bidders are aware of their strong position, they might either be reluctant to take on the risk of submitting lower bids because of low-value bidders' more aggressive bidding behavior, or be willing to take such a risk in hopes of increasing their average payoff.[22]

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[18]This kind of mixed response for high-value bidders is observed at individual level too. The frequency mode for high-value bidders decreasing their bids is 0.50. For low-value bidders, the frequency mode of increasing their bids is 1.

[19]Kagel *et al.* (1987) found that a large percentage of bidders increase their bids after a public signal was revealed (67%), while a large majority of deviations from this prediction involved no change in bids (between 17% and 27%).

[20]This behavior do not change over time. However, the probability of a high-value (low-value) bidder decreasing (increasing) her bid is positively correlated and significant with respect to a similar action in a previous period when playing the same role.

[21]In this experiment, subjects were asked at the end of each session to write down what their bidding strategies were once they learned their positions as either high-value bidder or low-value bidder. Most of answers were as follow: "If I was a low I raised my bid. While, if I was a high I lowered my bid." Just a few participants indicated an apparently more sophisticated reasoning: "Once I knew I was a high bidder, I usually lowered my bid. Sometimes I highered (sic) it because I knew the other person knew they were a low bidder, so they might also increase their bid."

[22]Previous experimental studies have evaluated simple games where iteration of dominance eliminate one, two or three strategies (see, for example, Beard and Beil, 1994 and Schotter, Weigelt and Wilson, 1994). These studies have found little support for more than one step of deletion of

These strategic considerations however do not seem enough to explain deviations from predicted behavior. In particular, the baseline of the comparative-statics predictions in LRWZ is what risk-neutral, fully rational bidders bid under the symmetric condition. However, a well known pattern of bidding above RNNE in first-price independent private value auctions is replicated here (Kagel, 1995). The overbidding factor, $\lambda_i = \frac{b_i(v) - b_i^*(v)}{v_i}$, $i =$L,H,S, is the relative deviation of the actual bid with respect to the RNNE bid. The mean of the overbidding factor under the symmetric condition is 15.6 percentage points more than the RNNE response, which represents 44 cents. The same overbidding pattern is found for the high-value bidders under the asymmetric condition. The mean of the overbidding factor for high-value bidders is around 8.0 percentage points more than the RNNE response, which represents 27 cents. The proportions of bids above the RNNE are 82.6 and 68.9 percent, respectively.[23] A significant proportion of low-value bidders also bid above the RNNE (67.8 percent). However, the overbidding factor is 1.6 percentage points, which is *not* significantly different from zero.[24] This percentage difference represents 9 cents.[25] In conclusion, *bidders move toward the asymmetric RNNE after information is released*. However, *high-value bidders keep bidding above it*.[26,27]

dominant strategies. Although few subjects violate dominance, most of them seem unwilling to bet heavily that others will obey dominance (Camerer, 2003).

[23] Using a one-tailed binomial test statistic on the observed bids compared with the theoretical bids, the null hypothesis that the proportion of actual bids above the RNNE is lower than or equal to 50 percent is rejected for all auction markets within each information condition for $p < 0.01$.

[24] This is confirmed by a one-tailed Kolmogorov-Smirnov test on observed bids against theoretical bids at every period.

[25] For the single-auction markets, a pattern of overbidding behavior is found under the symmetric condition. Under the asymmetric condition, a similar pattern is found for high-value bidders, while not for low-value bidders.

[26] If we look at the system of differential equations without imposing any restriction in the upper bound of the distribution, the overbidding factor for low-value bidders is 0.1 percentage points, which represents less than 5 cents.

[27] Experimental results also indicate that bidding behavior for the symmetric bidders and for the high-value bidders move respectively toward each of the RNNE over time. However, they seem to converge over time at lower rates, keeping bidders for the last period bounded away from each of the RNNE. In contrast, low-value bidders' bidding behavior do not change over time.

In order to reconcile these experimental results, I consider a modify version of LRWZ's model assuming a constant relative risk-aversion utility function (Cox *et al.*, 1988). Since a ceiling in bidding is not perceived, no restriction is imposed in the upper bound of the distribution. Under the assumptions that the underlying distribution of valuations is uniform and that both agents are risk-averse, both agents maximization problems can be reduced to the following differential equation system by the first order necessary conditions with just one boundary condition:

$$l'(b)\,(h(b) - b) = r_H l(b)$$

$$h'(b)\,(l(b) - b) = r_L(h(b) - l(b))$$

$$h(0) = l(0) = 0$$

where r_H and r_L are the risk aversion coefficients, and $l(\cdot)$ and $h(\cdot)$ are the inverse bid functions of b_L and b_H, respectively. Thus, $b_H(v) = \frac{1}{1+r_H}v$ and $b_L(v) = \frac{(1+r_H+r_L)}{(1+r_H)(1+r_L)}v$. The bidding response for the symmetric model is: $b_S(v) = \frac{1}{1+r_S}v$ (Cox *et al.*, 1988). Therefore, the following linear specification is estimated for each kind of bidder: $b_{kt} = \beta v_{kt}$, where b_{kt} is the player k's bid sent in period t and v_{kt} is the player k's valuation in period t.[28]

Table 6 reports the estimated parameters of each regression, $\widehat{\beta}$, using the pooled data.[29] This table also reports the risk-aversion coefficients, $\widehat{r}$, as well as the standard deviation of the estimates, $\widehat{s}(\cdot)$, for the each of the bid functions. $\widehat{b}_L$ and $\widehat{b}_H$ correspond to the estimated bid functions under the asymmetric condition for low-value and high-value bidders, respectively. Meanwhile, $\widehat{b}_S$ corresponds to the estimated bid function under the symmetric condition. All coefficients are significantly different from zero for a $p < 0.0001$.

These bid functions estimates based on the experimental data indicate that *revealing the ranking of valuations induces low-value bidders to bid more than high-value*

[28] The estimation of a non-linear specification (such as $b_{it} = \beta v_{it}^{\alpha}$) indicates that α was not significantly different from one, showing a strong linearity in the bid functions.

[29] To account for individual agent variability, I used a random effect model. For these estimations, the fixed effect estimates do not differ significantly from the random effect estimates.

Table 6: Estimated Parameters of Bid Functions

Bid Function	Estimates $\widehat{\beta}$	$\widehat{s}(\widehat{\beta})$	$\widehat{r}$	$\widehat{s}(\widehat{r})$
$\widehat{b}_S$	0.601*	0.006	0.663+	0.017
$\widehat{b}_L$	0.779*	0.007	1.060	0.051
$\widehat{b}_H$	0.570*	0.010	0.755+	0.030

*: Reject $H_0 : \beta = 0.0$ for $p < 0.0001$

+: Reject $H_0 : r = 1.0$ for $p < 0.0001$

bidders with the same valuation. This result is consistent with the second of the comparative-statics predictions of LRWZ (i.e., $b_L(v) > b_H(v)$, $\forall v \in (0,6)$).[30] It also supports our previous empirical finding that low-value bidders tend to bid more aggressively under the asymmetric condition and high-value bidders are inclined to bid less aggressively.[31] According to the estimated bid functions, high-value bidders shave off their reserve value approximately 20.9 percentage points higher than low-value bidders. Thus, low-value bidders, on average, bid 63 cents more than high-value bidders. This difference can be broken down into two components. Low-value bidders shave off their reserve value around 17.7 percentage points *less* under the asymmetric condition than under the symmetric one, thus representing an additional bidding of approximately 53 cents. Meanwhile, high-value bidders shave off their reserve value around 3.2 percentage points *more* under the asymmetric condition than under the symmetric one, resulting in a lower bidding of approximately 10 cents.[32]

[30] The null hypothesis that β_H is larger than or equal to β_L is rejected for a $p < 0.0001$.

[31] The null hypothesis that β_S is larger than or equal to β_L is rejected for a $p < 0.0001$. The null hypothesis that β_S is larger than or equal to β_H is not rejected.

[32] Each group of bidders improves the average monetary payoff per auction after information is released. Numerical results indicate that, if high-value bidders were using the bid function previous to the revelation of the ranking, $\widehat{b}_S(v)$, the unconditional average payoff would drop from \$1.70 to \$1.60 per auction (by around 11 cents per auction); meanwhile, the probability of winning the item would increase from 0.74 to 0.78. As result, their average monetary payoff, conditional on winning would fall. Numerical results also indicate that, if low-value bidders were bidding using the bid function previous to the revelation of the ranking, $\widehat{b}_S(v)$, they would suffer a reduction in their average monetary payoff conditional on winning (of around 12 cents per auction).

Table 7: Effect of Ranking Information on Revenue

Statistics	Symmetric Condition p_S	Asymmetric Condition p_A
Mean	2.610	2.572
s.e.	(0.037)	(0.038)
Median	[2.655]	[2.620]
$^a t$	-2.049	
$^b W$	-2.378	

^{a}: Matched Pairs t-test. H_0: $p_A(b) \leq p_S(b)$ against H_1: $p_A(b) > p_S(b)$.
^{b}: Matched Pairs Wilcoxon test. H_0: $p_A(b) \leq p_S(b)$ against H_1: $p_A(b) > p_S(b)$.
*: Reject H_0 against H_1 at $p < 0.05$.

On the other hand, *these changes in bidding behavior are consistent with a reduction on bidders' aversion toward risk.* As shown in Table 6, the risk-aversion coefficients for both kind of bidders increases after information is released.[33] In particular, low-value bidders become closer to risk-neutrality after information about the ranking is released. Therefore, the information revelation about the ranking seems to alleviate the strategic uncertainty associated with the first-price auction, and consequently to induce bidders to change their attitude toward risk.

4.2 Expected Revenue and Efficiency

With the high-value bidders decreasing their bids, the enhanced revenue possibilities of the first-price auction with the ranking of valuations revealed no longer necessarily holds; rather it becomes an empirical question of whether high-value bidders' decreasing bids dominate low-value bidders' increasing bids after information is released.

Table 7 reports the mean, standard error and median of the observed price realization for each information condition. Each average price realization represents

[33] The null hypothesis that r_S is equal to r_L is rejected for a $p < 0.0001$. The null hypothesis that r_S is equal to r_H is rejected for a $p < 0.01$.

the observed seller's expected revenue for a particular information condition j: p_j, j =S,A. According to LRWZ, seller's revenue expected to be higher under the asymmetric condition than under the symmetric condition ($p_A > p_S$).

As noted in the statistics in Table 7, however, the mean of the selling prices under the symmetric condition ($2.61) is slightly higher than under the asymmetric condition ($2.57). This observation is confirmed by a one-tailed Matched Pairs t-test statistic (t), the result of which is displayed at the bottom of the same table. The null hypothesis that the price realization under the symmetric condition is larger than or equal to the price realization under the asymmetric condition could not be rejected, showing that the seller's expected revenue does not always increases after information is released.[34]

In conclusion, *the experimental data do not support the prediction that the seller's revenue increases after information about the ranking is released.*[35] As discussed, this is due to a significant reduction of the high-value bidders' response under the asymmetric condition.[36]

Table 8 reports the following two measures of optimal allocation and economic efficiency: *i*) Pareto-Optimal Allocations (POA), reported as the percentage of objects given to the high-value bidder; and *ii*) Mean Efficiency (ME), reported as the percentage of the maximal payoff that was generated as a result of the auction. Since low-value bidders generally have a positive probability of obtaining the item, the percentage of efficient allocations was expected to be lower under the asymmetric

[34]Testing for every auction period, the null hypothesis that the price realization under the symmetric condition is larger than or equal to the price realization under the asymmetric condition could not be rejected in nineteen out of the twenty auction periods for a $p < 0.05$.

[35]For the single-auction markets, the average price realization under the asymmetric condition is not higher than under the symmetric condition. This observation is confirmed by a one-tailed t-test. The null hypothesis that the price realization under the symmetric condition is larger than or equal to the price realization under the asymmetric condition could not be rejected for every auction period for a $p < 0.05$.

[36]Notice that due to the significant pattern of overbidding behavior, the average revenue for each information condition was significantly higher than the expected revenue at the risk-neutral equilibrium. For the dual-auction markets, the average price realization for the asymmetric (symmetric) condition was $2.57 ($2.61).

Table 8: Effect of Ranking Information on Efficiency

Concepts	Symmetric Condition	Asymmetric Condition
${}^a ME$ ${}^b POA$	97.2 [87.1]	94.8 [74.8]
${}^c Z_{ME}$	2.376*	
${}^d Z_{POA}$	6.134*	

[a]: Mean Efficiency: $ME = \frac{v_{winner}}{v_h} \times 100$.

[b]: Percentage of Pareto-Optimal Allocations: POA.

[c]: Population Proportion test. H_0: $ME_S \leq ME_A$ against H_1: $ME_S(b) > ME_A$.

[d]: Population Proportion test. H_0: $POA_S \leq POA_A$ against H_1: $POA_S(b) > POA_A$.

*: Reject H_0 against H_1 at $p < 0.05$.

condition than under the symmetric condition.

As seen in the calculations displayed in Table 8, the percentage of POA and ME are consistently higher under the symmetric condition than under the asymmetric condition. This result is due to the more aggressive bidding of the low-value bidders and to the less aggressive bidding of the high-value bidders under the asymmetric condition. In the same table, a one-tailed Population Proportion (Z) test statistic for each measure of optimal allocation is reported. The null hypothesis is rejected in favor of the alternative hypothesis that the efficiency under the symmetric condition is higher than under the asymmetric condition.[37]

In conclusion, *the first-price auction is, in the aggregate, more efficient in the absence of information.*[38] This result confirms the prediction about the reduction of the proportion of optimal allocations.

[37]Testing for every auction period, the null hypothesis is rejected in favor of the alternative hypothesis that the efficiency under the symmetric condition is higher than under the asymmetric condition in nineteen of the twenty auction periods for a $p < 0.05$.

[38]A similar result was observed for the single-auction markets. The percentage of POA and ME are consistently higher under the symmetric condition than under the asymmetric condition. These results are consistent with the more aggressive behavior of low-value bidders and the less aggressive behavior of high-value bidders under the asymmetric condition as compared to the symmetric condition.

5 Conclusion

A first-price private-values auction experiment was conducted in which the same two bidders had to bid for a single item in two markets and under two different information conditions. The purpose of this experiment was to examine the impact of information about the ranking of valuations on bidding behavior in first-price private-values auctions.

Experimental results indicate that, after information about the ranking of valuations was released, the two groups of bidders responded differently: As theory predicts, low-value bidders were inclined to bid more aggressively. Contrary to the theory's prediction, high-value bidders tended to submit lower bids. Thus, the probability of low-value bidders winning the item increased. As expected, the proportion of efficient allocations decreased with respect to the first-price auction in the absence of information. Contrary to the predictions, seller's expected revenue did not increase on a regular basis because high-value bidders decreased their bids once information was released.

Experimental result also indicate a larger variation in the response of high-value bidders than in that of low-value bidders. As said, this result could be attributed to the greater complexity of bidding strategies for high-value bidders once information is released: Once aware of their strong position, high-value bidder might either be reluctant to take on the risk of submitting lower bids because of low-value bidders' more aggressive bidding behavior, or be willing to take such a risk in hopes of increasing their average payoff.

Since these strategic considerations are not sufficient to explain deviations from predicted behavior, a modified version of LRWZ's model assuming a constant relative risk-aversion utility function is considered. Changes in bidding behavior due to information revelation about the ranking are consistent with a reduction of bidders' aversion toward the risk involved in the first-price private-value auction.

References

[1] Andreoni, J, Y-K Che, and J. Kim (2005), "Asymmetric Information about Rivals' Types in Standard Auctions: An Experiment," University of Wisconsin, Mimeo.

[2] Athey, S. (2001) "Single Crossing Properties and the Existence of Pure Strategy Equilibria in Games of Incomplete Information," *Econometrica*, 69: 861-889.

[3] Beard, T. R. and R. Beil (1994) "Do people rely on the self-interested maximization of others? An experimental test," *Management Science*, 40, 252-62.

[4] Camerer, C.F. (2003), *Behavioral game Theory: Experiments in Strategic Interaction*, Russel Sage Foundation and Princeton University, New York.

[5] Cox, J. C., V. L. Smith and Walker, J. M. (1988), "Theory and Individual Behavior in First-Price Auctions," *Journal of Risk and Uncertainty*, 1, 61-69.

[6] Elbittar, A.A. and M. U. Ünver (2001), "On Determination of Optimal Reserve Price in Auctions with Common Knowledge about Ranking of Valuations," *Advances in Economic Design*, M. Sertel and S. Koray (eds.), Springer, Berlin.

[7] Fang, H. and S. Morris (2003), "Multidimensional Private Value Auctions" Cowles Foundation Discussion Paper No. 1423, Cowles Foundation for Research in Economics at Yale University.

[8] Güth, W., R. Ivanova-Stenzel and E. Wolfstetter (2004), "Bidding Behavior in Asymmetric Auctions: An Experimental Study," Discussion Paper at Max Planck Institute for Research Into Economic Systems and Humboldt University of Berlin.

[9] Isaac, R. M. and D. James (2000) "Just Who Are You Calling Risk Averse?," *Journal of Risk and Uncertainty* 20, 177-187.

[10] Kagel, J. H. and D. Levin (1986), "The Winner's Curse and Public Information in Common Value Auctions," *American Economic Review*, 76, 894-920.

[11] Kagel, J. H., R. M. Harstad and D. Levin, (1987), "Information Impact and Allocation Rules in Auctions with Affiliated Private Values: A Laboratory Study," *Econometrica*, 55, 1275-1304.

[12] Kagel, J. H. (1995), "Auctions: A Survey of Experimental Research," in *The Handbook of Experimental Economics*, J. Kagel and A. Roth (eds.), Princeton University Press.

[13] Kaplan, T. R. and S. Zamir (2000), "The Strategic Use of Seller Information in Private-Values Auctions," Hebrew University of Jerusalem. Discussion Paper.

[14] Kim, J. and Y-K Che (2004), "Asymmetric Information about Rivals' Types in Standard Auctions," *Games and Economic Behavior*, 46, 383-397.

[15] Klemperer, P. (1999), "Auction Theory: A Guide to Literature," *Journal of Economic Surveys,* 13, 3, 227-286. (Re-printed in *The Current State of Economic Science*, 2, 711-766. S. Dahiya (ed.), 1999.)

[16] Klemperer, P. (2003), *Auctions: Theory and Practice*, Princeton University Press.

[17] Krishna, V. (2002), *Auction Theory*, Academic Press

[18] Landsberger, M., J. Rubinstein, E. Wolfstetter and S. Zamir (2001), "First-Price Auctions when the Ranking of Valuations is Common Knowledge," *Review of Economic Design* 6 3-4, 461-480.

[19] McAdams, D. (2004) "Characterizing Equilibria in Asymmetric First-Price Auctions," MIT, Working Paper.

[20] Maskin, E. and J. Riley (2000), "Asymmetric Auctions," *Review of Economic Studies*, 67, 413-438

[21] Milgrom, P.R. and R. J. Weber (1982), "A Theory of Auctions and Competitive Bidding," *Econometrica*, 50, 1089-1122.

[22] Myerson, R. B. (1981), "Optimal Auction Design," *Mathematics of Operation Research* 6, 58-73.

[23] Pezanis-Christou, P. (2002), "On the Impact of Low-Balling: Experimental Results in Asymmetric Auctions," *International Journal of Game Theory*, 31, 1, 69-89.

[24] Plum, M. (1992) "Characterization and Computation of Nash-Equilibria for Auctions with Incomplete Information," *International Journal of Game Theory*, 20, 4, 393-418.

[25] Riley, J. G., and W. F. Samuelson (1981), "Optimal Auctions," *American Economic Review*, 71, 381-392.

[26] Schotter, A., K. Weigelt and C. Wilson (1994), "A laboratory investigation of multiperson rationality and presentation effects," *Games and Economic Behavior,* 6, 445-68.

[27] Vickrey, W. (1961), "Counterspeculations, auctions, and competitive sealed tender" *Journal of Finance*, 16, 8-37.

[28] Wolfstetter, E. (1996), "Auctions: An Introduction" *Journal of Economic Surveys*, 10, 367-420.

[29] Wolfstetter, E. (1999), *Topics in Microeconomics*, Cambridge University Press.

A Instructions

A.1 Treatment 1

Single-Auction Markets (Asymmetric Condition) This is an experiment in the economics of market decision making. Funding for this research has been provided by the University of Pittsburgh. The instructions are simple, and if you follow them carefully and make good decisions you may earn a CONSIDERABLE AMOUNT OF MONEY which will be PAID TO YOU IN CASH at the end of the experiment.

1. In this experiment we will create a market in which you will act as buyers of a fictitious commodity in a sequence of trading periods. A single unit of the commodity will be auctioned off in each trading period. There will be several trading periods. Your task is to submit written bids for the commodity along with one (1) other buyer.

2. In each trading period you will be assigned a BUYER VALUE for the item. Your BUYER VALUE is the value to you of purchasing the item. The computer will randomly assign BUYER VALUES from the interval \$0 to \$6.00. Any value in this interval has an equally likely chance of being drawn and assigned to one of you as your BUYER VALUE. New BUYER VALUES for all bidders will be generated in each auction period.

3. The person you will be paired with in the market will change from period to period with pairings randomly determined by the computer in each auction period. Pairings have been randomized so that you will never be paired with the same buyer in two consecutive periods. Further, you will not know who you are paired with in any given period. There will be several markets going on simultaneously, so that everyone will be bidding in each trading period.

4. The high bidder obtains the item and earns a profit equal to the difference between his/her BUYER VALUE and the PRICE he/she bid. That is:

   HIGH BIDDER'S PROFIT = HIGH BIDDER'S BUYER VALUE - HIGH BIDDER'S BID

   If you do not make the high bid, you earn zero profits for the trading period.

5. After all bids have been entered the computer will sort them, determine the high bidder and his/her profits, and post your bid and the other buyer's bid, along with the underlying private valuations, on the terminal screens. Since the terminal screens can only display a limited amount of information, we have got pencils and paper available for you to keep supplementary records if you wish.

6. No one may bid less than \$0.00 for the commodity. Bids must be rounded to the nearest penny to be accepted. In case of ties for the high bid, the computer will randomly determine who will earn the item.

7. In each auction period you will know whether you have a higher or lower buyer value than the person you have been paired with for that period. You will not, however,

know how much higher or lower your buyer value is than the person you have been paired with.

8. If you have the low buyer value, the high-value buyer may have a value as small as one cent ($0,01) above your value or as large as the difference between your value and $6.00 (the maximum possible buyer value). For example, if the low buyer value is $3, then the high-value buyer will be between $3.01 and $6.00. In fact any value between your buyer value and the upper bound of buyer values ($6.00) has an equally likely chance to be the buyer value for the high-value buyer you have been paired with for that period.

9. If you have the high buyer value, the low-value buyer may have a value as small as one cent ($0.01) below your buyer value or as much as the difference between your buyer value and $0.00 (the lowest possible buyer value). For example, if the high buyer value is $3, then the low-value buyer will be between $2.99 and $0.00. In fact any value between the lower bound of buyer values ($0.00) and your buyer value has an equally likely chance to be the buyer value for the low-value buyer you have been paired with for that period.

10. Your position as a low or high-value buyer will be determined randomly at the start of the experiment and will remain fixed through the first 10 auction periods played for cash. Things will change after that.

11. You are not to reveal your bid, or profits, nor are you to speak to any other subject while the experiment is in process. This is important to the validity of the study.

12. All bids are binding. So be careful to double check before confirming your bid. Once the bid is confirmed it's binding. The confirmation key allows you to change your bid if it's in error. That's why we have it.

13. Buyers who start out in the low buyer value position will be given an extra $5 at the end of the experiment.

14. There are obvious strategic trade-off in this auction. The higher your bid the more likely you are to be the high bidder, but the lower your profits should you earn the item. Similarly, the lower your bid, the higher your profits should you earn the item, but the less likely you are to be the high bidder. Further, you never want to bid above the value of the item, since if you do so and earn the item you are guaranteed to lose money. Finally, in thinking about bidding, earning the item is of no intrinsic value so that your sole objective should be to maximize your earnings.

- Summary of Instructions:

    1. Each bidder will be randomly assigned a buyer value from the interval 0 to $6.00. This is the value to you from purchasing the item. New random draws will be made in each auction period.

    2. The high bidder in each market earns the item and pays the amount he/she bid.

3. Profits to the High Bidder = High bidder's buyer value less the amount he/she bid. Profits for the other bidder are zero.

4. Prior to bidding you will know if you have the higher or the lower of the buyer values in your market. Your positions as a high or low-value buyer in your market will remain fixed for the first 10 periods played for cash.

5. The computer will randomly pair you with a different bidder in each trading period. Your will never be paired with the same bidder in two consecutive periods.

6. There will be two dry runs followed by 10 periods played for cash, which will then be followed by another 20 periods played for cash under somewhat modified conditions.

7. Your will be paid your total earnings in cash at the end of the experiment.

- Are there any questions?

Information on the Computer Screen

1. Top of the screen: At the top left of the screen, you can see your identification number. Going across this line you next see the auction period and session number. In the second line, you can see the lower and upper bounds of the buyer values.

2. Cash Balances: Your cash balance is in the upper center of the screen. After each auction period, it will change in response to the results for that period.

3. Information Feedback: Below your cash balance, there is the information you will receive for each period. On the left side of the screen, below your cash balance, you will see your buyer value. Below this, there is a space to enter your bid, also a space where the computer will report back your earnings. Below this, with the green background, there is listed your designation as the high or low value bidder (whatever the case may be). Remember your designation as the high or low value bidder in your market will not change for these practice periods or for the first 10 periods played for cash. The information on the right side of the screen below your cash balance is for the person you have been paired with for this auction period and will be filled in after all bids have been collected and sorted.

4. First Practice Period: In entering your bid do not use the dollar sign but be sure to enter the decimal point where you want it. When you have decided what bid you wish to make, type in the bid and hit the enter key. If you make a mistake in typing in your bid, you can change it by hitting the backspace key. After you have entered your bid, you will be asked to confirm it by typing 'y' for yes or 'n' for no and then hitting enter key again. If you type 'n', then you will have the opportunity to change your bid. Be sure to review your bid before typing 'y', once you have hit 'y' you can not change your bid. Please make your bids now. Once everyone has made their bids, the results for your auction market will be reported back to you. Notice that if you earned the item and made positive profits, your cash balance has been updated. Do

you all see this? When we begin the real auction, your cash balance will return to $0.00.

5. Record Sheet: We have also provided a record sheet on which you must write you buyer value and bid for each period. First write down at the top your Player ID number located on the upper left side of the screen. Now, please go ahead and write your buyer value and bid for this auction period in the first row marked practice in the appropriate columns. Last please record your earning from the auction and the bid for the person you have been paired with. Once everyone has done this we will continue. Are there any questions?

6. Privacy: As a remainder, information on your screen is strictly for you alone to look at. You are not to look at anyone else's computer screen. You are not to reveal your buyer value, bid, earning or label identification to any other subject, nor are you to speak to any other subject while the session is in progress. Are there any question?

7. Second Practice Period: We will have one more practice period.

8. Any question? Okay we are ready to play for cash now.

Cross-Over Instructions: From Single-Auction Markets to Dual-Auction Markets

1. From now on you will be bidding in two auctions markets at once. Further, you position as the high or low-value bidder in your market will vary randomly between auction periods as a function of your buyer value and the buyer value of the other bidder in your market. That is, from now on, on average, half the time you will be the high-value bidder and half the time you will be the low-value bidder in your market. This just depends on the buyer value you draw and the buyer value the other bidder in your market draws.

2. After receiving your buyer values, you will first be asked to bid in a market not knowing if you have the higher or lower buyer value in your pair. After all bids have been collected and sorted, but before the results have been reported back to you, you will be asked to bid again. In bidding for the second time, your buyer values will remain the same, as will be the person you have been paired with for this market period. Only now you will know if you have the higher or the lower of the two buyer values in your market. As before, you will not know how much higher or lower your buyer value is than the person you have been paired with.

3. After this second set of bids have been entered and sorted, the computer will randomly pick one of the two markets to pay off in.

4. As before, you will be paired with a different bidder in each market period. Also, as before, buyer values will be randomly drawn from the interval $(0.00,6.00) with any value in this interval equally likely.

- Are there any questions?

- A Practice Period: Before playing for cash we will have one dry run with this dual-market bidding. Your cash balance will return to their original values after this dry run.
- Any question? Okay, we are going to play for cash now for another 20 auction periods.

A.2 Treatment 2

Single-Auction Markets (Symmetric Condition) This is an experiment in the economics of market decision making. Funding for this research has been provided by the University of Pittsburgh. The instructions are simple, and if you follow them carefully and make good decisions you may earn a CONSIDERABLE AMOUNT OF MONEY which will be PAID TO YOU IN CASH at the end of the experiment.

1. In this experiment we will create a market in which you will act as buyers of a fictitious commodity in a sequence of trading periods. A single unit of the commodity will be auctioned off in each trading period. There will be several trading periods. Your task is to submit written bids for the commodity along with one (1) other buyer.
2. In each trading period you will be assigned a BUYER VALUE for the item. Your BUYER VALUE is the value to you of purchasing the item. The computer will randomly assign BUYER VALUES from the interval \$0 to \$6.00. Any value in this interval has an equally likely chance of being drawn and assigned to one of you as your BUYER VALUE. New BUYER VALUES for all bidders will be generated in each auction period. Since buyer values are randomly drawn in each auction period, a high or low-value in one period has no effect on whether or not you will have a high or low-value in the next trading period.
3. The person you will be paired with in the market will change from period to period with pairings randomly determined by the computer in each auction period. Pairings have been randomized so that you will never be paired with the same buyer in two consecutive periods. Further, you will not know who you are paired with in any given period. There will be several markets going on simultaneously, so that everyone will be bidding in each trading period.
4. The high bidder obtains the item and earns a profit equal to the difference between his/her BUYER VALUE and the PRICE he/she bid. That is:

   HIGH BIDDER'S PROFIT = HIGH BIDDER'S BUYER VALUE - HIGH BIDDER'S BID

   If you do not make the high bid, you earn zero profits for the trading period.
5. After all bids have been entered the computer will sort them, determine the high bidder and his/her profits, and post your bid and the other buyer's bid, along with the underlying private valuations, on the terminal screens. Since the terminal screens can only display a limited amount of information, we have got pencils and paper available for you to keep supplementary records if you wish.

6. No one may bid less than \$0.00 for the commodity. Bids must be rounded to the nearest penny to be accepted. In case of ties for the high bid, the computer will randomly determine who will earn the item.

7. You are not to reveal your bid, or profits, nor are you to speak to any other subject while the experiment is in process. This is important to the validity of the study.

8. All bids are binding. So be careful to double check before confirming your bid. Once the bid is confirmed it's binding. The confirmation key allows you to change your bid if it's in error. That's why we have it.

9. There are obvious strategic trade-off in this auction. The higher your bid the more likely you are to be the high bidder, but the lower your profits should you earn the item. Similarly, the lower your bid, the higher your profits should you earn the item, but the less likely you are to be the high bidder. Further, you never want to bid above the value of the item, since if you do so and earn the item you are guaranteed to lose money. Finally, in thinking about bidding, earning the item is of no intrinsic value so that your sole objective should be to maximize your earnings.

- Summary of Instructions:

    1. Each bidder will be randomly assigned a buyer value from the interval 0 to \$6.00. This is the value to you from purchasing the item. New random draws will be made in each auction period.

    2. The high bidder in each market earns the item and pays the amount he/she bid.

    3. Profits to the High Bidder = High bidder's buyer value less the amount he/she bid. Profits for the other bidder are zero.

    4. The computer will randomly pair you with a different bidder in each trading period. Your will never be paired with the same bidder in two consecutive periods.

    5. There will be two dry runs followed by 10 periods played for cash, which will then be followed by another 20 periods played for cash under somewhat modified conditions.

    6. Your will be paid your total earnings in cash at the end of the experiment.

- Are there any questions?

Information on the Computer Screen The changes with respect to the previous treatment are the following:

1. Information Feedback: Below your cash balance, there is the information you will receive for each period. On the left side of the screen, below your cash balance, you will see your buyer value. Below this, there is a space to enter your bid, also a space where the computer will report back your earnings. The information on the right side of the screen below your cash balance is for the person you have been paired with for this auction period and will be filled in after all bids have been collected and sorted.

2. First Practice Period: In entering your bid do not use the dollar sign but be sure to enter the decimal point where you want it. When you have decided what bid you wish to make, type in the bid and hit the enter key. If you make a mistake in typing in your bid, you can change it by hitting the backspace key. After you have entered your bid, you will be asked to confirm it by typing 'y' for yes or 'n' for no and then hitting enter key again. If you type 'n', then you will have the opportunity to change your bid. Be sure to review your bid before typing 'y', once you have hit 'y' you can not change your bid. Please make your bids now. Once everyone has made their bids, the results for your auction market will be reported back to you. The computer will also report back if you had the higher or lower buyer value than the other bidder in your market. Notice that if you earned the item and made positive profits, your cash balance has been updated. Do you all see this? When we begin the real auction, your cash balance will return to $0.00.

Cross-Over Instructions: From Single-Auction Markets to Dual-Auction Markets

1. From now on you will be bidding in two auctions markets at once. First, you will be bidding just as before. However, after all bids have been collected and sorted, but before the results have been reported back to you, you will be asked to bid again. In bidding for the second time your buyer values will remain the same, as will be the person you have paired with for this market period. Only now you will be informed prior to your bid if you have the higher or the lower of the two buyer values in your market. You will not, however, know how much higher or lower your buyer value is than the person you have been paired with.

2. If you have the low buyer value, the high-value buyer may have a value as small as one cent ($0,01) above your value or as large as the difference between your value and $6.00 (the maximum possible buyer value). For example, if the low buyer value is $3, then the high-value buyer will be between $3.01 and $6.00. In fact any value between your buyer value and the upper bound of buyer values ($6.00) has an equally likely chance to be the buyer value for the high-value buyer you have been paired with for that period.

3. If you have the high buyer value, the low-value buyer may have a value as small as one cent ($0.01) below your buyer value or as much as the difference between your buyer value and $0.00 (the lowest possible buyer value). For example, if the high buyer value is $3, then the low-value buyer will be between $2.99 and $0.00. In fact

any value between the lower bound of buyer values ($0.00) and your buyer value has an equally likely chance to be the buyer value for the low-value buyer you have been paired with for that period.

4. After this second set of bids have been entered and sorted, the computer will randomly pick one of the two markets to pay off in.

5. As before, you will be paired with a different bidder in each market period. Also, as before, buyer values will be randomly drawn from the interval $(0.00,6.00) with any value in this interval equally likely.

- Are there any questions?

- A Practice Period: Before playing for cash we will have one dry run with this dual-market bidding. Your cash balance will return to their original values after this dry run.

- Any question? Okay, we are going to play for cash now for another 20 auction periods.