The effect of bidding information in ascending auctions*

Mun Chui[a]
School of Economics and Smith's Center for Experimental Economics Research, Shanghai Jiao Tong University, 535 Fa Hua Zhen Road, Shanghai 200052, China
Email: mcui@sjtu.edu.cn

David Porter, Stephen Rassenti, Vernon Smith
Economic Science Institute, Chapman University, One University Drive, Orange, CA 92866, USA
Email: dporter@chapman.edu (David Porter), rassenti@chapman.edu (Stephen Rassenti), vsmith@chapman.edu (Vernon Smith)

Abstract

We study the effect of the drop out and reenter information in an environment where bidders' values involve both private and common value components. We find that (1) providing bidding information does not have a significant effect on expected revenue and expected efficiency. (2) The effect of information on winner's expected profit depends on the range of uncertainty of the common value component and the level of Nash profit prediction, which the auctioneer has no a priori knowledge. In our environment, where bidders have a private component to their value and the auction takes place in ascending clock format, (3) bidders do not suffer from the winner's curse when information is not provided. (4) Information substantially increases the variability of revenue and winner's profit when the range of uncertainty of the common value component is large. (5) Bidders' response to information depends on the range of uncertainty.

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[a]Corresponding Author. Tel: 86-021-52302536. Fax: 86-021-52301352.

1. Introduction

In an ascending price auction, when values are interdependent, bidders can use bidding information concerning when other bidders drop out of the auction to form an estimate of their own value for the object. This suggests that the prices at which others drop out might become an integral part of a bidder's decision process in such an auction. The concern for controlling bidding information in auctions arises from the dilemma that, on one hand, bidding information can assist bidders in estimating the value of the auctioned items and increase auction revenue, but, on the other hand, bidding information can facilitate and sustain collusive outcomes, especially in multi-object environment. Because of these opposing effects on auction performance the problem of controlling bidding information is a two-edged sword (Cramton, 1998). In fact, this was exactly the major concern when the Federal Communications Commission (FCC) was considering whether to disclose bidding information.

"*The FCC could have hindered collusion by revealing only the bid amounts between rounds, and not the bidders' identities. It chose not to do this in the broadband auction and instead gave out full details of each round's bidding, because it judged that the risk of collusion was outweighed by benefits of the information*."
-- McAfee and McMillian, "Analyzing the Airwaves Auction", 1996.

However, is information really beneficial to bidders in ascending auctions? This is the major question to be addressed in this paper.

The major support for providing bidding information in auctions comes from the theoretical result that when bidders' signals concerning the value of the object are affiliated, English auctions generate more revenue than sealed bid auctions (Milgrom and Weber, 1982). However, laboratory evidence does not fully confirm this result. Levin et al. (1996) show that when bidders are

inexperienced, English auctions generate less revenue than first price sealed bid auctions; winning bidders earn more in English auctions. English auctions generate more revenue for sellers only when bidders become experienced. Under a specific environment[1], Kirchkamp and Moldovanu (2004) show theoretically and with experiments that English auctions generate higher efficiency, the same revenue for the seller and higher profit for the winning bidder, when compared to second price sealed bid auctions.

Goeree and Offerman (2003) show that, under the assumption that bidders' signals are independent, expected efficiency, revenue and winner's profit are the same under both English and sealed bid auctions in an environment with both private and common value components.[2] In other words, this model provides theoretical support for the proposition that bidding information is *not* beneficial to auction performance. If the proposition turns out to be supported by the experimental results, it provides the evidence for auction designers to reevaluate the impression that "information is beneficial" when the current environment is under consideration in practice. Otherwise, depending on the results, further research under different environments should be carried out. To understand the effect of bidding information in ascending auctions, we conduct experiments that examine this theory's validity.

We consider an English 'clock' auction with reentry (EWR). At the beginning of the auction, price is set at a very low level. The auctioneer continuously raises the price and bidders simply determine whether to remain active (continue to demand) or drop out. The drop out decision is revocable meaning that a bidder can later choose to demand at a higher price even though he "dropped out" at a lower price. (In the treatment with full information the drop out and reenter

[1] In their setting, there are three bidders, each bidder's value depends on his own signal plus a parameter times the signal of his right hand side bidder (imagine the bidders are sitting at a round table).
[2] The properties of auction models with both private and common value components have also been discussed by Dasgupta and Maskin (2000), Jehiel and Moldovanu (2001), Maskin (1992), Jackson (2005), Mikoucheva and Sonin (2004) and Pesendorfer and Swinkels (2000).

decisions would be announced to all bidders.) The auctioneer awards the item to the last bidder who remains active in the auction. In the traditional English clock auction model, where bidders' decisions are irrevocable (Milgrom and Weber, 1982), only bidders remaining active in the auction can take advantage of the information revealed by previous drop out bidders. However, EWR allows bidders who have already dropped out to take advantage of the information revealed by bidders who drop out later, therefore, all bidding information can be utilized by every bidder in the auction.

We examine bidding information as a treatment effect in the EWR[3] because a lack of testable empirical evidence leaves auctioneers uncertain about how much information to provide bidders. The experimental design, which will be discussed in detail later, consists of one treatment where bidders have no knowledge about how many and which bidders remain active (no information case), and another treatment where bidders know the exact identity of the active bidders at each price (full information case). Our results show that providing bidding information has no significant effect on expected revenue or expected efficiency. However, providing bidding information increases the variability of revenue and winner's profit when the uncertainty level of the common value component is high. Information can have a significant effect on winners' profits depending on the level of common value uncertainty and Nash profit prediction.

This paper is organized as follows. Section 2 discusses the economic environment and auction institution implemented. Section 3 provides the theoretical predictions and hypotheses to be tested. Section 4 discusses the experimental design and procedures. Section 5 provides the results. Section 6 concludes.

[3] Bikhchandani and Riley (1991) classify open ascending auctions with different levels of information revealed and possibility of reentry into six categories. They show that when bidding information is totally concealed, the strategies in auctions with and without reentry allowed are isomorphic for more than two bidders.

2. The Environment and Auction Design

We consider an auction which allocates a single object among n bidders. Bidders' values for the object are comprised of both common and private value components. Each bidder has a common value signal c_i (i indexes the bidder) and a private value p_i. The common value, C, which is unknown to bidders at the time of bidding, is the arithmetic mean of the n common value signals ($C = \frac{1}{n}\sum_{i=1}^{n} c_i$). The actual value v_i of the object for each bidder is the common value plus the bidder's private value, i.e., $v_i = C + p_i$. Bidders who are not allocated the object earn zero profit while the bidder who is allocated the object (winner) earns v_i minus the auction price.

The object is auctioned-off using an ascending clock auction. A clock, which indicates the current price of the auctioned object, is initialized at a low price at the beginning of the auction and is increased through a series of fixed size price increments. At each increment, bidders indicate whether they are willing to buy (demand) the object at the current price. The clock rises to the next increment level whenever the number of demanders is greater than 1.

Bidders have two options. One is to indicate that they are willing to buy and the other one is to indicate that they are not willing to buy at the current price. Bidders can switch between these two options as long as the auction has not ended. This paper will use the terms 'drop out' and 'exit' interchangeably to describe the action of not demanding and use the terms 'come back' and 'reenter' interchangeably to describe the action of demanding again after having exited.

The auction stops when the number of demanders is less than or equal to 1. In the case where the number of demanders is equal to 1, the object is allocated to the remaining active bidder at the current price (i.e. the price where the last competing bidder dropped out). In the case where

demand is zero (i.e. more than one bidder dropped out at the current price), the winner will be randomly selected from one of the bidders who dropped out at the current price and he will pay the previous price.

3. Predictions and Hypotheses

For symmetric equilibria, without loss of generality, we can focus on any one bidder, say bidder 1's bidding strategy. Bidder 1's type is defined as $t_1 = \frac{c_1}{n} + p_1$.[4] In the second price sealed bid auction, when bidders are uncertain about their true values, the equilibrium bidding strategy suggests that a bidder should submit a bid equal to his expected value of the auctioned item assuming that his type equals the maximum of all other bidders' types. If the bidder wins the auction and has to pay what he bids, he can infer that the highest type of all other bidders is the same as his, which is exactly what he expects when forming his bidding strategy (see (Krishna, 2002), p.88). Let $y_1 = \max_{i=2,\ldots,n}\{\frac{c_i}{n} + p_i\}$ denote the highest type of the *n-1* other bidders. Then bidder 1's risk neutral strategy is to bid:

$$B(x)=E(C+p_1|t_1=x, y_1=x), \qquad (1)$$

where E is the expected value operator. If each risk neutral bidder follows the strategy defined in (1), this will be a Nash equilibrium of the second-price auction.[5]

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[4] Type t_1 is a variable that summarizes the private value signal and common value signal for bidder 1. Goeree and Offerman (2002, 2003) call it surplus and use *s* as the notation. Note that bidder 1's true surplus is $C+p_1$, which is equal to $\frac{c_1}{n} + p_1 + \sum_{i\neq 1}\frac{c_i}{n}$. Since bidder 1's private information is c_1 and p_1, the first order condition for profit maximization, the actual private information that determines bidder 1's profit is $t_1 = \frac{c_1}{n} + p_1$.

[5] Derivation can be found in Goeree and Offerman (2003).

For the ascending clock auction with reentry and with no bidding information, the Nash equilibrium bid function will be the same as that in (1). The intuition is simple. Suppose all other bidders follow the equilibrium bidding strategy in (1). During the auction and before the price reaches *B*, bidder 1 is unable to infer the types of any other bidders because he does not know at what prices they dropped out of the auction. If he tries to infer the type of others by temporarily dropping out before reaching *B*, there are two possibilities. Either the auction stops immediately, or the clock price will continue to rise. If it stops, bidder 1 may have lost to someone with a lower type than himself and forgone some profit because he dropped out before *B*. If it rises, he has learned nothing. If bidder 1 drops out at *B* and sees that the price is still moving up, he can infer that there are at least two bidders with types higher than himself. Since winning the auction with the type that is not the highest is not expected to be profitable[6], bidder 1 should not reenter the auction. By the same token, bidder 1 should not drop out later than *B*.

Thus, without bidding information, the ascending clock auction and the second price auction are isomorphic[7].

In the ascending clock auction, when bidders are uncertain about their true values, the equilibrium bidding strategy is recursively defined. When no bidder has dropped-out, a bidder keeps demanding the item until the price reaches his expected value assuming that his type equals all other *n-1* bidders' types. This is to assure that if all bidders drop out at the same price, the bidder who is allocated the item pays the price equal to what he expects when forming his bidding strategy. After the first bidder drops out, other bidders infer his type from his drop out price and reformulate their expected value of the item using this new piece of information and assuming that

[6] The expected profit of winner is t_1-t_2, where t_1 is the highest type and t_2 is the second highest type.

[7] Bikhchandani and Riley (1991) prove the same result in their common value model. Similar to us, they use the mean of all bidders' common value signals as the value for all bidders. The differences are that they do not consider a private value component and the bidders' signals are strictly affiliated.

their types equal all other *n-2* bidders' types. This strategy is recursively defined for the remaining *n-1* bidders (see (Krishna, 2002), p.91).

Thus, the symmetric Nash equilibrium bidding strategy for the ascending clock auction with bid information is given by:

$$B_0(x) = E(c_1 + p_1 \mid t_1 = x, y_1 = x, ..., y_{n-1} = x),$$
$$B_k(x; b_1, ..., b_k) = \frac{n-k}{n} E(c_1 \mid t_1 = x, y_1 = x, ..., y_{n-k-1} = x)$$
$$+ E(p_1 \mid t_1 = x, y_1 = x, ..., y_{n-k-1} = x) + \frac{1}{n}\sum_{i=0}^{k-1} E[c_1 \mid B_i(t_1; b_1, ..., b_i) = b_{i+1}] \qquad (2)$$

where $B_k(x; b_1, ..., b_k)$ is the highest price bidder 1 is willing to pay in the auction given his type $t_1=x$ and that k bidders have dropped out at the prices $b_1,\ldots,b_k$.[8]

When bidding information is provided in the ascending clock auction with reentry, nothing changes. Whenever a bidder exits (not demanding the object at the current price), other bidders infer his type from his exiting price. Whenever the bidder reenters into the auction, other bidders can change their inference of the reentering bidder's type as if he has never exited before. Using equation (2), bidders change their bidding strategy of $B_k(x;b_1,\ldots b_k)$ to $B_{k-1}(x;b_1,\ldots,b_{i-1},b_{i+1},\ldots b_k)$. Therefore, bidders have no way to affect other bidders' valuations by exiting then reentering the auction.[9]

When considering whether a bidder would deviate from the equilibrium strategy, it is essential to consider whether it would be profitable to do so. Under the current auction setting, bidders cannot benefit from exiting without reentry because the profit of not winning is 0. Since exiting with reentry does not affect the valuations of other bidders, exiting earlier is not profitable. How about

[8] Derivation can be found in Goeree and Offerman (2003).
[9] Izmalkov (2003) shows that bidders are unable to earn additional profit by temporary exit in a revocable exit auction.

exiting later? A bidder can potentially earn a positive profit only by delaying his exit until he becomes the winner of the auction. Note that each B_k is strictly increasing in x. This implies that winner has the highest type. Suppose t_2 is the highest type. Bidder 1, who has t_1, delays his exit and becomes the winner. Suppose all bidders except bidder 1 follow the bidding strategy in equation (2). Upon winning, bidder 1's expected profit is $t_1 + 1/n\sum_{i=1}^{n-1} E(c \mid t = t_{i+1}) - B_{n-2}(t_2)$ where $B_{n-2}(t_2)$ can be written as

$(1/n)\sum_{i=2}^{n-1} E(c \mid t = t_{i+1}) + (2/n)E(c \mid t = t_2) + E(p \mid t = t_2)$. Therefore, bidder 1's expected profit is $t_1 + (1/n)E(c \mid t = t_2) - (2/n)E(c \mid t = t_2) + E(p \mid t = t_2) = t_1 - t_2$. Since t_2 is the highest type, bidder 1's expected profit is negative.

Suppose bidder 1 bids according to equation (2) and determines to exit at price level B. If bidder 1 drops out at B and sees that the price is still moving up, the equilibrium bidding strategy suggests that he should not reenter the auction because the outcome implies that he is not holding the highest type. In this equilibrium, the expected profit from winning, if a bidder does not have the highest type, is negative.[10]

Therefore, the strategy in the ascending clock auction with bidding information is the same as the strategy in the English auction.

Goeree and Offerman (2003) prove that the expected efficiency, winner's profit and seller's revenue are the same under second price sealed bid auction and English auction in the common/private value environment we have posed. We demonstrated the intuition that, although provided with the reentry option, bidders should not utilize the reentry feature. When bidding information is provided, the equilibrium bidding strategy follows the one in English auction and

[10] Harstad and Rothkopf (2000) use similar argument for the equivalence of equilibrium bidding strategy under "Alternating Recognition" English auction model with and without reentry.

when bidding information is not provided, the equilibrium bidding strategy follows the one in second price sealed bid auction. Putting these conditions together we form the following hypotheses:

H_1: $\text{Revenue}_{\text{NoInfo}} = \text{Revenue}_{\text{Info}} = \text{Revenue}_{\text{Nash}}$

H_2: Winner's $\text{profit}_{\text{NoInfo}}$ = Winner's $\text{profit}_{\text{Info}}$ = Winner's $\text{profit}_{\text{Nash}}$

H_3: $\text{Efficiency}_{\text{NoInfo}} = \text{Efficiency}_{\text{Info}} = \text{Efficiency}_{\text{Nash}}$

H_4: Number of $\text{Reentries}_{\text{NoInfo}}$ = Number of $\text{Reentries}_{\text{Info}} = 0$

Testing the first three hypotheses answers questions concerning whether bidding information is beneficial in ascending auctions and whether theory well predicts those outcomes. Testing the last hypothesis allows us to understand whether the bidders' behavior closely follows the theoretical prediction that reentry has no strategic value.

When a bidder fails to incorporate the negative information that others dropping out implies, he could fall prey into the winner's curse which cannot be accounted for in the equilibrium bidding strategy because the latter assumes fully rational behavior. Previous laboratory results suggest that bidders fall prey to the winner's curse more seriously when bidding information is not provided: we will see whether this phenomenon continues in our environment.

4. Experimental Design

The motivation for this research is to study the effect of disclosing bidding information in an auction environment where bidders are uncertain about the value of the auctioned object. Based on the auction format discussed in section 2, two treatments regarding information are conducted. In one information treatment, bidders are only informed about the current clock price of the object

being auctioned (No bid Information is provided (NI)). In other words, bidders only know whether there is excess demand or not at the previous price level. In the second information treatment bidders are provided with the identity of bidders who demanded the object at each clock price (Full bidder Information (FI)). These two information treatments are tested against two levels of the common value signal range, creating less or more uncertainty in the common value portion of the item's value. In one treatment, the common value signals are uniformly distributed between 475 and 525, that is c_i ~U[475,525] (small range (SR)). In the other treatment, the common value signals are uniformly distributed between 425 and 575, that is c_i ~U[425,575] (large range (LR)). Since the Nash predicted earnings are different under different common value signal ranges, the exchange rates were chosen[11] such that the expected earnings in US dollars were the same under the different ranges. The treatments are summarized in table 1.

Each session used 4 subjects (n=4) who participated in a sequence of 20 auctions. The same set of private value signals were used for the nth auction in all sessions. Private values were uniformly distributed from 475 to 525, i.e., p_i ~U[475, 525], which is the same as the distribution of common value signals in the SR treatment.

[Table 1 here]

The common value signals in SR and LR were correlated through a mean preserving algorithm. For each auction in the SR sessions, a set of common value signals was drawn. Let c_{sr} represent a common value signal in the small range and let c_{lr} represent the corresponding common value signal in the large range. c_{sr} is transformed to c_{lr} using this formula c_{lr}=(c_{sr}-500)x((575-425)/(525-475))+500. This is to ensure that the difference between each signal

[11] The currencies used in the experiment are e-dollars. In the SR treatment, e-dollars are converted to US dollar at the rate of 2 e-dollars=1 US dollar. In the LR treatment, e-dollars are converted to US dollar at the rate of 3 e-dollars=1 US dollar.

and the means of SR and LR relative to their ranges are identical and prevent inconsistent results due to different random draws in different ranges.

All private and common value signals were rounded to the nearest integer. The sets of common value signals under SR/NI and SR/FI are the same and the set of common value signals under LR/NI and LR/FI are the same.

Subjects were recruited from the student population of George Mason University. When each session was ready to begin, each subject was assigned a seat at a visually isolated computer terminal from which they made their decisions during the session. Each subject was given a set of instructions and scratch paper. Instructions were read aloud by the session monitor[12]. After reading the instructions, subjects participated as bidders in two trial auctions (no earnings). This was to familiarize them with the auction software.

At the beginning of each session, subjects were endowed with either 50 (in SR) or 75 (in LR) e-dollars as their initial bank balance. Each subject's earnings from each subsequent auction (either positive or negative) were added to or subtracted from his bank balance. If any subject's bank balance reached zero (bankruptcy), the monitor ended the session. The subject who went bankrupt was paid the $7 USD show-up fee. Each subject who did not go bankrupt was paid the $7 USD show-up fee plus the cash equivalent of his bank balance.

In each auction, each subject was randomly allocated a bidder ID (1, 2, 3 or 4) to reduce any repeated game effects. At the beginning of each auction, bidders were privately told their private and common value signals. Then, the clock started to rise at a rate of 1 e-dollar per second. Bidders were provided the identities of all bidders demanding at each price under the FI treatment. Bidders

[12] The instructions for the SR/FI treatment is in the Appendix.

made their decisions using two buttons. One button indicated their willingness to buy at the current price and the other indicated their willingness not to buy at the current price. (A screen shot of the bidders' computer interface is provided in Appendix)[13]. The bidders were assumed to carry over their decisions from one price level to the next. At the end of each auction, bidders were told the common value of the object, and to whom it was allocated at the final price. Bidders were informed of only their own profit earned in each auction and not the profits of others. There were 20 auctions held in each session but bidders were not informed of this until the final auction ended.

Every auction each bidder was given a piece of information called the "**Will Lose Point**" that showed the bidder his highest possible value for the auction object. It was simply calculated as a function of each bidder's own private information and the assumption that all other bidders had received the highest possible common value signal (525 for SR treatments and 575 for LR treatments). If the bidder bought at a price beyond this point, he would make a loss for sure, though it was likely that he would make a loss at prices significantly lower than this point depending on the common value draws of the other bidders.

5. Results

A total of 18 sessions were run (5 sessions for each SR treatment and 4 sessions for each LR treatment[14]). In only 3 sessions out of 18 was a bankruptcy recorded. One bankruptcy occurred at the 19th auction during a session of the SR/FI treatment. Another occurred at the 4th auction during a session of the LR/NI treatment. And the third occurred at the 15th auction during a session of the

[13] We used the term "group value" to refer to common value, "group value signal" to refer to common value signal and "individual value to refer to private value in the experiment.

[14] The original design was to have 4 sessions for each treatment. However, substantial variation among sessions was found in the SR treatments. We suspected that it might because of session effect and decided to collect more data for the SR treatment.

SR/NI treatment.[15] Results 1, 2 and 3 below focus on the performance of revenue, winner's profit and efficiency respectively. Each of them provides the result comparing FI and NI and actual auction performance relative to the Nash prediction. In the linear mixed effects models that support the results, auctions are indexed by r and sessions are indexed by j. $Information_j$ =1 if full information is provided in session j and 0 otherwise. $Auction\_no_j$ is the auction number in session j. α_j, the random effect for session j, and ε_{rj}, are error terms that are assumed to be distributed normally with a zero mean. Result 4 reports the effect of bidding information on bidders' reentry. Result 5 answers whether there is any relationship between reentry activities and winners' profits. All data are reported in terms of e-dollars.

Result 1a. *Providing bidding information has no effect on revenue.*

<u>Support</u>. The hypothesis that revenue under NI treatment equals to revenue under FI treatment is tested using the following linear mixed effects model for SR and LR separately:

$$\begin{aligned} Revenue_{rj} = \alpha + \alpha_j &+ \beta_1 \, Information_j + \beta_2 (Predicted\_price_r - \overline{Predicted\_price}) \\ &+ \beta_3 (Auction\_no_j - 10) \\ &+ \beta_4 Information_j \times (Predicted\_price_r - \overline{Predicted\_price}) \\ &+ \beta_5 Information_j \times (Auction\_no_j - 10) + \varepsilon_{rj} \end{aligned} \tag{3}$$

$Revenue_{rj}$ is the price that winner paid in auction r in session j. $Predicted\_price_r$ is the Nash equilibrium price prediction in auction r and $\overline{Predicted\_price}$ is the mean predicted price. $Predicted\_price_r$ is added to the model to explain the movement of revenue due to the difference of equilibrium price across auctions. For sessions without information, equilibrium prices are

[15] Because the bidder who went bankrupt in the SR/NI treatment reported that the reason he went bankrupt was that he was busy calculating and forgot to pay attention to the bidding screen, data from the 15th period has not been used in our analysis.

calculated based on the second price sealed bid equilibrium bidding strategy. For sessions with information, equilibrium prices are calculated based on equilibrium bidding strategy of English auction.α is the intercept of the model, which represents the expected mean revenue at auction 10 of NI treatment when evaluated at the average predicted price (1002.15 for SR and 991.44 for LR). If information has no effect on revenue, β_1, β_4 and β_5 will not be significantly different from 0 and the joint hypothesis that $\beta_1 = \beta_4 = \beta_5 = 0$ will not be rejected. Results are shown in Table 2.

[Table 2 here]

It is clear that the effect of bidding information on revenue is insignificant (the hypothesis that $\beta_1 = \beta_4 = \beta_5 = 0$ cannot be rejected for both SR and LR).

We observed that auction number can partially explain the movement of revenue in NI and FI of SR and in FI of LR (β_3 is significantly different from 0 for SR at a 10% level, and the joint hypothesis that $\beta_3 + \beta_5 = 0$ is rejected at a 1% level for SR and at a 10% level for LR). Since this observation is not predicted by the theory, it leads us to test the hypothesis that the winning bid equals the Nash prediction (see result 1b). ◆

Result 1b. *Actual revenue is significantly different from the Nash revenue prediction in SR/NI at a 10% level; it is significantly different from the Nash revenue prediction in LR/NI at a 5% level and in SR/FI and LR/FI at a 1% level.*

<u>Support</u>. We test the hypothesis that revenue equals to the Nash prediction using the following linear mixed effects model for each SR/NI, SR/FI, LR/NI and LR/FI treatments:

$$Revenue_{rj} - Predicted\_price_r = \alpha + \alpha_j + \beta_1 (Auction\_no_j - 10) + \varepsilon_{rj} \quad (4)$$

α is the intercept of the model, which represents the expected difference between actual revenue and the Nash predicted price in auction 10. The definition of other variables follows that in model (3). If the actual price is not different from the Nash prediction, we would expect that the joint hypothesis that $\alpha = \beta_1 = 0$ will not be rejected. Results are shown in Table 3. The *p*-values of the joint hypothesis $\alpha = \beta_1 = 0$ are 0.0709, 0.0000, 0.0483 and 0.0035 for SR/NI, SR/FI, LR/NI and LR/FI respectively. ◆

[Table 3 here]

Although information does not have an effect on revenue in general, the repeated nature of the experiment tends to lower revenue in SR and this tendency is more severe when bidding information is provided. From table 3, β_1=-0.4 for SR/NI and β_1=-0.87 for SR/FI. The negative sign of these two coefficients shows that relative to the predicted revenue, actual revenue is decreasing through out the experiment. Combined with the intercept term, these estimates show that at the beginning of the experiment (i.e. auction 1), actual revenue is higher than the predicted one (expected difference is -1.16+(-0.4)(-9)=2.44 for SR/NI and 0.82+(-0.87)(-9)=8.65 for SR/FI). The situation reverses near the end of the experiment (at auction 20, the expected difference is -1.16+(-0.4)(10)=-5.16 for SR/NI and 0.82+(-0.87)(10)=-7.88 for SR/FI). The rate of revenue decrease in FI is more than double the rate in NI.

In LR/NI, the actual revenue is lower than the predicted one at the beginning of the experiment (at auction 1, expected difference is -9.96+(1.12)(-9)=-20.04) and gradually increases and becomes higher than the Nash predicted (at auction 20, expected difference is -9.96+(1.12)(10)=1.24). In LR/FI, the actual revenue is lower than the predicted one through out the experiment (at auction 1, expected difference is -19.93+(1.77)(-9)=-35.86 and at auction 20, expected difference is

-19.93+(1.77)(10)=-2.23) .

One possible explanation of the reverse tendency of actual revenue relative to predicted in SR and LR is that since common value uncertainty in SR is low, bidders become "comfortable" bidding in SR more quickly and therefore the auctions become highly competitive earlier in the experiment. Because of the repeated nature of the experiment, bidders gradually realize that bidding aggressively hurts their profits and they lower their bids; they learn this faster when bidding information is provided. On the other hand, because of the high common value uncertainly in LR, bidders tend to bid cautiously at the beginning of the experiment and the initial auctions are far from competitive; bidders gradually become familiar with the environment and become more competitive. It is interesting to notice that when bidding information is provided, bidders are bidding more aggressive at the beginning of the experiment in SR (comparing expected difference of actual and predicted revenue of 2.44 for SR/NI and of 8.65 for SR/FI at auction 1); while in LR, bidders are bidding more cautiously when information is provided (comparing expected difference of actual and predicted revenue of -20.04 for LR/NI and of -34.73 for LR/FI at auction 1). Interestingly, this suggests that bidders' reaction to information is not uniform; it depends on the size of the uncertainty (the range of the common value signal).

While examining the fitted model for result 1a, we found that the model for LR needs to be corrected for heteroscedasticity in terms of different information treatments. This leads us to suspect that the variability of revenue in different information treatments is different.

Result 1c. *The variance of difference between actual revenue and predicted revenue is substantially larger in FI than in NI for LR. However, it is essentially the same in FI and NI for SR.*

Support. The variance of error for model (4) is reported in table 3. σ_{ε}^{2} is 94.38 and 94.09 for

SR/NI and SR/FI respectively. However, σ_{ε}^{2} increases by 84.7% from 502.52 for LR/NI to 928.29 for LR/FI. ◆

Result 1c complements the discussion in result 1b suggesting that bidders react to information differently under different range of uncertainty. Result 2a and 2c give further support to this insight from the winner's profit perspective.

Result 2a. *The magnitude of the effect of information depends on the level of Nash predicted profit. In the small range treatment, when the level of the Nash predicted profit increases, profits increase faster than when there is no information provided. Just the opposite occurs in the large range treatment.*

<u>Support</u>. The hypothesis that winner's profit under NI treatment equals to winner's profit under FI treatment is tested using the following linear mixed effects model for SR and LR separately:

$$\begin{aligned} Profit_{rj} = \alpha + \alpha_j &+ \beta_1\, Information_j + \beta_2 (Predicted\_profit_r - \overline{Predicted\_profit}) \\ &+ \beta_3 (Auction\_no_j - 10) \\ &+ \beta_4 Information_j \times (Predicted\_profit_r - \overline{Predicted\_pofit}) \\ &+ \beta_5 Information_j \times (Auction\_no_j - 10) + \varepsilon_{rj} \end{aligned} \qquad (5)$$

$Profit_{rj}$ is the profit earned by the winner in auction r in session j. $Predicted\_Profit_r$ is the actual value of the predicted winner minus the equilibrium price predicted in auction r. $\overline{Predicted\_profit}$ is the mean predicted profit. α is the intercept of the model, which is the expected profit in auction 10 of NI when predicted profit is 6.44 for SR and is 8.17 for LR. If information has no effect on winner's profit, we would expect that β_1, β_4 and β_5 are individually insignificantly different from 0 and that the joint hypothesis test that $\beta_1 = \beta_4 = \beta_5 = 0$ cannot be

rejected. Results are shown in Table 4.

[Table 4 here]

Results show that information has a significant effect on revenue in SR but not in LR (hypothesis test of $\beta_1 = \beta_4 = \beta_5 = 0$ has a *p*-value of 0.0269 and 0.2396 for SR and LR respectively). Results indicate that the effect of information depends on the predicted profit; β_4 has a low *p*-value of 0.0058 and 0.0556 for SR and LR respectively. Providing information generates different levels of profit for winners when the predicted profit varies. Notice that when the predicted profit is greater, actual profit is greater (β_2 is positive). Because β_4 is positive and significant (at the 1% level) in the SR treatment, the data suggests that when the predicted profit is greater, the actual profit is greater if information is provided. The top panel of figure 1 is a scatter plot of Nash predicted profit versus actual profit in the SR treatment. The fitted regression lines for FI and NI indicate that the actual profit under FI is less than that under NI for lower values of predicted profit, but FI profit surpasses NI profit as the Nash prediction increases.

[Figure 1 here]

Because β_4 is negative and significant (at the 10% level) in the LR treatment, the data also suggests that when the predicted profit is greater, the actual profit is lower if information is provided. The bottom panel of figure 1 is a scatter plot of Nash predicted profit versus actual profit in the LR treatment. The fitted regression lines for FI and NI indicate that the actual profit under NI is less than that under FI for lower values of predicted profit, but NI profit surpasses FI profit as the Nash prediction increases.

Results further indicate that actual profit can be partially explained by auction number in the

information treatment (the joint hypothesis test of $\beta_3 + \beta_5 = 0$ gives a very low *p*-value of 0.0248 for the SR model). This leads us to test the hypothesis that profit equals the Nash prediction (see result 2b). ◆

Although this result cannot tell us the specific effect information will have on the winner's profit when considering whether information should be provided during a particular auction, it provides insights into the interaction of information and the level of predicted profit. Specifically, it suggests what auction format (whether information is provided) a bidder might prefer. Consider a bidder who thinks that the range of uncertainty is small and the Nash predicted profit is high; he would rather participate in an ascending auction where information is provided because the actual profit can be expected to be higher. If he thinks that the Nash predicted profit is low, he would prefer an ascending auction where no information is disclosed. The bidder will make opposite choices if he thinks that the range of uncertainty is large. This line of reasoning is summarized by the following table:

[Table 5 here]

Result 2b. *While actual profit is not significantly different from the Nash profit prediction in SR/NI and LR/NI, it is significantly different from the Nash profit prediction in SR/FI and in LR/FI.*

<u>Support</u>. We test the hypothesis that actual profit equals the Nash prediction using the following linear mixed effects model for each SR/NI, SR/FI, LR/NI and LR/FI treatment:

$$Profit_{rj} - Predicted\_Profit_r = \alpha + \alpha_j + \beta_1 (Auction\_no_j - 10) + \varepsilon_{rj} \quad (6)$$

α is the intercept of the model, which represents the expected difference between actual profit and

the Nash predicted profit in auction 10. The definition of other variables follows that in model (5). If the actual profit is not different from the Nash prediction, we would expect the joint hypothesis test that $\alpha = \beta_1 = 0$ cannot be rejected. Results are shown in Table 6. Results show that actual profit is not statistically significantly different from the Nash predicted profit in SR/NI and LR/NI, but it is statistically significantly different from Nash predicted profit in SR/FI at a 1% level and in LR/FI at a 10% level. ◆

Bidders on average earn higher than Nash predicted profit in all auctions in LR/FI (table 6 shows that model (4) estimates α to be 13.54 and estimate β_1 to be insignificantly different from 0). Result 2b shows that bidders do not suffer from winner's curse in SR/NI, LR/NI and LR/FI.[16] Figure 2 shows a box plot of average profit compared with Nash prediction under different treatments. We can see that in the LR condition, even when bidding information is not provided, bidders earn more than the Nash prediction. In the SR condition bidders earn close to the Nash prediction when information is not provided. Although bidders earn less than Nash prediction in SR/FI, they earn a positive profit on average. The result of not suffering from winners' curse is contrary to results from pure common value environments (Kagel and Levin, 1996)[17] and the experimental analysis of first price seal bid auctions under an environment with both private and common value components (Goeree and Offerman, 2002). This suggests that the simultaneous conditions of having a private value component in the bidder's valuation function and using an ascending

[16] Kagel (1995) defines the deviation from bidding above the expected value given one has the highest signal value as a measure of the extent a bidder suffers from winner's curse. Nash equilibrium predicts that a bidder bids assuming that all remaining bidders' are the same as him when information is provided and his signal is the same as the second highest one when information is not provided. This condition is more stringent than the expected value condition. In other words, a bidder following the Nash bidding would bid lower than what he would have bid by simply avoiding the winner's curse. And a bidder who bids simply by avoiding the winner's curse would earn less profit than the one who follows Nash strategy. Since the actual profits our bidders earned were not significantly different from the Nash predictions in SR/NI and LR/NI, and even higher in LR/FI, we conclude that our bidders do not suffer from winner's curse in these conditions.

[17] Kagel and Levin (1996) report inexperienced and one-time experienced bidders earn negative profit on average in English auctions in a common value environment. Note that there is a subtle difference between how the common value signals are determined in (Kagel and Levin, 1996) and in this paper. While bidders' common value signals are independent in this paper, the signals in (Kagel and Levin, 1996) are affiliated (as defined in (Milgrom and Weber, 1982)).

auction are necessary to help bidders avoid the winner's curse.

[Figure 2 here]

Again, while examining the model for result 2a, we correct the heteroscedasticity in terms of different information treatments for LR. We suspect the variability of winners' profits is different for NI and FI and report it in the following result.

Result 2c. *The variance of difference between actual profit and predicted profit decreases from NI to FI for SR. However, it substantially increases from NI to FI for LR.*

Support. The variance of error for model (6) is reported in table 6. σ_{ε}^{2} decreases 24.1 % when comparing SR/NI (150.75) and SR/FI (114.44). However, σ_{ε}^{2} increases by 80.78% from 616.37 for LR/NI to 1114.25 for LR/FI. ◆

Result 2c again suggests the non-uniform effect of information on auction performance. Information does not necessarily stabilize bidders' earnings. In fact, the variability of winners' profits slightly decreases when information is provided in SR. However, the variability of winners' profits dramatically increases when information is provided in the LR treatment.

Result 3a. *Providing bidding information has no effect on efficiency.*

Support. Efficiency is defined as follows:

$$Efficiency = \frac{v_{winner}}{v_{\max}},$$

where v_{winner} is the value of the winner (p_{winner}+C) and v_{max} is the value of the bidder with the

maximum private value drawn (p_{max}+C). The hypothesis that efficiency under NI equals to efficiency under FI is tested using the following linear mixed effects model for SR and LR separately[18]:

$$\begin{aligned} Efficiency_{rj} = \alpha + \alpha_j + \beta_1\, Information_j + \beta_2 (Auction\_no_j - 10) \\ + \beta_3 Information_j \times (Auction\_no_j - 10) + \varepsilon_{rj} \end{aligned} \qquad (7)$$

$Efficiency_{rj}$ is the efficiency in auction r in session j. α is the intercept of the model, which represents the expected mean efficiency at auction 10 of NI treatment. If information has no effect on efficiency, we would expect that β_1 and β_3 are individually insignificantly different from 0 and that the joint hypothesis test that $\beta_1 = \beta_3 = 0$ cannot be rejected. Results are shown in Table 7.

The test result gives a p-value of 0.7382 for the SR treatment and a p-value of 0.4689 for the LR treatment. Therefore, the information effect under the two range treatments is insignificant. ◆

[Table 7 here]

Since β_2 in table 7 is insignificantly different from 0 for both SR and LR, the efficiency is not explained by auction number in the NI treatments. However, the hypothesis test that $\beta_2 + \beta_3 = 0$ is rejected at a 10% level for LR, this indicates that auction number may partially explain efficiency in LR. We test the hypothesis that efficiency equals the Nash prediction in SR and LR (Result 3b). Surprisingly, it shows that the theory's prediction on efficiency is not good in SR as well.

Result 3b. *Actual efficiency is significantly lower than the Nash efficiency prediction in both SR and LR treatments.*

[18] Since the Nash predicted efficiency is the same for all periods in SR (equal 1), we encounter singularity problem when we estimate models that include predicted efficiency as an independent variable. Therefore, we choose a model different from those we use for estimating revenue and profit. To maintain consistency, we estimated the same model for SR and LR.

Support. We test the hypothesis that actual efficiency equals the Nash prediction using the following linear mixed effects model for each SR/NI, SR/FI, LR/NI and LR/FI treatment:

$$Efficiency_{rj} - Predicted\_Efficiency_{r} = \alpha + \alpha_{j} + \beta_{1}(Auction\_no_{j} - 10) + \varepsilon_{rj}$$

Predicted_Efficiency$_r$ is the Nash equilibrium efficiency prediction in auction *r*. α is the intercept of the model, which represents the expected difference between actual efficiency and the Nash predicted efficiency in auction 10. The definition of other variables follows that in model (7). If the actual efficiency is not different from the Nash prediction, we would expect the joint hypothesis test that $\alpha = \beta_1 = 0$ cannot be rejected. Results are shown in Table 8. We observe that the hypothesis that actual efficiency is equal to the Nash predicted is rejected at a 1% level for SR/NI and LR/FI and at a 5% level for SR/FI and LR/NI. ◆

[Table 8 here]

Besides the observation that actual efficiency does not equal to the Nash prediction, we observe, from table 8, that relative to predicted efficiency, actual efficiency rises along with auction number in LR/FI (β_1 has a positive estimate and is significantly different from 0). This observation is not found in other treatments.

We again observe a heteroscedasticity problem in the model estimated in result 3a. In fact, the variability of efficiency is higher in NI than in FI for SR. However, since the changes in efficiency are infinitesimal, we choose not to report this result in detail.

Result 4. *The number of reentries is not significantly different between FI and NI in both SR and*

LR treatments. However, the number of reentries is significantly greater than 0 in both SR and LR treatments.

Support. Theory predicts that bidders would not utilize the reentry options under either treatment and therefore the numbers of reentries under both treatments would equal zero. We formally test the hypothesis that the numbers of reentries are equal between FI and NI using a two-sided Wilcoxon Rank Sum test. The average number of reentries per subject per auction in a session is the unit of observation. The number of observations for the SR treatment and LR treatment are 5 and 4 respectively. The test result gives a *p*-value of 0.3016 for the SR treatment and a *p*-value of 0.6286 for the LR treatment.

We use a one-sided Wilcoxon Signed-Rank Test to test the null hypothesis that the number of reentries (which cannot be less than zero) per bidder per auction in a session exactly equals zero. The average number of reentries per bidder per auction in a session is the unit of observation. Number of observations for the SR treatment and LR treatment are 5 and 4 respectively. The descriptive statistics and test results for the average number of reentries per bidder per auction are summarized in table 9. The null hypothesis that the number of reentries in SR equals zero is rejected at a 5% level (*p*-value=0.0313 for SR/FI, *p*-value=0.0313 for SR/NI). The null hypothesis that the number of reentry in LR equals zero is rejected at a 10% level (*p*-value=0.0625 for LR/FI, *p*-value=0.0625 for LR/NI). ◆

Bidders do make use of reentry when making their decisions: this leads us to enquire whether the bidder's perceived value in reentering manifests itself in increased profit for winners who engage in such strategy (result 5).

[Table 9 here]

Result 5. *The winners who engage in reentry do not earn higher profit than those who do not engage in it.*

Support. We find that the average normalized profit (actual profit – Nash predicted profit) for winners who engage in reentry (i.e. reenter at least one time in winning an auction) is higher than that of the average normalized profit for winners who do not engage in reentry only in the LR/FI treatment. The difference is insignificant (*p*-value for two-sided *t*-test is 0.8048). Figure 3 shows the average normalized profit in different treatments. The average number of reentries for the winners who reenter on the way to winning are 1.56, 2, 1.73 and 1.2 for treatments SR/FI, SR/NI, LR/FI and LR/NI respectively. ◆

[Figure 3 here]

6. Conclusion

The model considered in this paper provides a theoretical proposition that bidding information is not beneficial to any party in an English auction where objects have a certain private plus uncertain common component to value. We test the model and find that information alone does not have a significant effect on expected revenue and expected efficiency. However, information does have an effect on expected profit when taking into account the range of public uncertainty and the level of Nash profit prediction, which cannot be known a priori. There is no evidence that bidders suffer from winners' curse when information is not provided in this environment for both small and large range of uncertainty. In fact, in the treatment where the common value component has a larger range, winners tend to earn more profit than Nash prediction on average. However, in the smaller range treatment where information is provided, winners earn slightly less than the Nash prediction

but their average profit remains positive. We observe that at the beginning of the experiment, the expected revenue in the information treatment is higher than that of the no information treatment relative to the predicted revenue when the uncertainty in the common value component is small, while the opposite occurs when the uncertainty in the common value component is large. Furthermore, information has no effect on the variability of revenue and decreases the variability of winners' profits when the uncertainty is small, while it substantially increases the variability of revenue and winners' profits when the uncertainty is large. Combined with the information effect on winners' expected profits, these findings suggest that bidders' response to information is not uniform; it depends on the uncertainty level of the common value component. Although a significant number of reentries is observed, the data do not show that winners who engage in reentry earn higher profits.

We find no evidence that bidding information is beneficial to auction performance in our environment. It appears that bidders do not suffer from the winner's curse when there is a private value component in the valuation function *combined with* an ascending auction. This suggests that auction designers need not worry much about bidders losing money in open ascending auctions. The effect of bidding information under different environments still waits to be tested. For example, auction theory suggests that when bidders' signals are affiliated, providing information will raise more revenue for the seller. A two-signal model in which common value signals are affiliated is a potential extension of our study.

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Table 1: Treatment Design

	Only Clock Price Reported	Bidders' Identity Reported
Small Range (SR)	SR/NI	SR/FI
Large Range (LR)	LR/NI	LR/FI

Caption: This 2X2 design relates two Information treatments, one that provides no information concerning bidder drop-out and reentry decision at each clock price and one that supplies only the clock price; the second treatment examines the range from which the common value component signals are drawn that is a mean-preserving spread.

Table 2: Estimates of Linear Mixed-Effects Model for Revenue

$$\begin{aligned} Revenue_{rj} = \alpha + \alpha_j &+ \beta_1\, Information_j + \beta_2 (Predicted\_price_r - \overline{Predicted\_price}) \\ &+ \beta_3 (Auction\_no_j - 10) \\ &+ \beta_4 Information_j \times (Predicted\_price_r - \overline{Predicted\_price}) \\ &+ \beta_5 Information_j \times (Auction\_no_j - 10) + \varepsilon_{rj} \end{aligned}$$

where $\alpha_j \sim N(0, \sigma_\alpha^2)$, $\varepsilon_{rj} \sim N(0, \sigma_\varepsilon^2)$

	Estimate	Std. Error	DF	*t-statistic*	*p-value*
Small Range					
Intercept (α)	1000.94	1.92	179	521.16	0.0000
Information (β_1)	2.04	2.70	8	0.76	0.4718
(Predicted_price-1002.15) (β_2)	0.96	0.11	179	8.89	0.0000
(Auction_no - 10) (β_3)	-0.41	0.21	179	-1.93	0.0558
(Information x (Predicted_price-1002.15)) (β_4)	-0.24	0.15	179	-1.57	0.1176
Information x (Auction_no - 10) (β_5)	-0.47	0.29	179	-1.61	0.1097
H$_0$: $\beta_1 = \beta_4 = \beta_5 = 0$ Wald statistic=5.63 DF=3 *p*-value=0.1308					
H$_0$: $\beta_3 + \beta_5 = 0$ *t*-statistic =-4.35 DF=179 *p*-value=0.0000					
Large Range					
Intercept (α)	979.49	8.97	132	109.22	0.0000
Information (β_1)	-7.90	12.70	6	-0.62	0.5567
(Predicted_price-991.44) (β_2)	0.42	0.11	132	3.75	0.0003
(Auction_no - 10) (β_3)	0.66	0.60	132	1.09	0.2760
(Information x (Predicted_price-991.44)) (β_4)	-0.17	0.17	132	-1.05	0.2937
Information x (Auction_no - 10) (β_5)	-0.49	0.91	132	0.54	0.5904
H$_0$: $\beta_1 = \beta_4 = \beta_5 = 0$ Wald statistic=1.98 DF=3 *p*-value=0.5761					
H$_0$: $\beta_3 + \beta_5 = 0$ *t*-statistic =1.67 DF=132 *p*-value=0.0977					

Caption: Information has no effect on revenue in both small range and large range of the common value signals. The significance of β_3 for small range and the low *p*-value of the hypothesis test that $\beta_3 + \beta_5 = 0$ for both small range and large range indicate that auction number partially explain actual revenue in both no information and information treatments.

Table 3: Estimates of Linear Mixed-Effects Model for the Difference between Actual Revenue and Nash Predicted Revenue

$$Revenue_{rj} - Predicted\_price_r = \alpha + \alpha_j + \beta_1(Auction\_no_j - 10) + \varepsilon_{rj}$$

where $\alpha_j \sim N(0, \sigma_\alpha^2)$, $\varepsilon_{rj} \sim N(0, \sigma_\varepsilon^2)$

	Estimate	Std. Error	DF	*t*-statistic	*p*-value
SR/NI					
Intercept (α)	-1.16	2.07	88	-0.56	0.5776
(Auction_no-10) (β_1)	-0.40	0.18	88	-2.23	0.0280
Estimate of variance of error (σ_ε^2): 94.38 H_0: $\alpha = \beta_1 = 0$ Wald statistic=5.29 DF=2 *p*-value=0.0709					
SR/FI					
Intercept (α)	0.82	1.81	93	0.45	0.6526
(Auction_no-10) (β_1)	-0.87	0.17	93	-5.11	0.0000
Estimate of variance of error (σ_ε^2): 94.09 H_0: $\alpha = \beta_1 = 0$ Wald statistic=26.23 DF=2 *p*-value=0.0000					
LR/NI					
Intercept (α)	-9.96	11.85	59	-0.84	0.4039
(Auction_no-10) (β_1)	1.12	0.50	59	2.27	0.0271
Estimate of variance of error (σ_ε^2): 502.52 H_0: $\alpha = \beta_1 = 0$ Wald statistic=6.06 DF=2 *p*-value=0.0483					
LR/FI					
Intercept (α)	-19.93	7.96	75	-2.50	0.0145
(Auction_no-10) (β_1)	1.77	0.75	75	2.36	0.0207
Estimate of variance of error (σ_ε^2): 928.29 H_0: $\alpha = \beta_1 = 0$ Wald statistic=11.32 DF=2 *p*-value=0.0035					

Legend: SR: Small range of uncertainty treatment, LR: Large range of uncertainty treatment, NI: No Information treatment, FI: Full Information treatment

Caption: The hypothesis that actual revenue equals Nash predicted revenue is rejected at a 10% level for SR/NI, at a 5% level for LR/NI and at a 1% level for FI in both SR and LR. Relative to predicted revenue, actual revenue decreases in both NI and FI of SR but increases in LR through out the experiment. Providing information does not have an effect on the variability of revenue in SR but it substantially increases the variability of revenue in LR.

Table 4: Estimates of Linear Mixed-Effects Model for Winner's Profit

$$\begin{aligned} Profit_{rj} = \alpha + \alpha_j &+ \beta_1\, Information_j + \beta_2 (Predicted\_profit_r - \overline{Predicted\_profit}) \\ &+ \beta_3 (Auction\_no_j - 10) \\ &+ \beta_4 Information_j \times (Predicted\_profit_r - \overline{Predicted\_pofit}) \\ &+ \beta_5 Information_j \times (Auction\_no_j - 10) + \varepsilon_{rj} \end{aligned}$$

where $\alpha_j \sim N(0, \sigma_\alpha^2)$, $\varepsilon_{rj} \sim N(0, \sigma_\varepsilon^2)$

	Estimate	Std. Error	DF	*t*-statistic	*p*-value
Small Range					
Intercept (α)	5.23	1.62	179	3.22	0.0015
Information (β_1)	-1.84	2.27	8	-0.81	0.4419
(Predicted_profit-6.44) (β_2)	0.48	0.12	179	3.96	0.0001
(Auction_no - 10) (β_3)	0.09	0.25	179	0.35	0.7269
(Information x (Predicted_profit-6.44)) (β_4)	0.47	0.17	179	2.79	0.0058
Information x (Auction_no - 10) (β_5)	0.46	0.35	179	1.31	0.1933
H_0: $\beta_1 = \beta_4 = \beta_5 = 0$ Wald statistic=9.19 DF=3 *p*-value=0.0269					
H_0: $\beta_3 + \beta_5 = 0$ *t*-statistic =0.55 DF=179 *p*-value=0.0248					
Large Range					
Intercept (α)	15.50	8.51	132	1.82	0.0710
Information (β_1)	6.06	12.07	6	0.50	0.6335
(Predicted_profit-8.17) (β_2)	1.37	0.18	132	7.61	0.0000
(Auction_no - 10) (β_3)	-0.32	0.66	132	-0.49	0.6276
Information x (Predicted_profit-8.17) (β_4)	-0.51	0.26	132	-1.93	0.0556
Information x (Auction_no - 10) (β_5)	-0.70	1.01	132	-0.69	0.4893
H_0: $\beta_1 = \beta_4 = \beta_5 = 0$ Wald statistic=4.21 DF=3 *p*-value=0.2396					
H_0: $\beta_3 + \beta_5 = 0$ *t*-statistic =-1.34 DF=132 *p*-value=0.1814					

Caption: For small range of the common value signals, the regression estimates show that information has a significant effect on profit (Hypothesis $\beta_1 = \beta_4 = \beta_5 = 0$ is rejected). Information has an interaction effect with Nash predicted profit (*p*-value of hypothesis $\beta_4 = 0$ is 0.0058). Auction number partially explains movement of actual profit in information treatment (*p*-value of hypothesis $\beta_3 + \beta_5 = 0$ is 0.0248).

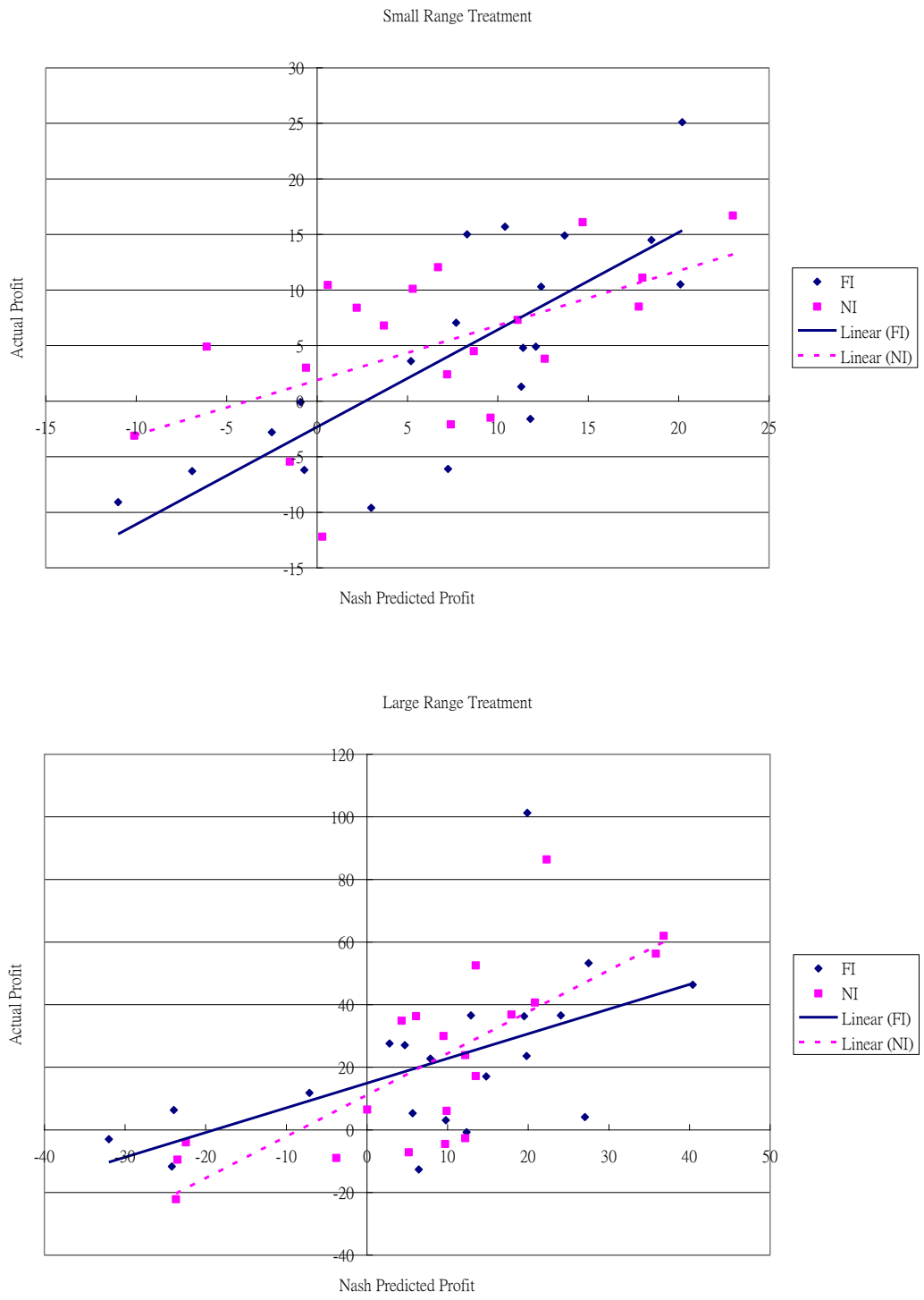
For large range of the common value signals, the effect of information alone is insignificant. However, there is an interaction effect between information and the Nash prediction (*p*-value of hypothesis $\beta_4 = 0$ is 0.0556).

Table 5: Bidders' Preferences of Auction Formats given Different Levels of Nash Predicted Profit and Different Ranges of Uncertainty

	High Nash predicted profit	Low Nash predicted profit
Small range of uncertainty (SR)	Full Information (FI) preferred	No Information (NI) preferred
Large range of uncertainty (LR)	No Information (NI) preferred	Full Information (FI) preferred

Caption: The availability of information has an effect on winner's profit that is dependent on the level of Nash profit prediction and the range of uncertainty. A bidder who thinks that the range of uncertainty is small and the Nash predicted profit is high would rather participate in an ascending auction where information is provided because the actual profit is higher. If he thinks that the predicted profit is low, he would prefer an ascending auction where no information is disclosed. The bidder will make opposite choices if he thinks that the range of uncertainty is large.

Figure 1: Actual Profit Plots against Nash Predicted Profit under Small (top panel) and Large (bottom panel) Range of Uncertainty Treatments.



Caption: Actual profit is the average of auction profit across sessions. In the small range of uncertainty treatment, winner's profit in full information (FI) treatment is less than winner's profit in no information (NI) initially but it catches up later. In the large range of uncertainty treatment, winner's profit in FI is more than winner's profit in NI when predicted profit is less but the results of profit comparison reverses when predicted profit is large.

Table 6: Estimates of Linear Mixed-Effects Model for the Difference between Actual Profit and Nash Predicted Profit

$$Profit_{rj} - Predicted\_Profit_r = \alpha + \alpha_j + \beta_1(Auction\_no_j - 10) + \varepsilon_{rj}$$

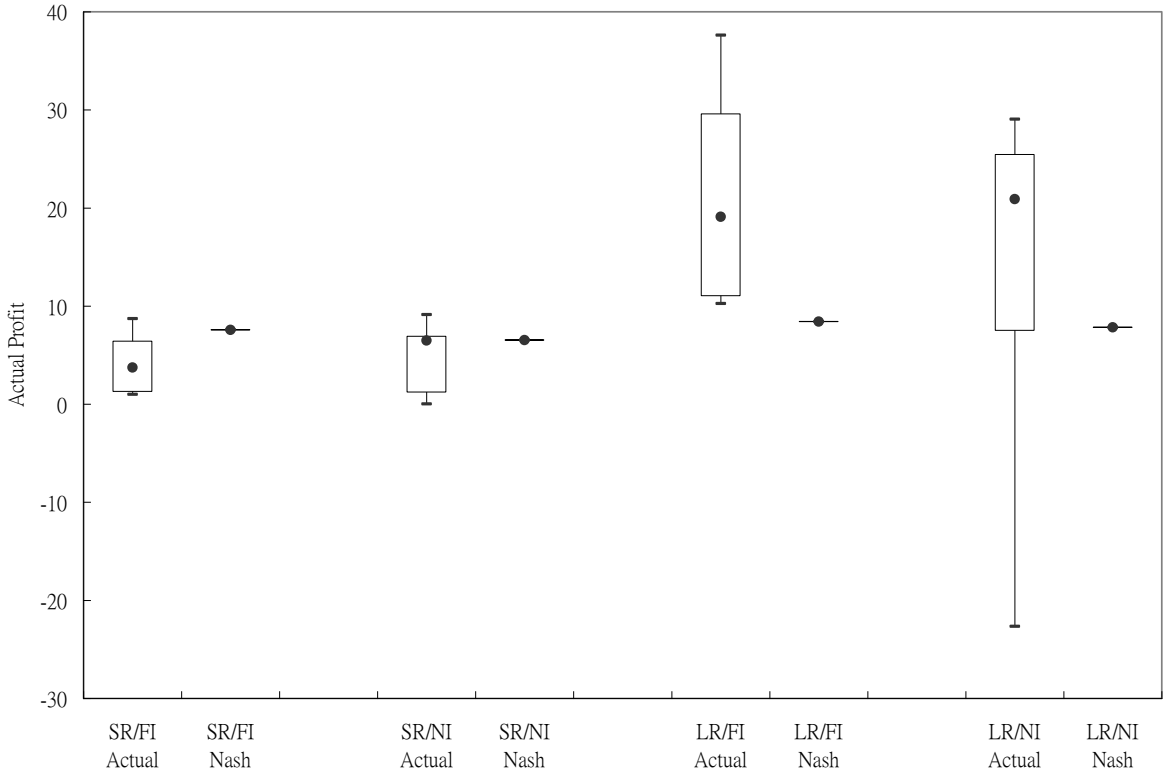
where $\alpha_j \sim N(0, \sigma_\alpha^2)$, $\varepsilon_{rj} \sim N(0, \sigma_\varepsilon^2)$

	Estimate	Std. Error	DF	*t-statistic*	*p-value*
SR/NI					
Intercept (α)	-1.04	1.72	88	-0.61	0.5464
(Auction_no-10) (β_1)	0.27	0.27	88	1.03	0.3048
Estimate of variance of error (σ_ε^2): 150.75 H_0: $\alpha = \beta_1 = 0$ Wald statistic=1.43 DF=2 *p*-value=0.4898					
SR/FI					
Intercept (α)	-3.08	1.52	93	-2.03	0.0450
(Auction_no-10) (β_1)	0.56	0.23	93	2.41	0.0181
Estimate of variance of error (σ_ε^2): 114.44 H_0: $\alpha = \beta_1 = 0$ Wald statistic=9.35 DF=2 *p*-value=0.0093					
LR/NI					
Intercept (α)	4.80	12.22	59	0.39	0.6957
(Auction_no-10) (β_1)	-0.73	0.55	59	-1.33	0.1898
Estimate of variance of error (σ_ε^2): 616.37 H_0: $\alpha = \beta_1 = 0$ Wald statistic=1.98 DF=2 *p*-value=0.3722					
LR/FI					
Intercept (α)	13.30	6.95	75	1.91	0.0596
(Auction_no-10) (β_1)	-0.99	0.78	75	-1.27	0.2098
Estimate of variance of error (σ_ε^2): 1114.25 H_0: $\alpha = \beta_1 = 0$ Wald statistic=5.00 DF=2 *p*-value=0.0819					

Legend: SR: Small range of uncertainty treatment, LR: Large range of uncertainty treatment, NI: No Information treatment, FI: Full Information treatment

Caption: Actual profit is statistically significantly different from the Nash prediction for both SR (at 1% level) and LR (at 10% level) when bidding information is provided. Relative to Nash profit prediction, actual profit rises along with auction number for SR/FI (*p*-value of hypothesis β_1=0 is 0.0181). When comparing to NI, FI decreases the variability of winner's profit in SR. However, it dramatically increases the variability of winner's profit in LR.

Figure 2: Box Plot of Actual Profit and Nash Predicted Profit



Caption: Actual profit is the average of profit across all auctions and all sessions. Nash profit is the average of Nash predictions of each auction. In the large range of uncertainty (LR) treatment, even when bidding information is not provided (NI), bidders earn more than the Nash prediction on average. In the small range of uncertainty (SR) treatment bidders earn close to the Nash prediction when information is not provided. Although bidders earn less than Nash prediction in small range of uncertainty (SR) and full information (FI) condition, they on average earn positive profit.

Table 7: Estimates of Linear Mixed-Effects Model for Efficiency

$$Efficiency_{rj} = \alpha + \alpha_j + \beta_1 \, Information_j + \beta_2 (Auction\_no_j - 10) + \beta_3 Information_j \times (Auction\_no_j - 10) + \varepsilon_{rj}$$

where $\alpha_j \sim N(0, \sigma_\alpha^2), \quad \varepsilon_{rj} \sim N(0, \sigma_\varepsilon^2)$

	Estimate	Std. Error	DF	*t*-statistic	*p*-value
Small Range					
Intercept (α)	0.9966	0.0011	181	875.08	0.0000
Information (β_1)	0.0002	0.0016	8	0.1542	0.8813
(Auction_no - 10) (β_2)	-0.0000006	0.0001	181	-0.0056	0.9956
Information x (Auction_no - 10) (β_3)	-0.0001	0.0001	181	-0.7653	0.4451
H_0: $\beta_1 = \beta_3 = 0$ Wald statistic=0.61 DF=2 *p*-value=0.7382					
H_0: $\beta_2 + \beta_3 = 0$ *t*-statistic =-1.30 DF=181 *p*-value=0.1969					
Large Range					
Intercept (α)	0.9928	0.0019	134	532.74	0.0000
Information (β_1)	-0.0016	0.0025	6	-0.6311	0.5513
(Auction_no - 10) (β_2)	0.0001	0.0002	134	0.2834	0.7773
Information x (Auction_no - 10) (β_3)	0.0003	0.0003	134	1.0615	0.2904
H_0: $\beta_1 = \beta_3 = 0$ Wald statistic=1.51 DF=2 *p*-value=0.4689					
H_0: $\beta_2 + \beta_3 = 0$ *t*-statistic =1.89 DF=134 *p*-value=0.0607					

Caption: The regression estimates show that information has no effect on efficiency for both small range and large range of the common value signals. However, the significant result of the hypothesis test of $\beta_2 + \beta_3 = 0$ for large range of the common value signals suggests that auction number may partially explain the movement of actual efficiency in information treatment.

Table 8: Estimates of Linear Mixed-Effects Model for the Difference between Actual Efficiency and Nash Predicted Efficiency

$$Efficiency_{rj} - Predicted\_Efficiency_{r} = \alpha + \alpha_j + \beta_1 (\text{Auction\_no}_{\text{j}} - 10) + \varepsilon_{rj}$$

$$\text{where } \alpha_j \sim N(0, \sigma_\alpha^2), \quad \varepsilon_{rj} \sim N(0, \sigma_\varepsilon^2)$$

	Estimate	Std. Error	DF	*t*-statistic	*p*-value
SR/NI					
Information (α)	-0.0033	0.0006	88	-5.38	0.0000
(Auction_no-10) (β_1)	0.000001	0.0001	88	0.01	0.9913
H_0: $\alpha = \beta_1 = 0$ Wald statistic=28.98 DF=2 *p*-value=0.0000					
SR/FI					
Information (α)	-0.0031	0.0014	93	-2.25	0.0268
(Auction_no-10) (β_1)	-0.0001	0.0001	93	-1.31	0.1920
H_0: $\alpha = \beta_1 = 0$ Wald statistic=6.93 DF=2 *p*-value=0.0312					
LR/NI					
Information (α)	-0.0054	0.0024	59	-2.27	0.0270
(Auction_no-10) (β_1)	0.0003	0.0002	59	1.35	0.1824
H_0: $\alpha = \beta_1 = 0$ Wald statistic=7.31 DF=2 *p*-value=0.0259					
LR/FI					
Information (α)	-0.0069	0.0013	75	-5.34	0.0000
(Auction_no-10) (β_1)	0.0007	0.0002	75	2.98	0.0039
H_0: $\alpha = \beta_1 = 0$ Wald statistic=34.89 DF=2 *p*-value=0.0000					

Legend: SR: Small range of uncertainty treatment, LR: Large range of uncertainty treatment, NI: No Information treatment, FI: Full Information treatment

Caption: Actual efficiency is statistically significantly different from the Nash prediction for both SR and LR under different information treatments. Relative to Nash efficiency prediction, actual efficiency rises along with auction number for LR/FI (*p*-value of hypothesis β_1=0 is 0.0039).

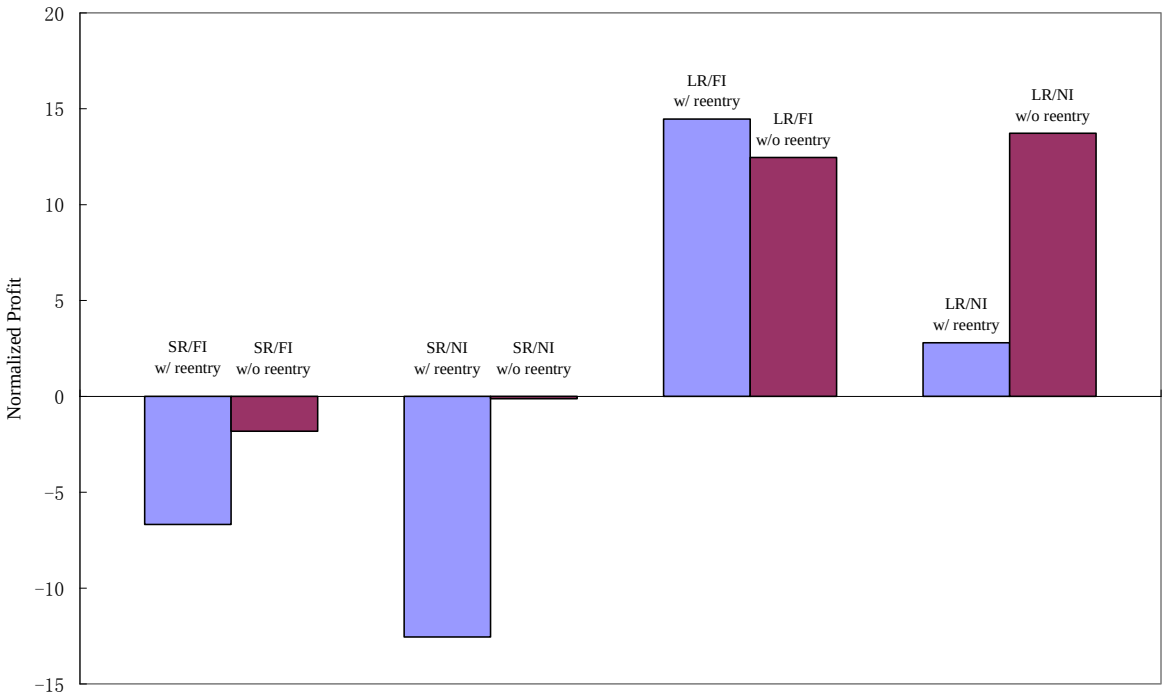
Table 9: Descriptive Statistics and Test Results for the Average Number of Reentries per Bidder per Auction

	SR/FI	SR/NI	LR/FI	LR/NI
Mean	0.19	0.12	0.77	0.16
Standard Deviation	0.17	0.11	0.97	0.08
p-value (one sided Wilcoxon Signed-Rank Test) H_a:Number of reentries >0	0.0313	0.0313	0.0625	0.0625

Legend: SR: Small range of uncertainty treatment, LR: Large range of uncertainty treatment, NI: No Information treatment, FI: Full Information treatment

Caption: The null hypothesis that the number of reentries in small range of uncertainty treatment equals zero is rejected at a 5% level. The null hypothesis that the number of reentry in large range of uncertainty equals zero is rejected at a 10% level.

Figure 3: Average Normalized Profit for Winners with (w/) and without (w/o) Reentry



Legend: SR: Small range of uncertainty treatment, LR: Large range of uncertainty treatment, NI: No Information treatment, FI: Full Information treatment

Caption: Normalized profit (actual profit – Nash predicted profit) is averaged across all auctions and all sessions for winners. Winners who have reenter at least one time are classified into the w/ reentry category, otherwise they are classified into the w/o reentry category. The average normalized profit for winners w/ reentry is found to be higher than that of the average normalized profit for winners w/o reentry only in LR/FI.

Appendix

Bidder's Screen Shot

Caption: This is a capture of bidder 1's screen. The bidder is in auction 1 and he has a private value of 498 and signal of the common value of 513. If the bidder uses is common value of signal of 513 as the estimate of the average of the common value signals his expected total value would be 1011. At the current price of 966 Bidder 1 is still demanding a unit and at the past price of 965 bidders 1, 2, 3 and 4 were also demanding the unit. Bidder 1 also has current cash account of 50, so that if the experiment ended with no further allocation to Bidder 1, he would make 50 e-dollars.

Instruction (small range of uncertainty, bidding information provided)

Welcome! You are going to participate in a decision experiment. The instructions for this experiment are simple. If you understand the instructions, you will be able to earn a considerable amount of money which will be paid to you in cash. In the following instructions, you will be presented with some basic information followed by the market rules in this experiment. Raise you hand whenever you have question about the instructions.

In this experiment, a series of market periods will be conducted. In each period, one hypothetical object will be sold. There are four participants in the market.

In each period, each market participant receives an **individual value** and a **group value signal** for the object. These are your private information. Do not reveal them to other participants.

Individual value is a number drawn between, and including, 475 and 525. Every whole number in this range is equally likely to be your individual value.

Group value signal is a number drawn between, and including, 475 and 525. Every whole number in this range is equally likely to be your group value signal.

Group value, which is the same for all participants, is the average of all participants' group value signals (This number will be rounded to 1 decimal place).

Your true value of the object = group value + individual value.

Example 1:

Player ID	Group Value Signal	Individual Value	True Value
1	476	523	523+497.5=1020.5
2	489	486	486+497.5=983.5
3	502	490	490+497.5=987.5
4	523	510	510+497.5=1007.5

The group value of the object will be (476+489+502+523)/4=497.5.

Only one participant will be allocated with the object in each period. The participant who is allocated with the object will receive **his true value − price paid**. If the price paid is higher than your true value, you will make a loss. Participants who are not allocated with the object in a period earn zero for that period.

Example 1 Continues…
If the price is 1000 and Player 1 is the winner, his profit is 1020.5-1000=20.5 (a **profit** of 20.5).
If the price is 1000 and Player 2 is the winner, his profit is 983.5-1000=-16.5 (a **loss** of 16.5).
If the price is 1000 and Player 3 is the winner, his profit is 987.5-1000=-12.5 (a **loss** of 12.5).
If the price is 1000 and Player 4 is the winner, his profit is 1007.5-1000=7.5 (a **profit** of 7.5).

The currency used in the experiment is called e-dollar. At the beginning of the experiment, each participant will be allocated with 50 e-dollars in their money balance. Any earning in the experiment will be added to (if it is positive) or subtracted from (if it is negative) the money balance.

At the end of the experiment, e-dollar will be converted to US dollar at a rate of US$1= 2 e-dollars. In other words, if you have 20 e-dollars in your money balance, you earn US$10.

We will keep checking your money balance throughout the experiment. If your money balance is less than or equal to zero, you will not be allowed to participate in the experiment. You are free to leave the lab and you will be paid with your show-up fee.

Here is a summary of how you will be paid at the end of this experiment:

If your money balance is greater than zero
Total Earnings = Show up Fee+ Money balance in terms of US dollar

If your money balance is less than or equal to zero
Total Earnings = Show up Fee

To avoid making negative profit, keep in mind that period profit = Winner’s true value – price paid

Rules

Each participant in a market period will be randomly allocated Player ID 1, 2, 3 or 4. After a period is started, your individual value, group value signal and the current price of the object will be displayed on the screen. 15 seconds after a period is started, the price will start to rise at the rate of 1 unit per half second. Through out the period, participants can choose to demand or not to demand the object through two radio buttons. In every second, the system will check the number of demand at the current price. If the number of demand is more than 1, the current price continues to go up. If the number of demand equals to 1, the period ends and the object will be allocated to

the remaining bidder at the current price. If the number of demand equals to 0, the period ends and the system will randomly allocate the object to one of the participants who were demanding at the last price. Through out the period, participants will be informed the identity of participants demanding at each price.

Note: Talking or any form of communication is not allowed in this experiment. If the experimenter finds any of these, the experiment will be stopped and all subjects will only be paid with their show up fee.

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