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BIDDING BEHAVIOR
UNDER COSTLY INFORMATION ACQUISITION:
AN EXPERIMENTAL STUDY

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ABSTRACT

This paper presents the results of an experiment on the economics of endogenous information acquisition. The experiment consists of a series of auctions where subjects compete for an object with private but unknown value. The information regarding the value of the object is costly. The experiment tests a theoretical model of bidding equilibrium and analyzes the effects of variations in the parameters (such as information costs and level of uncertainty) on the endogenous variables (such as the proportion of bidders who buy information and the winning bid). Bidders' decisions concerning the purchase of information are closely consistent with a Risk Neutral Rational Expectations model. The winning bids, however, are persistently above the equilibrium predictions suggesting the presence of risk aversion.

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Bidding Behavior Under Costly Information Acquisition: An Experimental Study

I. INTRODUCTION

This paper presents the results of an experiment on bidding behavior with endogenous information acquisition. The experiment consists of a series of auctions where the subjects compete for an object with a private but unknown value. The distinctive feature of the environment is that the information about the private values of the object is costly: a bidder only discovers his own valuation provided he pays some amount to become informed.

Therefore, the subjects in the experiment are dealing with a sequential decision problem. They must decide whether or not to acquire information and then, conditioned on that previous decision, they must determine what their optimal bid should be. Some auctions introduce an additional source of uncertainty: whereas the information acquisition involves a certain cost, there is some probability that the auctioneer will prefer not to sell the object after the bids have been presented. Later, we will provide a motivation for our interest in this variable, that we will call the "level of hypotheticalness" of the auction.

The main objectives of the experiment are to test a theoretical model of bidding and to analyze how the agents' decisions --i.e., whether or not to buy information and what bid to offer-- are affected by changes in (*a*) the distribution of valuations and information costs, (*b*) the number of potential competitors, and (*c*) the probability that a winning bid will actually result in a transaction.

The structure of the paper is as follows. Section II provides a concise discussion of the literature on costly information acquisition and a motivation for this research. Section III presents the theoretical model in which our analysis is based, while section IV describes the design of our experiment. The main results are discussed in section V. Finally, the paper closes with some conclusions.

II. BACKGROUND

The role of information in auctions has been extensively studied, both from theoretical and empirical standpoints.[1] Indeed, a commonly stated motivation for the study of auctions is that they provide a convenient device for the analysis of the price system under informational asymmetries. In that spirit, the following fundamental features have been shown to hold under certain conditions: (*i*) if a bidder is better informed than his competitors, he might profit by acquiring additional information, particularly if this is done in a visible way; (*ii*) it is convenient for the uninformed bidders to acquire some of the informed bidder's information, whenever this can be done

[1] See Milgrom (1981) and Milgrom and Weber (1982) for theoretical treatments of the issue. See also Kagel et al. (1987) for a representative empirical study.

covertly; and (*iii*) the profit of the seller increases when he is able to make public any part of the information of the well-informed bidder.[2]

An unpleasant shortcoming of the conventional approach, however, is that the information level of the bidders is typically treated as an exogenous variable. That is, most models take a certain level of information as a given, and then consider the effects of arbitrary changes in that level. Of course, it would be more realistic to view the information possessed by each agent as a decision variable, whose level depends on the comparison between its acquisition cost and its expected benefit.

As a natural illustration, consider the process of soliciting bids to perform some task, such as constructing a new military jet. The bidders know their cost imperfectly, but at some cost can narrow their uncertainty. Similarly, if a group of art dealers is bidding for a controversial painting, each bidder might be unsure about the exact price at which she will be able to resell the item, but she can discover that information provided she spends some resources. In either case, the optimal decision of a bidder will depend on her cost of information compared with the expected benefit of becoming well informed. To analyze those auctions ignoring this fundamental fact, can lead to misleading inferences.

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[2] Milgrom (1985) provides a throughout survey of the effects of differential information in auction contexts. The results above were first proved by Milgrom and Weber (1982a).

Surprisingly, models with endogenous information acquisition are relatively scarce. In a comprehensive survey by McAfee and McMillan (1987), for example, the case of costly information acquisition is exhausted by a single footnote.[3] A similar observation is valid for the survey by Wilson (1992), in which the topic merits a single reference.[4] Indeed, the number of papers in which the acquisition of information is endogenous is quite short. Mathews (1984) and Lee (1985) were perhaps the first to set up auction models focused on that topic. Schweizer and Ungern-Sternberg (1983), in turn, used simulation methods to analyze the role of costly information in a two-agent framework. More recently, models have been put forward by Engelbrecht-Wiggans (1988) and Guzman and Kolstad (1995).

The same pattern can be found in experimental research. Although there are a number of studies dealing with the effects of information, almost all are confined to the following topics: the effects of public provision of information on the revenue of the seller,[5] the effects of feedback information about previous outcomes in repeated auctions,[6] and the effects of uncertainty about the number of bidders.[7] In an extensive survey of the empirical literature by Kagel (1995) no reference is made to any

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[3] McAfee and McMillan (1987), p. 722, fn. 21.

[4] Wilson (1992), p. 241.

[5] Kagel and Levin (1986)

[6] Isaac and Walker (1985), Cox et al. (1984).

[7] Dyer et al (1989), Battalio et al. (1990).

direct study of bidders’ behavior under costly information acquisition.

This paper attempts to fill that gap, setting up an experiment in which the endogenous nature of information acquisition plays a major role. More specifically, the auctions in the experiment are characterized by the fact that, contrary to previous experiments, the acquisition of information is an endogenous variable, rather than an exogenous parameter.

Our goal is to examine the strength of the economic incentives in a well-controlled environment. How rational are the bidders with respect to the acquisition of information? How does the additional complexity of the environment affect their ability to take optimal decisions? Can the outcome of the auctions be accurately predicted by some particular paradigm? How is the seller's revenue affected by the ignorance of the bidders about their valuations? In spite of their relevance, these interesting problems have never been submitted to close examination through experimental research. The only way to do it, of course, is to take into explicit account the possibility of costly information acquisition, but that has not been done in previous experiments.

Thus, although its structure is probably very specific, we feel that our experiment suggests a fertile direction for additional research on a topic usually neglected in the auction literature. Moreover, it represents an experimental bridge between the economics of search and the economics of bidding behavior.

III. THE MODEL

The theoretical basis of our experiment comes from the equilibrium model developed in Guzman and Kolstad (1995), for which this section provides a concise exposition. The model considers a large number of risk neutral bidders, $i = 1, 2, ...,$ N, who are trying to buy an object in a first-price sealed-bid auction. The object has some particular value, V_i, for each particular bidder, i, but the value V_i is unknown, even to the agent i himself. In fact, the valuations of the object are independent random draws from a continuous density function f, with support in the interval $[V_l, V_u]$. The density function f is common knowledge.

Each individual can follow one of two alternate strategies. He may spend an amount c_i in order to discover the true value that the object represents for him or herself, and then use his findings to form an optimal bid. On the other hand, this agent might save c_i and just use the expectation of V_i as an estimate of his (unknown) true valuation. The costs of information are also independent random draws from a common distribution. Specifically, $c_i \sim g$, $i = 1, 2, ..., N,$ where g is a continuous density function in the interval $[C_l, C_u]$. Each agent knows her particular cost but she ignores the costs of other bidders; however, the density function g is also common knowledge.

We assume that each bidder conjectures that a proportion p of bidders chooses not to buy information about their valuations and consequently are just using the common expectation, $\underline{V}$, as their bid. Therefore, if a bidder pays c_i and then he discovers that his valuation is V, his optimal bidding strategy would have the form $b_i = B(p, V)$. If the agent refuses to buy information, he will find it optimal to bid just $\underline{V}$, given his conjectures that (pN) other bidders are behaving in identical way.[8]

For any particular p, it can be shown that in a unique symmetric equilibrium, the bidding function for the informed

$$B(p, V_i) = V_i - \frac{\int_{\underline{V}}^{V_i} F(\Theta)^{[(1-p)N-1]}\, d\Theta}{F(V_i)^{[(1-p)N-1]}} \qquad (1)$$

bidders with valuation above $\underline{V}$ is:

In turn, the value of information is given by:

$$\Pi(p) = \int_{\underline{V}}^{V_u} \left[\int_{\underline{V}}^{\Phi} (F(\Theta))^{[(1-p)N-1]}\, d\Theta \right] f(\Phi)\, d\Phi \qquad (2)$$

Therefore, the decision of whether or not to acquire information is clearly given by the optimal rule:

(3)
Buy information if $c_i \leq \Pi(p)$
Do not buy information otherwise

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[8] See Guzman and Kolstad (1995) for a discussion of this specific issue.

It follows that a rational expectations equilibrium is given by a value p^e such that the actual proportion of bidders for which $\Pi(p^e) < c_i$ is (nearly) equal to p^e itself.[9] That is,

$$1 - G(\Pi(p^e)) = p^e \tag{4}$$

Guzman and Kolstad (1995) show that, subject to some regularity conditions, this equilibrium exists and is unique. Then, we can combine the results above to obtain an expression

$$E(B) = \int_{\underline{V}}^{V_u} \left[z - \int_{\underline{V}}^{z} \left(\frac{F(\Theta)}{F(z)}\right)^{[(1-p)N-1]} d\Theta \right] \gamma_{N^*}(z)dz + \underline{V}\ \Gamma_{N^*}(\underline{V}) \tag{5}$$

for the expectation of the maximum bid:

where B represents the winning bid, γ_{N^*} is the density function of the maximum in a sample of [(1-p)N] draws on V, and Γ_{N^*} represents the corresponding distribution function.

The following comparative statics results can be shown to hold:

(1) A greater number of bidders implies no larger proportion of bidders acquiring information, but a greater number of well-informed bidders. Therefore, an increase of the number of bidders implies an increase of the expectation of the winning bid.

(2) The effect of a change in the distribution of information costs depends on the change in G(.) when evaluated at the initial equilibrium value of information, $\Pi(p^e)$. If $G(\Pi(p^e))$ increases, then both the proportion of informed bidders and the expectation of the winning bid will

[9] For the sake of exposition, here we are ignoring the discrete nature of p.

increase; if $G(\Pi(p^e))$ decreases, then both variables will decrease.

(3) An increase of the level of "hypotheticalness" implies an increase of the proportion of uninformed bidders and a decrease of the expectation of the winning bid.

The statement in (1)simply says that the decrease in the proportion of informed bidders is never enough to neutralize an exogenous increase in the total number of bidders. Statement (2) is perhaps surprising at first sight, since it says that, except for a single point, changes in the distribution of costs are irrelevant. The statement in (3) is straightforward, and it can be related to the following interpretation. From the point of view of the seller, we can think of the efficiency of an auction as its ability to induce revelation of the true values of the bidders: the most efficient auction would induce the individual with valuation V_u (the maximum) to reveal him or herself. In this sense, the more hypothetical is the auction, the less efficient it is. We have argued elsewhere that this idea has relevant implications for several economic situations.[10]

IV. THE DESIGN OF THE EXPERIMENT

A. General Description

The whole experiment consisted of two separated *sessions*, each with a different set of subjects. Each session, in turn,

[10] An example is given by the case of firms going public. Usually, the firms ask some investors to state the price that they would be willing to pay for some shares. Depending on the information received, the firm decides whether or not to go public. The implication is that, since the investor do not have strong incentives to really investigate the true value of the firm,

consisted of four *sets* of auctions. Finally, a set of auctions was composed of four *auctions* with identical structure, except that some particular variable was changed from one auction to another. A graphical description of the structure of the experiment is given in Figure 1.[11] Auctions were conducted with each participant at an individual computer screen, and the computers were networked to a central auctioneer computer.

In each auction, the "item" posted for sale was a bundle of "tokens." The number of tokens in the bundle could be different from one bidder to another, and each individual was ignorant of the amount that he might receive as his eventual prize -- hereinafter, his private value. However, each individual was given the opportunity to pay some amount of tokens --hereinafter, his information cost-- in order to receive that information.

For each auction, we selected in advance the intervals where all private values and information costs should lie, and then those intervals were publicly announced to the bidders. Next, a computer program randomly selected private values and costs for each subject; each subject then faced the decision of whether or not to buy information about their private valuations. In addition, the bidders were informed that, after the maximum bid was determined, we would spin a probability wheel to determine whether or not the transaction would actually be consummated.

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this procedure might be almost uninformative. See Guzman and Kolstad (1995).

[11] In addition, we carried on an initial set of four auctions with the objective of familiarizing the subjects with the general structure of the game, but the results of this benchmark set were not used in the statistical analysis of the data.

The probability of consummation of the sale was also publicly announced in advance. Summing up, a typical auction consisted of six steps: (1) the ranges for private values and information costs, and the probability of consummating the auction, were made public; (2) each bidder was privately informed of her private information cost; (3) if a bidder agreed to buy information, then she was secretly informed about her valuation, and her information cost was subtracted from her current balance; (4) bids were submitted and the winning bid of the auction was determined; (5) a probability wheel was spun (in some auctions) to determine whether the sale should be consummated; (6) the winning bidder received her prize.

B. Financial and Informational Issues

The operations of the bidders were financed by a current account provided to each bidder. At the beginning of an experimental session, the balance of each current account was set to 1000 tokens and, as we already mentioned, these balances were updated after each auction. For the winning bidder, the following was added to his account:

$$\chi_v(V_i - b_i) - \chi_c c_i \qquad (6)$$

where V_i, b_i, and c_i represent his valuation, bid, and information cost, respectively; χ_v is an indicator variable equal to 1 when the sale is consummated and 0 otherwise; and χ_c is equal to 1 when the agent has bought information and 0 otherwise. For other bidders, the updating of balances simply required subtracting the amount $\chi_c c_i$.[12]

After each set of auctions, the balance of the current account of any bidder was added to the previous balance of the bidders' *cumulative account*, while the new current balance was again set to 1000 tokens. The cumulative accounts could not be used to finance current operations of the bidders and their function was just to measure the amount accumulated for each bidder up to any particular moment. To motivate the subjects to take their decisions seriously, we announced that at the end of the experiment, a prize of 75 dollars would be awarded by lottery among all the participants, using for each a probability of winning proportional to his or her accumulated balance at the end of the experiment. The objective of this procedure was twofold. First, to ensure that the budget constraint was not binding for any set of auctions, since we were not interested in analyzing the effects of budget constraints; second, to guarantee that all participants were really motivated to accumulate as many tokens as they could over the whole experiment.[13]

The subjects were not allowed to communicate with each other.

[12] It should be emphasized that the subtraction of the information cost was certain and totally independent of whether or not the sale was ultimately consummated.

[13] A discussion of cash balance effects is found in Hansen and Lott (1991).

Thus, all public information was provided by a proctor, and any private information was sent to each bidder through his computer screen. Similarly, their decisions concerning whether or not to buy information, as well as the bids, were sent to the proctor through a computer system specifically designed for the experiment.

C. The types of Auctions

A summary of the relevant variables for each auction is given in Table 1.[14] In the first set, the range of private values was changed from one auction to another while the ranges of information costs and the number of bidders were maintained fixed. In the second set, the range of information costs was changed from one auction to another, all other parameters remaining fixed.

In the third set, the relevant variable to be changed was the probability of consummation of the sale after a winning bid has been determined; thus, in contrast to the other sets, here we set a positive probability that the auction was just a hypothetical one. Finally, in the fourth set, we controlled for the number of bidders, decreasing that number from 15 individuals (in the first auction of the set) to only 3 bidders (in the last auction).

[14] All the auctions (except in the case when we controlled by the number of bidders), involved 15 bidders. Since we run two experimental sessions with identical structure, the data was combined to have a total number of 30 observations. Five observations were disregarded because they revealed, above any reasonable doubt, a misunderstanding of the rules of the auctions. This yields a final sample of 25 observations. All the subjects were MBA and undergraduate students of the University of Illinois at Urbana-Champaign.

V. EXPERIMENTAL RESULTS

In this section, we will pursue two related objectives. First, we will test the predictive accuracy of the risk-neutral Rational Expectations (RNRE) model outlined in section II; this will require an analysis across *all the auctions of the experiment*. Given the uniform distribution of private values and information costs, it is a simple matter to compute the equilibrium values for the most relevant variables in each auction, and then those values can be compared with the factual observations. Second, we will discuss the sensibility of some relevant variable with respect to specific changes in exogenous parameters; this will require an analysis *across the auctions of a given set*.

A. Evaluating the Predictions of the RNRE Model.

The predictive accuracy of the model is first tested through the comparison of the expected and actual values of the proportion of uninformed bidders, p, and the winning bid, B. The values of those variables for the different auctions are summarized in Table 2. Figure 2-5 present a graphical summary of the same data.

An informal inspection of the graphs suggests that both the proportion of uninformed bidders and the winning bid track very closely the movements of the equilibrium values. In the case of the winning bid, however, the level of the sample values seems to be above the equilibrium: in all but one auction, the winning bid is higher than the prediction of the model. Of course, this would imply that the (risk neutral) equilibrium persistently *underestimates* the actual winning bid.

A regression between sample and predicted values is a convenient way to formalize that observation. Specifically, we will use the regressions

$$p^s = a_0 + b_0 p^e$$

and

$$B^s = a_1 + b_1 B^e \tag{7}$$

as the basis for testing some appropriate hypotheses about the parameters a_i and b_i, i = 0, 1, where the superscripts {s, e} denote the sample and theoretical equilibrium values, respectively.

The results of the regressions are given in Table 3. It can be seen that the "b" coefficient is slightly <u>below</u> 1 for the proportion of uninformed bidders, while slightly <u>above</u> 1 for the winning bid. However, the difference is not statistically significant for either case, so that the null hypothesis

$$H_0\ (i):\quad b_i = 1 \tag{8}$$

cannot be rejected for either i = 0 or 1. A similar result applies to the hypothesis

$$H_0\ (i):\quad a_i = 0 \tag{9}$$

However, a different result is obtained when we test the joint hypothesis

$$H_0\ (i):\quad a_i = 0,\quad b_i = 1 \tag{10}$$

which amounts to test the equality of actual and equilibrium values. In this case, the hypothesis cannot be rejected for the proportion of uninformed bidders, but it is clearly rejected for the winning bid. Overall, this validates the heuristic caveat that the "movements" of the winning bid are reasonable predicted by the equilibrium values, but the "level" of the bid might be underestimated.

An alternate approach to measure the predictive power of the theoretical model is given by a Goodness-of-fit test applied to the proportion of bidders acquiring information. The idea is simply to compare the number of bidders in each category (i.e., "buying" or "not buying" information) with the predicted numbers given by the expressions $N(1-p^e)$ and Np^e, respectively. The test

$$\chi^2 = \frac{(Np^s - Np^e)^2}{Np^e} + \frac{(N(1-p^s) - N(1-p^e))^2}{N(1-p^e)} \qquad (11)$$

is based in the statistic
where N denotes the size of the sample, p is the proportion of bidders <u>not</u> acquiring information and, as usual, the superscript distinguishes the sample and predicted values.[15] Table 4 shows that only in two cases --i.e., auctions 8 and 12-- are the prediction of the model statistically different from the actual

[15] It is well known that the statistic follows a χ^2 distribution with one degree of freedom. An elementary exposition can be found in Senter (1969).

realization.[16]

B. The proportion of "Information Acquisition Errors"

As a counter to these conclusions, it might be argued that the Goodness-of-fit test has the following drawback. It allows the possibility that the "information acquisition errors" of some bidders are canceled out by the errors of others.[17] Thus, even if the observed numbers in each category agree with the predicted numbers, this could hide significant departures if we look at the behavior of each individual bidder. Therefore, we will follow an alternate approach that takes this into consideration.

Let us begin by defining the variable J_i as the proportion of decision errors in auction i. The relevant question is whether or not this variable tends to be below some reasonably small cutoff. Since the selection of the threshold is necessarily arbitrarily, we will follow a conservative approach by testing the hypotheses:

$$\begin{aligned} H_0: &\quad J_i \leq 0.20 \\ H_a: &\quad J_i > 0.20 \end{aligned} \tag{12}$$

Of course, a rejection of the null would imply that decision errors are common and systematic, rather than purely random and

[16] In some cases, the application of the test requires some cautious because a very good approximation to the X^2 distribution needs Np^e and $N(1-p^e)$ to be greater or equal to 5. Consequently, this test was not applied to auctions 13-16 in which the number of observations wass too small.

[17] By "information acquisition error" we refer to the decision of an agent who buys information when, given his information cost, the model suggests not to buy it, or vice versa.

negligible.

The results of this test for auctions 1-12 are shown in Table 5, where we also present the number of “wrong” decisions in each auction. The test is based on the comparison between that number and the critical number corresponding to the 10% tail of a binomial distribution with parameters (25, 0.20, 0.80).[18] If, assuming the null hypothesis holds, the probability of drawing a number of errors equal to the actual number is below 0.20, then the null should be rejected. As shown in the table, this is the case in three (3) auctions, so that the null cannot be rejected in the remaining nine (9) auctions. Later on, we will provide some additional comments about the number of decision errors in auctions 5-8.

C. The Symmetry of the Equilibrium with Costly Information

An important implication of the standard private values model is that the equilibrium is efficient, in the sense that the object is won by the bidder with the highest valuation. This fact has been commonly verified in experimental research, giving support to the relevance of the symmetric Risk-Neutral Nash Equilibrium model (RNNE).[19] When we introduce costly information, of course, that is not true anymore: the bidder with the highest valuation might decide to remain uninformed, and then the auction can be won by another bidder. Indeed, the probability of an

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[18] The use of the binomial distribution follows from the binary nature of the variable *J*. Here we consider a "correct decision" as a success, and a "wrong decision" as a failure.

[19] See, for example, Dyer et al. (1989, fn. 10) and the references there.

efficient outcome can be made very small, just by shifting the distribution of costs in an appropriate way. This remains essentially true even if alternate criteria for efficiency are adopted -- as, e.g., that the auction is won by the bidder with a highest value $V_i - c_i$. In short, efficiency is not a testable implication of the Risk-Neutral Rational Expectations (RNRE) model.

Yet, the model still predicts that, *after* buying information, all bidders would use the same bidding function, increasing in valuation. This follows immediately from the fact that, after buying information, all bidders face the same situation, whatever their information costs might have been. Then, the bidder with the highest valuation among the informed bidders will also present the highest bid, and that does impose a constraint that our data should satisfy.

Overwhelming evidence indicates that this is, in fact, the case: in all the auctions of the experiment, the highest bid among the informed bidders was presented by the bidder with the highest valuation. A representative pattern for the relationship between valuations and bids for informed bidders is given in Figure 6. In addition, in Table 6 we report the coefficients of correlation between valuations and bids for those auctions where the number of informed bidders allows such a computation. It can be seen that the coefficients are always positive and, in most cases, relatively high. Although the amount of observations in each auction is very small for formal tests, we think it is not unreasonable to conclude that the symmetry of the bidding strategies predicted by the RNRE model is clearly verified in our data.

D. The effects of the Exogenous Parameters

Here we will discuss now the sensitivity of some endogenous variables with respect to changes in the parameters of the model. We consider as exogenous parameters the level of hypotheticalness, α, the distribution of information costs, and the total number of bidders, N. The small number of observations (four auctions in each set) will not permit us to rely on formal procedures to test for statistical significance of the changes within a given set. Thus the following will be necessarily heuristic and will rely on an informal description of the data. Our attention will be confined to the proportions of (un)informed bidders and decision errors, not only because they represent the *leit motif* of our study, but also because movements in other variables are not as easily readable from our limited data.

The effects of changes in the distribution of values are measured through the first auction set (auctions 5-8), by changing the maximum feasible valuation from one auction to another. The model predicts that the proportion of uninformed bidders should be sensitive to changes in V_u, decreasing monotonically as V_u is increased.

In Table 7, panel a, our presumption is weakly validated in the sense that the average p of the first two auctions is clearly above the average of the latter auctions, although the movement in p is not monotonic. For further reference, we notice that the proportion of decision errors is not particularly sensitive to the changes in V_u.

The effects of changes in the distribution of information costs are measured through the second set (auctions 5-8), where the range of information cost is changed from one auction to another. The model predicts that, as the maximum feasible cost is decreased, the proportion of uninformed bidders would also go down. Thus, as shown in panel b, the movement in p is in the right direction: when we move from the fist to the last auction of the set, the tendency of p to decrease is unambiguous. On the other hand, the proportion of decision errors increases systematically as the range of information costs is reduced. In fact, the proportion of decision errors in the first auction of the set is doubled in the second, and then tripled in the fourth.

The last result is somehow surprising because it suggests that the possibility of judgmental errors increases when the range of information costs is narrowed. This is even more striking when compared with the results in the other sets, where the proportion of decision errors is not particularly sensitive to parametric changes in other variables. The following argument will allow us to advance a tentative conjecture about this curious fact.

In theory, a reduction of C_u leads to a new equilibrium with a greater number of informed bidders and, consequently, greater competition among the informed bidders. In turn, this reduces the value of increases the value of becoming informed; that is, it shifts to the left the threshold $\Pi(p)$ in (3). Our conjecture is that such a decrease of the value of information is wrongly exaggerated in the perception of many bidders, so that they stop buying information even when is profitable to buy it.

To support our conjecture, we separate the total number of decision errors into two groups. The first group includes the bidders who buy information when they should not do so given their information costs; the second group includes those bidders who do not buy information when they should buy it. It can be seen from Table 8 that the huge increase in the number of decision errors is driven by the second group, which is precisely the content of the conjecture above. Whether this result is systematic or just a casual puzzle from our data cannot be determined conclusively without further research.

The effects of changes on the level of hypotheticalness, α, is measured through the third set of auctions (9-12). The model predicts that the proportion of uninformed bidders will increase as the level of hypotheticalness increases; also, we find it reasonable to expect that the proportion of decision error will decrease when the level of hypotheticalness approaches 100%, because then the correct decision (not to buy information) tends to be obvious without too much computation. The data reproduced in panel c shows that the proportion of errors does decrease:

while its average value in the first two auctions is 18%, the average of the last two auctions is around 8%. In turn, the change in p moves quickly from auction 9 to auction 10, although is partially reverted at the last auction of the set.

Finally, the effect of changes of the number of bidders is measured through the fourth set of auctions (13-16). In this case, the reaction of the sample p looks particularly strong. As shown in panel d, it decreases from 81% in auction 13 to only 25% in the last auction of the set. The proportion of errors also decreases, but in a smaller magnitude. We interpret this data as indicating that, in this case, the bidders accurately realize that a smaller number of competitors increases the value of information and, consequently, the incentive to become informed.

E. Nash Equilibrium vs. Rational Expectations

The final issue we address involves a comparison of our experimental results with the predicted winning bids from a risk neutral nash equilibrium (RNNE) bidding model as well as the RNRE model. Figure 7 shows how these three possible auction outcomes compare for each of the sixteen auctions. Although we are unable to draw any statistically valid conclusions, it is striking that the experimental results appear to be bounded above by the RNNE outcome and below by the RNRE outcome. This contrasts with the conventional result in the experimental economics literature (Kagel, 1995) that the RNNE model under-predicts the winning bid in experiments. Risk aversion can be used to bring the Nash equilibrium outcome into closer agreement with the experimental results.

This result suggests the relevance of information acquisition in predicting the outcome of an auction. Suppose one wishes to predict the outcome of an auction. A common assumption would be that using a RNNE model to predict the outcome would underestimate the winning bid. One might then introduce risk aversion to correct for this. Our results would suggest that this would increase the prediction error rather than decrease it, at least if information costs are significant. In fact, a prediction somewhat below the RNNE might be most appropriate.

VI. CONCLUSIONS

We can now summarize our main conclusions:

1. The predictions of the Risk-Neutral Rational Expectations (RNRE) model about the proportion of bidders who acquire information are highly consistent with the results obtained in our experiment.

2. The predictions of the model concerning the winning bid are consistent with the movement in the actual winning bid, but they underestimate its actual level.

3. In our sample, the proportion of bidders buying information is particularly sensitive of changes in the number of bidders and costs. It is less sensitive to changes in the level of hypotheticalness and the distribution of values.

4. The proportion of information acquisition errors is extremely sensitive to changes in the distribution of information costs. Specifically, the number of decision errors increases systematically when the range of cost is reduced. This is tentatively interpreted as an overreaction in the perception of the bidders concerning the reduction of the benefit of becoming informed. It remains as a topic for further research whether this is a systematic or a casual fact.

The second conclusion above coincides with a familiar result in experimental studies. That is, the actual winning bid is above its equilibrium value. This result usually is found in experiments without endogenous information acquisition.[20] Since those controversial issues have not been convincingly solved in a simpler framework, we will not presume to solve them in our more general structure. A very brief comment will suffice here.

A usually adopted explanation is that the result is driven by some type of risk aversion in the behavior of the bidders. The introduction of risk aversion in our costly information framework might be a little tricky because, in spite of improving the fit of the winning bid, it is also likely to worsen the fit of the proportion of informed bids. The reason is that risk aversion would increase the bids of informed bidders, but it would also increase the (insurance) benefit of being well informed, driving p down. A closer treatment of the problem would require reworking the costly information model introducing explicit risk aversion. Our current view is that risk aversion should be consider as an explanatory element, but we are not so sure that it can provide a complete solution of the riddle. That is material for further research.

In general, the results of this paper should be considered as basically suggestive, without further presumptions given the

[20] See Kagel (1995) for a discussion.

limitations of the data. However, we hope that our experiment represents a convenient framework to analyze, through experimental settings, the fundamental issue of information acquisition and its relation with bidding behavior.

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TABLE 1
STRUCTURE OF THE AUCTIONS

(a) First set: Changing Range of Private Valuations

Auctions	V_l	$\mathbf{V_u}$	C_l	C_u	Hypothetical Level	Bidders per Auction
1	0	**100**	0	60	0	15
2	0	**200**	0	60	0	15
3	0	**300**	0	60	0	15
4	0	**500**	0	60	0	15

(b) Second Set: Changing Range of Information Costs

Auctions	V_l	V_u	C_l	$\mathbf{C_u}$	Hypothetical Level	Bidders per Auction
4	0	300	0	**130**	0	15
5	0	300	0	**30**	0	15
6	0	300	0	**15**	0	15
7	0	300	0	**5**	0	15

(c) Third Set: Changing the Level of Hypotheticalness

Auctions	V_l	V_u	C_l	C_u	**Hypothetical Level**	Bidders per Auction
9	0	300	0	30	**10%**	15
10	0	300	0	30	**40%**	15
11	0	300	0	30	**60%**	15
12	0	300	0	30	**90%**	15

(d) Fourth Set: Changing the Number of Bidders

Auctions	V_l	V_u	C_l	C_u	Hypothetical Level	**Bidders per Auction**
13	0	300	0	60	0	**13**
14	0	300	0	60	0	**9**
15	0	300	0	60	0	**6**
16	0	300	0	60	0	**3**

TABLE 2
WINNING BID AND PROPORTION OF UNINFORMED BIDDERS

Auction	p^e	p^s	B^e	B^s(*)
1	0.87	0.80	54.63	97
2	0.81	0.88	117.73	158
3	0.76	0.76	187.70	276
4	0.71	0.64	330.31	486
5	0.84	0.84	169.29	200
6	0.69	0.72	202.26	292
7	0.59	0.52	219.07	282
8	0.40	0.64	240.55	239
9	0.70	0.72	200.32	251
10	0.76	0.96	187.70	246
11	0.79	0.96	180.97	210
12	0.91	0.84	154.48	293
13	0.75	0.81	182.50	232
14	0.70	0.71	173.90	249
15	0.63	0.72	166.52	237
16	0.50	0.25	156.29	222

(*) Computed as the average of the winning bids of the two experiment sessions.
NOTE: The superscripts "s" and "e" denote the sample and equilibrium value, respectively.

TABLE 3
TEST OF RELEVANT HYPOTHESES

(a) Equilibrium p vs Sample p

Variable	Estimated Coefficient	Standard Error	*t*-statistic
Constant	.067900	.175291	.387357
P^e	.934584	.241871	0.27000(*)

F-statistic = 0.26790(**)

R-squared = .516079
Durbin-Watson statistic = 1.86211
Variance of residuals = .015617
Std. dev. of dependent variable (p^s) = .173550
Number of observations = 16

(b) Equilibrium B vs Sample B

Variable	Estimated Coefficient	Standard Error	*t*-statistic
Constant	19.3998	32.5789	.59547
P^e	1.25149	.1704	1.47530(*)

F-statistic = 24.68142(**)

R-squared = .7937
Durbin-Watson statistic = 2.2717
Variance of residuals = .1448.63
Std. dev. of dependent variable (B^s) = 80.9699
Number of observations: 16

(*) For H_0: $b_i = 1$
(**) For H_0: $a_i = 0$, $b_i = 1$.
NOTE: The superscripts "s" and "e" identify the sample and equilibrium value, respectively.

TABLE 4
GOODNESS-OF-FIT TEST

Auction	χ^2	
1	0.29	
2	1.00	
3	0.21	
4	0.18	
5	0.00	
6	0.18	
7	0.16	
8	4.16	(*)
9	2.67	
10	1.51	
11	1.51	
12	9.17	(*)

(*) H_0 is rejected at 10% level of significance.

TABLE 5
TEST OF HYPOTHESIS $J_i \leq 0.20$

Auction	Decision Errors	
1	5	
2	6	
3	7	
4	4	
5	4	
6	8	(*)
7	10	(*)
8	12	(*)
9	5	
10	4	
11	1	
12	3	

(*) H_0 is rejected at 10% level of significance.

TABLE 6
CORRELATION BETWEEN VALUES AND BIDS
FOR INFORMED BIDDERS

Auctions	ρ	Number of Obs.
1	0.99	5
2	0.89	3
3	0.88	6
4	0.85	9
5	0.87	4
6	0.97	7
7	0.56	12
8	0.91	9
9	0.71	7
12	0.99	4
14	0.99	4

TABLE 7
SUMMARY OF RESULTS BY SETS OF AUCTION(*)

(a)
Set 1: Changes of Values Range

Auction	V_u	p^s	p^e	Information Acquisition Errors(%)
1	100	0.80	0.87	0.20
2	200	0.88	0.81	0.16
3	300	0.76	0.76	0.28
4	400	0.64	0.71	0.16

(b)
Set 2: Changes of Costs Range

Auction	V_u	p^s	p^e	Information Acquisition Errors(%)
5	130	0.84	0.84	0.16
6	30	0.72	0.69	0.32
7	15	0.52	0.59	0.40
8	5	0.64	0.40	0.48

(c)
Set 3: Changes of Hypothetical Level

Auction	α(**)	p^s	p^e	Information Acquisition Errors(%)
9	10%	0.72	0.70	0.20
10	40%	0.96	0.76	0.16
11	60%	0.96	0.79	0.04
12	90%	0.84	0.91	0.12

(d)
Set 4: Changes of Number of Bidders

Auction	Bidders per Auction	p^s	p^e	Information Acquisition Errors(%)
13	13	0.81	0.75	0.32
14	9	0.71	0.70	0.29
15	6	0.72	0.63	0.33
16	3	0.25	0.50	0.20

(*) The last column refers to the ratio (Information acquisition errors)/ (total number of bidders in the auction.)

(**) α denotes the level of hypotheticalness; i.e., the probability that the sale is not consummated after the bids have been presented.

TABLE 8(*)
DECISION ERRORS BY GROUPS

Auction	GROUPS 1	2	Total
5	3	1	4
6	4	4	8
7	4	6	10
8	4	8	12

(*) Group 1 is composed of the bidders who buy information when they "should" not do so; group 2 is composed of the bidders who do not buy information when they "should" buy it.

FIGURE 1
STRUCTURE OF THE EXPERIMENT

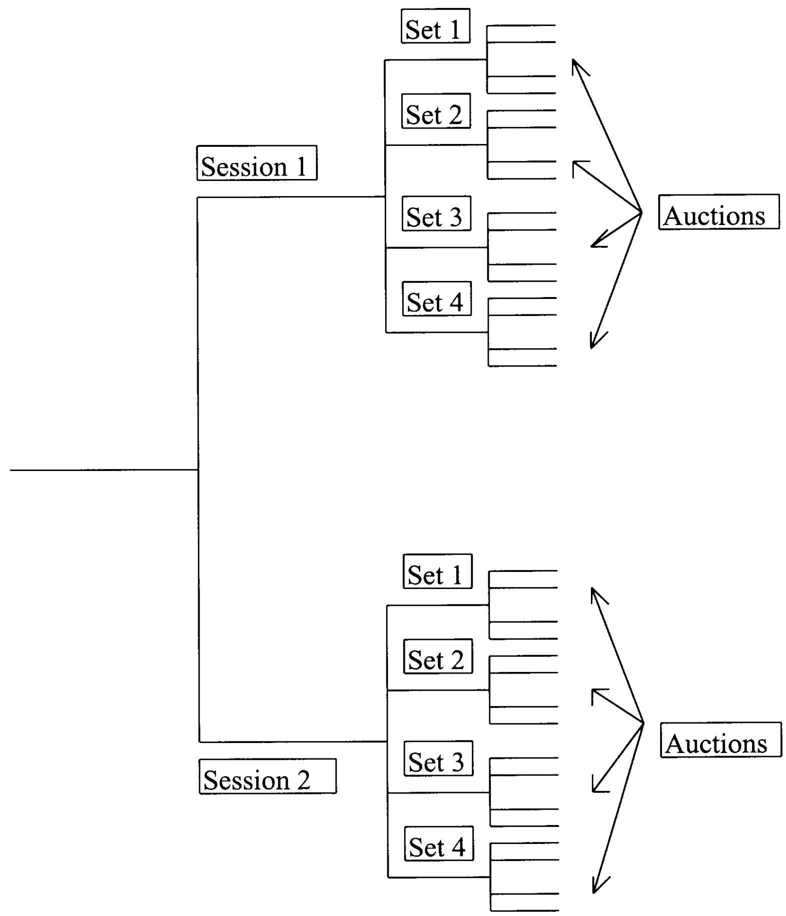


FIGURE 2
EQUILIBRIUM AND SAMPLE PROPORTIONS OF UNINFORMED BIDDERS PER AUCTION

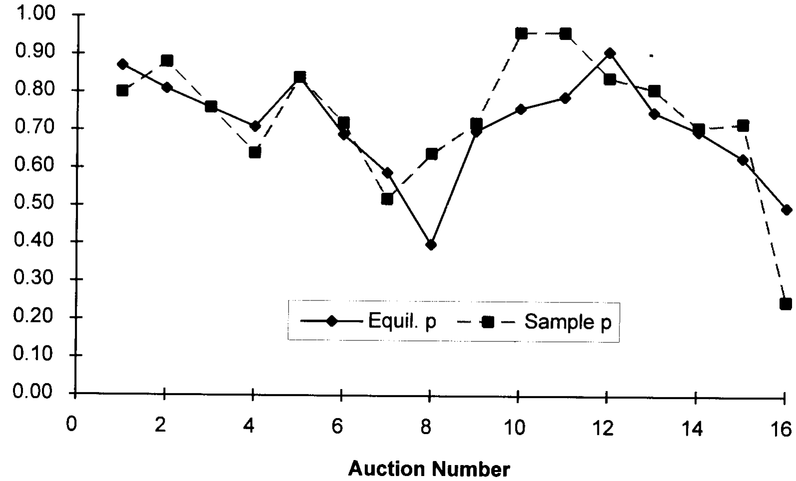
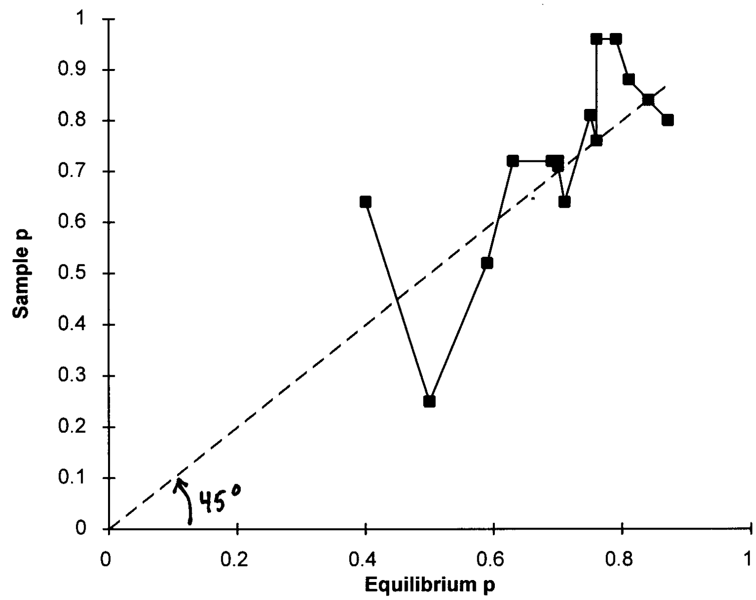
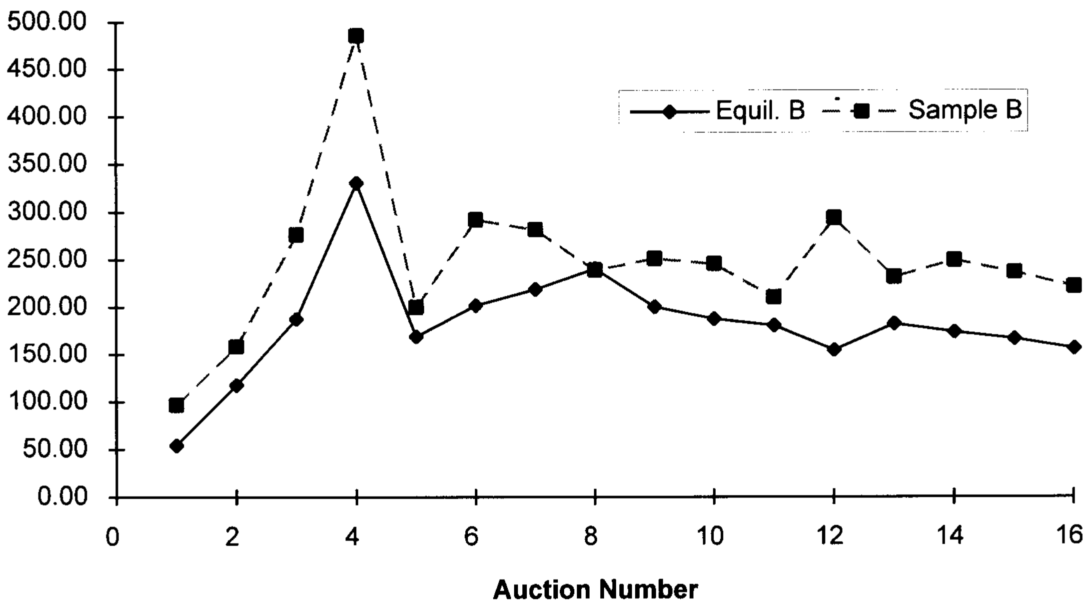


FIGURE 3
EQUILIBRIUM VS. SAMPLE PROPORTIONS OF UNINFORMED BIDDERS



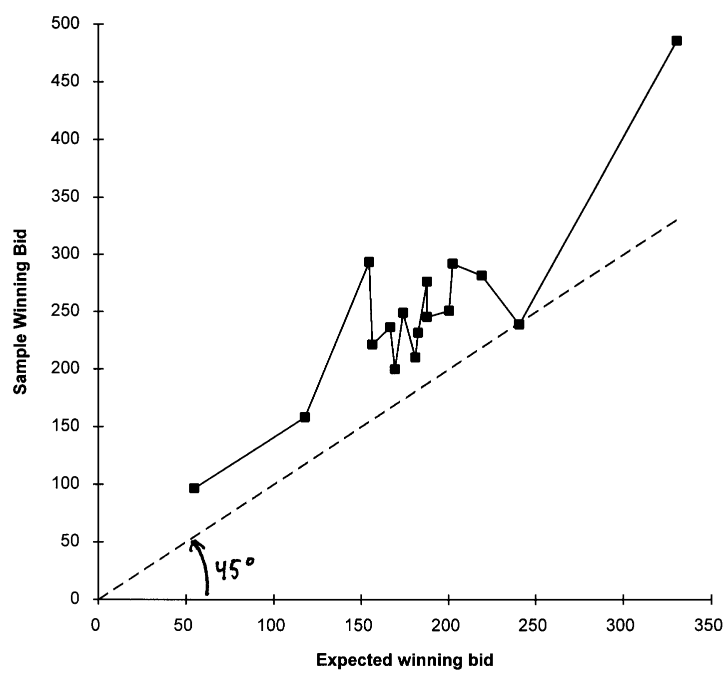
1
0.9
0.8
0.7
0.6
0.5
0.4
0.3
0.2
0.1
0
Sample p
0
0.2
0.4
0.6
0.8
1
Equilibrium p
45°

FIGURE 4
EQUILIBRIUM AND SAMPLE



WINNING BIDS PER AUCTION

FIGURE 5
EQUILIBRIUM AND SAMPLE



WINNING BIDS

FIGURE 6
VALUES AND BIDS OF INFORMED BIDDERS

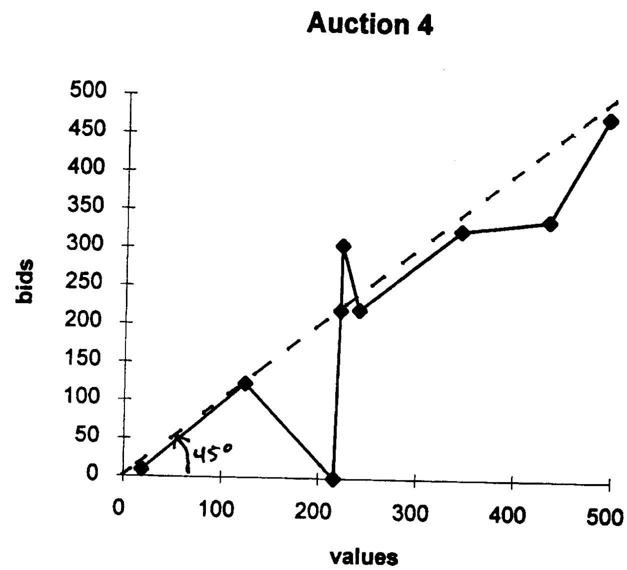


FIGURE 7
A COMPARISON OF THEORETICALLY PREDICTED WINNING BIDS FROM THE RISK-NEUTRAL NASH EQUILIBRIUM (RNNE) AND RATIONAL EXPECTATIONS (RNRE) MODELS WITH EXPERIMENTAL RESULTS