Statistical Characterization of Heterogeneity in Experiments

by

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ABSTRACT

We propose a statistical approach for capturing the heterogeneity of the decision processes being used in economic experiments. As a case study, we explore individual behavior in first-price sealed bid auctions. Using a statistical mixture modeling approach, we allow the data to support several models simultaneously. Such an approach allows a sufficiently richer characterization of behavior and leads to several unique insights. For example, we find that received theory describes behavior well for auctions with a small number of bidders but performs poorly for auctions with a larger number of bidders. Further, we find that more experienced agents are much more likely to follow Nash bidding strategies than their lesser experienced counterparts. More generally, we believe that our experimental and modeling approaches hold promise for a broad array of empirical queries.

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One of the enduring contributions of experimental economics has been the confrontation of received theory with data that demands alternative theoretical specifications. This confrontation has often been framed as a horse race, with the winning theory being declared on the basis of some statistical test.[1] Pursuing the metaphor, experiments have also identified certain domains in which theory seems to do better, just as some horses run better over different lengths and in different weather.[2] The problem with this approach is that it glosses the heterogeneity of the population, by implicitly assuming that one theory fits every individual. In other words, we seem to pick the best theory by "majority rule." If one theory explains more of the data than another theory, we declare it the better theory and discard the other one.

This approach is acceptable only if there is no reason to believe that decisions can differ within the sample considered. This may be appropriate for some settings, in which we only want one theory that best accounts for the data. But it is inappropriate when the objective is to understand the appropriate domain of applicability of each theory. If we want to identify which people behave according to what theory, and when, then we need to allow the data to reveal that information.[3]

One way that heterogeneity can be recognized is by collecting information on observable characteristics, and allowing for unobserved individual characteristics when appropriate with panel data. For example, a given theory might allow some individuals to be more risk averse than others as a matter of personal preference. When we measure risk attitudes we can condition on individual characteristics and evaluate if there is heterogeneity. But this approach only recognizes heterogeneity within a given theory. This may be important to correct invalid inferences that theory cannot explain

[1] A classic example is the Grether and Plott [1979] study of preference reversals.

[2] The Nobel Lecture of Smith [2003] stresses this point, contrasting experimental findings in the domain of impersonal market exchange with experimental findings in the domain of personal social exchange.

[3] There is also a purely statistical reason to want to recognize heterogeneity in behavior. If we have reason to believe that there are two or more population processes generating the observed sample, one can make more appropriate inference if the data are not forced to fit a specification that assumes one population process.

data,[4] but it does not allow for heterogeneous *theories* to co-exist in the same sample.

One way to allow explicitly for alternative theories is to simply collect sufficient data at the individual level, and test the different theories for that individual. One classic example of this approach is the experimental study of expected utility theory by Hey and Orme [1994]. In one experimental treatment they collected 100 binary choice responses from each of 80 subjects, and were able to test alternative estimated models for each individual.[5] Thus, at the beginning of their discussion of results (p.1300), they state simply, "We assume that all subjects are different. We therefore fit each of the 11 preference functionals discussed above to the subject's stated preferences for each of the 80 subjects *individually*." Their approach would not be so remarkable if it were not for the prevailing popularity of the "representative agent" assumption in previous tests of expected utility theory.

We consider the more familiar case in which one cannot collect considerable data at the level of an individual, or where the data involve strategic interactions between individuals. How is one to account for heterogeneous population processes in such settings? We propose the use of statistical mixture models, in which the "grand likelihood" of the data is specified as a probability-weighted average of the likelihood of the data from each of K>1 models.[6] In other words, with two modeling alternatives the overall likelihood of a given observation is the probability of model A being true times the likelihood conditional on model A being true, plus the probability of model B being true

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[4] For example, Holt and Laury [2002] infer that one must add a "stochastic error" story to explain observed responses in an experiment eliciting risk attitudes, when this inference is due to the extreme assumption that every individual has the same risk attitude. As it happens, the data does support some such stochastic error story even when one conditions on individual characteristics, but not as a logical necessity.

[5] They also collected an additional 100 observations from the same individuals in a later session, so one could view these data as consisting of 200 responses per subject.

[6] Mixture models have an astonishing pedigree in statistics: Pearson [1894] examined data on the ratio of forehead to body length of 1000 crabs to illustrate "the dissection of abnormal frequency curves into normal curves,...". In modern parlance he was allowing the observed data to be generated by two distinct Gaussian processes, and estimated the two means and two standard deviations. Modern surveys of the evolution of mixture models are provided by Titterington, Smith and Makov [1985] and Everitt [1996].

times the likelihood conditional on model B being true.

One challenge with mixture models of this kind is the joint estimation of the probabilities and the parameters of the conditional likelihood functions. If these are conditional models that each have some chance of explaining the data, then mixture models will be characterized numerically by relatively flat likelihood functions. On the other hand, if there are indeed K distinct latent processes generating the overall sample, allowing for this richer structure is inferentially useful. Most of the applications of mixture modeling in economics has been concerned with their use in better characterizing unobserved individual heterogeneity in the context of a given theory about behavior,[7] although there have been some applications in environmental economics that consider individual heterogeneity over alternative behavioral theories.[8]

We consider an important case in which there has been considerable debate over the ability of received theory to account for behavior: bidding in a first-price sealed-bid auction characterized by private and independent values.[9] Auction theory is very rich, and has been developed specifically for the parametric cases considered in experiments (e.g., Cox, Roberson and Smith [1982] and Cox, Smith and Walker [1988]). We undertake artefactual field experiments in which we replicate previous procedures, but in a setting in which subjects naturally participate in auctions.[10] We also elicit information from subjects that allows us to parameterize the risk attitudes of the subject, since risk posture is a critical characteristic of the predicted bid under the standard model (e.g., Harrison

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[7] For example, see Heckman and Singer [1984], Geweke and Keane [1999] and Araña and León [2005]. The idea here is that the *disturbance term* of a given specification is treated as a mixture of processes. Such specifications have been used in many settings that may be familiar to economists under other names. For example, stochastic frontier models rely on (unweighted) mixture specifications of a symmetric "technical efficiency" disturbance term and an asymmetric "idiosyncratic" disturbance term; see Kumbhakar and Lovell [2000] for an extensive review.

[8] For example, see Werner [1999], who uses mixture models to characterize the "spike at zero" and "non-spike" responses common in contingent valuation surveys.

[9] See Kagel [1995] and Harrison [1989][1990][1992] for a flavor of the debates.

[10] The term "artefactual field experiments" is due to Harrison and List [2004], and refers to laboratory experiments that are undertaken in the field. Our methods for recruitment follow List and Lucking-Reiley [2000].

[1990]). We then posit three alternative models, and estimate a grand likelihood function that allows each to have different weights.

We report several insights. First, when auctions consist of a small number of bidders, received theory does a wonderful job of characterizing behavior. But when auctions consist of more and more bidders, received theory does increasingly poorly. The evidence suggests that received theory is relevant for "small auctions" but not for "large auctions." [11] Second, we find that more experienced bidders tend to bid more in line with Nash expectations than their lesser experienced counterparts. This result, which is consistent with List [2004], suggests that individual behavior converges to neoclassical predictions as trading experience increases. Thus, if one were testing received theory it would matter on what domain the data were generated.

In section 1 we review theoretical predictions and outline our empirical approach. In section 2 we describe our experimental procedures. In section 3 we examine the results. Section 4 draws conclusions.

1. Theoretical Predictions and Empirical Approach

Cox, Roberson and Smith [1982] develop a model of bidding behavior in first-price sealed bid auctions that assumes each agent has a CRRA utility function $U(y) = y^r$, where U is the utility of experimental income y and $(1-r_i)$ is the Arrow-Pratt measure of risk aversion. To allow distinct risk attitudes, each agent has their own r_i. However, r_i is restricted to lie on the closed interval [0,1], where $r_i = 1$ corresponds to risk neutrality. Hence this model only allows (weak) risk aversion, and

[11] Cox, Roberson and Smith [1982] reported different results, with the smallest of their auctions (N=3) generating the data that seemed to most obviously contradict the risk-averse NE bidding model. However, this could have been due to collusion. In *all* of their experiments the same N bidders participated in multiple rounds, facilitating coordination of collusive under-bidding strategies that wreak havoc with the one-shot predictions of the theory.

does not admit risk-loving behavior.[12] Each agent knows their own risk attitude, their own valuation v_i, that everyone's risk attitudes are drawn from the closed interval [0,1], and that everyone's valuation is drawn from a uniform distribution over the interval $[v_0, v^1]$. It can then be shown that the symmetric Bayesian Nash Equilibrium implies the following bid function:

$$b_i = v_0 + [(N-1)/(N-1+r_i)]\ (v_i - v_0)$$

where there are N active bidders. In the risk-neutral case in which v_0=0 and v^1=1, this model is isomorphic to Vickrey [1961], and calls for bidders to bid using a simple rule: take the valuation received and shade it down by (N-1)/N.

We propose two alternative models of bidding behavior. The first is motivated by the simple heuristic logic of the Vickrey bidding rule, and assumes that subjects bid some fraction α of their individual valuation. We allow α to be a linear function of the key parameters of the task from a strategic perspective: the number of bidders. We refer to this as our "Heuristic model."

The second alternative model is intended as a residual catch-all to capture a "zero intelligent" (ZI) bidding rule β that can vary across individuals but that does not use any information of strategic relevance, such as the valuation of the bidder, the risk attitudes of the bidder, or the number of bidders. Such a bidding model is consistent with the spirit of the ZI agents proposed in a classic study by Gode and Sunder [1993] of efficiency in the double oral auction. We implement this model as a linear function of characteristics of the individual: whether they are a dealer or not, whether they are male, and their age in years.[13]

The default model, of course, is the Nash Equilibrium (NE) bidding model. Assuming we

[12] Cox, Smith and Walker [1988] offer a generalization that admits some degrees of risk-loving behavior.

[13] In our sample 21% were dealers, 86% were male, and the average age was 39 years, with a standard deviation of 12.5 years (the youngest person was 17, and the oldest was 70). There are many ways to specify ZI agents, as illustrated by the constrained and unconstrained specifications used by Gode and Sunder [1993]. Ours is just one that keeps faith with the core idea that they not use any information that a rational agent would use.

know the risk attitude of the individual, we generate a prediction that conditions on their risk attitude. Our overall prediction is that behavior will be explained by one of these three models, with probability weights given by π^{NE}, π^{α} and π^{β}, which sum to one. The likelihood function for this mixture model can be defined as follows:

$$L(\pi^{\alpha},\pi^{\beta},\sigma,\alpha,\beta) = \sum_{i=1}^{n} \log\left[\pi^{\alpha}\,\phi\left(\frac{bid_i - b_i^{H}}{\sigma}\right) + \pi^{\beta}\,\phi\left(\frac{bid_i - b_i^{ZI}}{\sigma}\right) + (1-\pi^{\alpha}-\pi^{\beta})\,\phi\left(\frac{bid_i - b_i^{NE}}{\sigma}\right)\right],$$

where $b_i^{H} = \alpha v_i$, $b_i^{ZI} = \beta X_i$ for a vector of individual characteristics X_i defined here to include a constant, $b_i^{NE} = v_0 + [(N-1)/(N-1+\hat{r}_i)]\,(v_i - v_0)$, $\hat{r}_i$ is the estimated CRRA coefficient for subject i, bid_i is the observed bid for subject i, and $\phi(\cdot)$ is the probability density function of the standard normal distribution.[14]

2. Experimental Design and Procedures

Each subject in our experiment participated in a single session consisting of two tasks. In the first task, subjects participated in a first-price sealed-bid auction followed by a brief survey designed to collect individual characteristics. The second task involved a sequence of choices designed to reveal each subject's risk preferences. Appendix A lists a sample of the instructions for one of the treatments

The experiment was conducted using volunteer subjects who attended one of two sportscard and memorabilia shows. Both shows took place at the Dulles Expo Center in Chantilly, VA. The subjects were randomly selected from the floor of the sportscard show and asked if they would like to participate in an experiment that would give them the opportunity to earn monetary rewards. Upon acceptance, each subject was randomly assigned to a treatment and given an explanation of

[14] Our numerical implementation re-parameterizes so that we estimate a linear function of $\ln\sigma$ instead of σ.

the instructions. The subject was then asked to draw an individual valuation and proceeded to place a bid in the auction. Once the bid was entered the subject was asked to fill out a short survey. At the end of the survey the subject was read the instruction for the second task and asked to proceed with their choices. Each subject was immediately paid their earnings for the second task and asked to stop by our dealer table within the hour to collect their auction earnings.

The experiment included 3 auction treatments. One treatment, denoted 50x, had one session consisting of one first-price auction with N=50 subjects; another treatment, denoted 5x, had five sessions, each consisting of one first-price auction with N=5 subjects; and the final treatment, denoted 2x, had twenty-four sessions, each consisting of one first-price auction with N=2 subjects. Thus, we had a total of 50 subjects in the 50x treatment, 25 subjects in the 5x treatment, and 48 subjects in the 2x treatment, for a total of 123 subjects.

In summary, each subject was privately assigned induced values in their auction which were randomly drawn, by the subjects themselves, with replacement from a bag of slips representing the support of a uniform distribution. Cox, Roberson and Smith [1982] show that for risk neutral subjects the expected earning of each subject in a first-price auction is $(v^1-v_0)/N(N+1)$, where v^1 and v_0 are the upper and lower bound for the support of the induced values. To maintain uniformity of subject motivation across the treatments, v^1 and v_0 were chosen to equalize expected risk-neutral earnings at $0.40 in all treatments. For the 2x treatment the bag had 25 slips of papers numbered from $0.10 to $2.50 in $0.10 increments. The bag used in the 5x treatment had 61 slips of paper numbered from $0.10 to $12.10 in $0.20 increments. In the 50x treatment we used a bag of 102 paper slips numbered from $10 to $1020 in increments of $10.

Subjects in each session were informed (a) of the number of other bidders in the auction; (b) that the other bidders' induced values were, like their own, drawn from a uniform support with bounds given above; and (c) that their earnings in the auction would equal their induced value minus their bid if they made the highest bid, or zero otherwise.

The second task of the experiment was designed to measure individual risk postures. Holt and Laury [2002] (HL) devise a simple experimental measure for risk aversion using a multiple price list design, and we employed their procedure. Each subject is presented with a choice between two lotteries, which we denote A or B. Table 1 illustrates the basic payoff matrix presented to subjects. The first row shows that lottery A offered a 10% chance of receiving $2 and a 90% chance of receiving $1.60. The expected value of this lottery, EV^A, is shown in the third panel as $1.64.[15] Similarly, lottery B in the first row has payoffs of $3.85 and $0.10, for an expected value of $0.48. Thus the two lotteries have a relatively large difference in expected values, in this case $1.17. As one proceeds down the matrix, the expected value of both lotteries increases, but the expected value of lottery B becomes greater than the expected value of lottery A. The prizes in these lotteries span the range of expected income in the auctions.[16]

The subject is asked to choose A or B in each row. One row is later selected at random for payout for that subject. The logic behind this test for risk aversion is that only risk-loving subjects would select lottery B in the first row, and only risk-averse subjects would select lottery A in the second-to-last row. Arguably, the last row is simply a test that the subject understood the instructions, and has no relevance for risk aversion measures. A risk neutral subject should choose A for the first four rows and B thereafter.

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[15] The EV columns of Table 1 were not presented to subjects.

[16] Following the received auction theory we characterize risk attitudes using a CRRA specification. If we were to use more flexible functional forms for the utility of money, such as those employed by Holt and Laury [2002] to allow for varying RRA over prizes, we would need to use a wider range of prizes in the risk elicitation task.

3. Results

In Figure 1 we report the results of estimating the risk attitudes of each subject. For this specification we use the more common form of CRRA used by Holt and Laury [2002], to aid comparability across studies. They specify that $U(y) = (y^{1-r})/(1-r)$, where r is the CRRA coefficient. With this parameterization, $r = 0$ denotes risk neutral behavior, $r > 0$ denotes risk aversion, and $r < 0$ denotes risk loving behavior. When $r = 1$, $U(y) = \ln(y)$.[17] Figure 1 shows that we have considerable heterogeneity in risk attitudes, with a clear tendency for subjects to be risk averse. This is consistent with evidence from a wide range of experiments. For our purposes it generates some differences in the predicted bid for a given individual, even within the received theory. Figure 2 shows that the distribution of risk attitudes for dealers and non-dealers tends to be different, with dealers being less risk averse.

Figure 3 displays the raw bids in each treatment. These figures show the induced value on the bottom axis, a 45° line, and the risk-neutral bid prediction under that 45° line. The risk-neutral bid prediction is barely perceptible for N=50, since theory predicts an extremely small reduction in bids relative to values. The dots in Figure 3 represent observed bids. Under the received theory, risk averse subjects should bid somewhere between the risk-neutral line and the 45° line representing induced value. A visual comparison of the panels in Figure 3 makes it clear that received theory might do a good job of characterizing behavior for N=2, would have some problem for N=5, and would do a terrible job for N=50. To add structure to this anecdotal evidence, we estimate the mixture model described earlier.

Table 2 displays maximum likelihood estimates of this mixture model. We estimate the linear function determining the coefficients in the Heuristic model defined by β, the linear function

[17] When we estimate individual risk attitudes for use in the statistical model of bidding, below, we instead use the "power function" specification of Cox, Roberson and Smith [1982].

determining the coefficients in the Zero Intelligent model defined by α, a linear function defining a multiplicative heteroskedastic error term ($\ln \sigma$), and linear functions defining the mixture probabilities π^{α} and π^{β}. Since we know that $\pi^{NE} = 1 - \pi^{\alpha} - \pi^{\beta}$, we can use the estimates of π^{α} and π^{β} to infer π^{NE}.

Based on these maximum likelihood estimates, we can estimate the weight attached to each of the three models. Overall, we estimate 37% support for the NE model, 49% for the Heuristic model, and 14% for the ZI model. However, these aggregate estimates hide important insights about *when each model does best*. Figure 4 displays the predicted probabilities of each model as a function of the main treatment, variations in the number of bidders. Empirical results match the intuition from Figure 3: when N=2 the weight on the NE model is extremely high (89%), and the weight on the other models is correspondingly low. But as we move from N=2 to N=5 or N=50, the mixture model puts the greatest weight on the simple Heuristic model. As we shift to N=50 it puts some noticeable weight on the ZI model, but it does appear that subjects are taking notice of some of the strategic aspects of the task, as embodied in the Heuristic model.

Figures 5 and 6 reveal that support for the alternative models depends on observable characteristics. Consider the total effect of different characteristics on predicted support for each model. Men use the NE model more than women, women use the Heuristic model more than men, and they split about evenly in terms of use of the ZI model. Dealers behave more consistently with the NE model than non-dealers, in lieu of using the ZI model.[18] This latter finding is consistent with other evidence that suggests that standard neoclassical models perform well in describing behavior of experienced agents (e.g., List [2004]).

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[18] A proportions test for the equality of the predicted probability estimates from the mixture model rejects the null hypothesis in favor of the one-sided alternative that dealers place more weight on the NE bidding model at a *p*-value of 0.049.

4. Conclusion

When studying individual behavior in important decision-making environments, empirical economists can be sure of one thing: individual heterogeneity. This fact has been highlighted in thousands of microeconomic data sets, both experimental and non-experimental, in the social sciences. We propose a statistical approach for capturing the *heterogeneity of the decision processes, and not just heterogeneity of decisions within a single process*. We showcase our methodology by examining individual bidding data in a field experiment, where subjects endogenously select into the market, the experimental environment is natural, and the task is a typical experience for most subjects.

We report several insights. First, received auction theory describes behavior well for auctions with a small number of bidders but performs poorly for auctions with larger number of bidders. To our knowledge, this result is novel to the literature, which is surprising since the study of various auction institutions has been one of the richest areas of research in economics for over three decades. Second, the general data patterns are consistent with the notion that more experienced agents conform to classical theory whereas lesser experienced agents are more likely to behave according to alternative models. These results highlight that the domain of applicability, whether it be institution specific particulars or subject level market experience, is an important consideration when attempting to assert that laboratory evidence is a good indicator of behavior in the field. More generally, we believe that our experimental approach, using induced values with practiced market participants in their natural environments, holds considerable promise for future empirical queries.

Table 1: Design of the Holt and Laury Risk Aversion Experiments

Lottery A				Lottery B						
p($2)		p($1.60)		p($3.85)		p($0.10)		EV^A	EV^B	Difference
0.1	$2	0.9	$1.60	0.1	$3.85	0.9	$0.10	$1.64	$0.48	$1.17
0.2	$2	0.8	$1.60	0.2	$3.85	0.8	$0.10	$1.68	$0.85	$0.83
0.3	$2	0.7	$1.60	0.3	$3.85	0.7	$0.10	$1.72	$1.23	$0.49
0.4	$2	0.6	$1.60	0.4	$3.85	0.6	$0.10	$1.76	$1.60	$0.16
0.5	$2	0.5	$1.60	0.5	$3.85	0.5	$0.10	$1.80	$1.98	-$0.17
0.6	$2	0.4	$1.60	0.6	$3.85	0.4	$0.10	$1.84	$2.35	-$0.51
0.7	$2	0.3	$1.60	0.7	$3.85	0.3	$0.10	$1.88	$2.73	-$0.84
0.8	$2	0.2	$1.60	0.8	$3.85	0.2	$0.10	$1.92	$3.10	-$1.18
0.9	$2	0.1	$1.60	0.9	$3.85	0.1	$0.10	$1.96	$3.48	-$1.52
1	$2	0	$1.60	1	$3.85	0	$0.10	$2.00	$3.85	-$1.85

Note: Our design follows Holt and Laury [2002]. The third panel (EV^A, EV^B, Difference) was not included in the instructions.

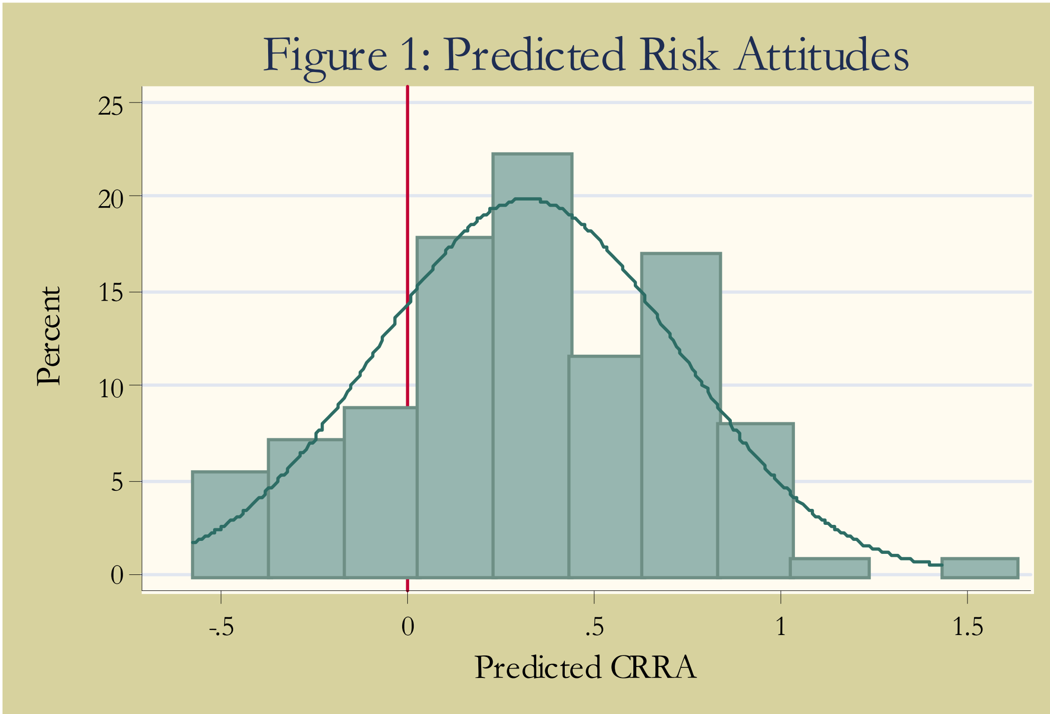

Figure 1: Predicted Risk Attitudes

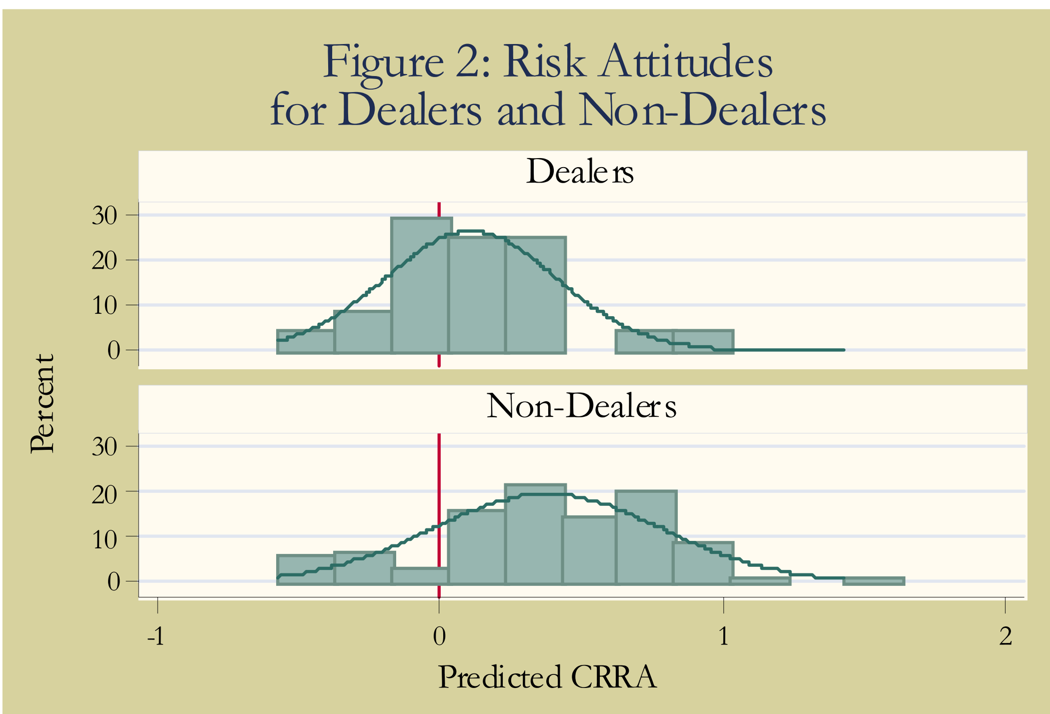

Figure 2: Risk Attitudes for Dealers and Non-Dealers

Figure 3: Bidding Behavior

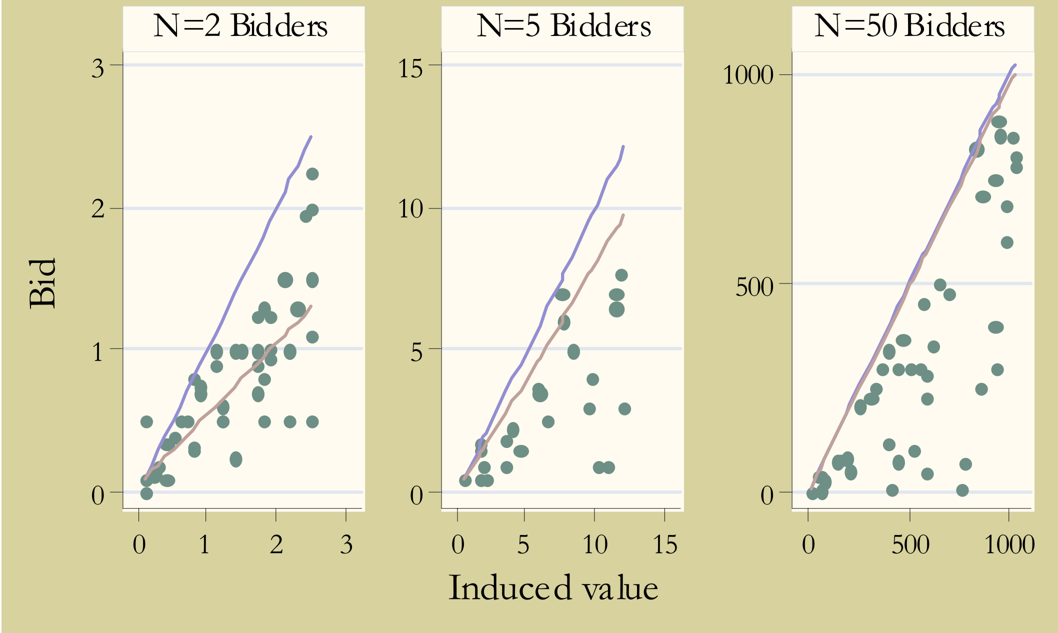

Figure 4:
Support for Alternative Bidding Models

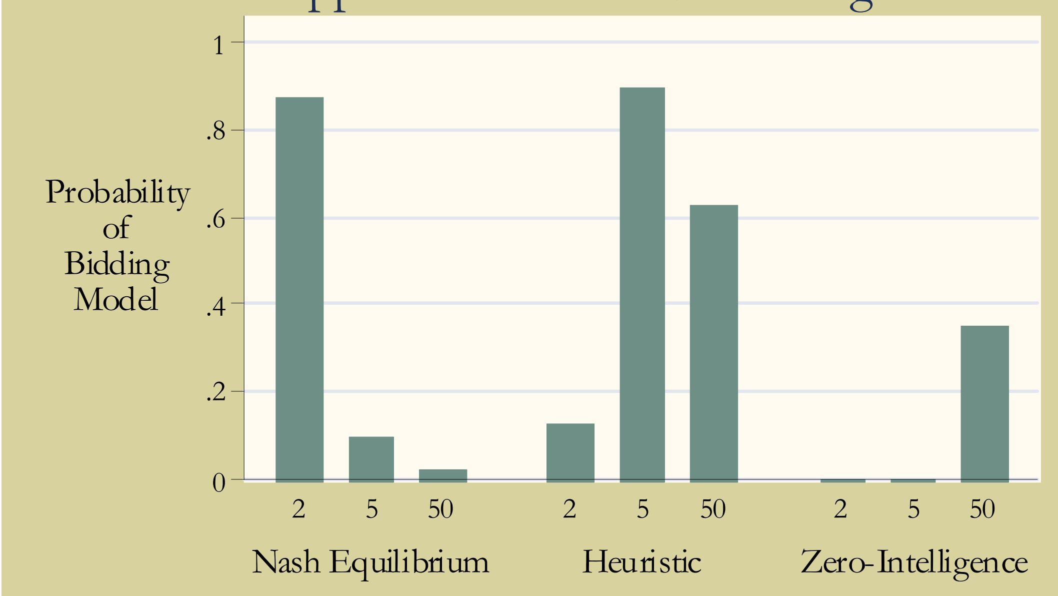

Table 2: Maximum Likelihood Estimates for Mixture Model of Bidding Behavior

Equation	Variable	Point Estimate	Standard Error	*p*-value	Lower 95% Confidence Interval	Upper 95% Confidence Interval
α	N = 2	-0.16	0.15	0.29	-0.46	0.14
	N = 5	0.41	0.16	0.01	0.11	0.72
	N =50	0.35	0.17	0.04	0.02	0.68
β	Constant	271.24	269.88	0.31	-257.72	800.21
	Dealer	-26.32	49.09	0.59	-122.54	69.89
	Male	49.33	59.73	0.41	-67.75	166.40
	Age	-4.04	5.17	0.43	-14.18	6.09
$\ln \sigma$	Dealer	-0.02	0.30	0.94	-0.60	0.56
	Male	0.34	0.52	0.51	-0.67	1.36
	Age	-0.02	0.01	0.07	-0.04	0.00
	N = 2	-1.93	0.28	0.00	-2.47	-1.39
	N = 5	0.98	0.47	0.04	0.07	1.90
	N = 50	4.04	0.23	0.00	3.58	4.50
$\ln \pi^{\alpha}$	Dealer	-13.17	2.79	0.00	-18.65	-7.69
	Male	-3.67	5.77	0.52	-14.98	7.64
	Age	-0.09	0.23	0.69	-0.54	0.36
	N = 2	4.00	12.51	0.75	-20.52	28.52
	N = 5	20.56	17.85	0.25	-14.43	55.55
	N = 50	23.56	15.49	0.13	-6.80	53.92
$\ln \pi^{\beta}$	Dealer	-25.05	5.13	0.00	-35.11	-14.99
	Male	-3.47	6.18	0.57	-15.58	8.65
	Age	-0.08	0.23	0.73	-0.52	0.36
	N = 2	-10.97	11.65	0.35	-33.80	11.86
	N = 5	3.15	17.82	0.86	-31.77	38.08
	N = 50	22.61	15.41	0.14	-7.59	52.81

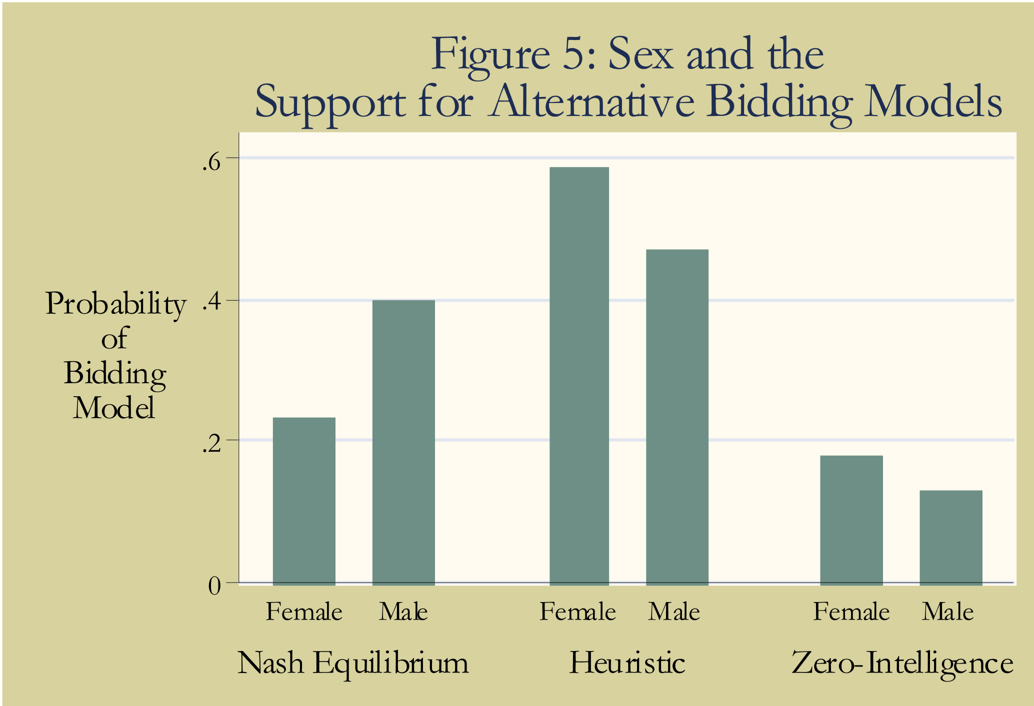
Figure 5: Sex and the
Support for Alternative Bidding Models
Probability of Bidding Model
.6
.4
.2
0
Female
Male
Female
Male
Female
Male
Nash Equilibrium
Heuristic
Zero-Intelligence

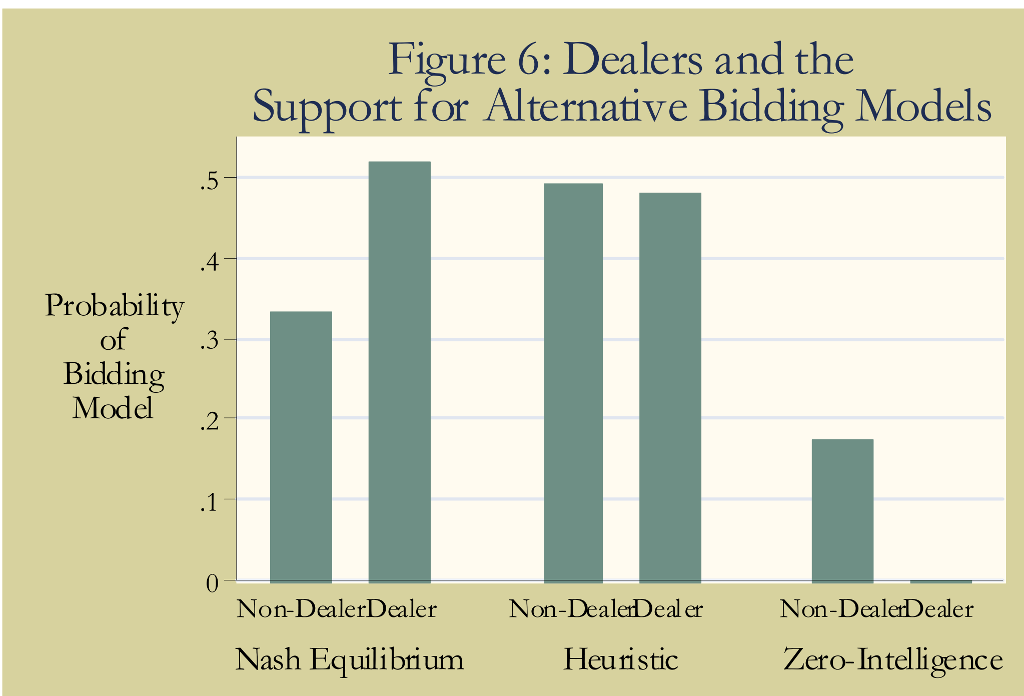
Figure 6: Dealers and the
Support for Alternative Bidding Models
Probability of Bidding Model
.5
.4
.3
.2
.1
0
Non-Dealer
Dealer
Non-Dealer
Dealer
Non-Dealer
Dealer
Nash Equilibrium
Heuristic
Zero-Intelligence

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Appendix A: Informed Consent Form and Sample Instructions

Informed Consent: An Experiment in Economic Decision-Making [printed on University of Maryland – College Park letterhead]

I state that I am over 18 years of age, and wish to participate in a program of research conducted by Professor John List of the Department of Agricultural and Resource Economics at the University of Maryland, College Park.

The research procedures require that I answer questions related to the good used in the study, and to fill out a brief questionnaire.

I acknowledge that I am participating voluntarily, and that I am free to ask questions or to withdraw from participation at any time without penalty.

I understand that all information collected in this study is confidential, and my name will not be identified at any time. The data I provide will be grouped with data others provide for reporting and presentation.

Furthermore, I understand that there are no physical or financial risks associated with my participation.

The goal of the study is to increase knowledge in the field of economic decision-making, and it is not designed to benefit me personally.

Principal Investigator:
Professor John List
2200 Symons Hall
College Park, Maryland
301.405.1288
jlist@arec.umd.edu

Printed Name of Subject ____

Signature of Subject ____

Date ____

Welcome to Lister's Auctions! You have the opportunity to bid in an auction today and can earn cash by participating.

Auction Rules:

In this auction you will bid against **one** other person and the person with the highest bid is the winner, and pays their bid price for the "good". The auction is a sealed bid auction so you don't know the bid of the other participant.

There are four steps in the auction process each of which are explained in detail below. The four steps include: 1. determining the value of the "good", 2. determining your bid, 3. determining the auction winner, 4. paying the auction winner.

1. Determining your good's value: The bag contains 25 slips of paper numbered form ten cents ($.10) to two dollars and fifty cents ($2.50) in ten cent ($.10) increments. You will draw one slip out of the bag and the value drawn will be the value of the good to you. The other bidder in your auction will have their good's value determined in exactly the same way.

2. Determining your bid value: After finding out your good's value you will choose your bid value for the good. In order to choose your bid here is how your earnings are calculated. If you are the person with the highest bid you are the winner of the auction. Your earnings are equal to your good's value minus your bid amount.

Earnings = your good's value - your bid

If you are the low bidder your earnings are zero. If there is a tie, the winner will be determined by the flip of a coin. Your bid can be any amount in the range from zero ($0) to two dollars and fifty cents ($2.50) in ten cent ($.10) increments.

3. Determining the auction winner: Your bid will be randomly matched with that of another participant in the auction at the top of the hour. The person with the highest bid amount is the winner and their earnings are calculated as noted above.

4. Paying the auction winner: Stop by any time in the next hour or until the close of the show. If you are the winner you will be paid in cash at that time.

Do you have any questions about the auction process?

Please draw a slip from the bag and then fill in the bid sheet on the back of this page.

My good's value is: $____________

My bid is: $____________

Email address______________________________

Survey

These questions will be used for statistical purposes only. THIS INFORMATION WILL BE KEPT CONFIDENTIAL AND WILL BE DESTROYED UPON COMPLETION OF THE STUDY.

1. How long have you been active in the sportscard and memorabilia market? ______yrs

2. Are you a sportscard or sports memorabilia professional dealer?________

3. How many sportscard or memorabilia shows do you attend in a typical year? _______

4. How many cards do you have professionally graded in a given year? ___________

4a. Do you deal in:
only graded cards   only ungraded cards   both graded and ungraded cards

4b. Are you affiliated with a grading company?   Yes   No

5. Gender: 1) Male   2) Female

6. Age ______   Date of Birth ____________

7. What is the highest grade of education that you have completed. (Circle one)

1) Eighth grade	3) 2-Year College	5) 4-Year College
2) High School	4) Other Post-High School	6) Graduate School Education

8. What is your approximate yearly income from all sources, before taxes?

1)	Less than $10,000	5)	$40,000 to $49,999
2)	$10,000 to $19,999	6)	$50,000 to $74,999
3)	$20,000 to $29,999	7)	$75,000 to $99,999
4)	$30,000 to $39,999	8)	$100,000 or over

9. ***This final question guarantees you that you will earn some cash.*** Here is how it works:

On the next page there is a decision sheet and each decision is a paired choice between OPTION A and OPTION B. You will make ten choices and record these in the final column. One of the choices will be used to determine your earnings. Before you start making your ten choices, let me explain how these choices will affect your earnings.

We will use part of a deck of cards to determine your earnings; cards 2-10 and the Ace will represent "1." After you have made all of your choices, we will randomly select a card twice, once to select one of the ten decisions to be used, and a second time to determine what your payoff is for the option you chose, A or B, for the particular decision selected. (After the first card is selected, it will be put back in the pile, the deck will be reshuffled, and the second card will be drawn). Even though you will make ten decisions, only one of these will end up affecting your earnings, but you will not know in advance which decision will be used. Obviously, each decision has an equal chance of being used in the end.

Now, please look at Decision 1 at the top. OPTION A pays $2.00 if the Ace is selected, and it pays $1.60 if the card selected is 2-10. OPTION B yields $3.85 if the Ace is selected, and it pays $0.10 if the card selected is 2-10. The other Decisions are similar, except that as you move down the table, the chances of the higher payoff for each option increase. In fact, for Decision 10 in the bottom row, the cards will not be needed since each option pays the highest payoff for sure, so your choice here is between $2.00 or $3.85.

So now please look at the empty boxes on the right side of the record sheet. You will have to write a decision, A or B in each of these boxes, and then the card selection will determine which one is going to count. We will look at the decision that you made for the choice that counts, and circle it, before selecting a card again to determine your earnings for this part. Then you will write your earnings in the blank at the bottom of the page.

Are there any questions?

OPTION A	OPTION B	DECISION
1/10 of $2.00, 9/10 of $1.60	1/10 of $3.85, 9/10 of $0.10	
2/10 of $2.00, 8/10 of $1.60	2/10 of $3.85, 8/10 of $0.10	
3/10 of $2.00, 7/10 of $1.60	3/10 of $3.85, 7/10 of $0.10	
4/10 of $2.00, 6/10 of $1.60	4/10 of $3.85, 6/10 of $0.10	
5/10 of $2.00, 5/10 of $1.60	5/10 of $3.85, 5/10 of $0.10	
6/10 of $2.00, 4/10 of $1.60	6/10 of $3.85, 4/10 of $0.10	
7/10 of $2.00, 3/10 of $1.60	7/10 of $3.85, 3/10 of $0.10	
8/10 of $2.00, 2/10 of $1.60	8/10 of $3.85, 2/10 of $0.10	
9/10 of $2.00, 1/10 of $1.60	9/10 of $3.85, 1/10 of $0.10	
10/10 of $2.00, 0/10 of $1.60	10/10 of $3.85, 0/10 of $0.10	