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The High/Low Divide: Self-Selection by Values in Auction Choice*

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Abstract

Most prior theoretical and experimental work involving auction choice has assumed bidders only find out their value after making a choice of which auction to enter. In this paper we examine whether or not subjects knowing their value prior to making an auction choice impacts their choice decision and/or the outcome of the auctions. The results show a strong impact. Subjects with low values choose the first price sealed bid auction more often while subjects with high values choose the ascending auction more often. The average number of bidders in both formats ended up being on average the same, but due to the self-selection **bias** the ascending auction raised as much revenue on average as the first price sealed bid auction. The two formats also generate efficiency levels that are roughly equivalent though the earnings of bidders are higher in the ascending auction.

JEL Codes: C91, D44
Key Words: bidder preferences, private values, sealed bid auctions, ascending auctions, endogenous entry

1 Introduction

While initial theoretical and experimental work on auctions focused on environments with an exogenously fixed number of participants, there has recently been increased attention paid to the importance of the entry decision of bidders. This is certainly an issue of practical importance to auctioneers because in many auction environments, revenue is increasing in the number of bidders participating (common values environments being the obvious exception). There are also potential efficiency implications from bidders choosing not to participate in auctions that may be of concern to government auctioneers. Understanding how these decisions are made is therefore quite important to practical auction design.[1]

There is of course a substantial theoretical literature examining the choice of entering an auction or not (e.g. Engelbrecht-Wiggans (1993), Smith and Levin (1996), Smith and Levin (2002), Pevnitskaya (2004) and Palfrey and Pevnitskaya (2008)) as well as additional papers examining a

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[1]In most auctions outside of the lab the objects perhaps the most reasonable assumption regarding the values is that they possess both common and private value components. Goeree and Offerman (2003) investigate auctions under these assumptions and demonstrate that revenue and efficiency increase with the number of bidders.

bidders decision of which auction to enter based on seeing different entry prices (e.g. Bajari and Hortacsu (2003), Lucking-Reiley (1999a) and Levin and Smith (1994)). Our interest lies in trying to understand why bidders may prefer one auction format over another when they differ along lines other than just entry price. One example of such a phenomenon is discussed in Klemperer (2002) in which he argues that ascending auctions can discourage the entry of any disadvantaged or weak bidders because they know their chances of winning are very small. This claim was investigated experimentally in Goeree, Offerman, and Schram (2006). In a situation in which bidders are *ex ante* identical, Ivanova-Stenzel and Salmon (2004) and Ivanova-Stenzel and Salmon (2008b) show that bidders have the opposite preference as they would generally prefer to enter an ascending auction. This preference was found in Ivanova-Stenzel and Salmon (2008a) (ISS08) to lead to a negation of the traditional revenue ranking between ascending and sealed bid auctions as when subjects were allowed to endogenously choose which type of auction to enter, more subjects chose to enter the ascending and this lead to the revenue raised in ascending and sealed bid auctions to be equalized.

A key element of the existing theoretical and experimental literature on situations involving choice between auction formats is the use of the assumption that when bidders are choosing between auction formats that they are unaware of their value for winning. [2] It is typically assumed that bidders learn of their value for winning only after choosing which format to enter. There are arguments for why this is not an unreasonable assumption which hinge on when an auction is truly considered to be entered. Consider an example of a person deciding they wish to acquire a digital camera in an online auction. While they may have some idea for the range of values they will have for such cameras, they likely will not form a final value or willingness to pay until after they have found a specific listing and examined the advertisement and seller carefully. The issue is at what point do we consider a bidder to have entered the auction? If we define "entry" as the prospective bidder visiting one auction site instead of another to find a camera then the assumption that value isn't finalized until after an entry choice is made might be considered as reasonable.

Another reasonable definition though might be that entry is defined as occurring when a bidder actually places a bid. Then of course, it is more reasonable to assume that value is known prior to entry.[3] If bidders know their value prior to making their entry decision then it is possible that the entry choice can be dependent on the value the bidder possesses. This could lead to self-selection effects in which bidders choose different auction types depending on their values and that in turn could lead to important effects on revenue and auction efficiency. This is the phenomenon that we investigate in this paper.

We present a set of experiments where subjects learn their value before deciding which auction to enter. Our results will show that there is indeed a strong self-selection effect of bidders with lower values preferring to enter sealed bid auctions while bidders with higher values prefer to enter into ascending auctions. The observed self-selection bias creates a high/low divide that leads to different sorts of bidders choosing to enter different sorts of auctions. The ultimate effect on revenue generation is that there is no statistically significant difference between the revenue in the two auction formats (just as in ISS08 where subjects learned of their value after their entry choice) and we find a similar result in regard to auction efficiency. Thus, we show that if the concern of the market designer is either revenue and/or efficiency, the issue of whether subjects make their

[2] We note though that in several of the previously cited papers on bidders choosing to enter an auction or not as well as those based on choosing among auctions differentiated by entry fees or reserve prices that this assumption was not used.

[3] This too is somewhat problematic though because there are potentially bidders who would have chosen to "enter," i.e. bid, but found that the reserve price or current high bid was above their value. These are bidders who likely should be considered to have entered the auction but would not be observed to have done so. Due to issues like this in field auctions it is quite difficult to observe a pure entry decision.

entry decisions behind the veil of ignorance or knowing their value is not that important as those key benchmarks of auction performance yield similar comparative statics under either assumption.

The remainder of the paper is organized as follows: Section 2 will present an overview of the experiments conducted for this study. Section 3 contains an analysis of the data developed through a series of results. Section 4 provides a concluding discussion.

2 Design of Experiment

The experiment consisted of two phases. The first phase we will refer to as the learning phase as in this phase we had the subjects participate in several rounds of ascending auctions (will be abbreviated henceforth as the"A" auction) and sealed bid first price auctions (will be abbreviated henceforth as the"SB" auction) with differing but exogenously fixed n's. This was to allow subjects to develop some experience with both auction formats and to give them some idea of how profit levels might vary with n. In the second phase, subjects were allowed to repeatedly choose to participate in either a sealed bid auction or an ascending auction[4] in which the number of competitors was endogenously determined.

We conducted four sessions with 12 subjects per session. In the learning phase, subjects participated in twelve rounds of fixed n auctions. In each round they were informed of their value for winning the auction which was drawn independently for each subject from a uniform distribution over the integers in the range $[0, 100]$. All values were denoted in a fictitious currency termed ECU for Experimental Currency Unit. The subjects then participated in both a SB and A auction using the same value. They would first submit a bid in the SB auction and then immediately participate in the A auction and only after the A auction was completed would they be informed of the results from both auctions. These twelve rounds consisted of two blocks of six period cycles in which the subjects participated in three rounds with $n = 2$ auctions and then three with $n = 4$. At the end of the learning phase the subjects received feedback telling them the session-wide average profit in each auction format and for each n. They also received information on their total profit up to this time.

For the main phase of the experiment, we split each session of twelve subjects into separate groups of six. These groupings were held constant throughout the rest of the session which keeps the two groups independent for statistical purposes. The choice of the size of the groups is a very important one for this experiment. Having six in the pool allows for auction sizes to vary in what is a key region for this issue. Auctioneers should be mostly concerned about choosing the right mechanism to maximize revenue in the small n range. At large n's one will find that the revenue differences between mechanisms, especially as a percentage of total revenue, get quite small but they are large for small n. Consequently, if an auctioneer knows he or she will get 8 or more bidders, the choice of an auction mechanism is much less important than if the number of prospective bidders is in the 2-6 range. This fact that the marginal increase in revenue from one additional bidder is largest for small n is the primary reason why we are concentrating on relatively small pools. Further, having an even number in the prospective bidder pools allows for the possibility that bidders can split evenly between auctions should that be their natural preference. Were we to use an odd number and find that one format attracted more bidders than the other, that would be less convincing since the result is almost required by the design. Thus having groups of size six allows

[4]The ascending auctions we used were clock auctions in which the price would start at 0 and increase by 1 ECU every second up to a maximum of 150 (which is above the maximum value of a subject). Each subject had a button on their screen to exit the auction and the auction ended when only 1 bidder remained with that bidder paying the price at which the last bidder dropped out.

us to concentrate exactly on the important range of the size distribution without rigging our results in favor of finding differences in the number of bidders choosing each auction.

Because we knew from prior work that subjects would generally prefer the ascending auction, we also wanted to minimize the rent seeking strategy of attempting to be the one person in the pool to choose the sealed bid. We wanted to guarantee that an auction would be competitive if someone chose it. We did this by taking two of our six group members in each round and placing one in the SB and the other in the A auction by default, allowing the other four to choose. This meant that anyone choosing to enter into an auction knew that they would face at least one other bidder. This too is a design choice that is somewhat controversial. Thus, we conducted an additional treatment where the auction format could be freely chosen by all bidders. We present the results of the new treatment as the final result of section 3 and discuss whether this design element has a significant impact on our main findings.

The choice of the bidders having multiple different ways to acquire the same item is in our view a very field relevant design for examining behavior in electronic markets. For example, a prospective eBay bidder wishing to procure a particular object could choose to enter an eBay auction for it while his alternatives could include choosing a different eBay auction, a Yahoo auction, an auction on some specialty auction site or purchasing from a retail outlet. While we could not allow for this full of a range of options, we believe our design captures the key element for our interest because our interest is whether or not one auctioneer can pull bidders away from another auctioneer based solely on the rules of the auction format he or she chooses. Our design also matches with the description of the formation of early internet auction markets described in Lucking-Reiley (1999b) in which sellers would be selling certain types of trading cards and different sellers would be differentiated largely by the mechanism they selected for use and in fact many of the sellers gave potential bidders a choice almost identical to the one we give in the experiment. So while our design may not capture the exact nature of the choice faced by current eBay bidders, it does come closer to capturing the choice bidders faced when these auction markets were forming and is therefore quite empirically relevant for trying to understand why over time sellers appear to have chosen to use variations on the ascending format much more often than the sealed bid format.[5]

The main phase of the experiment consists of 30 rounds in which subjects can choose in which auction to participate. To maximize the number of auction choice periods in the time allotted, we did not have the subjects actually play the auctions in each round. Instead, each set of auctions was only conducted with a 20% probability. This allowed us to get more observations on the auction choice behavior of the subjects which is important because this represents a non-trivial coordination problem that could take a while to equilibrate. Subjects were told their value for winning an object in that round prior to choosing an auction format.[6] We used the exact same value draws and matching scheme from the experiment in Ivanova-Stenzel and Salmon (2008a). Furthermore, we paired each session with a session from Ivanova-Stenzel and Salmon (2008a), and conducted the auctions in the same rounds as in the sessions from ISS08. This amounts to simply

[5] A valid alternative approach would have been to conduct experiments in which the choice of the bidders is to enter an auction or not, rather than to enter one auction or another auction, and then perform an indirect comparison across mechanisms this way. This approach has substantial advantages in terms of theoretical tractability but suffers from diminished field relevance where a person has many options for acquiring an object. Further, the nature of the outside option could certainly have substantial impacts on the entry decisions and calibrating an appropriate outside option would have been difficult. In our view, the appropriate outside option though is exactly the ability to obtain the object elsewhere, perhaps in another auction, which was the foundation for the design we chose to implement.

[6] In the experiments from Ivanova-Stenzel and Salmon (2008a), subjects were not told of their value before choosing which auction format to enter. It was only revealed after their entry choice and if the auctions were to be conducted that round. It was, however, made clear to them that they would receive the same value regardless of which format they chose.

	Type	1-A	1-B	2-A	2-B	3-A	3-B	4-A	4-B	Average	ISS08
Number of	**SB**	2.83	3.10	3.27	2.70	2.77	2.83	2.97	2.87	2.92	2.44
Bidders (F)	**A**	3.17	2.90	2.73	3.30	3.23	3.17	3.03	3.13	3.08	3.56
Number of	**SB**	3.17	3.08	3.60	2.60	3.40	3.40	2.75	1.25	3.00	2.63
Bidders (P)	**A**	2.83	2.92	2.40	3.40	2.60	2.60	3.25	4.75	3.00	3.38
Revenue	**SB**	49.25	49.83	59.40	39.20	58.60	51.00	41.75	5.00	46.48	51.95
	A	43.75	51.83	54.80	52.20	48.60	52.40	35.75	69.75	50.17	54.90
Avg Bidder	**SB**	43.44	35.17	39.76	38.78	41.09	35.55	37.69	39.14	38.77	48.15
Value (F)	**A**	55.00	51.09	58.71	57.23	52.45	61.92	56.49	38.77	55.93	48.76
Avg Bidder	**SB**	45.00	36.56	40.69	35.00	33.75	40.00	35.86	24.00	38.97	44.12
Value (P)	**A**	47.91	52.65	57.86	52.75	42.00	62.63	51.33	61.53	53.13	48.97
Avg. Bidder	**SB**	4.14	6.99	9.10	4.11	2.87	3.40	3.42	9.20	5.41	5.96
Surplus	**A**	9.96	6.71	4.93	7.10	6.80	9.45	14.21	9.88	8.42	6.48
Efficiency	**SB**	0.99	0.99	1.00	1.00	0.99	1.00	0.90	1.00	0.99	0.988
	A	1.00	1.00	1.00	1.00	0.98	1.00	1.00	1.00	1.00	0.988

Table 1: Summary of key descriptive statistics of experiment results. Note that the average column is done off of individual values. It is not an average of the group level averages.

using a pre-drawn set of random draws to determine which rounds will be chosen so our explanation to the subjects that any given round will be conducted with a 20% probability is still valid. Thus we could ensure comparability across the data sets of the two experiments.

In each round, subjects were told the number of people choosing both formats and whether the auctions were going to be conducted or not. Thus, if the auctions were being conducted that round, the subjects were informed about the number of bidders in their auction before the bidding started so that they would know the relevant n while formulating their bid. At the end of each round they were told whether or not they won that round, the price paid by the winner and how much profit they made.

Most participants were students of economics, business administration, and industrial engineering of Humboldt University Berlin. The software for the experiments was programmed using z-Tree (Fischbacher (2007)). Earnings from the experiment were translated into Euros at the exchange rate of 1 ECU = € 0.10. Subjects' total earnings ranged from €9.50 to €37.50 with an average of €22.84 in sessions that lasted approximately two hours each.[7]

3 Results

An overview of data from the new experiments can be found in table 1 which presents descriptive statistics on the key variables of interest broken out by independent groups and overall averages. We also include at the end the average of that same statistic from ISS08. The data contained in the table is sufficient for conducting any non-parametric test on the differences in distributions using the most independent unit of measure, i.e. the group level averages. For some statistics such as number of bidders in an auction and their values, we include the averages for the entire experiment (Full Sample or F) as well as the averages from only those periods in which auctions were conducted (Partial Sample or P). We will present our findings from this data through a series of results.

[7] These numbers include a show up fee i.e., starting capital, of €3.00.

	Number of Bidders		Revenue	Surplus
	Full Data	Partial Data		
Last 10 Periods	0.463	0.757	15.286	-2.641
	(0.297)	(0.552)	(10.947)	(2.189)
Constant	0.013	-0.2.45	-1.605	4.300**
	(0.161)	(0.450)	(8.628)	(1.896)
Observations (Groups)	240 (8)	52 (8)	52 (8)	52 (8)
Adjusted R^2	0.011	0.053	0.047	0.019

Robust standard errors in parentheses, *** p<0.01, ** p<0.05, * p<0.1

Table 2: Random Effects Panel regressions with robust standard errors. Dependent variables are difference between noted statistic in ascending and sealed bid auctions.

Result 1: *The number of bidders participating in each auction format is not statistically different and there is no time trend over the course of the experiment.*

Given that the average number of bidders in the SB and A auctions in the rounds in which auctions were conducted turned out to be exactly 3, and even in the full sample the averages were 2.92 and 3.08 respectively, the result here is quite clear. Statistical verification of this can be found in table 2 which presents panel regressions using random effects with robust standard errors of the difference between number of bidders, revenue and surplus in the A and SB formats. There are two specifications for this number of bidders regression; one using the full data set while the other uses only data from rounds in which the auction was conducted. The value of the constant term can therefore be used to test if the number choosing each format is different. Since we find the constant to not be significantly different from 0 for both the full and partial data cases, this means that there is no statistically significant difference in the numbers choosing each format. We also included a dummy variable equal to 1 during the last 10 periods of the session as a way to determine if there are any temporal effects and that variable is also insignificant. We use this dummy variable approach for modeling temporal effects because using a linear or even non-linear time trend that is continuous in nature would be problematic for the partial data regressions since each observation is separated by different numbers of rounds. This approach essentially allows for a non-parametric approach to detecting any shift in levels over time that works for both full and partial data samples.

Result 2: *The revenue and the efficiency generated by each auction is not significantly different and the revenue differential possesses no significant time trend.*

Again, the data in table 1 suggests rather strongly that there will be no differences in the revenue raised by both formats but statistical confirmation can be found in the third column of table 2. This presents a panel regression with the revenue differential (A-SB) as the dependent variable using random effects specification at the group level. Neither the constant nor the time measure is statistically significant providing clear support for the result.

Result 3: *The average surplus earned in the Ascending auction is greater than the average surplus earned in the Sealed Bid auction and again there is no significant time trend in the differential.*

Evaluating bidder earnings is slightly difficult in these experiments since the number of participants is not held constant, even though the numbers turn out to be approximately the same. Comparing raw earnings can still be somewhat misleading. Consequently we compare average earnings which is found by dividing the surplus of the winner of each auction by the number of bidders in that auction. Summary statistics are again in table 1 and a random effects regression

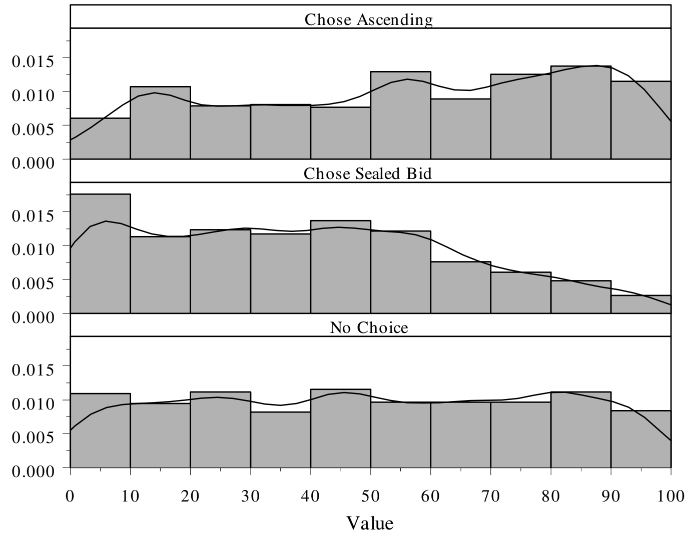

Figure 1: Distribution plots of the values of bidders choosing Asc vs. SB as well as value distribution of bidders with no choice.

with robust standard errors using the average surplus differential (A-SB) can be found in the last column of table 2. While the time measure is again statistically insignificant, the constant is now positive and significant at the 5% level which verifies that the average surplus or earnings in the A auction is higher than in the SB.

Result 4: *Bidders self select into auctions based upon their value but not based upon their risk aversion or general degree of overbidding as measured by bidding in Phase 1.*

The fundamental support for the self-selection based on values can be found in table 1 in which we see that the average value of a bidder in a SB auction is 38.77 while the average in an A auction is 55.93. That suggests that bidders with low values self-select into the SB. A graphical characterization of this result is in figure 1 which shows histograms and distribution plots of bidder values among those who chose the A, chose the SB and had no choice. The panel for the "No Choice" group basically shows a uniform distribution as would be expected since the values were drawn at random and subjects were randomly picked each round to have no choice. The panel for those who chose the A has a distribution which slopes slightly upward at the end while the SB panel has a definite downward slope on the right side.

Statistical verification of the self-selection result is found in table 3 which presents two different specifications of random effects Logit regressions with the dependent variable being Auction Choice which takes the value of 1 to denote the choice of A and 0 to denote the choice of SB.[8] The two different specifications differ according to the measure of risk aversion used. In the first we use the estimated CRRA risk aversion parameter for each individual based on their Phase 1 bids while the second contains a non-parametric risk aversion measure or a generic measure of how aggressive a bidder is in SB auctions which is just the coefficient on the variable for the bidder's value in a regression of the form $b_{it} = \alpha_i + \beta_i v_{it}$. This is essentially the fraction of their value a subject bid in

[8]Instances in which bidders had no choice were not considered in the regession.

	CRRA	Non-Parametric RA
Value	0.028***	0.028***
	(0.004)	(0.004)
Risk Aversion	-0.065	0.327
	(0.083)	(1.213)
Number in A - Number in SB $t-1$	-0.067*	-0.066*
	(0.037)	(0.037)
Last 10 Periods	0.324	0.324
	(0.319)	(0.319)
Last 10 * Value	0.003	0.003
	(0.006)	(0.006)
Constant	-1.316***	-1.592
	(0.250)	(0.991)
Observations (Groups)	928 (48)	928 (48)
LL	-551.117	-551.389

Robust standard errors in parentheses, *** p<0.01, ** p<0.05, * p<0.1

Table 3: Random effects logit panel regressions of auction choice where 1=A and 0=SB.

the phase 1 auctions. The results show that the bidder's value has a positive and very significant effect in their likelihood of choosing the A while both specifications of the risk / overbidding measure are insignificant. We also again find no time trend as we included a dummy variable for the last 10 periods and an interaction between that dummy variable and the bidder's value but both were insignificant. We also find a small but significant effect showing that bidders are less likely to choose the A auction the higher was the differential between the number in that format and the number in the SB in the previous round which is a perfectly sensible result showing that on the margin subjects move away from over-crowded auctions.[9]

To help interpret this self-selection result we need to calculate the expected utility of bidders for choosing either auction format. Since they know their value at the time of making their auction choice we must calculate these expected utilities conditional upon their value. These calculations are complicated by the fact that we need to account for how subjects actually place bids. In the A auction we can use the standard equilibrium construction of $b^*(v_i) = v_i$ as it largely matches individual behavior. For the SB first price auction we find the usual result that subjects bid above the risk neutral Nash equilibrium and so must use some other specification. Using the empirical bid function for each subject and doing separate computations is impractical to analyze while using an overall average bid function may hide important heterogeneity. In addition, since the underlying choice of auction formats involves evaluating uncertainty we also need to consider how individuals with differing risk parameters would choose and in doing that we also need to acknowledge that

[9] This effect does bring to light the possibility that there is some serial correlation in the choices of the subjects in that if they chose SB in a period, they might be less (or more) likely to choose it in the next. We have checked the robustness of our results with a number of different specifications to correct for the serial correlation including regressions with a lag of the dependent variable as well as FGLS specifications in which the error structure is modeled explicitly as an AR1 process. While the lagged term is generally significant in these regressions neither the sign nor significance of the coefficient on bidder value ever changes and typically the significance of the other variables remains the same as well. Given that and the congruence with basic choice theory to be demonstrated next we are confident that table 3 presents a reliable charactarization of the data.

bidding behavior should correlate with these preferences. As an approximation of behavior in the SB auction we will therefore use the standard CRRA bid function in conjunction with assuming general CRRA preferences, $u(x) = x^\alpha$ with $\alpha \in (0, 1]$ where $\alpha = 1$ means risk neutrality and $\alpha < 1$ means risk aversion, for auction choice behavior. As we will explain further, these calculations are meant to be benchmark calculations and we can not claim that they represent true expected utilities for our subjects.

The equations for performing the expected utility calculations can be found in the appendix but a key detail of how we are performing these calculations is that we are making the minimal assumptions on the bidding behavior necessary to perform the calculations. We do assume that the bidder for which the expected utilities are calculated is bidding as theory predicts but for determining his probability of winning (and expected price in A auctions) we use the empirical distributions of bids and auction sizes. Thus the way to interpret these results are that they calculate the expected utility for a bidder with a particular degree of risk aversion bidding as theory predicts but faced with the empirical distributions from the experiment. The results from these calculations are summarized in figure 2 which shows the expected utility graphs in both auction formats for five different levels of risk aversion ranging from extreme risk aversion, $\alpha = .1$, to risk neutrality, $\alpha = 1$. In each case, the expected utility of the first price auction is above that of the ascending for all values below 80. At values above 80, the expected utility of the ascending comes to dominate the first price and the less risk averse is the individual the later this domination occurs.

By comparing figure 2 to figure 1 we see a clear explanation for the self-selection. Figure 2 shows that for low values the SB provides greater expected utility for choosing to participate in it and figure 1 is showing that indeed bidders with lower values choose it more often. For higher values, i.e. values above 80, figure 2 shows that the A can come to dominate the SB and figure 1 shows a steep drop in people with high values choosing the SB auction. We see what might be considered two divergences between the actual results and predictions of these expected utility calculations. First, we see more choices of the A at low values than might be expected considering that the SB dominates the A in expected utility for low values. Further, the observed increase in the likelihood of subjects choosing the A seems to begin for values in the range of 70-80 which is lower than the lowest threshold suggested by figure 2. This is less of a concern though due to the difficulties in calculating these expected utilities carefully as such a discrepancy is quite minor. With the possible exception of some low value bidders choosing the A auction more than expected, this analysis shows that subjects appear to be best responding to the empirical distributions in their auction choice behavior.

This claim might seem counter-intuitive given that table 1 shows that the average surplus is higher in A than SB auctions. The obvious question is how that can be the case while figure 2 shows that the expected utility of SB auctions is higher over most of the value range. The first point is that with the exception of the $\alpha = 1$ case, the expected utility of the SB auction being higher does not equate with average surplus being higher. Since the risk profiles of both formats are different, expected utility could certainly diverge from expected surplus. More importantly, the calculations in figure 2 likely overestimate the utility in SB auctions due to the fact that there is an enforced relationship between the degree of risk aversion in auction choice behavior and the degree of overbidding in SB auctions. If there are additional explanations for overbidding in SB auctions such as regret, see Engelbrecht-Wiggans and Katok (2007), then even a risk neutral person would be bidding higher in SB auctions than assumed in our calculations which would lower the expected utility line for the SB. In fact such divergences from bidding as predicted by the CRRA model could well account for why the subjects started dropping out of participating in SB auctions at lower values than predicted in figure 2 as well as why some low value bidders still chose the A instead of

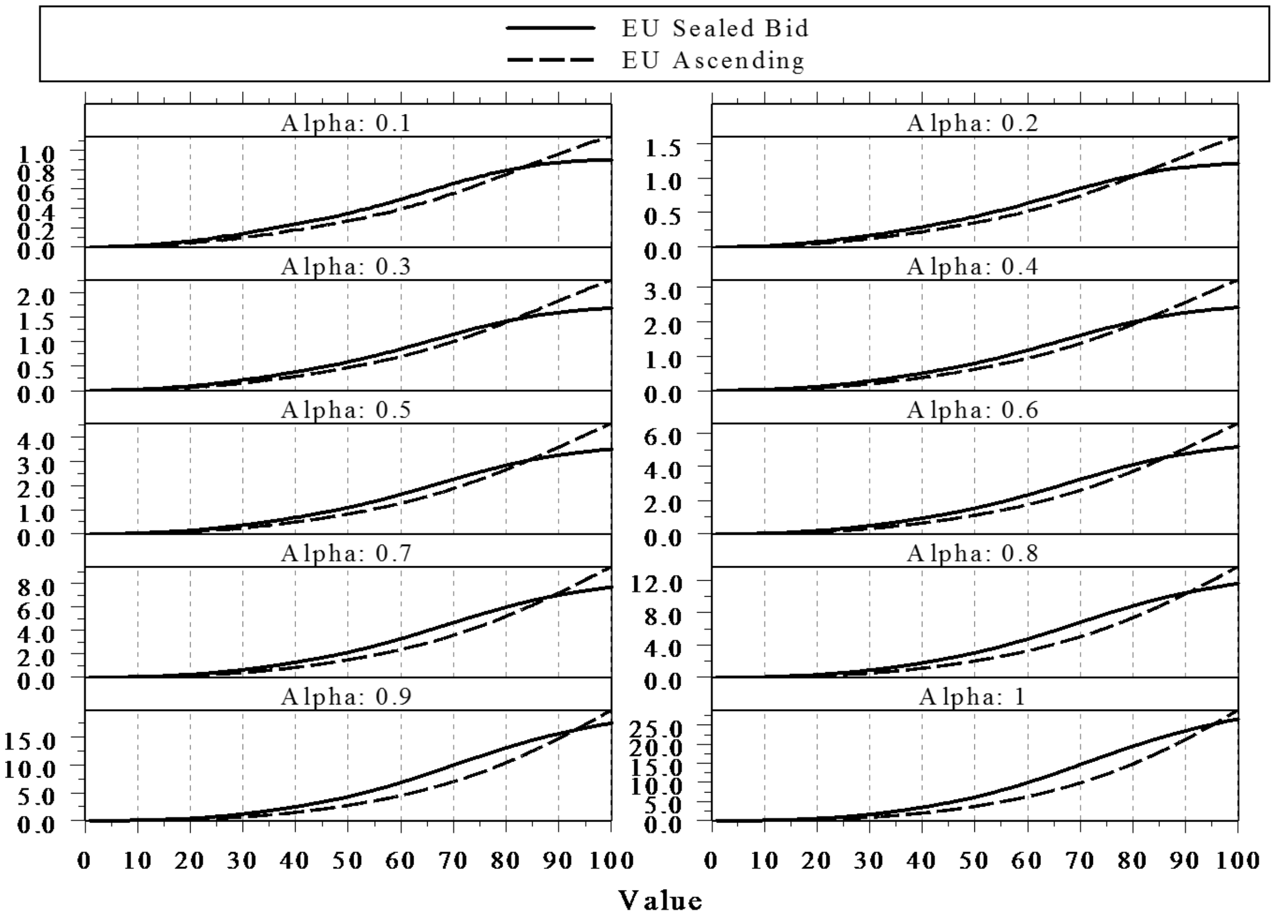

Figure 2: Expected utility of ascending and sealed bid auctions for varying levels of risk aversion.

the SB. For these reasons figure 2 should not be taken as a perfectly calibrated picture of how the expected utilities for the subjects really compared between the two formats but rather as a useful benchmark to use in understanding something about this relationship. A more precise calculation of the expected utilities would require a precise knowledge of the utility functions and bid functions of each individual which requires an analysis that is well beyond the scope of this study.

To check for the effect of forcing one bidder in each auction, we ran an additional treatment where all bidders were allowed to choose in which auction format to participate. To maintain consistency, everything else about the sessions was the same as the ones described above including the specific values and matching scheme. The results from this treatment leads to our final result.

Result 5: *The design choice of forcing one bidder into each auction format each round has no impact on the results.*

As this is a side point to the main analysis, we will not present this data in detail to conserve space but in general we find that none of the results above change based on this alternative design. The number of bidders choosing the two auction formats in these sessions was 2.8 (A) and 3.2 (SB) which is quite similar to those in table 1. Also random effects panel and logit panel regressions of auction choice (similar to those presented in tables 2 and 3) do not reveal any treatment effects nor any interactions between the treatment variable and each of the other variables. Standard distribution tests all fail to find a significant difference in the resulting distributions of values for the two auction formats after bidders' choice ($p-$values of 0.356 (A), 0.137 (SB) from a Mann-Whitney-U test as well as 0.752 (A), 0.615 (SB) from a Kolmogorov-Smirnov test). Moreover, since forced bidders and non-forced bidders in the auction also don't differ significantly in their bidding behavior, all other results with respect to revenue, surplus and efficiency seem not to be affected by this aspect of the experiment design.

4 Conclusion

The importance of taking entry choices into account when considering auction designs should be clear. While investigations of the revenue generation of sealed bid and ascending auctions with fixed numbers of bidders going back to Cox, Roberson, and Smith (1982) have shown that the sealed bid auction has a clear revenue advantage, this result is no longer clear once entry choice is allowed. Both here and in ISS08 we find that when endogenous entry is allowed revenue rises enough in the ascending auction relative to the sealed bid to remove the advantage in the sealed bid auction.

The intriguing aspect of the revenue result is that it occurs for very different reasons in the two studies. It turns out that the key factor is the timing regarding when bidders get to know their value. If the entry choices are made behind the veil of ignorance (as in ISS08) revenue is equalized by virtue of more bidders entering the ascending auction and since that delivers higher order statistics for the values of bidders in the ascending than the sealed bid auctions, the revenue ended up being equalized. If bidders know their values when deciding which auction to enter (as in this study), the number of bidders in both formats ended up being on average the same but the sealed bid auctions attracted bidders with lower values. Despite the aggressive bidding of those entering the sealed bid auctions, the fact that the bidders in the ascending auction had such higher values led to the revenue again being approximately the same between both formats.

While we do find that the revenue between the two formats becomes equalized irrescpective of whether subjects make their entry decisions behind the veil of ignorance or knowing their value,[10]

[10] In a related experiment design, Engelbrecht-Wiggans and Katok (2005), find the same result as well.

we do not intend this to be a claim that revenue is always equalized when endogenous entry choice is allowed. Theoretically, the issue is indeterminate under the assumption that bidders find out their value after entry as shown in Smith and Levin (1996), and as yet there is no theoretical treatment under the alternative assumption of bidders learning their values prior to choosing an auction. To make such a global claim empirically would require many more experiments with more general and varied value distributions and pools of bidders to demonstrate fully the robustness of the phenomenon. We argue only that these results show that under either assumption of the timing regarding when bidders learn their value related to choosing an auction, the revenue superiority of the sealed bid auction should no longer be assumed when endogenous entry is an important aspect of the environment.

This study investigates, for the first time, the impact of bidder values on entry decisions. It provides clear evidence that the knowledge of own value does influence auction choice. The results revealed that different auction formats attract bidders with different values The behavioral effects found in this study are themselves quite interesting. We noted in the introduction that Klemperer (2002) argued that bidders who are disadvantaged in the sense that their values are drawn from a dominated value distribution would be discouraged from entering into an ascending auction and would prefer a sealed bid auction wherein they might still have a chance of winning. We find that even when subjects are *ex ante* identical, i.e. have their values drawn from equivalent value distributions, those subjects whose values end up being on the lower end of the distribution self-select into the sealed bid auction for similar reasons to those argued for the asymmetric bidders.

APPENDIX A: Computation of Expected Utilities

For the analysis in this paper we needed to calculate the expected utility and expected surplus contingent on an observed value since this was known prior to entering into an auction. Since value distributions were not uniform in each institution, this must be taken into account in the calculations.

The equation for calculating expected utility in first price auctions is shown in equation 1. To calculate the expected utility in first price auctions, we first have to sum the expected utilities of ending up in auctions of sizes $1-5$ and multiply each by the probability of that auction size occurring. This probability, represented by $g(n)$ will be the empirical frequency of each auction size. There is an important detail which is that it was impossible for a bidder making a choice to enter a SB auction and have it be a 1 bidder auction. Thus when we wish to compare auctions from the point of view of analyzing a choice by a bidder we will begin the sum at $n = 2$. For an auction of each size, we simply have to calculate the expected utility which is their utility if they win (i.e. $v - b^*(v, \alpha)$) multiplied by the probability of winning. For this we are assuming this bidder is bidding according to the equilibrium bid function assuming risk aversion. While this may seem restrictive, since we calculate this for all $\alpha \in (0, 1]$ in increments of .01 (though only increments of .1 are displayed in the paper) we are able to get a good overall sense of the expected utility calculation for any way a subject might bid. We calculate the probability of any bid winning using a kernel estimate of the distribution based on the empirical bid distribution from all auctions conducted of each size which means we are taking no stand in regard to the process generating the competing bids. Thus, for any bid x we use the kernel density estimate of the the probability that the bidder draws $n-1$ opponent bids from the empirical distribution that are less than x. This is given by $W(x, n)^{n-1}$.

There is one remaining important detail about this calculation and this is the fact that we will be using as the equilibrium bid function the standard bid risk averse function under the assumption of homogenous risk preferences which is $b^*(v) = \frac{n-1}{n-1+\alpha}v$. Since there is heterogeneity in the data, this is a simplification but the only difference needed to account for heterogeneous risk preferences would be the "hook" in the bid function at high values which predicts a gradual flattening out out of the bid function. Were subjects following the bid function precisely, then we would be overestimating the actual expected utility of bidders for participating in a SB auction, but since most bidders are not as sensitive to this as suggested by the theory, the difference is likely minimal. We discuss several issues of this sort which might suggest these expected utility calculations may be imprecise in more detail in the text of the paper.

$$EU^{SB}(v,\alpha) = \sum_{n=1}^{5} \left((v - \frac{n-1}{n-1+\alpha} v)^{\alpha} W(\frac{n-1}{n-1+\alpha} v, n)^{n-1} \right) g(n) \tag{1}$$

To calculate the expected utilities in the A auction, we must follow a similar approach. Again we sum the expected utility of participating in an auction of size n over all possible auction sizes and multiply by the empirical fraction of auctions of each size, $h(n)$. Since bidders in A auctions do bid for the most part as theory predicts, there is no controversy in using their value as their predicted bid but since the distribution of values is no longer uniform there is an additional complication in the calculation. We must add over all the possible states of the world in which this bidder wins the auction (i.e. when the highest of the other $n-2$ values are lower) and to find the probability of each of these other values is the second highest we must use the CDF $J(v,n)$ and PDF $j(v,n)$ based off of kernel density estimates from the actual bids instead of the theoretical analogs. This calculation is given by equation 2.

$$EU^{A}(v,\alpha) = \sum_{n=1}^{5} \left[\left(\sum_{p=0}^{v} (v-p)^{\alpha} (n-1) j(p,n) J(p,n)^{n-2} \right) \right] h(n) \tag{2}$$

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