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An Experimental Test of Alternative Models of Bidding in Ascending Auctions

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Abstract The theory and behavior of the clock version of the ascending auction has been well understood for at least 20 years. The more widely used oral outcry version of the ascending auction that allows bidders to submit their own bids has been the subject of some recent controversy mostly in regard to whether or not jump bidding, i.e. bidders submitting bids higher than required by the auctioneer, should be allowed. Isaac, Salmon & Zillante (2005) shows that the standard equilibrium for the clock auction does not apply to the non-clock format and constructs an equilibrium bid function intended to match with field data on ascending auctions. In this study, we will use economic experiments to provide a direct empirical test of that model while simultaneously providing empirical evidence to resolve the policy disputes centered around the place of jump bidding in ascending auctions.

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Key words auction theory – ascending auctions – jump bidding

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1 Introduction

It is commonly thought that there is a well defined equilibrium bidding strategy for private value ascending auctions of simply remaining in the auction until the price passes your value and then dropping out. This is accurate for the clock version of the ascending auction in which bidders declare if they are interested in being "in" the auction, watch the price rise and choose when to drop "out" of the auction. The more common versions of the ascending auction used in practice though do not involve the use of price clocks. They are typically versions of what are called "oral outcry" auctions in which bidders repeatedly place bids to top a standing high bidder. These formats involve many more decisions on the part of the bidders that include when to bid as well as whether or not to submit a bid higher than the minimum required by the auctioneer.

It has become a popular belief that the equilibrium strategy for the clock auction translates smoothly into the non-clock mechanisms. This is a point also noted by Kamecke (1998) and can be found embedded in the language of some of the classic papers in the field of auction theory.[1] While it should be quite clear that the strategy does not translate directly between the two formats due to technical issues such as the expanded strategy space in the non-clock format, it still might be the case that an analog of the clock strategy might well apply to the non-clock setting. This would be a strategy called straightforward bidding (SFB) which involves a bidder submitting bids at the minimum level required until the price surpasses their value. We investigated this issue in Isaac et al. (2005) (ISZ) to determine if SFB could indeed be the equilibrium in a non-clock setting and found that it will generally not be. This is a finding corroborated in Kamecke (1998).

[1] Two examples of such statements:

> This is the '. . .progressive auction, in which bids are freely made and announced until no purchaser wishes to make any further higher bid' (Vickrey (1961) , p. 14). . . Therefore, the strategy of remaining in the bidding competition as long as the bid on the floor does not exceed the bidder's value for the object, and of dropping out as soon as it does exceed value, is a dominant strategy. (Cox, Roberson & Smith (1982) p. 2 and p. 8)

and

> In the English auction, the price is successively raised until only one bidder remains. This can be done by having an auctioneer announce prices, or by having bidders call the bids themselves. . . the dominant strategy is to remain in the bidding until the price reaches the bidder's own valuation. (McAfee & McMillan (1987) p. 702 and p. 708)

Not only is SFB not generally part of a Nash equilibrium in non-clock auctions but it also has problems matching empirical data. In both cases the problem is that in actual auction data and in the equilibria of non-clock auctions bidders submit a non-trivial number of "jump bids". Jump bidding is the act of bidding above the minimum required bid in an auction, and is incompatible with SFB. With the failure of SFB to capture the pattern of observed bids, the standard justifications for using ascending auctions in the field fall into doubt because they have for the most part rested upon either an assumption of the use of straightforward bidding (Demange, Gale & Sotomayor (1986) and Milgrom (2000)) or the clock version of the ascending auction.

The existence of jump bids has lead to claims in the literature suggesting that allowing bidders to make such bids in an auction has the potential to harm both efficiency and revenue. One source of these claims can be found in Cybernomics (2000), which is mostly contained in Banks, Olson, Porter, Rassenti & Smith (2003) and was part of a report commissioned by the Federal Communications Commission for their conference on combinatorial auctions in 2000. This paper, referring particularly to previous experiments found in Coppinger, Smith & Titus (1980) and McCabe, Rassenti & Smith (1991), argues that "jump bidding is encouraged by impatient bidders who desire to speed up the pace of the auction but sacrifice price and efficiency." The experiments that serve as a basis for that claim were all based on private value environments and consisted of a mix of single unit ascending auctions as well as different forms of multiple unit ascending auctions. This claim about the ill effects of jump bidding is not well defined in any of these cited papers in the sense that there exists neither a solid empirical foundation for such a claim nor is there a description of a mechanism through which jump bidding is intended to deliver these detrimental effects[2].

There have also been separate attempts to explain the process that generates jump bidding. Some of these results lead to the same negative impacts on auction revenue as claimed in Banks et al. (2003). The most common explanation of jump bidding is contained in the signaling models

[2] We should note, however, that at the end of McCabe et al. (1991), the authors do argue that an "important extension is to provide a model of progressive auctions that take into account the time preferences of participants." They then present a sketch of what such a model would look like that is similar to the Daniel & Hirshleifer (1997) model with bidding costs, but they do not provide a solution when time costs are positive.

of Avery (1998) (Avery) and Daniel & Hirshleifer (1997) (DH) which hypothesize that the jump bids are intended as signals to other bidders to indicate the signalling bidder has a high value and the other bidder(s) would be best served by dropping out of the auction. Bidders who are able to signal their value to other bidders and convince them to drop out of the auction could indeed severely hurt the revenue of an auctioneer, though the equilibria are still efficient. In ISZ we present an alternative model of jump bidding which shows that jump bidding could well be a phenomenon of strategic bidding and/or impatience which is at least nominally the mechanism that Banks et al. (2003) claims impairs the outcome of ascending auctions.[3] The key results in ISZ, however, show that jump bidding motivated by these concerns has either a neutral or a slightly positive effect on both revenue and efficiency when compared to bidders bidding straightforwardly.

Even beyond those claims, the use of ascending auctions in the field is often justified based upon their ability to generate efficient outcomes. The two primary foundations for this argument are Demange et al. (1986) and Milgrom (2000) that prove that if bidders engage in SFB then the outcomes will be approximately efficient. The evidence is quite clear, however, that jump bidding does exist,[4] indicating that bidders do not in fact engage in SFB and this invalidates the application of the proofs in Demange et al. (1986) and Milgrom (2000) as arguments for why one should expect field auctions to produce efficient outcomes. Part of our aim is to determine if the ISZ model (that accounts for jump bidding and demonstrates that efficient and profitable outcomes can be achieved in the presence of jump bidding) can start the process of providing a replacement theoretical justification for why we should expect ascending auctions to perform well in the field even if jump bidding does occur.

This leads to a set of questions that can only be answered through empirical investigation. Our first point of investigation is to empirically examine the validity of the claim that allowing jump bids can harm the revenue and efficiency of ascending auctions. The second main issue we are interested in examining is to conduct an empirical test of the model of bidding constructed in ISZ. As an auxiliary point, we can also examine the degree to which signalling might be occurring in these auctions. This investigation will ultimately lead to a discussion of when, where

[3] Impatience in bidder behavior is also observed and modeled in Katok & Kwasnica (2002) in regard to the effect of clock speed on Dutch auctions.

[4] See for example Börgers & Dustmann (2001), Plott & Salmon (2004), and Easley & Tenorio (2001).

and why one might wish to prohibit jump bidding. In section 2, we will present an overview of the various models of behavior that have been proposed to explain bidding in non-clock ascending auctions. Section 3 explains the design of our ascending auction experiments and section 4 presents the results of the experimental sessions and their implications for the issues we are seeking to investigate. Section 5 concludes.

2 Overview of Alternative Theories

2.1 Straightforward Bidding

The first model of bidding in ascending auctions is known as straightforward bidding. It is the simplest and is the analog of the standard equilibrium bidding strategy in clock versions of the ascending auction. A bidder engaging in SFB will simply place a bid at the minimum required each time he chooses to bid[5], up to the point that the required bid would surpass his value. Specific and testable predictions of this model involve a prediction that there should be no jump bids and that the revenue should be approximately equal to the second highest value. We point this out as a possible model of behavior because, while it is not generally an equilibrium strategy, bidders could still follow the strategy and it has been proposed so many times in the literature.

2.2 Signaling

The first class of models able to generate jump bidding in equilibrium involve bidders using their bids to signal their value to other bidders. The two most notable examples in the literature of presenting such models are Avery and DH. A complete description of the models and results from these two papers is beyond the scope of what we will cover here, but we will summarize the main points of the models and discuss the nature of the testable empirical predictions they make.

Although the specifics of the environments used in these two papers are different, the fundamental implications of the models are quite similar. Avery develops a model of signaling in

[5] The manner in which a bidder chooses when to bid, however, is not defined in the model.

ascending auctions under the assumption of affiliated values. The nature of the equilibrium strategies is that a bidder will place a very high initial bid that will signal that he has a value of at least a certain amount. The other bidder, upon seeing this, will determine if their value is higher than the signaled value and will either drop out immediately or bid back. The highly stylized version of the model assumes that if the bidder bids back, then straightforward bidding ensues until the price outstrips the value of one bidder or the other. DH develops a similar model in the context of independent values and costly bidding. In this case, since bidding is costly, a bidder will place an initial bid to perfectly signal his value. The other bidder will either refrain from bidding if his value is below the amount signaled or place a response bid that signals his value. The first bidder then refrains from bidding as he views the bid as a credible signal that the other bidder has the higher value. In either case the auction ends after the first or second bid.

The versions described are essentially boundary cases of broader classes of signalling equilibria inside of these environments. There are a large number of alternative formulations of these equilibria in these environments which lead to a general lack of a specific prediction of bid paths. For example, both models could be extended to require additional bids to signal higher values, leading to longer auctions. It is also possible to generate similar equilibrium signalling strategies in environments without affiliated values or costly bidding. Despite the lack of specific path predictions from these models, it is possible to develop one clear prediction that should emerge from any reasonable signalling theory. The only reason bidders would find it worthwhile to engage in signaling behavior (i.e. endure all of the cognitive costs involved) is if the result were a general lowering of the prices paid in the auctions.

The actual environment of the experimental auctions will include neither affiliated values nor explicit costs of bidding. Thus we do not intend to suggest that our experiments will provide a direct test of these models. Signaling equilibria similar to those described in Avery and DH could still be worked out in our environment though and it is at least conceivable that we might observe bidders behaving in this manner. The main reason for bringing up these models in the context of this paper is that should we find that the revenue in the experiments is on average substantially lower than the second highest value among the bidders then these signaling models might serve as an explanation for why that is occurring.

2.3 Strategic and Impatient Bidding

In addition to the ISZ model mentioned above, Rothkopf & Harstad (1994) presents a few results regarding the idea of jump bidding for strategic reasons. In that paper the authors investigate the possibility of jump bidding for distributional reasons which involve submitting a jump bid in order to foreclose bidders with values in a particular range from being able to bid back. While there is no full equilibrium bidding strategy of this sort derived in that paper, the authors do present a result showing that such bids will not be placed over non-increasing ranges of value distributions. This result predicts that if bidders are jump bidding purely for these distributional reasons, there should be no jump bids in the case of uniformly distributed values and there should be no jump bids past the mean value if the values are distributed normally.

The ISZ model allows for jump bidding due to both these distributional or strategic reasons and bidder impatience. For a full description of this model please see Isaac et al. (2005) as we will only summarize it briefly here. There are two main differences between this model and the Avery and DH signalling models. First, in our model bidders are assumed not to use the full history of actions in updating their beliefs on their opponent's value. Whether the current price is 10 as a result of several rounds of straightforward bidding or from a single jump from an opening price of 0 makes no difference to our bidders' decisions from that point on. We assume that the only information conveyed or perhaps the only information bidder i is smart enough to interpret from bidder j's bid is that it indicates j's value is at least as high as the bid. The potential fact that the bid was a jump bid and that perhaps only a bidder with one specific value would make that size jump will be ignored. This leads to a quasi Markov property to the game as the only important variable to determining future actions is the current price. There are two reasons for this assumption. The first is that we believe it more accurately captures the inference ability of most bidders and the second is to remove the possibility of signaling equilibria.[6] We desired to remove the signalling equilibria from the model as there are existing papers that examine signalling equilibria so we preferred to concentrate on other possible equilibria of these games.

[6] The equilibria we do derive could still be described as "signalling equilibria" as bidders are signalling some information about their values with each bid. We use the term, however, to distinguish between equilibria in which bidders are jump bidding for the express purpose of signalling information about their value, as in Avery and DH, versus cases in which bidders jump bid for other purposes and as a side effect signal information about their value.

The second difference between the ISZ model and the Avery or DH models is that we incorporate a discount rate, δ, to account for the possibility that bidders might prefer to have the auction end earlier instead of later.

To solve for the equilibrium of this model, we must solve the full dynamic programming problem to determine the best response a bidder can make for any value they might have and for every possible current price level. Because the value functions for this problem are inherently highly discontinuous, it must be solved computationally instead of analytically.[7] In ISZ, we solved the model for the cases of both uniform and normally distributed values on the range [1,100] and we then used a variety of combinations of discounts rates (.9, .95 .99 and 1) and minimum bid increments (1, 3, 7 and 10). While each combination of parameters lead to different specific quantitative results, the general nature of the predictions were quite systematic and consistent. The broad predictions of the theory are as follows:

- If $\delta < 1$ and/or the value distribution is increasing over part of the range of bidder values, jump bidding is part of the equilibrium strategy.
- Jump bidding decreases as the minimum increment rises and increases as δ decreases.
- In spite of the jump bidding, the auctions remain quite efficient with the main drag on efficiency being the size of the minimum bid increment. In fact, efficiency from equilibrium bidding (which involves jump bidding) is slightly greater than the efficiency generated by non-equilibrium SFB.
- Revenue effects from jump bidding are minor relative to standard predictions but revenue in the jump bidding equilibrium is typically slightly greater than what would be generated according to SFB.

Thus the predictions of the ISZ model differ from the SFB model mostly in regard to the path of the auction, not the outcome. The ISZ predictions are different from those generated from

[7] Due to the fact that this is a finite game, the solution algorithm will deliver a Bayes-Nash equilibrium of the game as the strategy will be a best response to itself given the belief structure. Since the beliefs in this model are not being updated with all possible information, the equilibria we find will not pass many perfection criteria. Our methodology does however guarantee the main and important qualities of a subgame perfect (or perfect Bayesian) equilibrium as it ensures that all players are playing a best response to their beliefs at every possible subgame and that these beliefs are being updated in a sensible and consistent manner. The equilibria we will find are similar in spirit to Markov Perfect equilibria for repeated games and the methods we use are similar to those developed in Maskin & Tirole (1988).

the signalling models in terms of revenue and bid patterns. The specification examined in ISZ is certainly only one possible way to model the idea that bidders would prefer an auction to end sooner rather than later. In addition or perhaps instead of a discount rate one could use either explicit costs of bidding or implicit opportunity costs from alternative activities not engaged in to motivate such a preference. We chose the discounting framework due to its simplicity but we believe that any similar framework that also contains the Markov property regarding belief updating would generate similar results. We view our model as demonstration of the impact of these considerations on bidding behavior. It is important to have such a demonstration due to the fact that these were not the outcomes previous authors had hypothesized would result from such a model.

In principle, one could conceive of attempting to achieve tighter predictions of the data with the ISZ model by first econometrically fitting δ to part of the data and then generating additional out of sample predictions for the rest of the data. We choose not to proceed in this direction for a number of reasons. First is that due to the computational burden of computing the equilibrium of the model for a given δ, it is not feasible to engage in such a process since one would have to calculate the fit from at least dozens of δ's. Second is that we do not intend to imply that the δ in our model is in any sense a true parameter of a bidder's discount rate that would be related to investment or other behavior. Our goal for the model is to demonstrate that it is possible to capture both the pattern of auction outcomes and the paths of auctions just by constructing a very simple model with the two features of impatience and the Markov property regarding belief updating. In order to compare the predictions of the ISZ model to the data generated in the experiments, we will therefore just use the results generated by the "median" case from our previous paper of $\delta = .95$ which were generated prior to conducting the experiments for the current paper. While it happens to be true that this particular case has the distinction of being about the closest "fit" to the data from among the values of δ we had computed results for in our previous paper, the qualitative predictions do not differ by much across the $\delta < 1$ cases we tried and were we to present the results from any of the other cases instead of the $\delta = .95$ case the general nature of our conclusions would remain unchanged as can be verified by examining the results presented in ISZ.

3 Design of the Experiments

The design of the experiments was chosen to be as close as possible to the conditions of the ISZ theory. This meant we conducted a series of experiments with two bidder ascending non-clock auctions with treatments on which we varied the value distribution used as well as the minimum required bid increment. The general design of each session involved having six or eight participants seated in a computer lab with dividers between the terminals to keep subjects from observing the screens of other subjects. At the start of the experiment, we used a verbal instruction script, available from the authors upon request, to explain to the subjects exactly how the auction format would work. This included having a practice software module that allowed the subjects to bid against a computer player in as many auctions as they wanted in order to ensure they were comfortable with the software. Also, since the value distribution used was crucial to the experiment design we also included a detailed description of how the values were distributed including giving each subject a chart showing them the exact probability with which each value would be assigned.

Subjects were told that (time permitting) they would be participating in 20 consecutive two-person single unit ascending auctions. In a few sessions we did not finish all 20 rounds. In the first round, each subject was randomly paired against another subject and all were randomly re-paired before the start of every subsequent round. When a round started, both bidders in an auction were allowed to try to place the first bid in the auction. Once a bidder was a standing high bidder, their opponent had the opportunity to place a bid to become the new standing high bidder and that bid was required to be at least a certain amount above the current standing high bid. The current standing high bidder was allowed to raise their own bid, but was also required to submit a bid at or above the minimum required level. The close of each auction was governed by a 30-second countdown clock. When the auction began there would be 30 seconds on a countdown clock and the auction ended when it hit 0. The clock would reset to 30 seconds any time either bidder placed a bid. Note that since no two auctions in a round were tied to one another, some auctions in a given round closed faster than others. Bidders whose auctions ended earlier than others were asked to wait patiently while the other auctions in that round closed.

The computer screen was divided into two windows, an auction status window and a bid submission window. Each bidder's auction status window displayed the current high bid, whether or not he held the current high bid, the minimum increment along with the minimum required next bid and the bidder's potential profit from the current auction if the auction closed with the current high bid. Bidders submitted bids in the auction by keying in the amount they wished to bid in the bid submission window and clicking the submit bid button. For most of the experiments, the only restriction placed on the bid amount was that it must be greater than or equal to the minimum next bid. This gave bidders the choice of bidding straightforwardly or jump bidding. Since bidders were allowed to increase their own currently winning bid there was no forced alternation of bids. Bidders were also allowed to bid above their values, although they were informed that bidding above their value could lead to them losing money in that round and therefore decrease their earnings in the experiment. In addition, if a bidder did bid above their value, this was pointed out in the auction status window by displaying in red the negative earnings they would receive in the event that they won the auction with that bid. Bidders began with a bank account of 10 experimental currency units (ECUs), and any bidder who depleted all of his accumulated earnings as well as the initial bank account was excused from the experiment with solely his $7.00 show-up payment. There were only 2 instances of bankruptcy in these experiments. As a result of these situations, there were times when an odd number of subjects remained in the experiment. In each round in which there were an odd number of subjects, one subject was randomly chosen by the software to be the "odd man out" for that round and asked to wait quietly until the round was over.[8]

There were two main experimental treatments, producing a four cell design. We conducted two sessions in each cell for a total of 8 sessions. The first treatment involved varying the minimum bid increment across sessions by setting it to either one or seven. Second, the value distribution was varied across sessions between a uniform distribution on the integers [1,100] and a normal distribution with mean 50.5 and standard deviation 15, truncated to the same range. For the normal distribution, the probability of drawing an integer $x \in [2, 99]$ was determined by assigning

[8] We note that in addition to these problems decreasing the number of auctions conducted, our software evidenced an occasional glitch in some sessions that did not allow a few auctions to be conducted. During the experiments we explained the problem. The subjects did not evidence much confusion, and, of course, these phantom auctions have been eliminated from consideration in the results section.

all of the mass between $(x - .5, x + .5)$ to x. All the mass from $(-\infty, 1.5)$ and $(99.5, \infty)$ was assigned to the probability values of 1 and 100 respectively. As explained above, the nature of these probability distributions was described to bidders in non-technical terms. Inside of a session, these treatment parameters remained constant. Also, for all sessions involving uniformly distributed values we used the exact same set of values across sessions, though we did not use the same pairings. So a subject who was bidder 1 in one session would have the same values as bidder 1 in another session, but they would be matched against different opponents. The same was true for the sessions involving normally distributed values.

There is a legitimate question about the use of different value distributions in the experiment in regard to whether or not subjects would be sophisticated enough in their behavior and sensitive enough to the changes in value distribution for this treatment to have any impact on behavior. Our intention for including results from both value distributions is intended as more of a robustness check to ensure that the general nature of the observed behavior is not unique to the uniform distribution. The question of whether or not the observed behavior will show the comparative static changes between distributions predicted by the theory is a somewhat lesser concern.

At the end of a session, bidders received a \$7.00 show-up fee as well as compensation for decisions made throughout the series of auctions. In order to make the expected dollar-valued earnings more equal across treatments, the exchange rate of ECUs into dollars varied with the probability distribution. Subjects received 5 cents per ECU when the uniform distribution was used and 10 cents per ECU when the normal was used. Since our comparisons will be made mostly between sessions with the same value distribution and not across value distributions, this should not greatly affect our results. Earnings per subject averaged \$20.21, including the \$7.00 show-up fee, for sessions that lasted from one and one-half to two hours.

A third treatment involved conducting a set of sessions where subjects were not allowed to place jump bids, i.e. were required to bid exactly at the minimum required level if they wished to bid. These straightforward bidding experiments allow us to test the claim directly that allowing bidders to jump bid harms efficiency and revenue compared to a situation in which they are not allowed. Except for the change in regard to not allowing bidders to place jump bids, the software and general manner of conducting these experiments worked the same as before. We conducted 1

Session	Value Distrib.	m	Jump Bidding?	Periods	Subjects
1	Uniform	1	Y	20	6
2	Uniform	7	Y	20	8
3	Normal	1	Y	20	8
4	Normal	7	Y	20	8
5	Uniform	7	Y	20	6
6	Uniform	1	Y	20	6
7	Normal	7	Y	20	8
8	Normal	1	Y	15	8
9	Uniform	7	N	20	6
10	Uniform	1	N	12	6
11	Uniform	1	N	2	8
12	Uniform	1	N	6	8

Table 1 Overview of sessions conducted.

session with a bid increment of 7 and 3 partial sessions with an increment of 1 all with uniformly distributed values. The 7 increment session was fully completed while the 1 increment sessions were not. In one of those we completed 12 periods, a second 5 periods and the third only 2. The two period session was a result of a catastrophic software failure in round 3 while in the other two the full 20 rounds were not completed simply due to the staggering amount of time necessary to conduct auctions when using such a small increment and bidders are only allowed to bid at the minimum increment. While we initially intended to conduct more sessions of this sort, the sessions we did conduct were enough to demonstrate the infeasibility of additional sessions. For a full overview of each of our sessions conducted, please see table 1.

4 Results

We will present the results from the experiments in three parts. In the first two parts we will demonstrate the broad characteristics of the experimental data and then present a series of results relating to how well each of the various theories described above match with the data. The final section will examine the claim made in prior papers that allowing bidders to jump bid is harmful to auction outcomes by reporting the results from the sessions in which subjects were not allowed to jump bid and comparing those results to the sessions in which they were allowed.

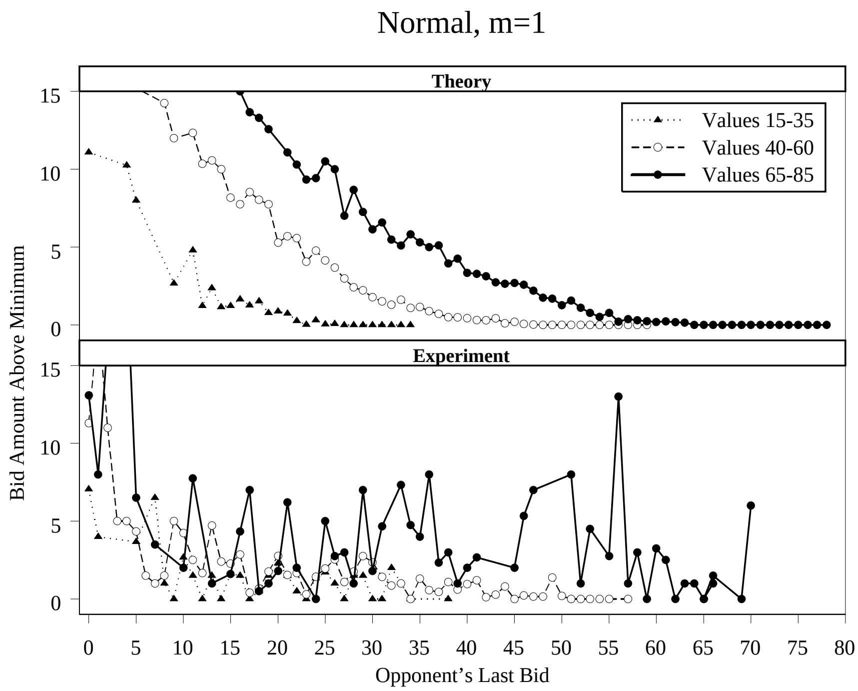

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Fig. 1 Comparison of empirical to theoretical bid functions. The theoretical bid functions were constructed assuming $\delta = .95$.

4.1 Bid Functions

To get a broad idea of the nature of the bidding behavior of the subjects we can examine some approximate empirical bid functions that can be inferred from the experimental data. There are several issues that complicate the graphical presentation of the observed bidding behavior. First, we do not observe a complete bid function from each individual subject as that would require observing the choice a particular subject would make for all possible values and at all possible price levels. Neither do we observe a complete bid function for a given value in the sense of looking across subjects and observing what a generic person with a value of x would bid at all possible prices. Nor can we easily present a simple 2D scatter plot of bids against values as is done with sealed bid auctions, as the bids in ascending auctions are sequences. In spite of these problems, we believe these graphs should prove quite helpful in demonstrating some key qualities of the subjects' behavior.

The approximations of bid functions were built by first constructing three disjointed groups of bidders; Group 1: $v_i \in [15, 35]$, Group 2: $v_i \in [40, 60]$ and Group 3: $v_i \in [65, 85]$. Next, we calculated the average bid made by all bidders when they had values in those ranges for every price (i.e. most recent bid of an opponent) faced by a person in that range. In these calculations, we only included bids made in periods 8-20 of the experiments. We have focused on this range of periods to remove any errant bids or mistakes that might have occurred early in the experiment. Even just a few such mistakes would have seriously distorted the figures because of the sparse nature of the data. There is no special significance to beginning with the 8^{th} period other than the thought that it seemed to be a good compromise between delivering enough data to fill out the bid functions while eliminating early mistakes. Figures 1 and 2 show some examples of the results of this process by showing the average amount above the minimum bid required made by bidders in each range of values at each price a bidder in that range was found to have faced. For easy comparison we have included in those figures analogs from the theoretical predictions of equilibrium bid functions derived from the ISZ model. The theoretical bid functions were generated under the assumption that $\delta = .95$.

The general pattern of bidding demonstrated in these figures is that when the minimum bid increment is low, see figure 1, the bidders submit a large number of jump bids. These jump bids were submitted throughout the course of the auction and were of relative even and moderate size throughout the auction. When the increment is increased, see figure 2, the number of jump bids falls substantially as only a few bidders submit jump bids at all and they are generally of small magnitude.

4.2 Aggregate Data

While the graphical bid functions are useful in developing a deeper picture of the data, we now turn to examining some aggregate statistics from the observed behavior in order to generate more precise tests. Table 2 contains a number of summary statistics regarding the nature of jump bidding as observed in the experiments and as predicted by the ISZ model, assuming

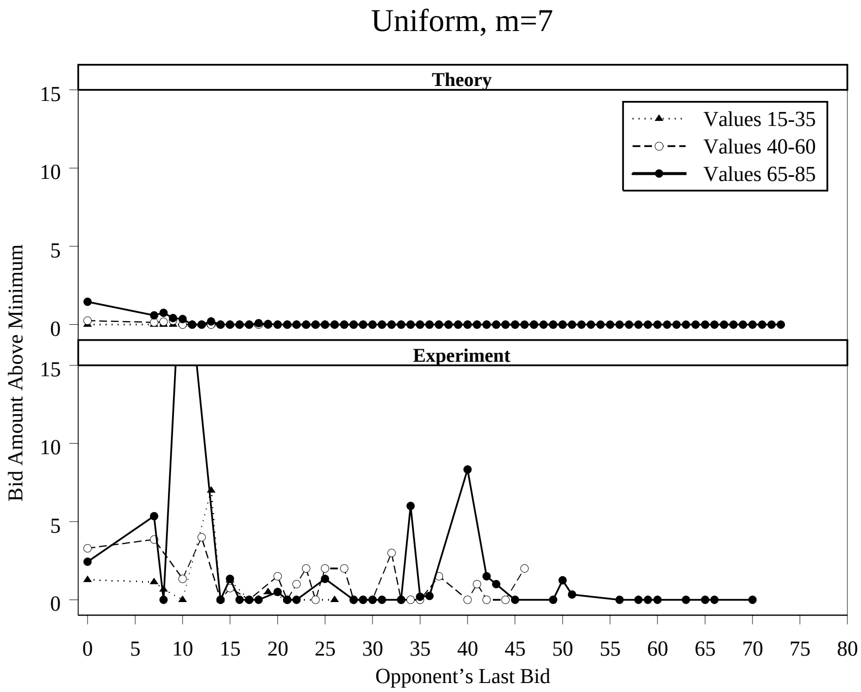

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Fig. 2 Comparison of empirical to theoretical bid functions. The theoretical bid functions were constructed assuming $\delta = .95$.

$\delta = .95$. The results from the experiments were calculated using all periods of the experiments[9]. The theoretical results were found by first computing the equilibrium bid functions for each bid increment and value distribution pair used as treatments in the experiment. Since we used the same value draws across experiments but not the same pairings, we then took the 8 values per round that were assigned to subjects and constructed bidder pairings using all 28 of the possible combinations of those values and did the same for all 20 periods giving us 560 value pairs that could have existed over the course of the experiments. For each value pair, we computed the equilibrium outcome that would result from two such bidders being matched up. Since the order of who bids first can be important, we calculated the auction outcomes a second time for each value pair alternating which value bid first which delivers the number in the tables of 1120 auctions for the theoretical results.

[9] We used all periods for these and all subsequent calculations (except where noted) because unlike with the graphical bid functions, a few errant early mistakes should have little impact on these aggregated statistics.

	Uniform Distribution				**Normal Distribution**			
	m = 1		**m = 7**		**m = 1**		**m = 7**	
	Exp	**Theory**	**Exp**	**Theory**	**Exp**	**Theory**	**Exp**	**Theory**
Num Bids	1365	10062	587	5666	1770	9520	596	4332
Num Jumps	778	6679	230	590	874	5169	255	1775
% Jumps	57%	66%	39%	10%	49%	54%	43%	41%
Avg Jump	3.83	4.99	5.37	2.99	4.60	7.43	10.08	9.17
Num Auctions	114	1120	132	1120	139	1120	139	1120
Bids Per Auc	11.97	8.98	4.45	5.06	12.73	8.50	4.29	3.87
Bids Past 50	150	2416	60	581	116	1617	18	189
Jumps Past 50	81	1093	18	0	47	335	6	0
% Jumps Past 50	54%	45%	30%	0%	41%	21%	33%	0%

Table 2 Comparison of levels of jump bidding between experiments and theoretical predictions assuming a discount rate of $\delta = .95$.

The results displayed in table 2 along with the empirical bid functions allow us to state our first result.

Result 1 - Jump bidding occurs in a regular and systematic manner that is inconsistent with straight forward bidding.

SFB predicts that bidders will always place bids at the minimum level required by the auctioneer and thus we should observe no jump bids in the experiment if this is a valid model of bidder behavior. As rows 2 and 3 of table 2, the number of jump bids observed in the experiments is non-trivial. While it is certainly the case that had we observed a small number or small percentage (i.e. less than perhaps 5%) of the bids being above the minimum required level it would have been reasonable to conclude that these were merely trembles or mistakes, we instead observe percentages that are typically over 40% which should strongly demonstrate that these jump bids are not merely trembles. Further, if one assumes that jump bids were purely irrational or accidental, that would lead to a lack of a systematic pattern to them. As shown in figures 1 and 2, though, the nature of jump bidding was clearly responsive to changes in the environment. Consequently, we may clearly dismiss SFB as being capable of explaining the individual bids placed by the bidders in the experiment over the course of an auction.

These data also allow us to support our second result.

Result 2 - The observed jump bidding is not purely a function of distributional or strategic bidding, though we can not conclude that these issues do not influence the bidding behavior at all.

This result is based on the theoretical proposition from Rothkopf & Harstad (1994) showing that such bidding is not optimal in the case of uniformly distributed values or after the mid point of normally distributed values. This prediction finds no support in the data as demonstrated by the large amount of jump bidding in the uniform distribution and the existence of jump bids past 50 when the values were distributed normally (last 3 rows of table 2). One should not, however, take this as an indication that the bidders definitely did not consider these issues when submitting their bids. If the bidders were impatient to any degree then the ISZ model shows that they will still be submitting jump bids in these value ranges. The valid conclusion then is that while the jump bids could be in part motivated by distributional concerns, it is clear that this was not the only motivation.

Of ultimate importance to an auction designer is the accuracy of the models in predicting the revenue and efficiency generated in the auctions. Recall from the introduction that the existing claim in the literature was that jump bidding definitely harmed revenue through signaling (DH and Avery) and may also harm efficiency through some other unknown mechanism (Banks et al. (2003)). These experiments allow us to verify whether this claim is correct because we have demonstrated that substantial jump bidding exists and we can now determine if these bids have the supposed negative impact on the outcome of the auction. Table 3 shows the actual effect of the observed jump bidding on both revenue and efficiency. We have again included the analogous specific predictions that would be made by the ISZ model by computing the average revenue and efficiency numbers according to the equilibrium bidding strategy for all possible value combinations given the values used in the experiment. In this case we decided it would be clearer to generate the theoretical predictions based upon the actual value pairs realized in the experiment and so for each value pair we generated two predicted auction outcomes, one for each bidder placing the first bid. Consequently there are twice as many theoretical auctions as experimental.[10]

[10] We also have results using all possible realizations of value pairs similar to the results in table 2 and the nature of the results and interpretation are the same.

	Uniform Distribution				**Normal Distribution**			
	m = 1		**m = 7**		**m = 1**		**m = 7**	
	Exp	**Theory**	**Exp**	**Theory**	**Exp**	**Theory**	**Exp**	**Theory**
Avg Revenue	37.89	37.92	38.99	39.66	41.59	43.34	42.98	42.02
StDev	22.69	21.32	23.19	22.01	15.31	12.58	13.62	11.42
Avg Losing Val	35.79	35.23	39.81	39.15	42.93	41.89	41.93	41.68
StDev	23.24	22.44	22.77	22.90	14.27	13.55	12.24	12.19
Num Auctions	114	228	132	236	137	274	132	264
Avg Efficiency	0.99	1.00	0.985	0.997	0.981	1.00	0.995	0.999
StDev	0.06	0	0.09	.04	0.07	0	0.03	0.004
Possible m Ineff	-	-	14	28	-	-	30	60
Actual m Ineff	-	-	4	4	-	-	5	2
Other Ineff	6	0	2	0	17	0	4	0

Table 3 Comparison of levels of revenue and efficiency between experiments and theoretical predictions assuming a discount rate of $\delta = .95$.

Combining the revenue results with the results earlier on the bid patterns leads to our next result.

Result 3 - The jump bids do not appear motivated in any substantial way by (successful) signalling.

It is certainly not possible for us to conclude that no subjects were attempting to send signals in the manner suggested by DH and Avery, but we can conclude that the key predictions of the signalling models find no support in our data. While it is difficult to generate much in the way of specific path predictions from signalling models, the general nature of the results in Avery and DH suggest that we should observe large initial bids followed by the auction immediately closing or SFB until the auction finishes. Figures 1 and 2 and table 2 show that the observed pattern of jump bidding is substantially different from that prediction. Jump bids occur throughout the auction at a moderate level and we do not observe many one bid auctions. While the signalling models are flexible enough to generate different path predictions, the main prediction of the signalling models is that we should observe revenue much lower than the value of the second highest bidder due to bidders observing the signals of the higher value bidder and dropping out. By examining rows 1 and 3 of table 3, we see that the revenue was on average quite close to the value of the losing bidder. Demonstrating that on average, bidders stayed in the auction until they could no longer profitably bid. This is in direct opposition to the spirit of the signalling models. Thus we can conclude that they have little predictive ability on either auction outcomes or on the bidding path of the auctions.

We should note that while the vast majority of the auctions closed at a point at which the losing bidder would realize no surplus by placing an additional bid, there were some auctions that closed with surplus remaining on the table. The actual number of auctions closing at prices at which the losing bidder could profitably bid (considering all rounds) were 9 for uniform $m = 1$ (8%), 3 for uniform $m = 7$ (2%), 20 for normal $m = 1$ (14%) and 8 for normal $m = 7$ (6%). For the $m = 7$ treatments the number of such cases are inconsequential and easily reconcilable as accidents. Of the 11 cases in the $m = 7$ treatments only 5 closed with the remaining surplus being greater than 3 ECU's and no single subject made a "large" mistake more than once. The results are a bit different in the $m = 1$ treatments as of the 29 cases there was a large number closing with double digit surplus remaining. Further, there were several subjects who dropped out early more than once (one particular subject accounts for 7 of the 29 observations). While some of these cases may be accidents, our belief is that due to the systematic variance of the frequency of these cases with the bid increment, it seems more likely that this is evidence of the frustration bidders face in auctions with low bid increments leading to them being willing to drop out early. This is a point we will return to.

With none of the alternative models proving successful in matching the experimental results, we can now turn to seeing how well the ISZ model performs in this task. The first point has to do with the degree to which the ISZ model can account for the level and nature of the jump bidding.

Result 4 - The general pattern of jump bidding observed in the experiments matches well with the predictions of the ISZ model and at a minimum the match is much stronger than with any of the alternative models. Further, there is an indication that this match improves as the experiment progresses.

The primary support for this point can again be found in figures 1 and 2. While we can not provide a formal statistical test of the match between the empirical and theoretical bid functions (we have essentially a sample size of 1 for the empirical bid function), we can examine the relative fit along several criteria of the ISZ model and the primary alternatives. There are several stylized properties exhibited by the empirical bid functions:

1. Jump bids are larger at lower prices and then their size decays as the auction progresses.
2. Jump bids occur even deep into the auction.
3. There is less jump bidding observed for larger increments.

Again, it is clear that SFB can account for none of these properties as that model predicts completely flat lines for figures 1 and 2. The signaling models can also not match any of these properties as they predict single large initial jump bids followed by the close of the auction, a second large jump bid that closes the auction or straightforward bidding until the close. Such predictions can not match the decay in the size of jump bids, the frequency at which they occur in the auction nor the change in the level of jump bidding with the increment. The theoretical bid functions of the ISZ model, as displayed in figure 1 and 2, can match all of these properties to some extent. Thus in a straight comparative test among the alternatives, the ISZ model is the only one to match the empirical observations to any degree.

If we examine the absolute fit of the ISZ model, it will match certain parts of the data well and other parts less well. The theory predicts that at low prices there will be quite large jump bids with the jumps decreasing in magnitude at higher prices. In the data, while we do observe that jump bids are slightly larger at low prices than high, the observed jumps at low prices are smaller in magnitude than predicted and the observed jumps at high prices are larger than predicted. Perhaps the worst absolute fit for the ISZ model is seen in the uniform $m = 7$ case. The theory predicts a dramatic drop in jump bidding when moving from normal $m = 1$ to uniform $m = 7$ and this comparative static response is observed. The actual level of jump bidding observed in the $m = 7$ case, however, is much larger than predicted.

While we can not subject the shape of the bid functions to more rigorous tests, we can construct a more quantitative comparison between the theory and the data using more aggregated statistics that can be found in table 2. In comparing the theoretical predicted level and nature of jump bidding to the observed, we observe that the theory matches quite well with the comparative statics of the data in terms of predicting how the percentage will change as we change the environment. It would be too much to expect to see the percentages match precisely between the theory and data, especially since the model is not fitted to the data, but they are still quite close in most cases. This match between theory and data holds too when looking at the next row which is the average size of the jump bids. The only anomaly is in the uniform $m = 7$ case where, as noted above, we observe substantially more and larger jump bids than predicted. The theoretical prediction in this case is a boundary solution of no jump bidding over most of the range. Any “errors” or minor deviations from this strategy will show up as jump bids. We are therefore not surprised that we see more jump bids than predicted in this case. There are a number of potential small biases such as biases in favor of bidding in round numbers, mistakes in entering bids and so forth that will lead to small deviations and that appears to be what we see here. The overall behavior can not be explained by such small biases as they could not deliver the systematic variation in bidding behavior we observe across treatments.

While table 2 contains the results from all periods, it is interesting to examine whether or not there was any change in behavior over time. Table 4 contains the key pieces of data for each case separated out into periods 1-8 and periods 13-20. What we observe is that in both $m = 1$ cases, the subjects appeared to learn to jump bid more often and more aggressively as the experiment progressed because the percent of bids that were jump bids and the average size of the jump bid both increased at least marginally. The opposite effect occurred in the $m = 7$ cases as subjects appeared to learn to jump bid less often and less aggressively. In general, these directions of learning are towards the theoretical predictions, though occasionally they may overshoot the theoretical predictions by a little. The largest shift seems to have occurred in the uniform $m = 7$ treatment cell in which the jump bidding propensity almost halves between the two sections of the experiment. In table 2 we saw that this was the worst fit between theory and data as the subjects were jump bidding substantially more than theory predicts. The results in table 4 indicate that subjects appear to be making a substantial shift in behavior to be more in line with the theoretical prediction.

These results suggest that the general nature of the bidding by the subjects matches at least loosely with the predictions of the ISZ model. Our interpretation of these results is not that the ISZ model is “correct”, but rather that the subjects appear to be sensitive to the trade-offs captured by the model. Thus we argue that the observed jump bidding is primarily driven by some form of impatience and perhaps some consideration of strategic or distributional issues.

	Uniform Distribution				**Normal Distribution**			
	m = 1		**m = 7**		**m = 1**		**m = 7**	
	1-8	**13-20**	**1-8**	**13-20**	**1-8**	**13-20**	**1-8**	**13-20**
Num Bids	653	500	241	265	1037	408	238	232
Num Jumps	356	329	120	75	418	251	110	86
% Jumps	55%	66%	50%	28%	40%	62%	46%	37%
Avg Jump	3.51	4.11	5.05	4.51	3.86	5.52	8.17	7.52

Table 4 Comparison of levels of jump bidding between first and last 8 periods.

Of course if the ISZ model were not able to also predict the outcome of the auctions, it would be of little use as a basis for auction design. This point is examined in our next result.

Result 5 - The ISZ model generates revenue and efficiency predictions indistinguishable from the auction outcomes.

The support for the revenue aspect of this claim is found in the top row of table 3 which indicates the average revenue raised in the actual auctions along with the predictions that would be made by the ISZ model assuming $\delta = .95$. For each case, there is no statistically significant difference between the distributions of predicted and observed revenue. As seen in the table, both the average revenue as well as the standard deviation of the distributions are approximately equal in each case and more explicit testing bears out the apparent similarity.[11] Since we have computed the theoretical predictions from the actual value pairs we can compute an expected revenue for each by averaging across the two predictions for each pair and then compare the experimental and theoretical results using paired Wilcoxon signed rank sum tests. The p-values from Wilcoxon signed rank sum tests regarding the equality of the theoretical and actual revenue distributions are as follows: Uniform $m = 1$, p-value $= 0.8187$; Uniform $m = 7$, p-value $= 0.8059$; Normal $m = 1$ p-value $= 0.2484$; Normal $m = 7$, p-value $= 0.5888$.

Examining the efficiencies achieved in the auctions allows us to simultaneously examine the claim found in Banks et al. (2003) that allowing jump bidding may harm efficiency as well as the predictive ability of the ISZ model. None of the observed distributions of efficiencies

[11] These theoretical predictions might seem counterintuitive especially in the normal case since the $m = 7$ treatments delivers lower predicted revenue than $m = 1$. This is the same revenue comparative static that would also be generated in the uniform case were we to use full population based expectations rather than just this limited sample. This issue is explored in detail and explained in ISZ.

are different from the theoretically predicted ones for any of the cases.[12] Since the predicted efficiencies themselves are either 1 or close enough so as to make little difference, the indication is that even when jump bidding is allowed, ascending auctions are quite efficient. The main point shown in regard to the efficiency is that the chief factor in causing decreased efficiencies is an increase in the minimum increment.

The last three rows in the table examine the inefficient cases in more detail. The third to last row indicates the number of "Possible m inefficient cases" by which we mean the number of auctions with value pairs that could have been inefficient due only to the increment, i.e. cases in which $v_1 - v_2 < m$ and $v_1 \neq v_2$. When this condition holds, the bidder with the second highest value could place a bid shutting out the higher value bidder without either doing anything irrational. The second to last row contains the number of those possibly m inefficient auctions that turned out to actually be inefficient. The final row indicates the remaining number of auctions that resulted in inefficient allocations based upon other issues such as one bidder dropping out at a point at which they could still profitably bid or another bidding above their value. In the $m = 1$ treatments, there can be no m inefficient value pairs and therefore all inefficiencies are from bidders who actually had the higher value dropping out below their value and foregoing at least some small profit or the lower valued bidder bidding above their value. In the $m = 7$ treatments, it is possible for m inefficient cases to exist and most of the inefficient outcomes were indeed from among this set.

We do note, however, that the ISZ model is not the only model able to generate accurate predictions regarding the auction outcomes.

Result 6 - It is also possible to generate revenue and efficiency predictions assuming SFB that are indistinguishable from the auction outcomes.

Table 5 shows the revenue and efficiency predictions that can be made under the assumption that bidders engage in SFB. The SFB predictions were generated by taking the actual value pairs used in the experiment and generating two auction paths for each value pair that differ

[12] We note that in the cases of the minimum increment equal to 1, because the predicted distributions have 0 variance, two sample tests are misspecified. Even single sample tests are suspect due to the one sided nature of the errors, but due to the small number of inefficent cases as shown in table 3, the comparison should be clear. For the $m = 7$ cases, there is enough variance to at least technically conduct the tests allowing us to use paired Wilcoxon signed rank sum tests. The associated $p-$values are 0.2926 and 0.1478 for the uniform and normal cases respectively.

	Uniform Distribution		Normal Distribution	
	m = 1	**m = 7**	**m = 1**	**m = 7**
	SFB	**SFB**	**SFB**	**SFB**
Avg Revenue	35.72	39.86	42.38	42.11
StDev	22.39	22.79	13.52	12.73
Avg Losing Val	35.23	39.22	41.89	41.84
StDev	22.39	22.93	13.52	12.38
Num Auctions	228	236	274	264
Avg Efficiency	1	0.999	1	0.997
StDev	0	0.011	0	0.014
Possible m Ineff	-	28	-	60
Actual m Ineff	-	6	-	11
Other Ineff	-	-	-	-

Table 5 Revenue and efficiency levels assuming SFB for value pairs used in experiment.

by which bidder is assumed to bid first which again gives us double the number of auctions as in the experimental data. These values can be compared back to those in table 3 to observe the similarity in predictions between the SFB and ISZ models. Both models do quite well at predicting the outcomes from the auctions. The p-values from Wilcoxon signed rank sum tests regarding the equality of the SFB predicted and actual revenue distributions are as follows: Uniform $m = 1$, p-value = 0.0001; Uniform $m = 7$, p-value = 0.4618; Normal $m = 1$ p-value = 0.4667; Normal $m = 7$, p-value = 0.3155. As is clear from examining the tables, the efficiency predictions are equally as accurate[13].

Due to the similarity of the predictions between the ISZ and SFB models, one might reasonably wonder about the conditions in which the two models might make different predictions. There are three dimensions along which to examine this issue. One would be to determine if the predictions diverged as the minimum increment increased. As the minimum increases, however, the need to jump for either impatience or strategic concerns is diminished which would lead to the predictions of the two models converging as the increment increases. Alternatively, one could imagine looking at how the predictions differ as the discount rate changes. Figure 3 shows how the revenue predictions vary as δ varies in the environment of uniformly distributed values for the cases in which $m = 1$ and $m = 7$. The clear result is that as δ falls (i.e. bidders get more

[13] As a side note, one can also observe the interesting fact that the ISZ model predicts slightly more efficient auctions than SFB would. This can be observed by seeing that the total number of predicted inefficient cases under the ISZ model was 6 which compares to 17 under the SFB model. This result is robust as shown in our companion theory paper.

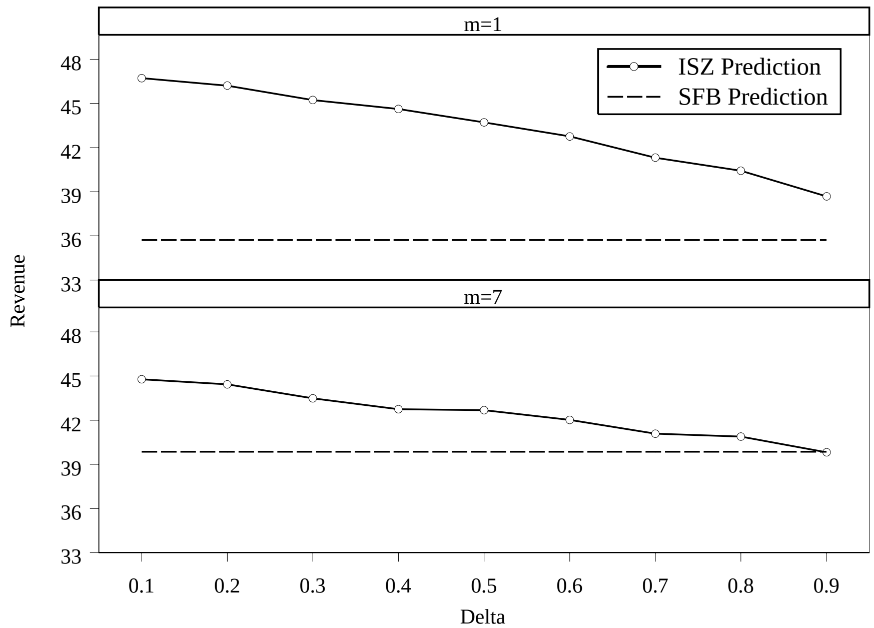

Fig. 3 This figure shows the revenue predictions of both the SFB and ISZ models as the discount rate, δ, varies between 0.1 and 0.9.

impatient) the expected revenue as predicted by the ISZ model rises (due to increased jump bidding) while the expected revenue predicted by SFB stays flat. The effect is more pronounced and differences are larger in the $m = 1$ case. The implication is that the more impatient are the bidders, the greater will be the separation between the two predictions. However, for the predictions to differ substantially the discount rates must be (perhaps unreasonably) low. Predicted cases of efficiency, however, do not change as the discount rate changes so it is not the case that auctions get more (or less) inefficient as δ falls. The last direction for examining the divergence between the two models would involve varying the value structure by examining common or affiliated values structures. That question is beyond the scope of this paper to address.

4.3 Forced Straightforward Bidding

In ISZ we speculated that even if bidders were forced to bid straightforwardly, or rather not allowed to place jump bids, the standard model would fail to describe their behavior as they might drop out of the auction earlier than expected, i.e. at a price lower than their value. This was based in part on evidence found in two other studies with institutions that did not allow jump bidding. Lucking-Reiley (1999) contains the results from a field experiment in which bidders specifically requested higher bid increments while Shachat & Swarthout (2002) contains some experimental auctions in which sellers in a procurement ascending auction dropped out of auctions earlier than they should have leading the authors to "conjecture that the tediousness of the English auction is responsible for the early exit behavior." If this conjecture is correct, then by not allowing bidders to jump bid, an auctioneer could have bidders exit the auction at lower prices than they would if they had been allowed to bid in a less tedious manner. To test this proposition we conducted additional sessions in which bidders were only allowed to bid exactly at the minimum increment if they wished to bid. This leads to our next result.

Result 7 - If bidders are not allowed to jump bid and the increment used by the auctioneer is small, bidders will drop out of auctions early leading to lower revenue for the auctioneer.

As noted above, we attempted to conduct several sessions of this treatment but the excessive time required to complete each auction as well as the tedious nature of the process itself became prohibitive. As such our results for this section are perhaps not as conclusive as one would like. Alternatively, one could consider the difficulty in running these sessions in a reasonable fashion as evidence enough that there are likely to be practical difficulties in running ascending auctions in the field without regard to these issues.

The first support for this claim can be found in noting that out of the 65 auctions conducted in the $m = 1$ case, 17 (26 %) closed at prices such that the losing bidder was leaving surplus on the table. In only 4 of those cases was the surplus foregone less than 10 ECU's and in only 6 was the foregone surplus less than 30 ECU's. This is a significantly greater percentage of such cases than was found when jump bidding was allowed. In the $m = 7$ case, however, only 4 of the 59 auctions (7 %) ended with surplus remaining which is about the same percentage of such cases when bidders were allowed to place jumps. The clear indication is that the increment of 1 frustrated subjects enough such that they gave up substantial surplus to end the auction early.

Table 6 shows the revenue effects of these early dropouts by showing the revenue and efficiency results from the experiments compared with what would have been expected were subjects to have engaged in SFB. In comparing the revenue generated between when jump bidding is and is not allowed (see table 3 for former case) we find that revenue is approximately equal to the value of the losing bidder for both treatments when $m = 7$. This again suggests that there is little difference from the treatment effect with a relatively large increment. In the $m = 1$ case when jump bidding is not allowed, the average revenue, 36.31, is well below the average value of the losing bidder, 42.69. When jump bidding is allowed, however, average revenue is slightly above the value of the losing bidder, 37.89 and 35.79 respectively. The difference in the average value of the losing bidder makes direct revenue comparisons difficult between the two treatments. The difference itself might seem confusing since the exact same set of bidder values were used for both treatments. The problem is that the first few rounds by chance had a few large values in them and since we were not able to complete many rounds in the no jump bidding treatment, we oversampled from these high values and pulled the average values above raw expectations. It is important to be clear that the average losing value was not pushed up because of an increase in inefficient allocations.

Due to this difference in values, a better test across treatments would be to look at a metric of the value of the losing bidder minus the auction price as this allows a test between treatments along a common scale of potential revenue. The average difference between loser value and price for the no jump bidding treatment was 6.38, indicating that bidders on averaged dropped out 6 ECUs below their value, while it was -2.11 in the treatment allowing jump bidding indicating that on average winners surpassed the loser value by an ECU or two more than necessary. Tests of the difference in these two distributions yields $p-$values of 0.005 using a $t-$test and 0.0018 using a Wilcoxon rank-sum test, both showing statistically significant differences[14]. The same

[14] One might reasonably object to these tests since the sessions in which jump bids were not allowed did not consist of as many rounds. We have recalculated all of these tests using only the first 12 periods of data from the sessions that allowed jump bids as the comparison group to the data from the experiments that did not allow jump bids. The results do not change, as the treatment that allows jump bidding achieves statistically significantly more revenue than the one that does not ($p-$values of tests of the equality of the distributions are .005 from $t-$test, .004 from Wilcoxon).

	Uniform Distribution			
	m = 1		**m = 7**	
	Exp	**SFB**	**Exp**	**SFB**
Avg. Revenue	36.31	41.21	35.47	35.18
StDev	24.03	24.90	22.84	22.70
Avg Losing Val	42.69	40.72	35.05	34.37
StDev	27.19	24.92	23.92	22.85
Num Auctions	65	130	59	118
Avg. Efficiency	0.976	1	0.990	.9996
StDev	0.08	0	0.05	.003
# Inefficient	8	-	8	2

Table 6 Revenue and efficiency in the forced straightforward bidding sessions.

test on the $m = 7$ treatments delivers test statistics with $p-$values of 0.43 and 0.56 for t and Wilcoxon rank-sum tests indicating a lack of a statistical difference. The mean values of the differences between loser values and prices are -0.42 in the no jump bidding case and -1.88 in the jump bidding case. The results therefore suggest that with a low bid increment, bidders will drop out substantially below their value while with a higher bid increment they may stay around.

Further evidence for this claim can be found in comparing the revenue found in the experiments disallowing jump bidding and the predictions of SFB. Table 6 shows that the SFB revenue in the $m = 7$ case matches closely with the outcome of the experiments, 35.18 and 35.47 respectively, and any statistical test will confirm a lack of a difference in the distributions. In the $m = 1$ treatment, SFB predicts revenue to be 41.21 on average which is much higher than the realized revenue of 36.31. Although there is a sizable difference in the two averages a Wilcoxon signed rank-sum test suggests there is no difference in the distributions($p-$value of 0.6966). A paired $t-$test, however, suggests that there is a statistically significant difference ($p-$value of 0.0488). This leads to a question of why the two tests differ and which is the "correct" test in this case. A closer examination of the data reveals that there were 35 cases in which the revenue from the experiment exceeded that of the SFB prediction and 30 that went the other way. A Wilcoxon test is based on comparing these counts and since the split is approximately equal, it will show no difference. In those 35 cases in which the experiment generated more revenue than the prediction, the average difference was 4.7 while in the 30 cases in which the experiment generated less revenue the difference was -16.1 which gives the overall average difference of -4.9. What appears to be happening then is that some auctions do proceed in the manner predicted by

SFB. There are others, however, that do not and these are cases in which a bidder drops out well under his or her value. While not necessarily large in number, these cases do have a substantial impact on revenue. So in this case it appears the $t-$test is the more valid for the question at hand and the reason the two tests arrive at different interpretations of the data speaks precisely to the problem in these auctions.

One argument for how to circumvent this problem of bidder frustration would be to shorten the bid clock below 30 seconds. Live auctions with professional bidders can be run very quickly with fixed increments[15], but such speed is not feasible in electronic auctions or ones without professional bidders. In electronic auctions, due to network traffic and processing delays, there is a minimum to which the time between bids can be realistically pushed. Further, while some subjects in our experiments did exhibit a preference for waiting out the 30 second clock, most bid back well before their time ran out. The average time between bids over all sessions and subjects was 12 seconds[16]. This is a fairly rapid turn around time as bidders in those 12 seconds must see the new bid, decide if they wish to bid back, determine what bid they wish to/are allowed to bid, type the bid in and press the submit button. Even at this relatively rapid pace, some auctions will still last an interminable amount of time. Consider two bidders with values of 84 and 95 and for simplicity assume 10 seconds between bids. At $m = 1$, this will take 84 bids to complete or 840 seconds (14 minutes). If it were possible to push the average bid time down to 5 seconds, the auction will still take 7 minutes, which subjects would still find quite painful to sit through. Consequently, while decreasing the time allowed on the bid clock may help the situation, it will not eliminate the problem for electronic auctions due to minimum time delays.

As a side point, we can also use the results from these sessions to obtain additional evidence on the level of impatience of the bidders, or at least their preference for speeding up an auction, by examining how often people top their own bid and how this changes with the minimum increment. Our software did allow a standing high bidder to increase their own bid, which in the case of the no jump bidding treatment can be interpreted as something similar to a pseudo-jump

[15] The tobacco house auctions that are modeled in Kaztman (1999), for example, take place as fixed increment ascending auctions in which professional bidders place bids by hand signals.

[16] The average time between bids in the sessions that did not allow jump bidding was 10 seconds indicating that these bids were slightly faster perhaps because bidders did not have to consider whether or not to submit a jump bid.

bid. In the no jump bidding treatments 22% of the bids submitted involved bidders raising their own high bid when $m = 1$ while only 5% of the bids submitted in the $m = 7$ case were bidders raising their own high bid. This compares to percentages of 1.5% and 4.2% of the bids submitted to top a bidders own high bid under the treatment allowing bidders to submit jump bids for the $m = 1$ and $m = 7$ cases respectively[17]. Thus in the $m = 1$ case, there is a dramatic increase in bidders topping their own high bid when they are not allowed to submit jump bids while there is virtually no change in the $m = 7$ case. The existence of that increase in the $m = 1$ case should be solid evidence that people have a very strong preference for speeding up the auction as that appears to be the only reasonable explanation that would explain the high incidence in that case, but the relatively low incidence in the other cases.

While we make no claims that our model as constructed can predict bidders dropping out of an auction before their value is surpassed, there are a number of ways of rationalizing such an action. One explanation is due to the bidders internalizing the opportunity cost of bidding by realizing that if they continued to bid in an auction, it would minimize their ability to participate in additional auctions as the time 2-hour limit might expire before all 20 rounds had been conducted. Our design minimized this as much as possible by forcing bidders to go through as a group which meant that even if two bidders finished their auction quickly, they had to wait for all others to finish before continuing. This minimized the effect of any single bidder on the pacing of the experiment. This increases the salience of explanations based on pure boredom effects, myopic impatience or even very minor "annoyance costs" of bidding due to having to click the mouse button. While we can not infer exactly what was driving the subjects to drop out early, these results should be evidence enough that even very minor opportunity costs or perhaps these other very minor costs can lead to negative effects on auction revenue if one does not pay close attention to the impacts of bid increments on the pacing of ascending auctions.

[17] Why there are any bidders in the auctions that allow jump bidding who top their own high bid is something of a question. We view these percentages, though, as small enough to represent occasional mistakes and see little additional significance to them.

5 Conclusion

The intent of this paper was twofold. The first goal of the paper was to determine the degree to which the ISZ model could match with the behavior observed in the experiments. The second goal was to investigate the actual impact that allowing jump bidding has on ascending auctions in order to test specific claims made in prior literature. Our results are quite conclusive and clear in regard to both of these main goals.

We have shown clear evidence that the standard notion of bidding in ascending auctions, straightforward bidding, can be rejected since we observe a large number of jump bids. We also find no evidence of effective signalling behavior on the part of the bidders. The model of impatient and strategic bidding found in ISZ, however, fares quite well in matching with the general character of the bidding behavior and in predicting the average outcomes of the auctions. While this is most certainly an imperfect model of the true bidding strategy used by bidders, we have shown it to capture the important aspects of bidding in these auctions. Our interpretation of this fact is that the jump bidding observed in many field auctions is much more likely to be generated by some form of impatience rather than signaling.

In regard to the impact of allowing jump bidding on the outcome of ascending auctions, we have confirmed the theoretical claim in ISZ that the effect is either neutral or positive depending on the environment, but most certainly not negative as claimed elsewhere in the literature. These results for single unit auctions confirm findings in Plott & Salmon (2004) showing that in a set of multiple unit ascending auction experiments jump bidding does exist, yet fails to impair efficiency or revenue. We can further show direct evidence corroborating speculation in ISZ and other papers that prohibiting jump bidding can have distinctly negative effects on the revenue of an auction. This is due to bidders dropping out of an auction early, most likely due to frustration with the speed of the auction. This is an effect that would be overlooked if one fails to consider bidder impatience in modeling bidding behavior in ascending auctions. While we do show that when jump bidding is allowed, the “standard model” of a bidder bidding their value does on average predict the revenue generated by the auctions in the experiment, an over reliance on this model would fail to pick up on the empirical regularity that revenue is depressed when jump bidding is disallowed.

There are, however, a couple of caveats we must place on our results. While the results of our experiments show little support for signalling equilibria, it is important to point out that the environment we used was not a direct replica of the environments used in the theories of either Avery or DH as values are independent, not affiliated as in Avery, and there are no direct costs of bidding, as in DH. Thus our experiments do not serve as a direct test of those models. One could construct analogs of their models in our environment, though, and we can say that there appears to be little signalling in this environment. We can not, however, definitively conclude that there would not be more signalling if values were affiliated or if there were direct costs of bidding.

Another important limitation of our results is that our experiments only involved single unit auctions and not multiple unit auctions in which bidders have multiple unit demand. In the latter type of auctions, jump bidding could be used to signal collusive equilibria which is not the case in our environment. Also, in combinatorial multiple unit auctions, it is possible that bidders wishing to acquire a large package of items could use jump bids as a means to make it more difficult for multiple bidders interested in small pieces of that package to coordinate their bidding to displace the package bidder. Kwasnica & Sherstyuk (2002) has begun the task of analyzing the impact on signalling in multi-unit auctions. Their experiments did allow for jump bidding and they do find that bidders were able to collude, but there was no noted interaction between the two.

While our experiments do not allow us to make truly general claims in this regard, they do allow us to make some insights into the question of when an auctioneer should be concerned about the prospect of signaling and/or the allowance of jump bidding. It is our view that bidders face an extremely difficult challenge in coordinating on a signalling equilibrium in single unit auctions to the extent that we find it quite implausible that they would emerge even in the Avery and DH environments. Coupling this observation with our results suggests little reason for an auctioneer to ever prohibit jump bidding due to a concern about signaling in single unit auctions. Further, if bidding is expected to be costly, our no-jump bidding treatment indicates that even very small and perhaps intangible costs to bidding can induce bidders to drop out early when the auctioneer only allows the auction to progress at a slow speed. Thus, in such environments, it is quite important for an auctioneer to carefully pace the auction. This could accomplished by either the careful choice of a bid increment, or (perhaps more easily) by allowing bidders to place jump bids and pace the auction themselves. This observation in regard to auction pacing should apply directly to multiple unit auctions as well as many of these same issues will emerge. The results in Kwasnica & Sherstyuk (2002) suggest that jump bidding is unlikely to be a problem in multiple unit auctions either, leaving little reason to suspect that allowing bidders to jump bids should cause problems in most environments.

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Appendix A: Experiment Instructions

We used the same basic instruction script for all sessions. Each treatment necessitated slightly different instructions though so we had to substitute different sentences and paragraphs depending on the treatment. Below we present the master instruction script with all of the language as well as the key indicating which sections were used for which treatments.

Verbal Instruction Script

{} Uniform
[] Normal
+ + Straightforward Sessions
| | Non- St Sessions
() Other Options

Thank you for participating in today's experiment. I will read through a script to explain to you the nature of today's experiment as well as how to work the computer interface you will be working with. I will be using this script to make sure that all sessions of this experiment receive the same information, but please feel free to ask questions as they arise. We ask that you please refrain from talking or looking at the monitors of other subjects during the experiment. If you have a question or problem please raise your hand and one of us will come to you.

{*UNIFORM SESSIONS*
You will be participating in a series of auctions in today's experiment. In each auction, you will be assigned a value for winning. This value is randomly drawn from a uniform distribution over the integers between 1 and 100. You have been handed a chart that shows you the exact probability of any particular value being drawn. Please pick it up and look at it now. Since the distribution is uniform, this means that each value in that range is just as likely to be drawn as any other. For example, the probability that you are assigned a value of 12 is 1%, the probability of being assigned a value of 45 is 1% and the probability you are assigned 97 is 1%. }

[*NORMAL SESSIONS*
You will be participating in a series of auctions in today's experiment. In each auction, you will be assigned a value for winning. This value is randomly drawn from a normal distribution over the integers between 1 and 100 with the mean being 50 and the standard deviation 15. You have been handed a chart that shows you the exact probability of any particular value being drawn. Please pick it up and look at it now. Since the distribution is normal, this means that the distribution has a bell shaped curve indicating that values in the middle of the range are more likely to be drawn than values at the extremes. For example, the probability that you are assigned a value of 12 is .1%, the probability of being assigned a value of 45 is 2.49% and the probability you are assigned 97 is .02%.]

These values are denominated in a fictitious currency called "Experimental Currency Units" or ECU's and will transform into real dollars at the rate of {$ 0.05} [0.10] per ECU. For example, if you end up with a balance of 150 ECU's at the end of the session you will be paid {$7.50} [$15.00]. If you end up with a balance of 210 ECU's you will be paid {$10.50} [$21.00] and so forth. In all cases, these earnings are in addition to the $7 show-up fee.

In each auction, you will be bidding against a single other bidder. You will be bidding in a series of 20 auctions and each time the bidder you are facing will be randomly reassigned. They too will have had their value for the auction randomly drawn from a {uniform} [normal] distribution over the integers between 1 and 100. These draws are made independently of each other as well as across time so if you receive a value of 84 in a period, this gives you no information about value the other bidder has received and should not be taken as any indication of future values you or any other bidder may receive.

Please turn to your computer screen and make sure that Internet Explorer is open and go to the link http://www2.xefs.fsu.edu/cgi-bin/practice.pl. This will take you to a practice page to demonstrate how the experiment will work. Notice that the screen has been divided into two frames. The frame on the left is your bid submission window and you will notice that it lists your value for the current auction. There is also a text box in which you can submit your bid and a bid submission button.

The frame on the right is the auction status frame. It shows you the status of the current auction you are in including the current winning bid, the minimum required bid and your current potential profit. There is also a countdown clock, which is currently ticking down. Ignore this for the moment. You can place a new bid by entering a bid amount in the text box on the bid submission frame and then pressing Enter or hitting the "Submit Bid" button. Any bid you submit has to be at least a certain number of ECU's above the previous high bid as indicated by the minimum next bid. |While you must submit a bid of at least this much if you wish to submit, you can submit a bid of any amount greater than or equal to this value. | +*ST Sessions*: You will only be allowed to submit bids exactly at the minimum required bid.+ For the practice rounds, this minimum increment will be 2 while for the real auctions it will be (1) (7). Try submitting a bid now.

You should have noticed two things happening. One is that the count-down clock in the Auction Status frame reset to 60 seconds. Second is that your bid showed up as the current bid and the box turned green. Whenever this box is green, that indicates you have the current high bid. When it is white your opponent has the high bid. In this practice phase you are bidding against a computer and it will bid back soon making the box turn white.

The count-down clock is what determines the close of each auction. In the practice rounds it will start at 60 seconds and begin counting down. When it hits 0 the auction for that round is over. Each time either you or the bidder you are bidding against places a bid, the clock will reset to 60 seconds and begin counting down again. In the real auctions the countdown clock will be set to 30 seconds but will function the same. Please be advised that due to the uncertainties of network traffic and server load, if you wait to submit a bid until the countdown clock reads 1-2 seconds, your bid may not be placed in time. Also, it may take a few seconds from when you click on the submit button for your bid to appear. Make sure you clearly press the button and then wait for it to show. If it does not appear in 5-10 seconds, you may need to submit again.

Each auction will progress with you and the other bidder placing bids to become the new high bidder until you both refrain from bidding and the clock counts down to 0. At that time, the bidder who is the current high bidder will be declared the winner. Their earnings for that round will be equal to their value for that round less their winning bid. For example, a bidder with a value of 60 who wins an auction with a high bid of 50 will make a profit of 60-50=10 ECU's. The bidder who does not win the auction makes no profit from that period. The amount of potential winnings with any bid is also noted in the status window as potential profit. If you are the current high bidder with a bid below your value this will show up as a positive number.

Should you place a bid above your value, your potential profit would be negative and should you win the auction at a price above your value, your earnings for the experiment will decrease. Notice that the ONLY way you can lose money in this experiment is by bidding above your value. You will begin with a small balance of 10 ECU's. As you win auctions and make money this balance will increase. Should this balance ever become negative you will be dropped out of future auctions and will receive only your show-up payment. You should therefore think carefully before submitting a bid above your value. Should someone in the course of the experiment be dropped out of the auction, there could be an odd number of participants remaining in the experiment.

In that case, one of you will not be matched with an opponent in each round and will be asked to wait patiently until the next round. The "odd man out" will be randomly determined in each round.

You can try playing a couple of quick auctions against the computer player now to get used to the interface. Anytime one of these practice auctions closes click on the next round button to go through a new one. You will receive no actual payment based on these practice auctions and they should be used purely to get used to the system. You should form no expectation of a relationship between the values you see in these practice auctions and the ones you will receive in the real auctions. Further, when the actual experiments begin you will be bidding against another human player among those currently in the room. Again, you will be randomly rematched with a different opponent for each auction. Should you and your opponent finish a round of auctions before the rest of the group, you will be asked to wait patiently until all have finished that round. When all have finished a "Next Round" button will appear and when all have clicked on it, the next round will begin.

When you feel you understand how the system works, please click on the logout button to be taken to the system for the main experiment. There you will be asked to login to the system with the Username and Password we have provided. Once you have logged in, please click on the "Next Round" button to begin the auction. When all participants have logged in and clicked the first "Next Round" button, the real auctions will begin.