Run Silent, Run Cheap?
A Study of a Charity Auction Mechanism

R. Mark Isaac and Kurt Schnier[1]

O. ABSTRACT. We analyze data from hundreds of auctions from three field silent auction sessions. We focus on the descriptive statistics and upon a parametric model of jump bidding. We then report data from six laboratory sessions of silent auctions. As a controlled environment, this allows us to evaluate the auctions in ways not available from the field. The laboratory experiments capture essential features of the field sessions, and thus comprise a credible laboratory testbed for further examination of institutional perturbations in the silent auction.

1. INTRODUCTION

Where there are multiple goods to be auctioned, the seller may choose a program either of sequential auctions (as in some oral art auctions) or of simultaneous auctions.[2] Simultaneous auctions using ascending prices have become popular in recent years. The FCC's spectrum auctions were built around this format. Many internet auctions have the property that ascending auctions for multiple goods are open at the same time (although they may not have the same stopping time).[3]

There is an older manifestation of simultaneous ascending auctions that has existed for years in many small, localized applications. This is the "silent" auction, a ubiquitous institution used by churches and other non-profit organizations for fund raising. In the world before computers, it appears that the silent auction developed as the institution of choice for many charity auctions. It is not that the silent auction is the only option. A small charity could hire (or choose) an auctioneer to conduct sequential open-outcry auctions. The advantages of the silent auction arguably include: no expenses for a trained auctioneer, speed to completion of the sales, and convenience and social amenities for the bidders (and hence attracting more bidders). The first purpose of this paper is to report on and analyze data from three naturally occurring silent fundraising auctions: two from a church, one from a secular private school. Our

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[1] Florida State University and the University of Rhode Island. We thank representatives of a church and a school in Tucson, Arizona, for making their records available. Tim Salmon provided much feedback on earlier drafts, as did seminar participants at the University of Florida and George Mason University. Arthur Zillante, Michael Bailey, and Michael Iachini assisted with conducting the experiments. As usual, the authors are solely responsible for all errors.
[2] Another possibility is a combinatorial sealed bid auction, (see Isaac and James [2000]).
[3] For a history and description of Internet auctions see Lucking-Reiley [2000].

second purpose is to present and discuss results from a series of controlled laboratory experiments investigating the same institution. Our third purpose is to discuss whether the experimental design can serve as a benchmark for further auction design research in the area of charity silent auctions.

Interest in the silent auction also derives, more generally, from interest in the design of optimal fund raising institutions for charitable organizations. In this context, the silent auction competes not only against other auctions, but also against different institutions such as direct contributions or lotteries. However, a comparison across such institutions will not be a part of this paper, and it should be noted that charities' choices over fund raising processes depend upon many things in addition to revenue.[4]

Section 2 of this paper provides a report on the silent auctions and the data that are the basis for the empirical analysis in the paper. Section 3 presents several organizing models that might provide a useful reference for bidding strategies within the silent auction. Section 4 presents analyses of the field data, including both descriptive statistics and formal estimation. Section 5 presents the design of a series of controlled laboratory experiments motivated by the silent auction. Section 6 presents the experimental results. Section 7 compares the field and experimental results. Section 8 offers a summary and some thoughts for using this experimental testbed for additional research on silent auctions.

2. THE SILENT AUCTION AND DATA OBTAINED FOR THIS STUDY

The silent auction, like any auction, is a collection of attributes of the bidders, the items for sale, and the rules for the auction. The following are attributes for a typical silent auction:

- There are multiple goods at auction.
- All items are displayed to all bidders, each of whom is free to bid on any number of the items.
- The auctions are held simultaneously for all goods, and close according to a common clock (or, in another variant, to a random device such as the burning down of a candle).

[4] See Morgan and Sefton [1997] for a comparison of institutions for fundraising for charitable activities. Davis, et al. [2003] have work in progress specifically comparing charitable auction and lottery revenues. Among the factors other than revenue that influence the choice of fund raising institutions are the legal climate as well as the social and entertainment properties of the process. While we know of no controlled field study, the word of mouth about silent auctions is that they are pleasant social activities in and of themselves, which draw people to the charitable event. This raises an additional important point in that comparative revenue for the charities is not simply the static revenue difference for a fixed number of participants, but also depends upon how many people are drawn to the event.

- The auctions are "silent" oral ascending auctions, i.e., there is no auctioneer; each bidder writes his new (higher) bid on the item's bidding sheet.[5]

- This "tick" of the auction (above any pre-specified minimum) is endogenous to the bidders' decisions in each auction; this allows for jump bidding.

- There is some charitable or public goods component to the seller's revenues.

The implications of some of these attributes merit further discussion.

Multiple goods. The multiple goods nature of a silent auction raises a couple of interesting possibilities. As in any multiple good auction there is the possibility that bidders have combinatorial values over the items. Yet the silent auction does not allow for combinatorial bidding. An argument can be made that it does allow bidders a chance to "adjust their portfolio" in real time in order to address combinatorial values. While combinatorial values are intriguing, they will not be a focus of this paper. On the other hand, we will consider at length the feature of a typical silent auction that the goods are geographically dispersed. It takes time to move from one bidding station to another.

Endogenous ascending ticks (possibility of jump biding). The possibility of jump bidding in silent auctions makes it similar to many other ascending auctions (FCC, Ebay and Amazon, etc.). This is surprisingly unlike much of the prior theoretical and experimental work on ascending auctions. Traditionally, ascending oral auctions have been both modeled by theorists and operationalized by experimentalists as ascending "clock" auctions in which the experimenter/auctioneer raises the price according to a preset formula, and bidders "drop out" (Cox, Roberson, Smith [1982], Kagel, Harstad, and Levin [1987]).[6] Jump bidding is not possible in a clock auction. Also, when a strategizing auctioneer tightly controls the tick, jump bidding is likely to be impossible or rare.[7] When one begins to look at bidding patterns in silent auctions it is critical that we not reach conclusions based upon a different (and

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[5] There is another version of the silent auction, which resembles simultaneous sealed bid auctions. In this version, each bidder writes his bid down on a slip of paper and places it in a jar next to the item. All auctions stop by a clock.
[6] The Coppinger, Smith, Titus [1980] paper suggests that ticks in their English experimental auctions were endogenous. Later related papers support this interpretation. Cox, Roberson, and Smith [1982] state that "in the [Coppinger, Smith, and Titus] English auctions the subjects named the amount of any increase over the previous bid, which was typically $.25." However, Cox, Roberson, and Smith derive the dominant strategy for the English auction simply as an analysis of when a bidder should drop out of the auction; the issue of what size "tick" to make is not addressed (page 8). Kagel, et al. explicitly used an ascending clock (p. 1280).
[7] This obviously depends upon the rules of the auction.

perhaps inapplicable) version of the ascending auction.

Clock closes the auction. Most models of ascending auctions do not incorporate clock ending. The silent auction is like Ebay and Amazon internet auctions, which close with some form of a clock.[8] For the silent auctions, one must also consider that auctions on multiple items close at the same time.

Seller revenue as a public good. A significant charitable component of silent auctions is the donation (or reduced cost) to the charity of the items for sale at the auction. There is also the possibility of a second level of charity (or recognition of a public good) in a silent auction. Specifically, bidders may place a positive value upon greater receipts to the seller, independent of their possession of any of the auctioned goods. An obvious research question is, "Do auctions behave differently when the seller's revenue takes on the attributes of a public good?"

This paper reports on data from nine silent auction sessions, where each session actually consisted of an event of numerous simultaneous individual auctions. Three of the data sets are from naturally occurring field auction sessions. The first field auction is a church auction, conducted in 1999. This auction was conducted by a large urban church with over 1,000 members. The proceeds were used to benefit the church's preschool. This auction offered 135 items for sale (we included only those which, from the records, appear to have gotten more than one bid). There were 88 active bidders.[9] The second auction was from the same church's 2000 preschool fundraiser. There were 194 items with 77 active bidders.[10] The third auction was conducted in 2001 by a private non-sectarian "college preparatory" junior and senior high school. We received data on 181 items with 198 active bidders.[11] We will also report on data from six laboratory experimental sessions, but a discussion of the design is deferred until Section 5.

3. MODELS

3.1 Prior models of ascending auctions

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[8] The two sites use different closing rules. Roth and Ockenfels [2000] demonstrate that the nature of the stopping rule can change bidders incentives.

[9] Including bidders who bid only on items with only one bidder, there were 91 bidders listed.

[10] This includes the same restrictions as in the 1999 auction.

[11] The church auctions lasted about two hours; the school auction lasted about four hours. The church auctions were in the context of a potluck dinner and family activities. The school auction was in the context of other activities including hors d'oeuvres; wine tasting, and separate sequential oral auctions for a small number of expensive goods.

To our knowledge, there has been no comprehensive model of an auction with all of the attributes of the silent auction. The English auction has been extensively modeled, but usually as a single unit auction and with exogenous ascension of prices. In the independent private values case comes the familiar result that it is a dominant strategy for each bidder to stay in the bidding until his value is called, with the exception of the winning bidder, who ceases bidding when she is the sole surviving bidder. Some of the attributes that distinguish the silent auction have been modeled separately, as discussed below.

3.2 Modeling for the Silent Auction.

At this point, we will state more formally those distinguishing characteristics of the silent auction that might have implications for theoretical models.[12]

a) These are auctions where the revenue benefits a charity. This creates the possibility that the revenue to the seller becomes a public good.

Let v_i be bidder i's value on a good, and let r be the revenue to the seller. Then, using a simple quasi-linear formulation, we can represent the utility to the winning bidders as $v_1 - r + u_1(r)$, and to the losing bidders as $u_j(r)$. Depending upon the sum of the benefits for the public good, this could describe a classic free riding situation, in which bidders, responding to private benefits, produce an inefficient level of the "public good." Notice that, unless there are side payments, a single person, the winning bidder, must bear the burden of providing the public good.

There are two possible scenarios by which such a public goods nature of the auction revenue could affect observed bidding behavior. One possibility is that, in equilibrium, the bid functions of bidders are altered. Engelbrecht-Wiggans [1994], Engers and McManus [2002] and Salmon and Isaac [2002] have worked with equilibrium bid functions in analogous models. While these papers do not explicitly model the ascending auction with jump bidding, they do model the second price auction, which, with independent private values, is the strategic sealed bid version of the English clock auction. These results demonstrate that equilibrium bid functions do change in the presence of various types of charitable preferences. The second possibility is that, apart from the equilibrium bid incentives, bidders behave

[12] As we have mentioned, we are setting aside the issue of combinatorial values.

differently in the presence of a public good. This would be an extension of the well-documented fact that, in voluntary contributions public goods situations, provision of the public good is usually greater than the equilibrium (free riding) prediction (see Isaac, Walker and Williams [1994]).[13]

b) The multiple auctions are simultaneous.

In order to switch bidding attention from one item to another, the bidders have to move from one part of a room to another. The bidders cannot follow the bidding on distant multiple items at the same time. The passage of time between submitting a bid on one good and then submitting a bid on another good can be non-trivial, depending on the geographical layout of the auction room. This could lead to an inefficiently low valued buyer winning an auction.

c) All auctions end with a clock.

Roth and Ockenfels have modeled two different versions of internet ascending auctions with clocks. One version is a hard stopping clock (such as with eBay) the other is a flexible clock which remains open with late bidding activity (such as with Amazon). Their data confirm that the clock rule matters; specifically, there is more late bidding with the hard stopping rule.

In the church auctions the clock was pre-announced and was the same for all items in the room. In the private school auction, ending times differed for different parts of the room. Because the ending time was not tied to bidding activity, there is the possibility that, for any given item, there are multiple bidders still active (that is, with values greater than the price on the bidding sheet) at the closing bell.

d) Jump bidding is possible.

Jump bidding is not only possible in an ascending auction, it may be an equilibrium, despite what one might expect from the "clock" formulation of the English (single unit) ascending auction. Different theoretical questions must be asked. When a bidder is allowed to jump above the minimum tick, why would she do so (or not)? How much should she jump the bid? Most of the models that have addressed this question have some overlap with the silent auction, but none covers all of the components. Rothkopf

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[13] It must be emphasized that the silent auction is not the voluntary contributions mechanism, and the value environments also differ.

and Harstad [1994] consider a single unit auction and a decision-theoretic bidder choosing an optimal bid increment. They sketch a proof in which the distribution of bidder values is important in predicting the incidence of jump bidding. Börgers and Dustmann [2004] have analyzed the data from a third-generation ascending wireless auction in the United Kingdom. Jump bidding was possible in these auctions. The authors point out that in this auction "straightforward bidding" (rational choice of items for bid plus no jump bidding) is an equilibrium but not a dominant strategy.[14] Avery [1998] considers a single-unit auction with affiliated values. Jump bidding is possible as a signal. Daniel and Hirshleifer [1997] also model jump bidding as a signal in a single-unit environment with costly bid preparation and strong assumptions about common bidder expectations. Isaac, Salmon, and Zillante [2005] model a single-unit auction where jump bidding is not a typical signaling phenomenon but rather reflects either equilibrium strategic considerations or bidder impatience, or both. Even though their model has no clock, the possibility of bidder impatience may very well also capture the uncertainty imposed by the geographic dispersal of the bidding stations in a silent auction. The role of bidder impatience may also be related to a similar effect suggested by Plott and Salmon [2004], studying both field data from U.K. wireless auctions and related experimental auctions. They conclude that the primary function of jump bids seemed to be speeding up the auctions. Speeding up the clock time of a silent auction is not possible, but jump bids could speed the generation of market information, which can be valuable as bidders must decide which auctions they want to monitor as the clock closes. Thus, the effect of speeding up the pace of the bidding (as opposed to speeding up the end of the auction itself) may be valued by a bidder.

4. THE FIELD SILENT AUCTIONS

4.1 Data Available for Analysis in the Field Silent Auctions

The data we collected from the three field auctions include a description of the goods, the bids in the order in which they were submitted, the minimum opening bids, the minimum bid increments and a bidder I.D. number. Obviously, these data categories leave much to be desired from the point of view of evaluating models of individual behavior in such auctions. Most importantly, we mostly have no

[14]It should be noted these auctions did not have a clock; they had an activity stopping rule.

information on bidder values (except for the retail value of a few items or gift certificates).[15] What we can construct from these data series are the jump bids. The jump bids will form the core of our analysis.

4.2 Jump Bids in the Silent Auction and the Received Models

Drawing upon the general design of silent auctions and the existing models, we can sketch four possible avenues by which jump bids could be a rational (even equilibrium) bidder choice: charitable, "see and be seen," impatience, and final-seconds crowding.

First, we consider two models in which the propensity to jump bid occurs at least partially in response to the public goods nature of the seller's revenue. In the simple "charitable" version the bidders value the seller's revenue regardless of who won the item. This means that in the model we introduced above, $u(r_1) = u(r_j)$. A variant of the charitable model also deserves some attention. These auctions are highly public. A large number of the bidders know each other. Bidders can watch which tables other bidders are visiting. And, while a "bidder number" is used in lieu of bidding by name, our impression is that these codes are only marginally private. This leads to the related concept that bidders raise prices in the auction not so much to encourage the production of the public good (the seller's revenue) *per se* but rather to "*see-and-be-seen*", specifically, to be seen as the person responsible for the seller's revenue.[16] In terms of the previous model this means, at the extreme, that $u(r_j) = 0$. As mentioned, several papers have modeled individual bidding behavior with charitable preferences in auctions. In second-price auctions, the analog of either the simple charitable model or the see-and-be-seen model leads to higher bid functions in second-price auctions.[17] In the strategically equivalent English auction, this can lead to bidding over the "value" (absent the charitable effects). By themselves these models do not address the issue of the influence of these factors on jump bidding. However, the results of Isaac, Salmon, and Zillante are suggestive that an increase in a bidder's limit value would increase jump bidding.[18]

Second are what we can call the two *crowding* models. One is similar to the models of jump

[15] In fact, unlike in the study by Börgers and Dustmann, there are no obvious restrictions to put on the data that give us much in the way of indirect restrictions on bidders value.
[16] The concept of "see and be seen" is thereby similar to Andreoni's "warm glow" effect [1990].
[17] For example, with identical bidders and a uniform distribution of values, see Salmon and Isaac (2003).
[18] The relationship is not strictly monotonic, and it must be emphasized that their results are just for two bidders.

bidding developed for single unit auctions: bidders are *impatient* to speed up the pace of the auction (which does not have to involve speeding up the close of an auction, an impossibility in silent auctions). Impatience could have the same origins as in single unit auctions or it could be specific to the silent auction (perhaps an impatience to obtain a geographic advantage). The results of Isaac, Salmon, and Zillante are that (with a single unit) impatience can play an important role in increasing the incidence of jump bidding. However, the geographical dispersion of the multiple units in a silent auction suggests a second crowding model: namely, that jump bidding represents a response to the fact that, in the *final seconds* of the auction, a bidder may decide to "leave" a table, requiring her to enter what is, in essence, a final "sealed bid."[19] We call this hypothesis the "final seconds crowding" model.

4.3 Statistical Analysis of the Field Auctions

4.3.1 Descriptive Statistics

Table 1 offers the summary descriptive statistics on jump bidding. The following are some observations and implications for the data in Table 1.

Bidders never jump their own bids. In a standard English auction framework, this would represent a minimal standard of rationality. However, jumping one's own bid might be part of a strategy for charitable bidding, see-and-be-seen bidding, or dealing with last second crowding.

Bidders seldom bid over publicly stated market values for items, although there is a difference in frequency between the church auctions and the school auction. Bidding over a clear market value could be a strong indication of either charitable or see-and-be-seen bidding, based upon the arguments above. This kind of overbidding never happens in the church auctions, but it happens around ten percent of the time in the school auction. Furthermore, in the school auction about half of the bids that exceeded stated value exceeded it by more than a minimum increment. The data in Table 1 report this measure only on items for which there was a clearly identifiable retail value (more common in the school auction).[20]

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[19] Our thanks to Tim Salmon for pointing this out. It is important to note that such a bidder does not know whether she is making the final bid among all bidders for that item.

[20] 47.83 percent of bids over stated value exceeded value by more than the minimum increment for that item. The values were intended to be retail values, but were often self reported. We present this figure because, if overbids

By themselves, the two observations above are not suggestive of a strong presence of either charitable or see-and-be-seen bidding in the church auctions, with more ambiguity in the school auctions.

Bidders frequently submit jump bids. There is a major difference in the frequency between the church auctions (38.55 percent and 37.09 percent of all bids) versus the private school data (8.92 percent). As with any uncontrolled comparison with field data, there could be numerous suspects for this effect, ranging from the bidding population to the different auction lengths and differences in details of the auction environment. However, we note here one difference for particular attention: the size of the church auctions' minimum bid increment was substantially lower than that used in the school auction. Most items auctioned by the church used a minimum increment of one dollar, whereas at the school auction the minimum increments were usually either five or ten dollars. We will examine this effect more formally during the parametric analysis.

Figure 1 displays the propensity of individual bidders to jump bid in the 1999 church auction, the 2000 church auction, and the 2001 school auction. This graph is a histogram in which an observation is a mean level of bid increments for a single bidder across all the bids that bidder placed in all the auctions that evening (we use a normalization that is relative to the minimum bidding increment).[21] The distribution is on percentage of all bidders in the auction. A Komolgorov-Smirnov test indicates that one cannot reject the hypothesis that the distributions in the church auctions in 1999 and 2000 are the same. One interesting property of these empirical distributions is that most of the bidders average a dollar or less, with a general pattern of tailing down. However, in two of the cases there is a "bump" of bidders at relatively large levels apparently aggressively pursuing jump bidding.

4.3.2. Parametric Analysis of Jump Bidding in the Field Auctions.

We next attempt a parametric analysis of jump bidding by item. The results were only partially successful as the estimations explain only a small part of the variation. Nevertheless, certain of the results

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were always less than the minimum increment, then we might simply be observing bidding "approximations" that were more difficult in the school auctions with larger minimum increments. But this level of overbids looks more like charitable or see-and-be-seen actions. We excluded a small number of items listed as "priceless."

[21] The x-axis marker on each column is the lower bound of that bin.

appear to be robust and are informative to the question of bidder behavior. For each night of auctions (i.e. Church 1999, Church 2000, and School) we conducted two estimations: a probit analysis of the incidence of a jump bid of any magnitude, and a Tobit regression on the magnitude of the bid increment.[22] The regressors included, and a discussion of why they are of potential interest, are as follows:

Number of Bidders In the theoretical models of charitable behavior in the second price auction, the equilibrium limit bid levels typically do not vary with the number of bidders. However, the number of bidders effect has not been worked out for the question of jump bidding in an ascending auction given the bidder's value. If charitable bidders are hoping to increase the amount paid to the seller, they may set a target value for an item that they are willing to pay, even if the bidding of others in an ascending auction stops before that point. (Note that this implies a slightly different structure to charitable bidder preferences than the models discussed previously.) If this is the case, a bidder may be more inclined to use large jump bids if there are only a small number of other bidders. If there are a large number of other bidders, they may be more likely to "free ride" on the bids of others. If bidders want to "see-and-be-seen", do they care only about the final outcome of the auction (the assumption of the models in 3.2) or do they also care about being seen as raising the bid as the ascending auction unfolds? If the latter, they would presumably engage in more flamboyant bidding in front of a larger number of other bidders. If bidders are impatient, one could make an argument about the effect of the number of bidders either way (again, Isaac, Salmon, and Zillante model only the case of two bidders). If individuals are worried about final seconds crowding as the clock ends the multiple auctions, they will presumably be led to engage in more jump bidding the more crowded is that auction.[23]

Dummy First Bid; Dummy Second Bid (the bid is the first one in an auction). Large initial jump bids

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[22] We used a scaling factor across all auctions where a bid equal to the minimum bid increment was a magnitude 1, and the difference between the minimum increment and size of jump divided by the minimum increment present in the auction defined the magnitude for bids that exceeded the minimum increment.

[23] Clearly, our "number of bidders" measure, the number of bidders who eventually placed a bid, is imperfect. The nature of these auctions is that all bidders are eligible to bid in all of them. The question is how many are going to be practically active in a particular auction? This is an endogenous outcome resulting from bidders' decisions throughout an auction. However, another feature of the silent auction is that bidders can watch the arrival of bidders at an auction station. The idea that bidders can guess which items are drawing the most attention is not far-fetched.

right out of the gate would be more explicable for charitable bidders wanting to increase the seller's revenue, for bidders wanting to be seen as charitable, and for impatient bidders wanting to speed up the price ascension. We would not expect it to be a feature of final-second crowding.[24] It might be thought that this would be an easily measured variable. However, as we were analyzing the data, we discovered that the bid sheets (at least for the church auctions) were ambiguous as to whether jump bidding was possible on the first bid. Indeed, the incidence of jump bidding on the nominal first bid is very low. Thus, both variables are included, with the expectation that Dummy Second may be the operational "first bid."

Dummy Last Bid (the bid is the last one in an auction). Large final jump bids would be consistent with the standard charitable model, with "see and be seen" bidding, and with bidders worried about final-seconds crowding. It would not make as much sense for a phenomenon of bidder impatience.

Dummy "Craft". This is a somewhat arbitrary variable with the following background. One of the authors, when examining the description of the items at the church auction, noticed that some of them were actually made or created by members of the congregation, in some cases even by groups of children. This raises the possibility that bidders might have a specific, magnified charitable interest in increasing the sales prices on these items, or in being seen to make large bids on them. We also included "**Dummy Craft x Dummy First**", "**Dummy Craft x Dummy Second"** and "**Dummy Craft x Dummy Last**".[25]

Bid Sequence. This is a proxy for how far along in the auction the bidding is. Recall that these field data sets are not time stamped, so we don't know the clock time. However, we can measure, for example, in an eventual 14 bids, whether the bid was second or tenth out of 14. One would expect that attempts to speed up the bidding would occur, almost by definition, early on. Indeed the theoretical model of Isaac, Salmon, and Zillante shows jump bidding continues into the auction, but decreasing as the auction progresses Jump bidding aimed at final seconds crowding would presumably increase as bid sequence increases. The effect on charitable activity is hard to pin down, and a see-and-be-seen model should show no effect.

Lag Bid. This picks up an effect on jump bidding as the revealed value of the goods increases either in

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[24] In fact, first jump bids are a prediction of Daniel and Hirshleifer.

[25] In the case of the school data, there were no items that could be classified as a "craft" in the terms used for the church auctions. Therefore, none of the variables using this declaration were used in the school auction estimations.

time or across goods. A charitable bidder ought to be no more likely to submit a jump bid on an item that has already moved high up in the bidding. The pooling of the cross-sectional and time series component makes the implications for speeding up the auction ambiguous.[26] Likewise, one could tell different stories about final-seconds crowding. Lag bid would seem to be of no import for the see-and-be-seen model.

Lag Jump Bid. A bidder worried about final-seconds crowding would presumably respond to the perceived jump bidding behavior of other bidders. One would expect that response to be positive. For a bidder hoping to increase the revenue of the seller, that effect should be negative (Higher jump bidding by others means that I don't have to jump bid as much). For someone there to "see and be seen" there should be no effect. And again, the effect on impatient bidders seems to be ambiguous.[27]

Value Variables. At the school auction, most items had a stated market value. So in only these auctions we included "**bid/value**," and "**minimum increment/value**" variables. These two variables would appear to have an ambiguous impact on the see-and-be-seen bidders or the bidders seeking to increase seller's revenue, with one exception. Bidders wanting to increase revenue to the seller might not be as aggressive when they see that the ratio of bid to value is high. These variables may have implications for impatient bidders. As "**minimum increment/value**" increases, jump bidding should decline (because small minimum increments would be most likely to understate the bidders' desired pace of the auction). One might make an argument either way for "**bid/value**". The same predicted effects, but for slightly different reasoning, would be true for bidders worried about crowding in the final seconds.[28]

These expected effects are summarized in Table 2 for each of the models. The estimation results are presented in Table 3.[29] A comparison between the expected effects and the actual effects in produced in Table 4 (where an X indicates an inconsistency between prediction and estimate).

The follow observations can be drawn from the estimations.

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[26] For example, looking simply at the time series of the auction, attempts to speed up the generation of information ought to be greatest at the beginning, when bids are lower. On the other hand, looking across goods, those generating higher bids might foster higher jump bids.

[27] The question is, if I see others submitting large jump bids, and I am interested in speeding up the auction, how should I respond. At our current level of modeling, there does not appear to be an unambiguous answer.

[28] We are not asserting an exactness of these stated values. However, they should serve as reasonable proxies.

[29] Since a previous draft, we have corrected a coding error in the bid sequence variable.

The number of bidders appears to have a negative effect on the incidence of jump bidding and on the magnitude of the jump bids. There is a negative sign on the coefficient in five of the six estimations (four of the five are significant at $\alpha = .05$).

Being the first bid (particularly as measured by the "Dummy 2" variable) is positively associated with both the incidence and the magnitude of jump bidding (significant in only two cases) .The coefficient on the last bid dummy is of mixed sign and significance (positive in five cases, significant in only one).

The variables relating to "craft" items appear to be playing a statistically significant role in several of the coefficients in the second church auction, but not the first. In terms of the sign, in the second church auction the craft auctions appear to generate a greater jump on the first and last bids, but a smaller jump in between.

Lag bids play a significant role in church auction estimations, but with the opposite signs in the church rather than the school auctions. In the church auctions, as the previous bid went up, so did the subsequent jump bid. The opposite (and insignificant) effects in the school could be due to the fact that the school auctions had enough observations with an announced value that we incorporated in the regression several value variables not included in the church auctions.

The lag of jump bids does not appear to be a consistently signed or consistently significant factor. The value variables were estimated only for the school auctions, where they show up significantly (the ratio of bid to value positive and significant, the ratio of minimum increment to value negative and significant).

4.3.3 Interpretation of the Statistical Results

We turn now to interpretations of the statistical results. Both the descriptive and parametric analyses suggest several broad conclusions. First, the data suggest that no single model significantly describes all the data, and there are results consistent with each model.[30] This should be expected. There is no reason that any one bidder could not simultaneously be a charitable bidder who also is worried about final seconds crowding, and so forth. And different bidders may have different characteristics within a category (such as differences in degree of charitable preferences). The differences between the church auction and the private school auction also stand out, and we will discuss them separately.

In the church auctions, a striking result is the predominance of (often significant) negative coefficients on the number of bidders. As the number of final bidders goes up, we find less jump bidding. This is a relatively supportive result for the charitable model (one can free ride more on a multiplicity of other bidders). It is a negative result for the proposition that bidders want to be seen raising the price (why

[30] The low pseudo-adjusted R-squares in the probit estimations are consistent with similarly weak results in a predictive accuracy table.

jump more when you are seen by fewer people?). It is also a negative result for the model of final seconds crowding (more bidders should induce more crowding and hence more jump bidding). We had said that the effect was ambiguous for the model of impatient bidders. The negative sign suggests that if the price is moving up steadily due to a stream of bids from a large number of bidders, there is less need to jump.

Similarly, all "Dummy Second" coefficients are positive, although the coefficients are not statistically significant. This weakly supports the charitable, see-and-be-seen, and impatience models. There are mixed results on the question of final bid effects.

There is not much else in the estimations for the church auctions that provide consistent support for the charitable model or the see-and-be-seen model. Especially in the 1999 auction, the models of bidder impatience seem to work the best. However, there is some indication in the 2000 church auction that the net effect of a craft item was to lead to more jump bidding in auctions with fewer bidders (compare the direct effects of the craft coefficient with the crossed effects). This effect is somewhat plausible. If a craft is produced by 5th graders, it may get a big jump out of the gate and again at the last if it has not seen a lot of action during the auction. This suggests a modified form of the charitable model in that some bidders care that some specific goods receive a high price.

We turn next to the school auctions. Recall that the descriptive statistics reveal that jump bidding is substantially less common. In the parametric results, there are both similarities and differences with the church auctions. As in the church auctions, the number of bidders is also significantly negatively related to jump bidding, and the dummy variables for first effects are positive and significant. There are no "craft" variables in the school auctions. The "lagbid" has the opposite sign (negative and insignificant) in the school auction, but that needs to be interpreted in light of the additional information available in the school auction regression, namely, a stated value for each item. The existence of the stated retail values allows us to include "value-related" variables directly in the estimation ("lagbid" may have been a proxy for value in the church auction estimations). In the school auctions, jump bids are negatively and significantly associated with the ratio of minimum increment of bidding to stated value. This is consistent with an argument that impatient bidders can substitute jump bids or higher minimum increments as a way of speeding up the pace of an auction or for dealing with final-seconds crowding. Also, jump bids increased as the ratio of bid to value increased. This seems to argue against only the charitable model.

As in the church auctions, the estimated coefficients coincide well with the predictions of the model of bidder impatience. In addition, it seems that it is only in the school auctions that the "see and be seen" model performs well. The additional evidence for this assertion is that in the school auction four to five percent of the items sold at prices exceeding the stated value did so by more than one bidding increment. We believe that it would not be controversial to describe the school auction as more of a social event, drawing more secular philanthropic leaders. The church auction was more informal, and bidders were largely church members and affiliates who interacted frequently. Finally, a noticeable difference between the two locales is that the final-seconds crowding model appears to work less well in the school auction. This is interesting because the school auction managers closed the auction in slightly divergent rounds (staggered approximately ten minutes or so) by clusters of tables. This system was known to the bidders. The strategic problems of a single closing time in geographically dispersed auctions may have been ameliorated in comparison with the church auctions, which used a single closing time for all items.

In summary, the behavior of bidders in all of these auctions meets minimum standards of rationality. There are many jump bids, especially in the church auctions, but they are by and large clustered at smaller levels where their economic significance is likely to be minimal. However, in each of the auctions, there are a small number of bidders averaging higher levels of jump bidding. Jump bids seem to be a means by which impatient bidders can accelerate the pace of the auction and/or deal with end period effects. There is some evidence of the two types of charitable behavior, but it is limited.

5 . SILENT AUCTION LABORATORY EXPERIMENTS

5.1 Experimental Design

One of the most binding limitations of field data is that we do not know the values that the bidders placed on any of the items.[31] Value information is needed to answer such questions as: "Do bidders in a silent auction bid over their values?" and, "Is the auction efficient?", and "Is there something

[31] Whether the announced value on the gift certificates is an exception is unclear.

in the nature of the bidders' values that explains jump bidding?" Also, idiosyncratic effects of individual bidders are difficult to address without value information.

From our discussion of the nature of the silent auction and what we hope to learn from experiments (informed by the field data above), we conclude that there are four obvious potential treatments of an experimental design for multiple unit ascending auctions, as follows: single or multiple units at auction, exogenous or endogenous tick size, clock close or activity close, public goods valuation or not.[32] The silent auction, by its very nature, solves some of these choices. Silent auctions are invariably multiple good, have an exogenous minimum bid increment but allow bidding beyond that increment, close auctions by a clock (or similar device), and they typically occur in the context of a public good or charity. Therefore, our choice of an experimental design will stay within those parameters.

Each of the aforementioned attributes requires a design choice, and each could be varied systematically as a design treatment, or held fixed throughout the research. In addition, the induced bidder values are a critical consideration. In the experiments reported here, we chose and held constant the number of bidders, the number of items at auction, the basic bidder values, the number of auctions, and the clock time for each auction. We chose two treatments for this phase of the research: minimum bidding increment, (varied across sessions) and the extent of induced public goods value on seller's revenue (varied within a session by period). The across-session comparison on minimum increment is represented by three sessions with a 25 cent minimum and 3 sessions with a 50 cent minimum (maximum value on each good was $20.00) Each session consisted of 5 sequential auction periods, with 16 items at auction in each section. The within-session comparison on public goods value was instituted by a NNYYN sequence in each session, where N represents an auction period in which there is no induced public goods value, and Y represents that there is, for some bidders, an induced public goods value. In the Y periods (that is, periods three and four), each bidder received a privately disclosed additional earnings amount, which was a percentage of the total sellers revenue for that period. Four individuals had no induced public goods value, two received one percent, and two received five percent. In other words, the total induced

[32] Notice that we simplified the design issues by setting aside the issue of combinatorial values.

"charitable" or public goods value was twelve percent of whatever total revenues were received by the seller for that period. Table 5 is a summary table of the experimental design. Figure 2 presents the standard geographical dispersion of auction stations we used during the experiments. Sample instructions are available at http://mailer.fsu.edu/~misaac/rsrcinst.pdf.

5.2 Experimental Results

5 .2. 1 Descriptive Results

We begin by presenting in Table 6 descriptive results with the field data compared side by side with the experimental data. We also present statistics that are available only from the laboratory data: market efficiency and relative revenue generation. The index of efficiency is calculated by looking at actual resale values for the winners divided by the maximum of the induced values. For the public goods periods, we do not include the induced public goods values. The revenue comparison is actual seller revenue received divided by the second highest value. For these calculations, we make the calculations primarily at a level of aggregation such that one period in one session is one observation. However, in parentheses, we have included the same calculations where each individual auction is an observation. Figures 3 and 4 present the same histogram as Figure 1 for the field data; that is, an observation is a mean level of bid increments for a single bidder across all the bids that bidder placed in all the auctions that session. The distribution is on percentage of all bidders in the auctions. The data are disaggregated into Figures 3 and 4 because the .25 minimum increment sessions display a different pattern than the .5 minimum increment sessions, as we will discuss below. Finally, in Figure 5 we present the time series of the number of jump bids across time (coded into fifteen-second intervals). Note that Figure 5 presents the number of jump bids, while Table 6 talks about the percentage of bids that are jump bids.

The following is a statement and discussion of observations about the descriptive statistics.

Bidders seldom jump their own bids.

Bidders seldom bid over their induced values for items.

Bidders frequently submit jump bids, and the frequency depends upon the treatment.

These observations are essentially the same as with the field data. Note that the existence of the public goods values seems to make little difference in either jumping one's own value or in bidding in excess of induced value. In terms of the incidence of jump bidding, inspection of the four treatments suggests some variation. A chi-squared test easily shows at the .05 level of significance that the individual frequencies are not replicates of the overall mean. The difference in simple means indicates that there is less incidence of jump bidding with the higher minimum bidding increment and a greater incidence of jump bidding with the public goods values. A similar test indicates that the differences in the proportion of bids that are a jump of the bidder's own bid or which are in excess of value are not significant.

These auctions are moderately efficient, and the level of aggregation makes little difference.

While the efficiencies (ca. 95 – 98 percent) may be slightly lower than we might expect from other experiments with single object ascending auctions (ca. 99 percent)[33], they are still capturing about 91 – 95 percent of the surplus relative to random assignment. Recall that these auctions are allocating sixteen goods in twelve minutes. A two-way Anova on the efficiency results yields the following. The p-value for the public goods treatment was .57; the p for the minimum increment treatment was .07. The .5 minimum increment auctions had higher efficiencies, on average, than the .25 minimum increment auctions.[34]

The revenue index is highly dependant on the level of aggregation.

With the greatest level of disaggregation, the calculations are especially sensitive to a small number of cases in which a winning bidder pays well above a low second-highest value. Greater aggregation is arguably more useful to anyone wishing to choose an auction mechanism, and at this level we see that the silent auction entails a non-trivial amount of absolute revenue loss. In a two-way Anova, the P on the public goods treatment is .77; the P on the minimum increment treatment is .02. The .5 minimum increment auctions had higher revenue, on average, than the .25 minimum increment auctions. Of course, while we cannot measure here the foregone revenue against cost saving features of the charity auction, it does suggest that it would be interesting for future research to consider changes in the silent auction that

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[33] Coppinger, et al. (1980) report that 96% of English auctions in one treatment, and 97% of English auctions in another treatment were fully efficient, but they don't calculate the overall average. McCabe, et al. (1991) report that a series of multiple unit ascending clock auctions averaged 99.99% efficiency.

[34] We based the efficiency measure only on the basic induced values on the objects. We did not attempt to factor in the preferences for high prices in the public goods periods.

might enhance revenue while preserving its favorable attributes.[35]

Bidders use jump bidding more aggressively in the experiments with the lower minimum bid increment. This is seen clearly in Figures 3 and 4.

Jump bids occur throughout the auction; the experiments with the higher minimum increment are more "front loaded."

Contrary to the family of signaling models, jump bids are not confined to the very first bids in an auction. In fact, Figure 5 shows that jump bids occur throughout the auctions. It is interesting that the auctions with the higher minimum increment appear to peak earlier in the auction. This is a pattern that appears to be consistent with the Isaac, Salmon, and Zillante model of jump bidding which features strategic and impatience motives for jump biddings.

5.2.2 Parametric Results

Tables 7 and 8 present the companion regressions to those we ran on the field data. These estimations are conducted with a random effects framework. The overall goodness of fit is measured using a pseudo R^2 (Wald) measure developed by Magee [1990]. Many of the variables are constructed in the same fashion as in the field (e.g., number of active bidders, dummy last, and so forth). Some of the variables are modified (values are now known and controlled by the experimenter and we now know actual clock time)[36]. Many of the results are strikingly uniform across the four categories. Jump bidding decreases as the bid on the floor gets closer to the bidder's value (eight coefficients significant). This is very consistent with an impatience model of bidding. There is a similar effect that jump bidding declines as time remaining in the auction decreases (five coefficients significant), which argues against final seconds crowding explanations. However, last bids tend to have higher jumps (four coefficients positive and significant), which is more consistent with final-seconds crowding. In addition, we were able to construct a variable that measures how "occupied" a bidder was; that is, how many items each bidder had in play elsewhere when making a bid. This variable is labeled "N of Objects." The crowding model would predict a positive relationship, which indeed is the case in six of the estimations. However, that

[35] An obvious candidate would be the sealed-bid version of the auction.
[36] We use log of (bid-value) to account for non-linear front-loading of jump bids.

coefficient is statistically significant in only three cases. Finally, the effect of the number of active bidders is negative in seven of the eight regressions, and it is significant in roughly half.

The remaining values present more heterogeneous results. The first period effects are mixed. The effect of previous jump bidding is usually negative but seldom significant. Surprisingly, the intra-group effect of minimum increment related to object value is typically negative but not significant.

We summarize our conclusions about the laboratory experiments as follows: The strong tendency for jump bids to decrease as the bid on the floor approaches value, the tendency for bids to decline across clock time, and the inter-group minimum increment effects are all suggestive that something in the nature of silent auctions induces a type of impatience on the bidders. The evidence is mixed on whether there is a separate effect due to end-period crowding. Indicators for the charitable model are that the number of bidders has a negative effect, and there is an inter-group effect on jump bidding based upon induced public goods values. However, there is no similar inter-group difference on bidding over value.[37] It is doubtful that there would be any motivation for "see and be seen" behavior in these experiments.

6. COMPARISON OF THE FIELD AND EXPERIMENTAL SILENT AUCTIONS

There are numerous similarities between the field data and the experimental data. In both environments, bidders seldom raise their own bids, and seldom bid above value. In both environments, jump bids are common, and they are common throughout the auctions. In terms of the parametric estimations, jump bidding is negatively associated with the number of bidders and with measures of progression of the auction.

A few differences between the field data and the experimental data stand out. First, in the school auction a respectable number of bids were above the stated values. This could be because the stated values did not correctly capture a true value, or those values could be accurate and these bids could, in fact, be above value. If the latter is correct, this could be direct evidence of either charitable behavior or of the desire to be seen as being a high bidder in the school auctions. Also, the distribution of jump bidding by bidders in the field auctions looks more like the .5 minimum increment experimental auctions.

[37] It should be emphasized that we might not observe every instance of a bidder willing to bid over his or her value.

As a summary comparison, we present in Table 9 the regression results from the two comparable environments: the 2000 church data and the .5 public goods experiments. We chose a church session because the incidence of jump bidding is closer to the laboratory sessions. We chose the .5 laboratory data because the distribution of bidders by jumping activity is more similar to the field pattern. For the laboratory data, we present two different regressions. The first is the laboratory data using only regressors we had in the field. The second is the laboratory data taking advantage of our additional possibilities of observation and control in the laboratory experiments; that is, the last column represents both the different data and the difference in our ability to observe and define regressors. Notice that field and laboratory estimations look similar when using the "field" form of the estimation. This suggests that the model we used in the field captures similar patterns in the laboratory data. However, notice that, in the third column, two of the new variables about *individual* bidder values and items in play are statistically significant, and the pseudo R^2 is higher. This demonstrates the value of the additional and more disaggregated information of the laboratory that was not available in the field.

7. SUMMARY AND CONCLUSIONS

The silent auction is a staple of American charitable fundraising. Given economists' recent experiences with and interests in the evaluation of auctions, it would seem logical to visit the silent auction. Obtaining data from three silent auctions, we have documented that this is a mechanism that transacts the sale of a large number of items in a short period of time, without the expense of professional auctioneers or auction designers. However, the field data do not allow for direct observation of bidder values, so that efficiency and revenue performance are unobservable. What we can observe is bidding. A striking feature is the presence of jump bidding. There is no reason to believe that only one model describes regularities in the jump bidding, however, there is persistent support for the conjecture that bidders jump because they are impatient.[38] There is some support for models of direct and indirect charitable activity. Our inability to observe value directly also hinders our ability to model jump bidding.

Laboratory experiments allow us to recreate essential features of a field silent auction in an

[38] Thus these results are consistent with the theoretical model of Isaac, Salmon, and Zillante.

environment of greater control and observability. The data from the experiments are remarkably similar to the field data in those dimensions that can be observed in both. In the laboratory alone we can measure efficiency and relative revenue generation of the auctions. We found that the silent auctions were moderately efficient but were somewhat under the standard competitive benchmark, a benchmark that has been approximated in previous single item auctions with both single and multiple units. Finally, several of the outcomes differed depending upon the minimum bid increment in the auction. For our design, the .5 minimum increment experiments had higher efficiencies, greater revenues, and a different time path and distribution of jump bidding than did the experiments with a .25 minimum bid increment. In general, it is the .5 minimum increment data that seem to most resemble our field data.

In addition to what we have learned immediately, these experiments establish that it is possible to construct a laboratory experimental design that acts as a credible testbed for research on silent auctions. Having done so, one can turn to more specific research on such topics in silent auction design as: the effects (on efficiency and revenue) of even larger minimum increments, the effects of even more extensive public goods preferences, the effects of an alternate type of public goods preferences, the effects of a single as opposed to staggered closing times, or the effects of changes in the silent auction itself. We are currently investigating the performance of the sealed bid version of the silent auction.

JEL CATEGORIES: D44, H41. R. Mark Isaac: 850-644-7081; (f) 850-644-4535; misaac@mailer.fsu.edu. Kurt Schnier: 401-874-4565; (f) 401-782-4766; schnier@uri.edu.

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Table 1 - Auction Data Description

Auction	% of time jump over min. jump	% of time jump own bid	% time bid > stated value
Church 2000	38.55%	0%	0%
Church 1999	37.09%	0%	0%
School Data	8.92%	0%	9.93%

TABLE 2 – Predicted Effects for Regressors on Jump Bids

Variable	Charitable	See-and-Be-Seen	Impatience	Final-Seconds Crowding
N of Bidders	-	+	?	+
Dummy 1^{st}	+	+	+	0
Dummy Last	+	+	0	+
Dummy Craft	+	+	0	0
Craft x $1^{st}(2^{nd})$	+	+	0	0
Craft x Last	+	+	0	0
Bid Sequence	?	0	-	+
Lag Bid	-/0	0	?	?
Lag Jump	-	0	?	+
Bid/Value	-	?	?	?
Min. Incr./Val	?	?	-	-

Table 3 - Probit and Tobit estimation of field data

Probit Estimation (Prob. of Jump Bid)	Church 1999	Church 2000	School 2001	Tobit Estimation (Mag. of Jump)	Church 1999	Church 2000	School 2001
Constant	-0.246	-0.275	-1.812	**Constant**	0.615	1.805	0.780
	-1.22	-1.64	-2.76		0.9	7.43	4.13
N-Bidders	-0.081	-0.028	-0.176	**N-Bidders**	0.032	-0.067	-0.87
	-3.56	-1.65	-2.74		0.42	-2.8	-5.02
Dummy 1st	0.229	-0.394	-0.869	**Dummy 1st**	1.314	-0.139	-0.009
	1.09	-2.1	-1.61		1.79	-.054	-0.06
Dummy 2nd	0.2	0.081	0.595	**Dummy 2nd**	0.988	0.364	0.30
	1.23	0.55	2.35		1.68	1.68	4.21
Dummy Last	-0.031	0.064	-0.030	**Dummy Last**	0.934	0.491	0.128
	-0.16	0.39	-0.09		1.38	2.07	1.27
Dummy Craft	-0.151	-0.282	N/A	**Dummy Craft**	-0.093	-0.235	N/A
	-1.8	-2.91			-0.31	-1.67	
Bid Sequence	-0.187	-0.382	-1.213	**Bid Sequence**	-1.18	-0.765	-0.601
	-0.77	-1.88	-1.74		-1.4	-2.58	-2.99
Lag Bid	0.016	0.025	-0.001	**Lag Bid**	0.065	0.043	-0.0001
	6.09	8.12	-1.23		17.06	10.24	-0.32
Lag Jump	0.011	-0.035	-0.22	**Lag Jump**	0.203	-0.012	-0.096
	0.65	-1.59	-1.37		5.82	-0.38	-2.25
Crft X dummy 1st	-0.342	0.438	N/A	**Crft X dummy 1st**	-0.51	0.985	N/A
	-1.25	1.63			-0.56	2.92	
Crft X dummy 2nd	0.117	0.153	N/A	**Crft X dummy 2nd**	-0.65	-0.123	N/A
	0.46	0.62			-0.7	-.34	
Crft X dummy last	0.243	0.464	N/A	**Crft X dummy last**	-0.825	0.552	N/A
	0.94	1.9			-0.9	1.53	
Bid / Value	N/A	N/A	3.76	**Bid / Value**	N/A	N/A	1.73
			7.03				11.94
Min. Inc. / Value	N/A	N/A	-8.642	**Min. Inc. / Value**	N/A	N/A	-3.06
			-3.20				-5.06
Pseudo R^2	**0.0899**	**0.052**	**0.1892**	**Pseudo R^2**	**0.0887**	**0.0249**	**0.1066**

Table 4: Consistency of Coefficients With Predictions: X = Inconsistent

		# Bidders	D. 1st	D. Last	D. Craft	D. 1st xCraft	D. Last xCraft	Bid Seq.	Lag Bid	Lag Jump	Bid/ Value	Min Inc/ Value
Church 1999												
charitable	incidence			**X**	**X**	**X**			**X**	**X**		
	magnitude	**X**			**X**	**X**	**X**		**X**	**X**		
see & be	incidence	**X**		**X**	**X**	**X**			**X**			
	magnitude				**X**	**X**	**X**		**X**	**X**		
impatience	incidence											
	magnitude											
final sec.	incidence	**X**		**X**				**X**				
	magnitude							**X**				
Church 2000												
charitable	incidence		**X**		**X**				**X**			
	magnitude				**X**				**X**			
see & be	incidence	**X**	**X**		**X**				**X**			
	magnitude	**X**			**X**			**X**	**X**			
impatience	incidence		**X**		**X**							
	magnitude			**X**		**X**						
final sec.	incidence	**X**			**X**			**X**		**X**		
	magnitude	**X**				**X**		**X**		**X**		
School												
charitable	incidence			**X**							**X**	
	magnitude										**X**	
see & be	incidence	**X**		**X**								
	magnitude	**X**						**X**		**X**		
impatience	incidence			**X**								
	magnitude											
final sec.	incidence	**X**	**X**	**X**				**X**		**X**		
	magnitude	**X**	**X**					**X**		**X**		

Key to classification: Where "+" or "-" is predicted, a coefficient of opposite sign (regardless of significance) yields an "X". Where "0" is predicted, a significant coefficient (at $\alpha = .05$) of either sign yields an "X." Where "?" is predicted, an "X" is never indicated.

TABLE 5: EXPERIMENTAL DESIGN

Number of Sessions	6	
Number of Auction Periods per Session	5	
Number of Goods at Auction per Period	16	for geographic dispersion, see Figure 4.
Number of Bidders Across all Goods	8	
Number of Potential Bidders per Good	2 -8	chosen randomly, uniform process
Bidder Values	$0 - $20	chosen randomly, uniform process
Public Goods Value (YES OR NO)	NNYYN	
Public Goods Value (Amount)	2 at 5%; 2 at 1%; 4 at 0%	percent paid on total sales revenue
Public Goods Value (Information)		how it worked, Y or N period, but not distribution
Minimum Bidding Increment	.25 (3 exps) .5 (3 exps)	
Clock time	12 minutes	displayed

TABLE 6 Data Set	Percent of Jump Bids	Percent of Bids That Jump Self	Percent of Bids That Exceed Value	Efficiency	Revenue Index
Church 1999 Data Set	37.09%	0%	N/A	N/A	N/A
Church 2000 Data Set	38.55%	0%	N/A	N/A	N/A
SIP 2001 Data Set	8.92%	0%	9.93%*	N/A	N/A
Experiment					
0.25 No Public Goods	57.42%	0.13%	1.08%	94.88% (94.58%)#	81.31% (87.35%)#
0.25 Public Goods	61.83%	0.09%	1.25%	95.30% (95.48%)#	86.34% (131.43%)#
0.5 No Public Goods	40.16%	0.16%	1.57%	96.87% (96.57%)#	92.71% (102.23%)#
0.5 Public Goods	48.38%	0.13%	1.43%	97.79% (97.57%)#	89.64% (101.63%)#

* indicates that the posted value of the item is used in place of an induced valuation
# main numbers are value weighted (aggregated) at the period level; numbers in parentheses are weighted by individual auctions
At the period-weighted level, random assignment efficiencies (including zero values) would be 39.6 % for no public goods and 39.48% for the public goods cases.

Table 7
RE - Probit Regressions

Variable	0.25 Without Public Goods	0.25 With Public Goods	0.5 Without Public Goods	0.5 With Public Goods
Constant	-.404	0.020	-1.09	-0.883
	-2.21	0.090	-5.46	-3.32
Number of Active Bidders	-0.025	-0.079	0.004	-0.008
	-1.08	-2.16	.13	-0.22
Dummy 1st	-0.210	-0.671	0.259	-.004
	-1.54	-3.85	1.67	-0.02
Dummy Last	-0.221	0.151	0.193	0.439
	-1.23	0.950	1.48	2.62
Seconds Remaining	0.0002	0.001	0.0007	0.0004
	1.02	4.09	2.61	0.88
Log Value Minus Lag Bid	0.156	0.376	0.442	0.437
	3.24	7.24	7.81	5.75
Lag Jump	0.037	0.002	-0.054	-0.023
	1.22	0.05	-2.17	-0.70
Min. Inc./Induced	-2.30	0.358	-1.37	-2.686
	-1.64	0.38	-1.40	-1.58
N of Objects	0.075	-.023	0.017	0.062
	3.90	-1.15	0.73	2.17
Pseudo R^2	**0.0402**	**0.0865**	**0.1155**	**0.1101**

Table 8
RE - Tobit Regressions

Variable	0.25 Without Public Goods	0.25 With Public Goods	0.5 Without Public Goods	0.5 With Public Goods
Constant	0.271	1.020	-0.157	-.173
	0.46	1.70	-0.38	-0.31
Number of Active Bidders	-.178	-0.221	-0.073	-0.181
	-2.21	-2.24	-1.05	-2.08
Dummy 1st	1.307	-0.347	1.662	-0.216
	2.74	-0.72	4.94	-0.52
Dummy Last	1.408	0.850	0.945	1.673
	3.18	1.97	3.11	4.41
Seconds Remaining	0.0006	0.003	0.0006	0.003
	0.08	3.99	3.97	3.29
Log Value Minus Lag Bid	1.07	1.205	1.270	1.348
	7.07	8.35	10.98	9.02
Lag Jump	-0.035	-0.121	-0.197	-0.028
	-0.34	-1.04	-0.35	-.038
Min. Inc./Induced	-0.364	-0.082	-0.123	0.317
	-0.33	-0.03	-0.32	0.86
N of Objects	0.265	0.094	-.030	0.009
	4.23	1.68	-0.60	0.14
Pseudo R^2	**0.0905**	**0.1404**	**0.1984**	**0.1897**

Table 9 Probit Regressions Variable	FIELD VARIABLES* Church 2000	FIELD VARIABLES 0.5 With Public Goods	LAB VARIABLES 0.5 With Public Goods
Constant	-0.275 -1.64	-0.165 -0.69	-0.883 -3.32
Number of Active Bidders	-0.028 -1.65	-0.038 -1.00	-.008 -.022
Dummy 1st (Dummy 2nd in field)	0.081 0.55	-0.568 -0.31	-.004 -0.02
Dummy Last	0.064 0.39	0.40 2.48	0.439 2.62
Seconds Remaining (-1 x bid sequence)	-0.382 -1.88	0.0013 3.71	.00004 0.88
Lag Bid	0.025 8.12	-0.004 -0.28	N/A
Lag Jump	-0.035 -1.59	-0.165 -0.69	-0.023 -0.70
Log(Value Minus Lag Bid)	N/A	N/A	0.437 5.75
Min. Inc. / Induced	N/A	N/A	-2.686 -1.58
N of Objects	N/A	N/A	0.062 2.17
Pseudo R^2	**0.052**	**.0395**	**0.1101**

***craft variables not displayed**

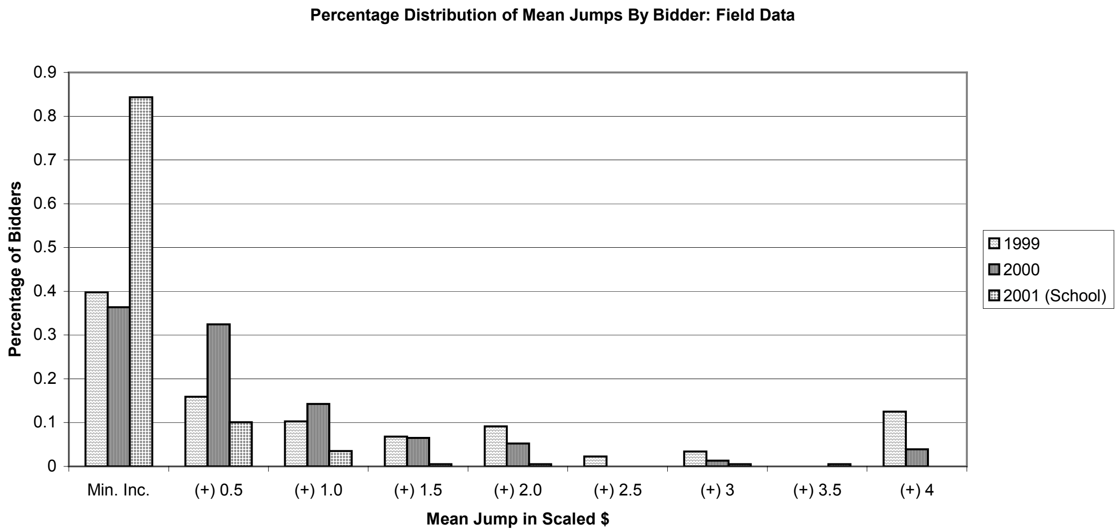
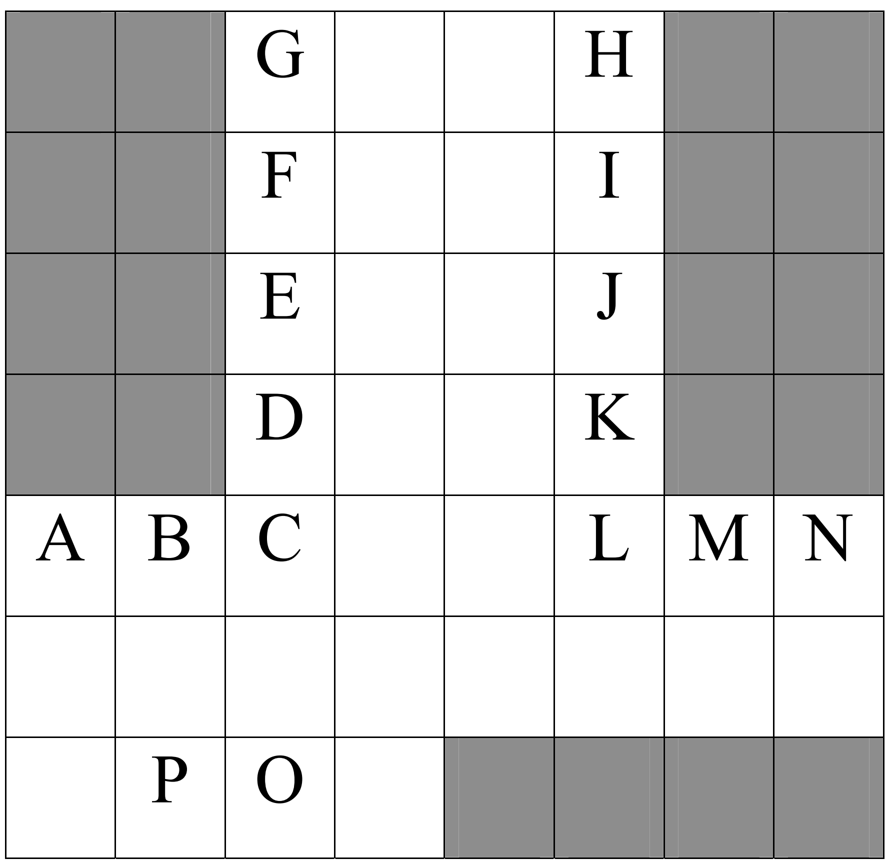


FIGURE 1

FIGURE 2



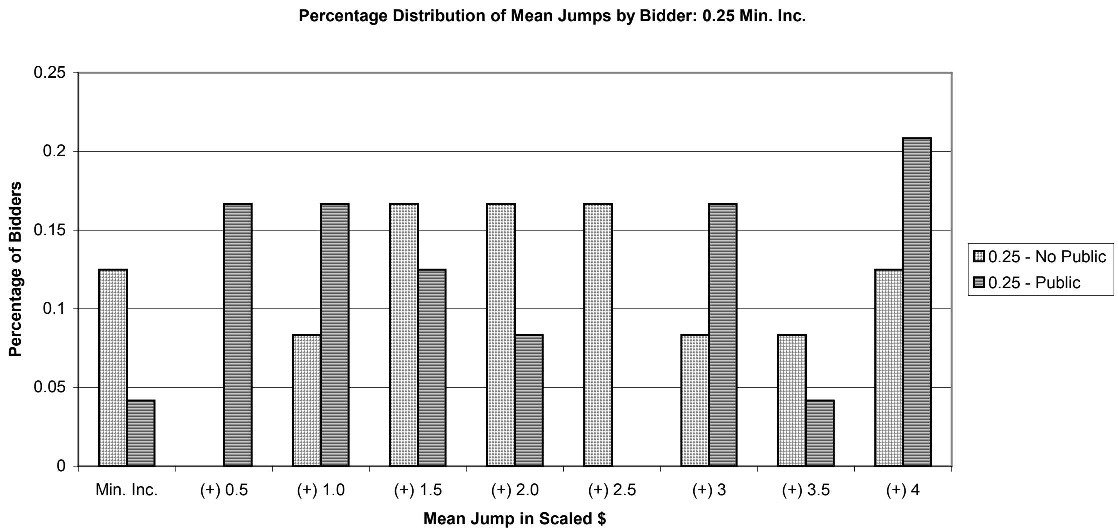


FIGURE 3

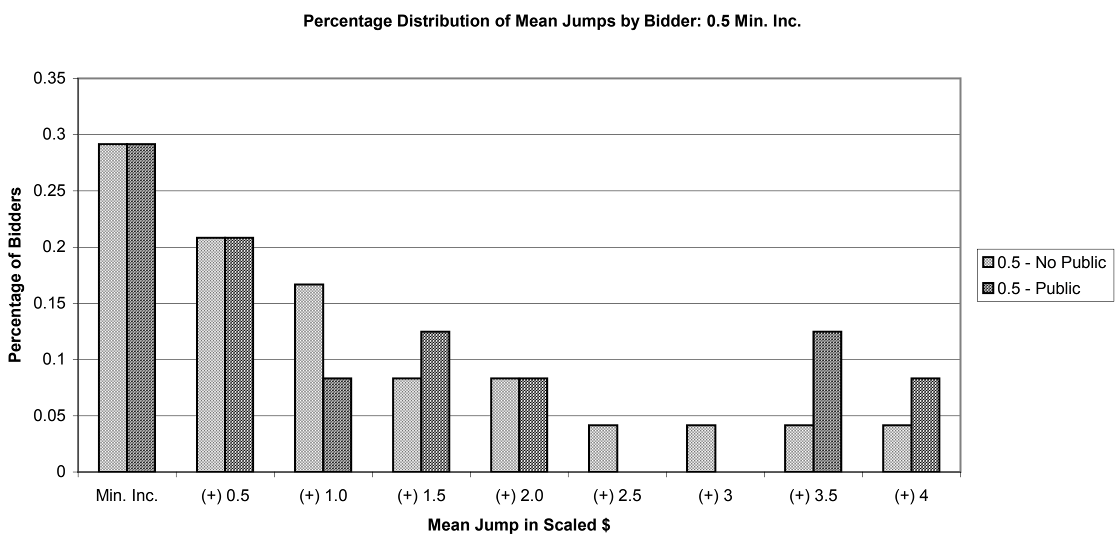


FIGURE 4

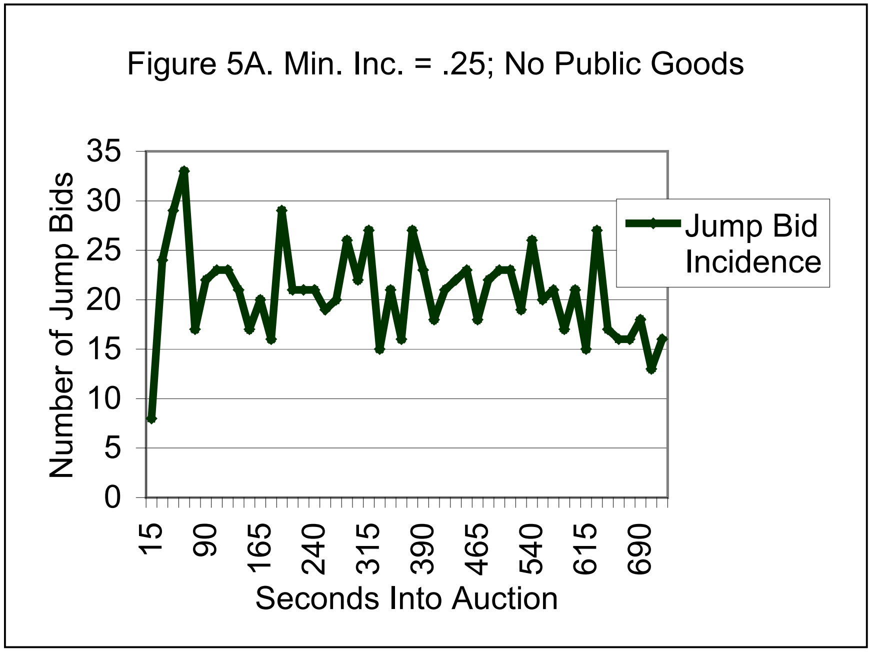


Figure 5A. Min. Inc. = .25; No Public Goods
Number of Jump Bids
35
30
25
20
15
10
5
0
15
90
165
240
315
390
465
540
615
690
Seconds Into Auction
Jump Bid Incidence

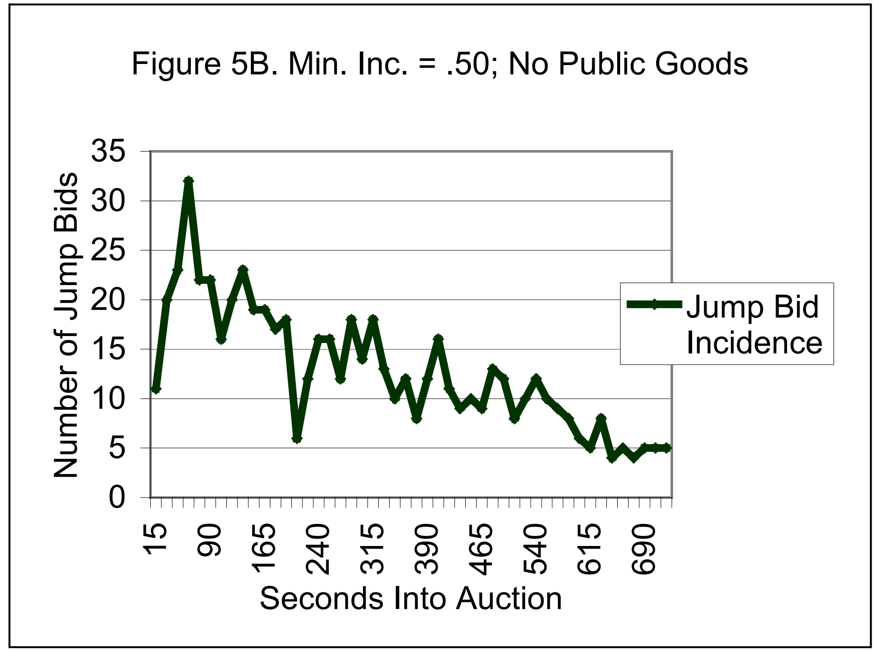


Figure 5B. Min. Inc. = .50; No Public Goods
Number of Jump Bids
35
30
25
20
15
10
5
0
15
90
165
240
315
390
465
540
615
690
Seconds Into Auction
Jump Bid Incidence

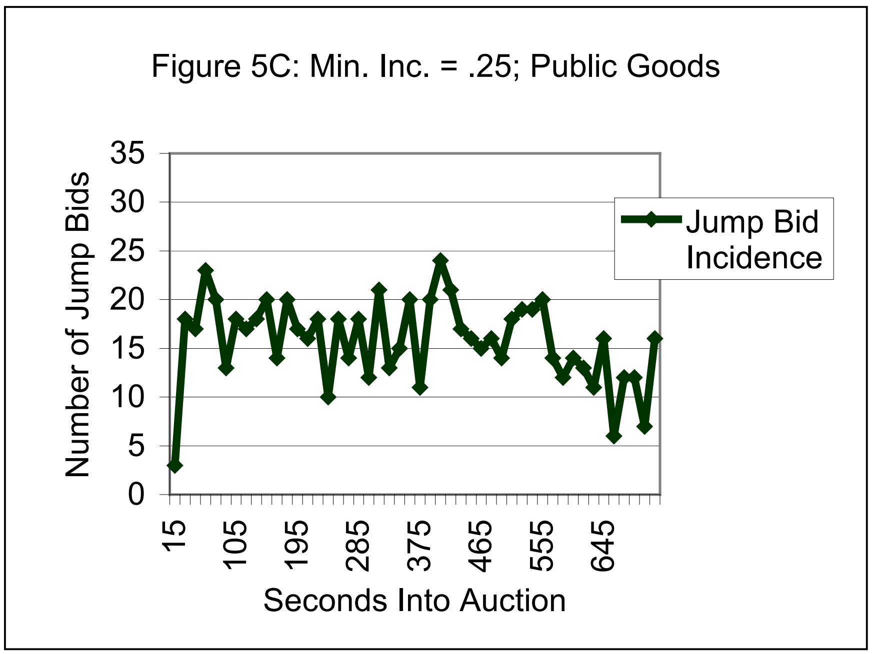


Figure 5C: Min. Inc. = .25; Public Goods
Number of Jump Bids
35
30
25
20
15
10
5
0
15
105
195
285
375
465
555
645
Seconds Into Auction
Jump Bid Incidence

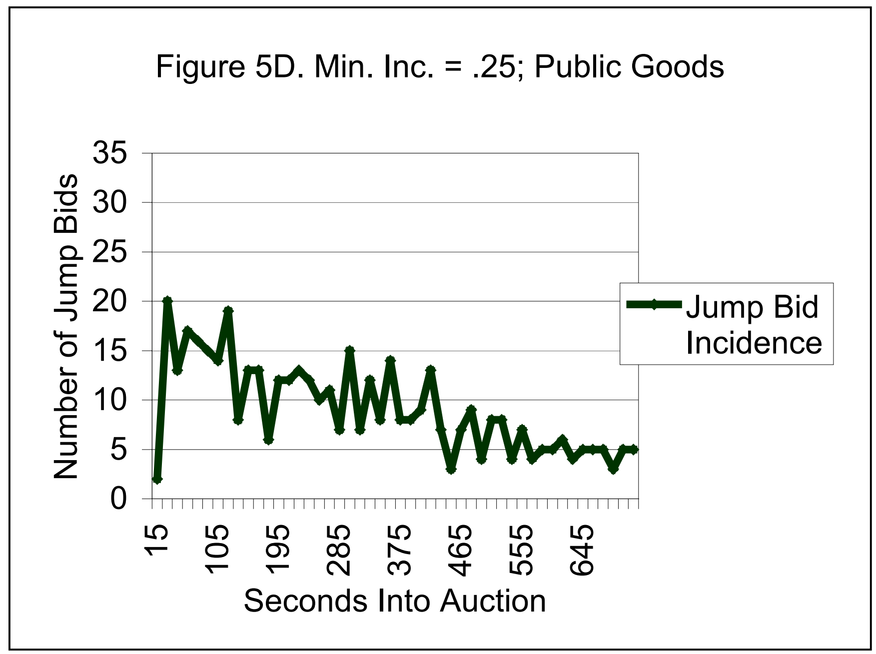


Figure 5D. Min. Inc. = .25; Public Goods
Number of Jump Bids
35
30
25
20
15
10
5
0
15
105
195
285
375
465
555
645
Seconds Into Auction
Jump Bid Incidence