Jumping, Squatting, Sniping, Soaring and Stumbling at the Silents: Does it matter for charities?*

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June 1, 2009

Abstract

Despite its popularity as a fundraiser for charities, very little research has been done on the bidding and revenue properties of the silent auction. This paper examines jump bidding, sniping, squatting and other bidding strategies in laboratory auction experiments in which participation is treated endogenously. Our results suggest that “jumping”, a strategy relied on by competitive and impatient bidders who want to telescope time, significantly increases revenue while “sniping”, a behavior more characteristic of high-value bidders with lots of experience, significantly depresses revenue. “Squatting” (submitting an initial bid substantially higher than the minimum), is relied on by competitive but risk averse bidders who expect more competition, but has very little impact on revenues. Bidding more than one’s value (“soaring”), a significant revenue-enhancer, is committed by impatient, low-value bidders whose numeracy skills are low. Lastly, more patient, numerate, experienced, high-value bidders are more likely to “stumble” (not bid up to one’s value), and more stumblers translates into lower revenues for the auctioneer.

1 Introduction

According to GivingUSA, charitable giving by individuals, foundations and corporations in the United States exceeded $300 billion for the first time in 2007. The importance of these donations should not be underestimated as contributions, gifts and grants account for nearly one quarter of all revenues raised by the approximately 1.5 million nonprofit organizations

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*We thank Phil Mellizo, Stella Nordhagen and Wesley Pech for research assistance, John Spraggan and John Stranlund for organizing access to the experimental lab at the University of Massachusetts and Carolyn Craven, Christina Fong, Steve Holmes, Corinna Noelke and the participants at the Middlebury College Workshop on Philanthropy for valuable comments. We also acknowledge the financial support of Middlebury College and the National Science Foundation (SES 0617718).

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in the US (The Urban Institute: National Center for Charitable Statistics). For many non-profits, especially those that receive “in kind” gifts, the most heavily relied upon fundraising mechanism is the silent auction, yet little research has explored either the bidding strategies employed by its participants or its relative fundraising potential. This paper attempts to fill that void by using experimental data to analyze the participation decision, bidding behaviors and resulting revenue implications for several variations of the silent auction as well as the standard English auction.

The popularity of the traditional silent auction is undeniable; many, if not most schools, churches and other charities rely on the silent auction as a primary fundraising mechanism. At the typical silent auction, guests walk around exhibit tables, where multiple items and their corresponding bid sheets are displayed openly. The bid sheets describe the item to be auctioned, and list both the current highest bid and all previous bids, with bidders identified by either name or number. There is a publicly announced closing time, one that is usually, but not always, common to all items. As guests travel around the room, they can identify items of interest, and make note of the number of bids, the number of unique bidders, and the current highest bid for each item. The popularity of the silent auction stems from the low expense and ease with which it can be implemented - no professional auctioneers are required, for example - its scalability, low pressure atmosphere, familiar rules, and its complementarity with other event entertainment.

But does this convenience come at a price? There are several reasons to be concerned that the standard silent auction is less competitive, and therefore produces lower revenues, than some alternatives like the English. One of the most familiar is the “sniping” characteristic of all fixed deadline mechanisms, in which bidders, to avoid costly bidding wars, wait until the final seconds to submit their first bids. The effects of “jumping” by raising one’s bid by substantially more than the minimum increment are perhaps less obvious: it could stifle competition through intimidation, or foster competition by allowing bidders to compete for several items with a common deadline. This leads to another consideration, namely, what the costs of such a deadline are. Is it the case that removing fixed deadlines and allowing the auction to continue until all bidders are satisfied will increase revenues or will impatient bidders become frustrated and limit their participation?

Some have also wondered if “squatting,” in which bidders jump not another bid but the reservation price directly at the beginning of the auction, is an attempt to intimidate and, as a
result, suppress bids. Because the events support charities and therefore all the participants benefit from the revenue garnered, there may even be some temptation to bid over one’s value, what we call “soaring” in the spirit of the apparent terminological convention. Soaring might be more common if it allows one to act like a “shill” forcing up the final price paid by some other higher-value bidder. Notwithstanding the possible efficiency consequences of soaring, one might be tempted to conclude that charities should be happy to have people engage in such hyper-competitive acts. However, this may depend on the response of the more calculating participants. If more experienced and patient bidders react by leaving the bidding before they reach their values, what we call “stumbling”, acts of intimidation like jumping and squatting or “shilling” for the charity may have mixed, overall, effects.

Despite its popularity and the rich behavioral landscape just described, very little research has been done on the bidding and revenue properties of the silent auction. This paper builds upon the work of Isaac and Schnier (2005) by examining jump bidding, sniping and the other bidding strategies in laboratory auction simulations. In addition to an English button format which we use as a basis for revenue comparisons, we focus on three variants of the traditional silent charity auction.¹ The first mimics the traditional silent auction in which bidders openly observe all bids and may submit bids at any time until the fixed close of the auction; the second, primarily designed to examine the propensity to snipe, eliminates the deadline by adding another 30 seconds to the auction every time a bid is submitted; and the third attempts to capture the essence of events in which some participants cannot stay for the entire duration of the auction. The last treatment may have implications for the propensity to jump.

This paper advances the literature on several fronts. First, following on our earlier work (Carpenter, Holmes and Matthews, 2008a) in which we remind readers that the number of bidders can be as important for revenue as the behavior of the representative bidder, we allow the participation decision to be endogenous, thereby (re)introducing an important element into mechanism design. Second, our experimental design also attenuates any effects that might come from “playing with house money” by having our participants earn their endowments at the beginning of the experiment. Third, because we collected a wealth of demographic and behavioral data on bidders, we are able to paint a more complete picture

¹The English button auction in which the price continues to rise as bidders press “buttons” to signal the highest price they are willing to pay and the winner is the last to press the button is strategically equivalent to an "open outcry" English auction conducted by an auctioneer.
of individual behavior and the determination of auction revenues. No one, to our knowledge, has linked bidder impatience or sunk cost sensitivity to auction outcomes, to mention two examples.

Our experiment suggests that while the standard silent auction does yield the highest rate of participation, it does relatively poorly when it comes to revenue because of its inability to discourage behaviors that are bad for revenue and foster those that enhance revenue. Although jumping, which we find is done by competitive and impatient bidders who want to telescope time, tends to be good for revenue, the standard silent does not elicit as much jumping as when people have binding time constraints. At the same time, squatting, which turns out to be bad for the median auction and is done by competitive but risk averse bidders who expect more competition, is neither more nor less prevalent in the standard silent auction. As expected, we find that sniping is bad for revenues, that it is done by high-valued bidders with lots of experience, but that it is only less common in the treatment in which we explicitly try to remove it. Soaring, which is obviously good for revenues when considered in isolation, is committed by impatient, low-value bidders whose numeracy skills are low. Because soaring occurs at roughly the same rate across mechanisms, it neither hurts nor helps the standard silent when compared to the other formats. Lastly, while stumbling, which is engaged in by patient, numerate, experienced, high-value bidders, turns out to be innocuous or bad for revenues, it appears to happen more regularly in the standard silent and may thus partially explain why this format under-performs.

Section 2 reviews the literature on silent auctions and bidding strategies in ascending auctions; Section 3 describes the experimental design and presents some descriptive statistics; Section 4 examines individual bidding behavior while Section 5 focuses on the revenue properties of the silent auction. In Section 6 we link revenue differences to the individual bidding behaviors and Section 7 summarizes the main findings and suggests practical implications for fundraisers.

2 Earlier Literature

The theoretical literature on auctions is extensive (see Klemperer, 2004 for an overview), although much less attention has been paid to charity auctions (see Engers and McManus, 2006; Goeree, Maasland, Onderstal and Turner, 2005 for recent examples). While several empirical studies have tested the theoretical predictions of charity auctions in the lab (e.g.,
Davis, Razzolini, Reilly and Wilson, 2006; Schram and Onderstal, 2006) and in the field (e.g., Carpenter, Holmes and Matthews, 2008a) most have concentrated on the first price winner pay, second price winner pay, standard raffle and/or the all-pay auction.

Despite its popularity, very little research has been done on the bidding and revenue properties of the silent charity auction. Isaac and Schnier (2005) is one exception; they focus on three naturally occurring auctions and six laboratory simulations. Although they find that higher minimum bid increments are associated with both greater efficiencies and higher seller revenues, their results on jump bidding are perhaps most interesting and relevant here. Unlike ascending auctions orchestrated by strategic auctioneers, silent auction participants have the opportunity to submit bids above the minimum increment (i.e., jump-bid) and Isaac and Schnier propose that it may be optimal to do so in the silent charity auction. In two of their three field auctions, over one-third of all bids were jump-bids while in the lab, 40-60% of all bids were above the minimum increment. The authors propose several justifications for jump-bidding as a rational bidding strategy: participants may jump-bid to increase the seller’s revenue as a response to the public goods nature of the charity auction (“charitable” justification), to be seen in the presence of others as the bidder responsible for the charity’s revenue (“see and be seen”), to speed up the pace of the auction or to obtain a geographic advantage in the room (“impatience”) and/or to submit a final bid before the clock ends in order to make bids on other items that may be closing (“final seconds crowding”). Their lab and field results support all four justifications, but they conclude that jump bids generally seem to be a “means by which impatient bidders can accelerate the pace of an auction and/or deal with end period effects”. This conclusion helps motivate one of our treatments.

Other studies, both theoretical (e.g., Avery, 1998; Easley and Tenorio, 2004; Isaac, Salmon and Zillante, 2007) and empirical (e.g., Plott and Salmon, 2004; Isaac, Salmon and Zillante, 2005, 2007; Raviv, 2008), have explored the behavioral foundations of jump-bidding in non-charity contexts. The theoretical models predict jump-bidding when there is some cost to submitting and later revising a bid (e.g., Daniel and Hirshleifer, 1998; Rothkopf and Harstad, 1994), when bidders wish to signal strength and intimidate opponents via aggressive bidding behavior (Avery, 1998), or when bidders are impatient and wish to speed up the close of the auction (Isaac, Salmon and Zillante, 2007). Plott and Salmon (2004) find empirical evidence that impatience may be the driving force behind jump-bidding in the third generation mobile phone services auction in the UK while Easley and Tenorio (2004)
rely on data from Internet Yankee-type auctions to show that jump-bids are most likely to occur in more competitive auctions and to appear early in an auction, where the signaling value is the highest. Raviv (1998) in his investigation of jump-bids in sequential oral English auctions for autos in New Jersey, also finds evidence that the first offer is often the largest jump.

Early jump bidding, or “squatting” as coined by Ely and Hossain (2006), is a strategy used to deter entry. The authors compare sniping, i.e., last-minute bidding, to squatting in eBay auctions for new DVDs and find that sniping significantly increases bidder surplus relative to squatting but by a small amount (about 1.4% of imputed value). Sniping improved the probability of winning by close to 10% relative to squatting.

Sniping has also been studied extensively in the context of Internet for-profit auctions. A common comparison in the literature is bid timing on eBay (where auctions have a “hard” end time or fixed deadline) with bid timing on Amazon (where auctions have a “soft ending” since they are automatically extended, as in one of our formats, until ten minutes have passed without a bid). For example, Roth and Ockenfels (2002) and Ockenfels and Roth (2003) find that bids are more likely to occur late in the eBay auctions, but earlier in the Amazon auctions. Ariely, Ockenfels and Roth (2005) find similar results in the lab. Roth and Ockenfels (2002) argue that sniping may be a rational strategy in auctions with a hard closing time if a sniper hopes to avoid a bidding war or outbid competitors whose bids are not successfully transmitted in the final seconds. They also suggest that sniping can be a rational strategy for bidders who want to gather information about others’ values but who prefer not to reveal information about their own value for the item; this may be a particular useful strategy for experts bidding against naïve participants. Roth and Ockenfels (2002) further suggest that sniping can be viewed as “tacit collusion” among bidders to lower seller revenue. Consistent with that prediction, Glover and Raviv (2007) find that seller revenue is significantly higher in soft-close auctions where sniping is attenuated. On the other hand, Gray and Reiley (2004) find no statistically significant differences in final price when a sniping strategy is pursued.

Elfenbein and McManus (2007) is one of very few studies to analyze sniping in charity auctions. In their comparison of eBay charity and non-charity auctions, they find significantly less last-minute bidding in auctions in which 100% of the proceeds are given to charity. Bajari and Hortacsu (2004) cite the unpublished finding in Ku, Malhotra, and Murnaghan (2003)
that there is a low frequency of sniping in online charity auctions and no evidence that fixed-deadline auctions cause more sniping than soft-ending ones. These results suggest that some of the justifications for sniping may not apply in the case of charity auctions (e.g., “tacit collusion” to lower seller revenue).

We also investigate the phenomenon of bidding more than one’s value, which we call “soaring.” Aside from the literature beginning with Kagel et al., (1987) of second price for-profit auctions, there is not much discussion of bidding over one’s value because this always leads to bidder losses in for-profit auctions. The same is true of the behavior we call “stumbling” which happens when bidders stop before they reach their values and possibly “leave money on the table.” However, as mentioned above, soaring bidders do not always lose in charity auctions because even losers receive some revenue proportional benefits or “warm glow”. While there are sometimes strategic reasons to do so in charity auctions, much of the soaring (and stumbling) we observed is, we believe, behavioral.

Since most of the studies rely on evidence from online auctions, very little is understood about the socioeconomic determinants of jumping, sniping, squatting, soaring or stumbling; that is, are men more likely to jump bid than women? Are competitive people more prone to sniping or squatting? Do risk loving people soar more or stumble less? Our experimental design allows us to answer these and other questions in the context of the silent charity auction. Our design also allows us to test for endogenous participation, an important contribution as will be seen below.

3 Experimental Design

This paper draws on data from a large scale laboratory experiment of charity auctions conducted at both Middlebury College and University of Massachusetts at Amherst. Subjects were recruited via email, posters and newspaper ads and included students, faculty, staff and community members. Table 1 provides the descriptive statistics for the subjects. The average age is 24 (although the range was 18 – 75), 53% of the subjects are male and 74% report “white” as their ethnicity. Less than 10% of the subject pool reported having participated in ten or more auctions (profit or non-profit). Not surprisingly, the sample pool appears to be risk neutral; the average subject reported themselves as a 5 on a scale of 1 – 10 with 1 being someone unwilling to take risks, and 10 being someone willing to take risks. The typical subject sees himself or herself as slightly competitive, reporting a mean of 6.13 on
a scale of 1 – 10 (with 10 being most competitive). On average, subjects answered two out of three questions correctly on a quiz designed to test numeracy in the specific context of the auction. Approximately 80% of the subjects are classified as “impatient” in the sense that in more than half the periods, they spent three seconds or less on the computer screen that provided a summary of the auction results or the screen that asked them to report the ease with which they could solve a puzzle of given difficulty. Lastly, despite predictions from rational choice theory about the irrelevance of sunk costs, roughly one-quarter of the subjects in this experiment considered sunk costs in their hypothetical decision-making.2

Three variations of the silent auction were tested in the lab and compared to the English button. The first treatment (Standard Silent) mimics the traditional silent auction in which bidders openly observe all bids and may submit bids at any time until the close of the auction. The second treatment (No Limit) reduces the effectiveness of sniping by extending the end time by 30 seconds every time a bid is submitted while the third treatment (Time Constraints) attempts to capture the fact that some participants are unable to stay until the bitter end by randomly assigning different end times to auction participants. We conducted five sessions per treatment with ten subjects attending each 1.5 hour session. There were ten periods in each session, providing fifty revenue observations per treatment and over five hundred bid observations per treatment because subjects in the silent auctions could submit more than one bid per period.

In all three treatments, subjects were provided a comprehensive set of instructions and ample time to read and ask questions.3 Prior to the start of the first period, subjects were asked to complete a short quiz designed to test basic numeracy and comprehension skills. At the conclusion of the quiz, participants were shown the answers to ensure proper understanding of the rules of the experiment. The experiment then proceeded in two phases. In phase one, subjects were asked to complete a series of word scrambles, similar in spirit to Gneezy, Niederle and Rustichini (2003) and Hoff and Pandey (2003). This “endowment phase” allowed us to partially attenuate the effects of unearned income (i.e., playing with house money). Subjects were paid a piece rate of one dollar (or 10 Experimental Monetary

2For the sake of brevity we sketch the experiment and direct the reader to Carpenter, Holmes and Matthews (2008b) (available at http://community.middlebury.edu/~jcarpent/papers/CAitEL.pdf) which provides a detailed description of the experimental procedures. Subjects committed the sunk cost fallacy if they answered “No” to the hypothetical movie ticket question and answered “Yes” to the Montreal weekend question.

3Sample instructions appear at the end of Carpenter, Holmes and Matthews (2008b).
Units, EMUs) per correct response and the scramble difficulty, piece rate and time limits were calibrated to generate a mean endowment (which was replenished at the beginning of each round) of about 150 EMUs with low variance. In other words, we wanted participants to feel as if they had earned their endowments but we did not want to introduce the latitude for endowments to matter much. Table 1 indicates a mean endowment of 139 EMUs with a standard deviation of 17.

Once the endowment phase concluded, the silent auctions with endogenous participation commenced. Each period, subjects were randomly assigned a private value in the interval [0, 100] and then asked if they wished to participate in an auction for a fictitious good. Subjects who chose not to participate could solve another word scramble for a piece rate of 15 EMUs per right answer. It is important to note that subjects were also told the level of scramble difficulty (on a scale of 1–5) at the time of the participation decision; this difficulty measure allows us to identify selection separately from bidding in the empirical analysis since puzzle difficulty likely affects the decision to participate but should not influence one’s bid amount. The random sequence of puzzle difficulties was set at the beginning of the experiment and was common to all sessions.

For those who chose to enter, the environment was such that the auction winner earned a surplus of the difference between this participant’s value and his or her bid. In addition, to induce the incentives common to the theoretical models of charity auctions reviewed above, all participants, regardless of whether they chose to bid in the auction or do the word scramble earned “revenue proportional benefits”. Specifically, a benefit equal to 10% of the final revenue was added to the payoff of every subject. On top of this, all bidders who ended up forfeiting their bids (in this case only the winner) earned an additional 5% on their bid amount as warm glow. Hence, because participants can bid up to 115% of their value and still earn surplus, we should see “overbidding” in equilibrium. In fact, across formats bidding up to 115% of one’s value dominates stopping before this point. Hence, for our purposes, “soaring” is defined as bidding more than 115% of one’s induced value.

The last two columns of Table 1 summarize auction-level data on revenue and bidder characteristics for both active and inactive participants. As one might expect, those people with higher values are more likely to enter the auction \((t = 13.89, p < 0.01)\) and, perhaps as a result of “false concensus” bias, we find that active bidders expect more competition in the auction than inactive puzzle solvers \((t = 17.69, p < 0.01)\). Other differences in Table 1
reflect selection pressures. It seems, for example, that active bidders in the silent auctions were more competitive (though not significantly), more risk tolerant \((t = 1.91, p = 0.06)\) and more impatient \((t = 2.90, p < 0.01)\), characteristics we explore in more detail in the next section.

4 The Behavior of Individual Bidders

At the individual level, we focus on participation and the five bidding behaviors - the propensities to jump, snipe, squat, soar and stumble - described above. An overview of these results is presented as Table 2. As one can see, participation is highest in the Standard silent auction (56%), lowest in the Time Constraints treatment (50%) and, although there are other differences, this is the only one that is significant \((t = 1.80, p = 0.07)\) when comparing summary frequencies. Because the first three bidding strategies were only possible in the silent auctions, we focus on these differences. Jumping is more prevalent in the Time Constraints treatment than the Standard, as we expected \((t = 1.75, p = 0.08)\) and, because there are no differences in the frequency of squatting which can only be interpreted as an attempt at intimidation, we have our first bit of evidence that jumping is used to “telescope” time. Our other prior is also confirmed in that we see significantly less sniping in the No Limit treatment than in either the Standard or the Time Constraints treatments \((t = 4.18, p < 0.01; t = 4.49, p < 0.01,\text{ respectively})\).

Soaring and stumbling could occur in all four formats and we do see significant differences between the silents and the English. While the differences among the silents are not significant, each silent format is itself significantly less likely to elicit soaring than the English \((p < 0.01\) in each case). Consistent with the soaring results, there is correspondingly more stumbling in the silents than in the English \((p < 0.01\) for all comparisons). Lastly, there also appears to be more stumbling in the Standard silent than the other silent formats \((p < 0.01\) for all).

To conduct a more thorough examination of individual behavior we estimate each bidding behavior as a probit with selection, using “puzzle difficulty” for identification. We compare these behaviors for just the three silent mechanisms, since, as mentioned above the first three aren’t possible in the English auction, in which an auctioneer dictates the pace of bidding.

The first column of Table 3 reports the estimated marginal effects, evaluated at the means, for participation. The most important of these is that even with a host of controls in place,
individual bidders are 7.6% less likely to participate in the Time Constraints treatment, and
5.8% less likely to participate in the No Limit, than the Standard, and that these effects are
significant at better than the 5% level. Consistent with our own previous work (Carpenter,
Holmes and Matthews 2008a), participation in these auctions is not just endogenous but
mechanism-specific. To the extent that the Standard can be reframed as a multiple unit
auction in which bidders are able to bid on each item until the end, this suggests that charities
and other non-profits could, if nothing else, increase interest by staggering deadlines.

The effect of variation in private value is also significant and consistent with previous
theoretical and empirical work on endogenous participation (Menezes and Monteiro 2000;
Carpenter, Holmes and Matthews 2009): a bidder whose induced value was 10 EMUs higher
than another, for example, is estimated to increase the likelihood of participation 7.0%.

Our design also allows us to identify a number of behavioral influences on the participation
decision. Bidders were asked to predict the number of auction participants at the start
of each period and, as expected participation rises by one bidder, for example, the likeli-
hood that an individual bidder participates rises by 5.6%, an effect that is also statistically
significant at better than the 1% level. Furthermore, this effect manifests itself even as puzzle
difficulty is estimated to have a strong and predictable positive effect on participation.
Because conventional wisdom holds that individuals who expect more participants should
conclude that their own expected benefits of participation are lower, the result seems almost
anomalous, evidence, perhaps, that the “thrill of the race” matters, too.

It seems that our measure of numeracy matters, too: while the mean respondent answered
(about) 2 of our 3 pre-auctions test questions correctly, we estimate that someone who
answered all three correctly is 5.8% less likely to participate. There are several possible
explanations, but the simplest, perhaps, is that because “smart bidders” were also better at
word scrambles, it costs them more to participate in the auction, even controlling for puzzle
difficulty.

Impatience exerts an even more dramatic effect, however. We find that impatient bid-
ders are 16.8% more likely to participate in auctions, a large effect in both the economic and
statistical (p < 0.01) senses. It is tempting to interpret both this and the expected participa-
tion effect in terms of the propensities of “hot” bidders first to join and then compete.
Once more, however, this increased participation is primarily beneficial to charities to the
extent that it leads to increased revenues but if so, it is reasonable to wonder whether this
“excited state” can be induced. It is sometimes said, for example, that silent auctions do better when there are complementary activities available.\(^4\)

While not statistically significant at the 10 percent level, the estimated effects of two other behavioral characteristics call for discussion. There is some evidence \((p = 0.22)\) to corroborate our “hot” bidder conjecture that it isn’t just impatient bidders, but competitive ones, who are more likely to participate, ceteris paribus. The effect is not a large one, however: someone who ranked herself as “most competitive” \((10\) on a scale from \(1\) to \(10\)) is predicted to be \(3\) \((= 4 \times 0.74)\) percent more likely to bid than the mean participant, who scored about \(6\). The more intriguing result is that subjects that we classified as sunk cost sensitive on the basis of their survey results were \(9.4\%\) less likely to participate, and that this large effect cannot be written off \((p = 0.16)\) even if the null hypothesis of no effect can’t be rejected at the 10 percent level.

The second column in Table 3 reports the estimated marginal effects for the possible determinants of jump bidding, controlling for selection into the auction. Jump bidding is defined here as bidding at least \(10\) EMUs more than the previous bidder in a period, where the minimum bid increment is \(0.10\). We note in passing that in the case of jumping, at least, there isn’t much evidence of selection bias \((\chi^2 = 0.12, p = 0.72)\).\(^5\) Instead of intimidation as a motive, the evidence suggests that bidders jump in order to “telescope time”. Recall that the Time Constraints treatment was constructed to test whether having less time to spend in the auction (and therefore not necessarily being around at the end) is a cause of jumping. Consistent with this hypothesis, the coefficient on the Time Constraints indicator in column (2) is positive - participants are \(5.3\%\) more likely to jump in this treatment compared to the Standard. However, the point estimate is not significant. At the same time, the Time Constraints estimate is significantly larger than the No Limit estimate \((p < 0.01)\) suggesting that there is more jumping in the former. In addition, testing for pure treatment differences may be too restrictive. Because of the random assignment of time limits in the Time Constraints treatment, some of the participants were assigned time limits very close to those in the other two treatments and therefore should have behaved similarly. It is therefore only participants with more restrictive limits that had reason to jump. Indeed, if we restrict the Time Constraints sample to those with limits less than \(100\) seconds (the participants in

\(^4\)See, for example, stepbystepfundraising.com.

\(^5\)Despite the fact the participation is endogenous, we do not find much evidence that it biases our behavioral estimates. However, because it does seem to matter for sniping in column 4, we chose to be conservative and control for selection in each case.
the other treatments had up to 120 seconds) we find a much stronger result: those with real
time constraints are 18% more likely to jump ($p = 0.02$) than in the baseline.

There is also considerable evidence to support the view that jumping is a behavioral, as
opposed to institutional, phenomenon. In particular, we find that, controlling for participa-
tion and other characteristics, competitive and impatient bidders are much more likely to
jump. Very competitive bidders, for example, those who reported themselves to be a “10”
on our competitive index, are estimated to be $8(= 4 \times 2)$ percent more likely to jump than
the mean bidder and the hypothesis that that there is no difference can be rejected at better
than the 5 percent level. Furthermore, a bidder classified as impatient is also 8% more likely
to jump, with a $p$-value of 0.029. And since impatience and competitiveness are themselves
positively correlated, our results continue to paint a picture of “hot” bidders more prone to
jump bid across mechanisms.

Impatience and competitiveness aren’t the only bidder characteristics that matter. High
value bidders, for example, are also prone to jump bid which might also be interpreted as a
desire to telescope. This said, the effect, while statistically significant at any level ($p < 0.01$),
isn’t all that meaningful: a 10 EMU difference in private values is estimated to increase the
likelihood that a bidder ever jumps just 4 percent. Lastly, it seems that “white men (and
women) can jump”: in fact, for reasons that aren’t obvious to us, white bidders were almost
10 percent more likely to have jumped at least once in a period.

The third column in Table 3 reports the estimated marginal effects for the particular
form of jumping known as squatting, defined here to be an initial bid of at least 10 EMUs.
There is no evidence that squatting is any more common under one format than another:
both treatment effects are small and statistically insignificant (in both cases, $p > 0.80$).
Competitive bidders, on the other hand, aren’t just more likely to jump once bidding is
underway but also out of the gate. Our most competitive subjects were $3.2 = (4 \times 0.8)$
percent more likely to have squatted at least once compared to their average counterparts.
And it isn’t just the competitiveness of bidders themselves, but the prospect of competition,
that causes them to squat: each additional expected bidder increases its likelihood 0.6%, and
the effect is significant at the 1 percent level. In a somewhat similar vein, high value bidders
tend to jump, both at the start ($p = 0.08$) and, as seen earlier, in the midst of an auction.
However, as in the case of column (2), the magnitude of the effect is small. In contrast,
high endowment bidders are less likely to squat: for bidders whose endowments differ by,
say, 10 EMUs, the difference in propensities is about 1 percent, and is almost, but not quite, significant at the 10 percent level. The simplest explanation for this is that, controlling for value, high endowment bidders are less concerned about “bidding wars” and therefore less tempted to try to “thin the herd.”

With some qualification, the similarities between jumping and squatting extend to “cold” bidders. A bidder who scored one better on the (three point) numeracy test, for example, is estimated to be 1.6% \((p = 0.24)\) less likely ever to squat, for example, while one with experience is 2.2% \((p = 0.16)\) less likely.

The estimated marginal effects on the likelihood that a bidder will be classified a sniper are listed in the fourth column. The definition of sniping is to some extent mechanism-specific. In the Standard format, a bidder is said to snipe if her only bid occurs in the final five seconds of the auction. In the Time Constraints, sniping occurs if one’s only bid is submitted in the final five seconds of that subject’s allowed submission time. In the No Limit, it occurs if the subject’s only bid occurs in the final five seconds whether or not the clock is reset. We first note that this is the one behavior in which selection matters \((\chi^2 = 4.76, p = 0.03)\). It comes as little surprise that under the No Limit format, the likelihood that someone will submit just one bid and not do so until the current clock has almost expired is much lower, or that this treatment effect is significant at better than the 1 percent level. There seems to be little difference in the likelihood of such behavior between the Standard and Time Constraints mechanisms, however.

There is some evidence, consistent with earlier research, that it is experienced or “cold” bidders who are most tempted to snipe: subjects who were classified as experienced were 2.5% \((p = 0.08)\) more likely to do so, a very large effect when one recalls that only 1.1% of all bidder-rounds meet our criterion for sniping. While the effect is small, but statistically significant, this might also explain the apparent willingness of high endowment bidders to wait. It is harder, however, to explain the qualitatively similar behavior of high value bidders.

The fifth column in Table 3 contains estimated marginal effects for soaring, or the likelihood that controlling for participation, a bidder bids more than 115% of his or her private value, behavior exhibited by one in ten of our bidders. As one might expect, it seems that “cold” bidders with more experience and higher numeracy, were more reluctant to cross this threshold. In particular, experienced bidders were 10.3% \((p = 0.03)\) less likely to do so - and therefore almost never did - while those who scored the maximum 3 points rather than the
mean 2 on our simple test were 5% ($p < 0.01$) less likely to bid more than 115% of their value. Consistent with our characterization of participants as either “hot” or “cold”, the one sort of bidder who is more likely to bid more than his or her own value is the impatient one, and the difference is significant in both the economic (9.7%) and statistical ($p = 0.011$) senses.

The last behavior that we consider in column (6) occurs when bidders withdraw from the auction before they bid up to their values. In other words, they stumble before getting to their values. Because there tends to be more stumbling in auctions in which other bidders jump or squat, this behavior may be the result of intimidation (intended or otherwise). In any case, these bidders give up prematurely. Clearly stumbling can only be bad for revenues and because it happens far less often in the No Limits treatment (15% less often, $p = 0.04$), there is more reason to believe that removing firm ending times can help revenues. It appears that “cold” bidders are significantly more likely to stumble. Those with more experience are 20% more likely ($p < 0.01$) and those who correctly solve one more numeracy question are 5.1% more likely to give up early ($p = 0.02$). At the same time bidders who are “hot” in the sense that they are impatient are 16% less likely to stumble ($p < 0.01$).

Our individual level data is rich. At the level of the treatments, not only do we find significant and large participation effects, we find that our treatments generate the intended effects: randomly reducing one’s time in the auction induces significantly more jump bidding and extending the endpoint of the auction significantly reduces sniping. In addition, our unique survey has provided evidence that allows us to compare two types of bidders in silent auctions. “Cold” bidders who are more experienced and numerate tend to participate less, soar less and snipe and stumble less. These bidders will be bad for revenue. By contrast, “hot” bidders who are more competitive and impatient than the rest, participate more, jump more both at the beginning of the auction and during it, and are more likely to bid more than their value and are less likely to be intimidated and give up.

5 Revenue

For charities and non-profits, the salient question is how the behavior described in the previous section affects revenues. To begin the discussion, Table 4 indicates that mean revenues under the No Limit mechanism (77.68) in which sniping and stumbling are reduced are close to those in the English benchmark (78.38) and exceed those under both the Standard
(69.09) and Time Constraints (71.93) mechanisms where participation is highest and jumping is more frequent, respectively. One’s initial impression then is it appears that if the costs of switching to the English format are not too substantial, charities might be better off doing so. However, it is not quite that simple. Given the substantial within-mechanism variation in revenue, for example, it is not obvious how significant these differences are. The variance of revenues isn’t just large, for example, but mechanism-specific: the null hypothesis that variance under any silent format is equal to that under any other format can be rejected at the 1 percent level. All these differences persist, again at better than the 1 percent level, when the nonparametric Kolmogorov-Smirnov test is used.

A brief examination of Figure 1, in which the cumulative distribution functions of revenue are plotted for each of the mechanisms, offers another perspective on these characteristics. For revenues below, for example, 75, the cdfs for the No Limit and English formats lie well below the cdfs for either the Standard or Time Constraints, but for revenues above 100, they lie well above both. Given these patterns it is no surprise that near the median the differences seem much smaller, consistent with the absence of significant differences in means.

At first blush, this seems difficult to reconcile with our previous results on participation: if revenues rise with the number of active bidders, then shouldn’t revenues under the Standard, the most attractive of the three mechanisms to potential bidders, be much higher? An important part of the answer is found in the heterogeneous treatment effects embodied in our data.

Because standard empirical methods can obscure the heterogeneous treatment differences seen in Figure 1, we estimated a set of pooled quantile regressions, and report the results in Table 5. The first column, for example, reports estimates for the 25th percentile for the benchmark model, which includes the Standard, No Limit and Time Constraints indicators, the number of active bidders, the means, over these bidders, of private value and endowment and, not listed, time period fixed effects. Consistent with Figure 1, the No Limit coefficient is positive but small, in both the statistical and economic senses. We estimate that, under rank invariance, the auction that generated 69.50 EMUs under the English rules, the 25th percentile, would have generated 5.29 EMUs more under the No Limit, but cannot reject the hypothesis that revenues would be equal. Under the Time Constraints format, however, revenues at the 25th percentile are predicted to be almost 12 EMUs less than the default English, and this difference is significant at the 5 percent level. Even more striking, we predict
that in otherwise low revenue auctions, the adoption of the Standard silent mechanism in lieu of an English will cost the auctioneer more than 18 EMUs in revenue, a loss of more than 25%. Whether or not there are (also) differences in mean revenues, these differences could well be salient to charities, most of all those which are risk and/or loss averse: while there does not seem to be much downside to switching from an English auction to silent auctions with no fixed end point, the same cannot be said about the adoption of the easier to implement Standard silent auction, and these costs must be weighed against its administrative benefits.

To answer our initial question about participation, however, this does not mean revenues are insensitive to the number of active bidders. On the contrary, each additional bidder is estimated to add almost 10 EMUs of revenue at the 25th percentile, and this effect is significant at better than the 1 percent level. Charities, in other words, must also be mindful of participation effects. The better interpretation of our results is that without the additional 0.22 bidders - the difference between the number of active bidders in the Standard (5.48) and No Limit (5.26) auctions - the difference in their revenues would have been $2.02 = 9.18 \times 0.22$ EMUs larger still. Our results also imply, however, that had the Time Constraints format not discouraged 0.24 = 5.26− 5.02 bidders relative to the No Limit, the revenue difference would have been $2.20 = 9.18 \times 0.24$ smaller.

There is also a significant ($p < 0.01$) and substantial “private value effect”: as the mean value of active bidders increases 1 EMU, revenues rise about two thirds (0.68) of an EMU. This outcome reflects the operation of one direct and several indirect pressures. The direct effect follows from the simple observation that high value bidders are prepared to bid more. The indirect effects reflect that the fact that high value bidders are also more likely to jump, squat, snipe and stumble, and less likely to soar. Last, we note that, as hoped, the mean endowment of bidders has no discernable effect on revenues.

The median regression estimates reported in the second column of Table 5 validate the empirical approach adopted here. As in low revenue auctions, there is no discernable “pure treatment loss” in the median auction when the No Limit format is substituted for the default English. But there is also no loss associated with the Time Constraints format now, suggesting that any problems associated with it are limited to, or exacerbated in, otherwise low revenue settings. In contrast, there is still a substantial cost associated with

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6To complete the picture, it is also the case that the No Limit format performs significantly better than the Standard or the Time Constraints ($p < 0.01$ in both cases). At the same time, the Standard and Time Constraints estimates do not appear to differ significantly at the 25th percentile.
use of the Standard (−15.75, \( p < 0.01 \)) mechanism. Given the unconditional differences in median revenue - the No Limit produced 82 EMUs, about the same as the English (80) and considerably more than the Time Constraints (75) or Standard (67) - and the continued significance of the coefficient on mean private value (0.613, \( p < 0.01 \)), it seems reasonable to conclude that the relative success of the median or representative No Limit auction owes much to the presence of a disproportionate number of high value bidders.

The final column of Table 5, which contains the estimates for the model at the 75th percentile, again corresponds nicely to the unconditional differences embodied in Figure 1. Despite the 75th percentile appearing to be the point in the distribution where the treatment effects are the most homogeneous, there is some evidence that the relative performance of mechanisms is reversed at the top of the distribution. Although none of the treatment effects is statistically significant at the 10 percent level, the No Limit coefficient flips substantially negative, the Time Constraints coefficient is now substantially positive and they are significantly different at the 8 percent level.\(^7\)

Consistent with the intuition that high revenues in silent auctions are often the outcome of bidding wars in which values become less important and wealth becomes more important, the private value effect is a little smaller, and less significant (0.608, \( p = 0.07 \)) while the endowment effect is considerable larger (0.22) if still insignificant.

We summarize the evidence of heterogeneous treatment effects in Figure 2, which plots the mechanism coefficients and their 95% confidence intervals between the 10th and 90th percentiles based on the benchmark specification. The No Limit produces a substantial positive effect at low revenues and a substantial negative one at high revenues, while the Time Constraints produces no real effect at low revenues and a negative one at high revenues.

6 Linking Bidding Behavior to the Revenue Differences

In previous sections, we hinted how some of the bidding behaviors described in more detail in Section 3 could impact revenues in silent auctions. In this section, we use two methods

\(^7\)The 75th percentile as the third point of comparison was chosen mostly for symmetry. If one looks at the 90th percentile instead, the evidence for the reversing of the relative performance of the formats is stronger. Here the Standard coefficient becomes large and positive and the Time Constraints coefficient becomes significantly positive (\( p = 0.03 \)). Further, the No Limit estimate is significantly different than both the Standard and the Time Constraints treatments (\( p < 0.05 \) in both cases).
to characterize this important link. The first is to “aggregate up” and add direct, auction-level, measures of the numbers of jumps, squats, snipes, soars and stumbles to the quantile regressions in Table 5. We are concerned, however, that these measures are endogenous and to this end, we instrument for each with the predictions based on Poisson models of the number of jumps, squats, etc. In addition to assuming that the bidding behaviors depend on the treatments, mean value, mean endowment and the number of participants as in Table 5, we use as instruments, the proportion of bidders who are experienced, mean competitiveness, mean willingness to take risks, mean numeracy, proportion of bidders who are impatient, proportion who are sunk cost sensitive and proportion white, where these are calculated over active bidders in each auction. The exception is whether or not someone squatted at the start of the auction, which we instrument with the predictions from a probit model. We then bootstrapped the standard errors, where we estimated all five behavioral (or first stage) models and the quartile regression for each sample, and report the results, including bias-corrected significance levels, in Table 6.\(^8\)

One of the most important implications of Table 6 is that the number of jumps improves auction revenues across the distribution. With each new jumper, revenues are estimated to rise between 16.1 (at the 25th percentile) and 20.1 (at the 75th percentile) EMUs, with all three effects significant at the 10 percent level or better.

Two other behaviors, the number of those who snipe and soar, are important in both medium and high revenue auctions, but not low revenue auctions. If the proposition that auction revenues rise as more bidders soar seems almost obvious, the data allow us both to confirm this and to estimate the relative size of this effect. With the addition of another soarer, revenues increase 5.0 EMUs \((p < 0.10)\) in the median auction, and 13.7 EMUs \((p < 0.01)\) at the 75th percentile, both substantial effects but smaller than the effects of another jumper.

The adverse consequences of snipers are also predictable - snipers avoid revenue-enhancing bidding wars - but the substantial size of the effect is less so: in the median auction, the presence of another sniper reduces revenues 15.8 EMUs \((p < 0.05)\) while at the 75th percentile, revenues are estimated to fall more than 25 EMUs, enough, in short, to transform an otherwise successful auction into an ordinary one.

\(^8\)Reporting bias-corrected significance levels implies that, in some cases, the apparent z-scores one could calculate from the ratio of the coefficient to the reported standard error do not always correspond to the reported significance.
The addition of a stumbler has a similar effect on revenues across the distribution but only in the median auction, where it is estimated to reduce revenues 6.1 EMUs, is the effect significant at the 10 percent level or better. There is little evidence, however, that the presence of a squatter exerts a significant effect on revenues.

There are two other important conclusions that can be drawn from Table 6. The first is that the addition of bidder behaviors has a substantial effect on treatment point estimates at all points of the revenue distribution. In low and medium revenue auctions, while the Standard coefficient decreases, the Time Constraints and No Limit coefficients decrease even more, leaving all three close in both value and significance. In short, it appears that the differences in revenue across silent auction formats can be explained in terms of mechanism-specific differences in the behaviors we focus on. The situation is more complicated in high revenue auctions, where the treatment coefficients aren’t similar even if none is statistically significant at any reasonable level. The second has more important practical implications. Once we control for the effects of various behaviors on revenue, all of the silent formats are less productive than the English baseline, especially in low and medium revenue auctions, with shortfalls equal to a third or more of average revenue.

Our second, more conservative, approach to the link between behavior and revenue is to estimate “reduced form quantile regressions” in which we add our various demographic and behavioral measures directly to the models in Table 5. The results are collected in Table 7.9 Our two main results are affirmed: relative to Table 5, the point estimates on the treatment indicators in Table 7 are much closer, None of the treatment differences significant at standard levels in Table 5 remain significant in Table 7. In other words, our demographics and behavioral propensities help to explain bidding strategies which, in turn, help explain the treatment differences in revenue among the silent auctions. Further, the observation that the Standard coefficient is not much affected, in size and significance, hints that whatever the effects of jumping, squatting, sniping or stumbling on low revenue auctions (soaring is not likely to be an important feature of such auctions) the poor performance of the Standard format owes (mostly) to something else.

The bottom of Table 7 returns our attention to the connections between behavioral propensities, bidding strategies and revenues. An increase in the number of experienced

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9With many fewer degrees of freedom, our revenue regressions are more parsimonious than our individual behavior regressions. In particular, the proportion male and mean age, neither of which is significant at any percentile, were dropped.
bidders, for example, produces a dramatic effect on revenues. Consider an auction with six active bidders, one of whom is experienced. The addition of a second experienced bidder, an increase in the fraction of experienced bidders from 0.167 to 0.333, a difference of 0.167, is estimated to contribute an additional $9.52 = 0.167 \times 57.20$ EMUs revenue at the 25th percentile, an effect that is statistically significant at the 1 percent level and increasing as one moves up the distribution of revenues.\(^{10}\) Clearly the effect of experienced bidders is negative because (recalling Table 3) with experience comes more sniping and stumbling and less soaring, all of which result in lower revenues according to Table 6.

On the other hand, despite the importance of the other “cold” characteristic, numeracy, as a predictor of soaring and stumbling, is economically but not statistically significant in middle and high revenue auctions.

There is less evidence in Table 7 that “hot characteristics” also matter. One explanation could be that some of these characteristics have multiple effects on revenue, not all of which operate in the same direction. Competitiveness, for example, fosters not just jumping, which tends to increase revenue, but also squatting, which, if anything, reduces it. In this case, the “tug of war” is only resolved at the median, where competitiveness has a significant effect on revenue. The strong effects of impatience on jumping, soothing and stumbling evident in Table 3 - and, in turn, the effects of at least jumping and soaring in Table 3 - are harder to reconcile with its low statistical significance in Table 7: revenues should increase but the coefficient is only positive at the 75th percentile.

For the opposite reason, the effects of sunk cost sensitivity are perhaps even more striking. Low revenue auctions in which more bidders are prone to “cry over spilt milk” tend to do worse than auctions with more “rational” bidders. Consider, once more, an auction with six active bidders, but suppose now that one of them is sunk cost sensitive. Holding the number of active bidders fixed, the addition of a second sunk cost sensitive bidder would increase their proportion from 0.167 to 0.333, a difference of 0.167, and would cause revenues to fall $7.75 = 46.41 \times 0.167$ EMUs at the 25th percentile, a substantial impact in both the economic and statistical ($p < 0.01$) senses. The question is, why? Our results on individual behavior don’t provide much guidance: the sunk cost sensitive are somewhat less likely to participate ($p = 0.15$) or stumble ($p = 0.18$), but none of these effects was significant at the 10 percent level. One explanation, as well as another rationale for our reduced form specification, is

\(^{10}\)The Proportion Experienced coefficient just misses statistical significance at the 75th percentile ($p = 0.12$).
that these characteristics are associated with behaviors we have not catalogued.

7 Conclusion

Our results provide fresh perspective on an important, if understudied, economic institution, the silent auction. Not only does our experiment confirm the importance of differential participation in the lab, it also illuminates the determinants of different bidding strategies in silent charity auctions and the importance of these behaviors for fundraising. From a broader perspective, however, we also see this work as a contribution to two broader literatures. The first is concerned with what Crawford et al (2009) call “behavioral auction theory,” itself an example of “behavioral mechanism design”. While the focus of Crawford et al are the effects of cognitive limits, our own includes, but is not limited to, the role of various “hot” and “cold” behavioral tendencies. The second is the extension of the principles of mechanism design, behavioral or otherwise, to the non-profit and, in particular, philanthropic sector. Given its importance in the current economic environment, this research is more important than ever.

8 References


Economic Inquiry, 43(4), pp. 715-33.


9 Tables and Figures

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Table 2: Participation and Bidding Overview

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<td>(0.021)</td>
<td>(0.014)</td>
<td>(0.005)</td>
<td>(0.017)</td>
<td>(0.022)</td>
</tr>
<tr>
<td><strong>I(Impatient)</strong></td>
<td>0.168***</td>
<td>0.080**</td>
<td>0.008</td>
<td>-0.007</td>
<td>0.097**</td>
<td>-0.160***</td>
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<tr>
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<td>(0.064)</td>
<td>(0.037)</td>
<td>(0.021)</td>
<td>(0.010)</td>
<td>(0.038)</td>
<td>(0.060)</td>
</tr>
<tr>
<td><strong>I(Sunk Cost Sensitive)</strong></td>
<td>-0.094</td>
<td>0.038</td>
<td>-0.014</td>
<td>0.005</td>
<td>-0.020</td>
<td>0.073</td>
</tr>
<tr>
<td></td>
<td>(0.066)</td>
<td>(0.075)</td>
<td>(0.017)</td>
<td>(0.005)</td>
<td>(0.044)</td>
<td>(0.054)</td>
</tr>
<tr>
<td><strong>I(White)</strong></td>
<td>0.066</td>
<td>0.098*</td>
<td>0.017</td>
<td>0.007</td>
<td>0.087**</td>
<td>-0.141***</td>
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<tr>
<td></td>
<td>(0.052)</td>
<td>(0.051)</td>
<td>(0.013)</td>
<td>(0.005)</td>
<td>(0.036)</td>
<td>(0.040)</td>
</tr>
<tr>
<td><strong>Puzzle Difficulty</strong></td>
<td>0.101**</td>
<td>0.000</td>
<td>0.000</td>
<td>0.000</td>
<td>0.000</td>
<td>0.000</td>
</tr>
<tr>
<td></td>
<td>(0.041)</td>
<td>(0.000)</td>
<td>(0.000)</td>
<td>(0.000)</td>
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</tbody>
</table>

Specifications include Male, Age, UMass and time period fixed effects; (standard errors) clustered on session. * p<0.10, ** p<0.05, *** p<0.01.
<table>
<thead>
<tr>
<th>Format</th>
<th>Revenue</th>
<th>Std. Dev.</th>
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<td>English</td>
<td>78.38</td>
<td>32.77</td>
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<tr>
<td>Standard Silent</td>
<td>69.09</td>
<td>36.92</td>
</tr>
<tr>
<td>Time Constraints</td>
<td>71.93</td>
<td>41.78</td>
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<tr>
<td>No Limit</td>
<td>77.68</td>
<td>22.11</td>
</tr>
<tr>
<td>Overall</td>
<td>74.27</td>
<td>34.14</td>
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</table>

Table 5: Quantile Revenue Regressions

<table>
<thead>
<tr>
<th>Format</th>
<th>(1) Q(25)</th>
<th>(2) Q(50)</th>
<th>(3) Q(75)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Standard</td>
<td>-18.467***</td>
<td>-15.748***</td>
<td>-11.000</td>
</tr>
<tr>
<td></td>
<td>(5.889)</td>
<td>(5.472)</td>
<td>(11.945)</td>
</tr>
<tr>
<td>Time Constraints</td>
<td>-11.984**</td>
<td>0.052</td>
<td>11.669</td>
</tr>
<tr>
<td></td>
<td>(5.681)</td>
<td>(5.514)</td>
<td>(11.872)</td>
</tr>
<tr>
<td>No Limit</td>
<td>5.292</td>
<td>-0.960</td>
<td>-8.092</td>
</tr>
<tr>
<td></td>
<td>(5.639)</td>
<td>(5.417)</td>
<td>(11.255)</td>
</tr>
<tr>
<td>Mean Endowment</td>
<td>-0.082</td>
<td>0.071</td>
<td>0.217</td>
</tr>
<tr>
<td></td>
<td>(0.146)</td>
<td>(0.177)</td>
<td>(0.263)</td>
</tr>
<tr>
<td>Mean Private Value</td>
<td>0.679***</td>
<td>0.613***</td>
<td>0.608*</td>
</tr>
<tr>
<td></td>
<td>(0.171)</td>
<td>(0.145)</td>
<td>(0.338)</td>
</tr>
<tr>
<td>Number of Active Bidders</td>
<td>9.183***</td>
<td>6.499***</td>
<td>8.475**</td>
</tr>
<tr>
<td></td>
<td>(1.567)</td>
<td>(1.432)</td>
<td>(3.401)</td>
</tr>
<tr>
<td>Constant</td>
<td>-19.256</td>
<td>-4.406</td>
<td>-20.977</td>
</tr>
<tr>
<td></td>
<td>(17.960)</td>
<td>(25.179)</td>
<td>(36.967)</td>
</tr>
<tr>
<td>Observations</td>
<td>195</td>
<td>195</td>
<td>195</td>
</tr>
</tbody>
</table>

Include time period fixed effects; (standard errors).
* p<0.10, ** p<0.05, *** p<0.01.
<table>
<thead>
<tr>
<th></th>
<th>(1)</th>
<th>(2)</th>
<th>(3)</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Q(25)</td>
<td>Q(50)</td>
<td>Q(75)</td>
</tr>
<tr>
<td>Standard</td>
<td>28.431**</td>
<td>-23.903**</td>
<td>-2.785</td>
</tr>
<tr>
<td></td>
<td>(16.758)</td>
<td>(15.578)</td>
<td>(21.857)</td>
</tr>
<tr>
<td>Time Constraints</td>
<td>-34.488*</td>
<td>-28.096</td>
<td>-13.624</td>
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<tr>
<td></td>
<td>(22.077)</td>
<td>(21.148)</td>
<td>(24.550)</td>
</tr>
<tr>
<td>No Limit</td>
<td>-25.434</td>
<td>-29.990**</td>
<td>-26.464</td>
</tr>
<tr>
<td></td>
<td>(21.803)</td>
<td>(17.005)</td>
<td>(20.393)</td>
</tr>
<tr>
<td>Mean Endowment</td>
<td>-0.118</td>
<td>-0.072</td>
<td>0.162</td>
</tr>
<tr>
<td></td>
<td>(0.325)</td>
<td>(0.298)</td>
<td>(0.322)</td>
</tr>
<tr>
<td>Mean Private Value</td>
<td>0.857***</td>
<td>1.006***</td>
<td>0.735***</td>
</tr>
<tr>
<td></td>
<td>(0.227)</td>
<td>(0.218)</td>
<td>(0.241)</td>
</tr>
<tr>
<td>Number of Active Bidders</td>
<td>9.698**</td>
<td>7.261***</td>
<td>5.452**</td>
</tr>
<tr>
<td></td>
<td>(4.386)</td>
<td>(3.492)</td>
<td>(4.398)</td>
</tr>
<tr>
<td>Number who Jump</td>
<td>16.049*</td>
<td>19.231**</td>
<td>20.106***</td>
</tr>
<tr>
<td></td>
<td>(9.879)</td>
<td>(9.211)</td>
<td>(10.727)</td>
</tr>
<tr>
<td>I(Did Someone Squat)</td>
<td>11.089</td>
<td>11.964*</td>
<td>14.850</td>
</tr>
<tr>
<td></td>
<td>(14.951)</td>
<td>(13.272)</td>
<td>(21.083)</td>
</tr>
<tr>
<td>Number who Snipe</td>
<td>-7.973</td>
<td>-15.791***</td>
<td>-26.029***</td>
</tr>
<tr>
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<td>(9.252)</td>
<td>(10.295)</td>
<td>(17.611)</td>
</tr>
<tr>
<td>Number who Soar</td>
<td>3.752</td>
<td>5.026*</td>
<td>13.696***</td>
</tr>
<tr>
<td></td>
<td>(4.382)</td>
<td>(4.223)</td>
<td>(5.301)</td>
</tr>
<tr>
<td>Number who Stumble</td>
<td>-5.113</td>
<td>-6.081</td>
<td>-7.672</td>
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<tr>
<td></td>
<td>(5.040)</td>
<td>(4.834)</td>
<td>(5.907)</td>
</tr>
<tr>
<td>Constant</td>
<td>-6.238</td>
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<td>2.920</td>
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<tr>
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<td>(48.100)</td>
<td>(44.846)</td>
<td>(51.996)</td>
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</table>

| Observations                  | 195       | 195       | 195       |

Include time period fixed effects; (bootstrapped standard errors clustered on session).

* p<0.10, ** p<0.05, *** p<0.01 based on bias-corrected confidence intervals.
Table 7: Quantile Revenue Regressions, Reduced Forms

<table>
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<tr>
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<th>(1)</th>
<th>(2)</th>
<th>(3)</th>
</tr>
</thead>
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<tr>
<td></td>
<td>Q(25)RF</td>
<td>Q(50)RF</td>
<td>Q(75)RF</td>
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<td>(7.510)</td>
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<td>(14.534)</td>
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<td>(6.663)</td>
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<td>(13.766)</td>
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<td>(7.108)</td>
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<td>0.008</td>
<td>0.139</td>
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<tr>
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<td>(0.219)</td>
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<td>(0.467)</td>
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<tr>
<td>Mean Private Value</td>
<td>0.695***</td>
<td>0.775***</td>
<td>0.578</td>
</tr>
<tr>
<td></td>
<td>(0.181)</td>
<td>(0.125)</td>
<td>(0.363)</td>
</tr>
<tr>
<td>Number of Active Bidders</td>
<td>9.621***</td>
<td>7.515***</td>
<td>7.741**</td>
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<td>(1.855)</td>
<td>(1.210)</td>
<td>(3.843)</td>
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<td>Proportion Experienced Bidders</td>
<td>-57.201***</td>
<td>-70.794***</td>
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<td>(19.847)</td>
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<td>(46.091)</td>
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<tr>
<td>Mean Competitiveness</td>
<td>1.017</td>
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<td>(2.297)</td>
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<td>(3.828)</td>
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<td>Mean Willingness to take Risks</td>
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<td>(3.821)</td>
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<td>(7.714)</td>
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<td>Proportion Impatient</td>
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<td>Proportion White</td>
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</table>

Include time period fixed effects; (standard errors).

* p<0.10, ** p<0.05, *** p<0.01.
Figure 1: Revenue Cumulative Distributions by Format
Figure 2: The Effect of Each Mechanism (Compared to the English) by Quantile