

CHARITY AUCTIONS: A FIELD EXPERIMENT*

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Auctions are a popular way to raise money for charities, but relatively little is known, either theoretically or empirically, about the properties of charity auctions. We conduct field experiments to see which sealed bid format, first price, second price or all-pay, raises the most money. Our experiment suggests that both the all-pay and second price formats are dominated by the first price auction. Our design also allows us to identify differential participation as the source of the difference between existing theory and the field.

Few people appreciate the size of the philanthropic market, the amount of funding that flows through charities, and the time and resources devoted to fundraising activities each year. For example, total giving to charitable organisations in the US in 2004 amounted to nearly \$250 billion (Giving USA 2005) and, according to a survey by Forbes Magazine, 200 major charities spent over \$2.5 billion on fundraising activities in 2001.¹ Despite the obvious size and importance of the market for philanthropy, surprisingly little is known about the fund-raising mechanisms most likely to generate the greatest revenue for non-profit organisations.

A variety of mechanisms are used to raise money for charities or to fund public goods. Secondary schools and religious congregations frequently rely on bakesales and raffles; institutes of higher education often employ student call centres and mass alumni mailings; hospitals host benefit concerts etc. (Andreoni, 2004). Interestingly, many non-profits raise revenue through auctions and, with the success of internet sites like Ebay, the popularity of charity auctions has increased.² The items auctioned vary to a large degree (e.g., local artwork, gift certificates for community services, weekend get-aways, cars etc.), but there are relatively few auction mechanisms that are used with any regularity. One of the most common is the silent auction which corresponds closely to the standard oral ascending (or English) auction in which bids are called out sequentially. The only major difference is that participants write bids down by some pre-specified time instead of calling them out. Considering sealed bids, one may occasionally see the first price auction and to a lesser extent, the second price (or Vickrey) auction implemented. However, all-pay auctions in which participants forfeit their bids regardless of whether they win or lose are rare. We think that we know why.

While the empirical literature remains thin, theory is not silent on the revenue generating properties of different charity auction mechanisms. Our immediate concern in this article is the proposition (Engers and McManus, 2002; Goeree *et al.*, 2005)

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¹ 'What's the Charity Doing with your Money?' 12/09/02.

² Ebay recently set up a special site to promote online charity auctions.

that charities will actually do better with all-pay than any other form of winner pay auction.³ In particular, we report on the results of a field experiment conducted at local (Addison County, Vermont) preschools that allow us to estimate the determinants of individual behaviour and total revenue in three types of sealed bid auctions: the first price, second price and all-pay. We find that the all-pay does not revenue dominate the others and that the principal reason for this is the differential effect of auction format on participation, an important practical consideration in the field.

We are not the first to collect experimental data on individual behaviour and total revenue in auctions for charities but there are, as far as we know, no other studies that compare these three mechanisms in the field and allow for non-participation. For example, Davis *et al.* (2006) conduct a laboratory experiment in which lotteries produce more revenues than English auctions, and find that this result is robust with respect to the distribution of private values, the rate of return on the local public good or repeated play, consistent with the previous work of Morgan and Sefton (2000). Inasmuch as lotteries can be viewed as an inefficient variation of the all-pay mechanism - the bidder who purchases the most tickets becomes the most probable winner - this is consistent with the spirit of Engers and McManus (2002) and Goeree *et al.* (2005). Goeree and Schram (2004) provide more direct support for this result: their experiment, which relies on altruistic private values induced in the laboratory, compares the first price, all-pay and lottery mechanisms, and finds that all-pays revenue dominate lotteries, and that lotteries revenue dominate first price auctions. The difference between the Davis *et al.* (2006) or Goeree and Schram (2004) results and ours, we believe, reflects the existence of a more complicated participation calculus in the field. In Orzen (2003), which Goeree and Schram (2004) cite, lotteries and two variations of the all-pay are compared but, in this experiment, values are common not private.

Considering other field work on for-profit auctions, List and Lucking-Reiley (2000) conduct an experiment in which they auction sports cards in sealed-bid uniform-price and Vickrey auctions. They find no significant difference in revenues across the auction formats. In a similar study, Lucking-Reiley (1999) conducts online auctions of collectible trading cards and finds that the Dutch auction produces 30% higher revenues than the first-price auction while there are no revenue differences between the English and second-price formats. Lastly, Isaac and Schnier (2003) analyse both the efficiency and revenue generation properties of silent auctions conducted in the laboratory and the jump-bidding behaviour observed in three silent auctions conducted in the field. In a related study, Isaac *et al.* (2007) use field data from spectrum licence auctions conducted by the FCC to analyse jump bidding behaviour in ascending auctions.

It is well known that field experiments present a unique opportunity to test both the mathematical and the behavioural predictions of economic models. By creating exogenous variation in a few key variables, researchers are able to exert some control over an experiment conducted in a real world setting. The present study may thus be of general interest to the growing number of economists concerned with testing the

³ That is, the Vickrey (1961) revenue equivalence theorem does not hold in the charity case because bidders obtain additional benefits from the amount of money raised. In second price charity auctions, for example, participants have an additional incentive to increase their bids because the second highest price determines the amount paid by the winner.

robustness of both theoretical predictions and laboratory results in more natural settings. It should be of specific interest to researchers focused on the economics of philanthropy. Lastly, the results of this field experiment should be of practical significance to fundraisers interested in maximising revenue in charity auctions.

Surprisingly, although the theoretical literature on charitable fundraising is rich and well developed (Andreoni, 1989, 1998, 2004), there have been only a handful of field experiments that explore the economics of charity. For example, Landry *et al.* (2006) empirically explore the economics of charity in a door-to-door fundraising field experiment. Both Karlan and List (2006) and List and Lucking-Reiley (2002) conduct direct mail solicitation experiments to examine the relationship between matching gifts and charitable contributions.

In Section 1, we discuss the recent theoretical advances and how they motivate the design of our field experiment. We describe our experimental protocol in Section 2, a protocol that allows us to collect more than the usual amount of data from all potential (that is, active and inactive) bidders. Section 3 summarises the field data and reports our estimates of various revenue and bid functions. We conclude in Section 4 by highlighting the importance of participation as a practical matter by estimating the lost revenues associated with each auction format due to reduced participation.

1. Predictions of the Charity Auction Literature

It should come as no surprise that the predictions of either the Engers and McManus (2002) or Goeree *et al.* (2005) models should be difficult to substantiate outside the experimental laboratory: both assume that private values can be modelled as independent draws from some common distribution, that the number of active bidders is predetermined and known to all, and that each of these otherwise identical bidders is risk neutral. In addition to the revenue proportional benefits that accrue to all the bidders, Engers and McManus (2002) allow winners to experience an additional ‘warm glow’ (Andreoni, 1989).

This said, we are of course interested in whether our field data is consistent with this theoretical literature. Engers and McManus (2002) consider a framework in which these independent private values v are drawn from a distribution with closed support $[\underline{v}, \bar{v}]$, and each bidder receives a benefit α for each dollar the charity collects, with an additional warm glow γ for each dollar that she herself contributes. We start with two predictions about bids:

$$B^S(v) > B^F(v) > B^A(v), \quad (1)$$

and:

$$\frac{\partial B^A(v)}{\partial N} < \frac{\partial B^S(v)}{\partial N} = 0 < \frac{\partial B^F(v)}{\partial N}, \quad (2)$$

where $B^k(v)$ is the optimal symmetric bid function where $k = F$ (irst price), S (econd price) and A (ll-pay) auctions and N is the number of bidders. The order of bids comes as no surprise because ‘run of the mill’ bidders will indeed bid less in the all-pay than either winner-pay although those all-pay bidders with (very) high values will sometimes bid

more than their values (Carpenter *et al.*, 2004). Further, bidders in first-price charity auctions have an incentive to ‘shade their bids’ relative to those in second price auctions, while most all-pay bidders, who fear that their bids will be lost (apart from the returns available to all), shade even more. Likewise, increased competition (N) causes first-price bidders to shade less and most all-pay bidders to shade even more. And like their non-charity counterparts, second price bidders are predicted to be impervious to competition, a result with sharp econometric implications.

To the extent that the effects of an increase in each bidder’s own attachment to the charity (γ) should have more or less the same effect as the subsidisation of bids in standard auctions, one would expect that:

$$\frac{\partial B^k(v)}{\partial \gamma} > 0 \text{ for all } k, \quad (3)$$

and this is indeed what the model predicts, once one controls for the per dollar benefits α that accrue to others. Because we have field data on individual attachment to our charities but no reasonable measures of this common return, we shall assume that this return is uniform across preschools, a plausible restriction in this context.

What are the revenue implications of these results? As long as the common return is positive, it follows that:

$$R^A > R^S > R^F, \quad (4)$$

where the first (but not the second) inequality requires that the number of bidders N exceeds some threshold. Furthermore, as N tends to ∞ , the difference between expected revenues in the first and second price auction tends toward zero. (To be more precise, $\lim_{N \rightarrow \infty} R^A = \bar{v}/[1-(\alpha + \gamma)] > \lim_{N \rightarrow \infty} R^F = \lim_{N \rightarrow \infty} R^S = \bar{v}/(1-\gamma)$.) In practice, the threshold could be quite small. Engers and McManus (2004) show, for example, that when the distribution of private values is uniform over the unit interval, three bidders are always sufficient and, for some parameter values, so are two.

Consistent with intuition, expected revenue rises with the number of bidders actively participating in each mechanism:

$$\frac{\partial R^k}{\partial N} > 0 \text{ for all } k. \quad (5)$$

Because an increase in each bidder’s own attachment to the charity γ produces ‘bid inflation’, it comes as no surprise that revenues will also rise:

$$\frac{\partial R^k}{\partial \gamma} > 0 \text{ for all } k. \quad (6)$$

2. Experimental Procedures

We decided to conduct our experiment in the field after weighing the costs and benefits of doing so. One factor that we considered to be a major benefit of a field implementation was that we were able to identify a population for whom bidding in our auctions would be saliently interpreted as an act of charity. Instead of inducing charitable preferences, as in Goeree and Schram (2003) and Davis *et al.* (2006) in tradi-

tional laboratory participants, we recruited participants who potentially had naturally occurring other-regarding preferences for the beneficiaries of our auctions. At the same time, however, relying on naturally occurring other-regarding preferences means that we did not induce valuations for the items auctioned. At first blush, this appears to be a cost of our field protocol because it hinders the analysis of efficiency, but we felt this cost would be small given other features of our procedures that we detail below.

While plenty of auction experiments have been conducted successfully in the field despite the drawback of not knowing bidder valuations, e.g., Lucking-Reiley (1999) and List and Lucking-Reiley (2000), we advance the literature and partially solve this problem by collecting demographic and attitudinal data from our participants that provides us with many of the correlates of individual private values. To assess the allocative efficiency of our mechanisms we asked, in the case of physical goods, for each participant's maximum willingness to pay for the item in a store and how much they would bid for the same item in a non-charity auction. For gift certificates we could only collect data on how much the bidder would bid in a non-charity auction. Because these data are format-specific, we can only use them to test within-item efficiency where ordinal ranking is what is important. Data on family income serves as our proxy for bidder private values in our estimate of bids. We also gathered information on bidder's attachment to the preschool including the number of child-years (i.e., the total number of years a bidder's child or children will be or have been at the preschool), sex (i.e., females tend to have more exposure to preschool) and recent donations to the preschool as proxies for γ , the measure of individual attachment to the charity.

One major aspect of our design that we consider to be an improvement over past experiments is our focus on participation. In addition to collecting bids, we also had as many of the attendants as possible fill out our survey, regardless of whether they bid on items or not. This survey allows us to control for demographic differences in our populations that may affect bidding behaviour when we test for differences in our auction formats.

Unlike other auction experiments in the laboratory or in the field that only collect positive bids, we collected all the bids, even if they were for \$0. We think this is a subtle, but significant contribution of our field protocol. Our intuition was that subjects come to the laboratory 'ready to play' (Carpenter *et al.*, 2005b) and are, therefore, much less likely to withdraw and not bid in an auction than they would be outside the laboratory in a more natural setting.

2.1. *Our Field Implementation*

Each spring, the preschools in Addison County conduct fund-raising festivals. In the spring of 2003, four of these preschools agreed to augment their festivals with charity auctions that we conducted. These fund-raisers are traditionally attended mostly by parents, other family members, and employees and board members of the schools. This fact implies that most of the attendees had some connection to the school and viewed the money raised by our auction as a public good benefiting their school. Because these auctions were part of the normal spring fund-raising activities of the schools, we consider our implementation to be a *natural field experiment* in which the subjects undertook a familiar task (defined broadly as fund-

Table 1
Auctioned Items and Revenues

Item	Type	Retail Value	First Price Revenue	Second Price Revenue	All-Pay(1) Revenue	All-Pay(2) Revenue
Deli	Gift Certificate	\$10	\$15	\$10	\$0	\$11
Children's Science Book	Book	\$13	\$15	\$15	\$1	\$0
Bakery	Tart	\$15	\$16	\$20	\$62	\$27
Chocolate Making Kit	Craft	\$15	\$15	\$10	\$0	\$1
Craft/Toy Store	Gift Certificate	\$20	\$35	\$25	\$20	\$5
Cadoo Cranium	Game	\$20	\$20	\$15	\$10	\$6
Sports/Clothing Store	Gift Certificate	\$25	\$30	\$30	\$52	\$13
Pizzeria	Gift Certificate	\$30	\$50	\$20	\$5	\$0
Kitchen Store	Gift Certificate	\$40	\$40	\$50	\$110	\$13
Garden Item	Spruce Tree	\$40	\$30	\$45	\$25	\$0
Pewter Item	Picture Frame	\$42	\$25	\$45	\$30	\$19
Restaurant (a)	Gift Certificate	\$50	\$75	\$65	\$104	\$58
Wooden Train Tracks	Toy	\$50	\$30	\$75	\$0	\$46
Performing Arts	Tickets	\$60	\$75	\$75	\$55	\$25
Auto Detailing	Gift Certificate	\$75	\$100	\$100	\$32	\$26
Restaurant (b)	Gift Certificate	\$75	\$125	\$100	\$88	\$40
American Girl Doll	Collectible	\$100	\$90	\$75	\$65	\$153
DVD Player	Electronics	\$100	\$75	\$100	\$10	\$120
Day Spa	Gift Certificate	\$200	\$165	\$100	\$100	\$54
TV/Video Player for Auto	Electronics	\$275	\$200	\$110	\$135	\$40
Totals		\$1,255	\$1,226	\$825	\$904	\$656

raising) in a familiar setting and did not necessarily know that they were participating in an experiment.⁴

2.2. Auction Details

We conducted four sealed bid auctions at four different preschools in the months of May and June. The format of the auction was unknown to the participants before the day of the event. There was one first price auction, one second price auction and two all-pay auctions. We conducted two all-pay auctions because the first price and second price auctions were relatively well attended but our first all-pay auction fell on a rainy day which reduced attendance. Therefore we conducted another all-pay auction at a different preschool to make the overall number of bidders in each format more comparable. While we conducted only four auctions, our sample size, for revenue purposes, is 80 because during each session we auctioned off the same 20 items that varied in retail value. Table 1 provides the descriptions and retail values of the 20 items we sold at each auction. The items vary from children books and games to gift certificates for services that parents typically need (auto detailing) or want (a vacation at a local spa) with retail values varying from \$10 to \$275.⁵ We spent considerable energy deciding on the mix of goods to sell and felt that including variation in the retail value

⁴ See Carpenter *et al.* (2005a) for a more detailed discussion of the taxonomy of field experiments.

⁵ The potential problem with selling gift certificates is that these items might have common value properties. However, we realised that the possibility of a secondary resale market evolving was extremely small and all the certificates were for local services that bidders would have surely formed private values for (e.g., not everyone loves the pizza at our local pizzeria).

and the type of good would not only appeal to a wide variety of bidders, it would also sharpen our subsequent analysis.

The exact procedures we used are as follows. When attendees arrived at the festival they were given a survey (see Appendix B) to fill out. Completed surveys were collected at our auction station. When each attendee was finished with his or her survey, s(he) was given a 'bid kit'. In each bid kit we placed a set of instructions for the auction and cards for each of the 20 items (see Appendix B for an example). Each item was displayed on a table with its retail value and a full description. Participants typically spent twenty or thirty minutes inspecting the items and filling out their bid kits. On each bid card we asked participants five questions in addition to asking them for their bids. We asked them whether they would buy the item in a store and how much they would pay for the item in a store (except for gift certificates), how much they would bid for the item in a for profit auction, the sex of the bidder, and how many people they thought would bid on the item. The first three questions provide us with information on the individual's private value for the item and the last question accounts for anticipated competition. We asked the participants to fill out each bid card completely, even if they decided to bid \$0 for the item.

As they were completed, bidders turned in their bid kits to one of the auctioneers who matched the bid kit number to the bidder's survey and gave the bidder a small slip of paper with the bidder's identification number on it. In each auction there was a predetermined time at which we stopped accepting bids. After this time, we privately sorted the bids into 20 piles and determined the highest (winning) bid for each item. We selected one winning bid at random in the few cases in which there were ties. This process typically took half an hour. When all the winning bids were determined, we gathered the bidders, announced the winner of each item, and collected payments (except in the all-pay auctions where we collected payments when bidders turned in their bid kits). Winning bidders wrote cheques directly to the preschool benefiting from the auction.

3. Experimental Results

Table 2 presents a comparison of the summary statistics by auction. Revenues varied from a low of \$656 in all-pay auction (2) to a high of \$1,226 in the first price format. The number of potential participants varied from 15 in all-pay (1) to 31 in the first price auction. We gathered bids from more attendees in the first price and second price auctions than in both all-pay auctions where participation was more limited. As mentioned above, the turn out for all-pay (1) led us to conduct all-pay (2) which did draw many more attendees, but as one can see in Table 2, participation under a particular auction format is a separate issue from the number of attendees. As we will explore in more detail later, average participation rates, defined as the number of potential bidders who actually submitted a positive bid on a given item, were quite low in the all-pay auctions (about 14%) compared to the second price (39%) and first price (53%) formats. One last comparison worth highlighting involves the socioeconomic status of the auction guests; the proportion of participants in the lowest income bracket was notably higher in all-pay auction (1) (73%) than in any of the other three auctions.

Table 2
Summary Statistics by Auction

Variables	First Price	Second Price	All-Pay (1)	All-Pay (2)
Number of Potential Bidders	31	30	15	21
Average Participation Rate	53%	39%	13%	14%
Total revenue	\$1,926	\$825	\$904	\$656
Average Revenue (dollars)	\$61.3 (52.64)	\$41.25 (25.89)	\$45.2 (42.92)	\$32.8 (40.24)
Proportion of Items Efficiently Allocated	0.50 (0.51)	0.3 (0.47)	0.6 (0.50)	0.4 (0.50)
Average Retail Value of Items	\$62.75 (65.17)	\$62.75 (65.17)	\$62.75 (65.17)	\$62.75 (65.17)
Average Bid (including zeros)	\$13.53 (22.80)	\$10.04 (18.76)	\$3.72 (13.48)	\$1.64 (6.14)
Average Bid (no zeros)	\$25.42 (25.98)	\$25.53 (22.36)	\$24.43 (26.50)	\$11.51 (12.38)
Average Expected Bidders per Item	23.56 (24.58)	18.33 (13.28)	8.04 (5.49)	17.31 (15.74)
Proportion of Missing Expectations	0.23 (0.42)	0.12 (0.33)	0.35 (0.48)	0.33 (0.47)
Proportion of Bids Submitted by Male	0.24 (0.42)	0.11 (0.31)	0.16 (0.37)	0.20 (0.40)
Proportion of Bids Submitted by Female	0.71 (0.45)	0.66 (0.48)	0.74 (0.44)	0.75 (0.43)
Proportion of Bids Submitted Jointly	0.05 (0.22)	0.22 (0.41)	0.08 (0.28)	0 (0)
Proportion with HH Income < \$75,000	0.42 (0.50)	0.43 (0.50)	0.73 (0.46)	0.38 (0.50)
Proportion with \$75,000 <= HH Income <= \$12,5000	0.29 (0.46)	0.37 (0.49)	0.20 (0.41)	0.33 (0.48)
Proportion with HH Income > \$75,000	0.16 (0.37)	0.17 (0.38)	0.07 (0.26)	0.24 (0.44)
Proportion with Missing Income	0.13 (0.34)	0.03 (0.18)	0 (0)	0.05 (0.22)
Average Preschool Donations (last 6 mos)	\$50.40 (112.96)	\$116.11 (177.85)	\$34.23 (61.44)	\$73.67 (189.40)
Average Future Child-Years at Preschool	0.87 (1.12)	1.63 (1.36)	0.63 (1.25)	1.05 (1.28)
Proportion who are Employees or Board Members	0.29 (0.46)	0.40 (0.50)	0.53 (0.52)	0.33 (0.48)

Note. Standard Deviations in parenthesis.

3.1. Revenue

Returning to Table 1, we now consider the revenue generated by item and auction. The first price auction generated the greatest total revenue (\$1226), followed by all-pay auction (1) (\$904), the second price auction (\$825), and lastly, all-pay auction (2) (\$656). Revenue comparisons by item further reveal that the first price auction earned the highest revenue (among all four auctions) for 11 of the 20 items.

To incorporate some mechanism-specific effects into our econometric specifications, we use a number of interaction variables. The first terms in our simple model of the observed revenue R_j for object j , for example, assume the form:

$$R_j = \beta_0 + \beta_1 AP_j + \beta_2 FP_j + \beta_3 N_j + \beta_4 (AP_j \times N_j) + \beta_5 (FP_j \times N_j) + \beta_6 \gamma_j + \dots + u_j, \quad (7)$$

where AP_j and FP_j are format indicators, N_j is the number of bidders, and the second price auction is the default. In our case, N_j was defined to be the mean, over all participants, of the expected number of bidders on each item, and not their actual number, which no one knew at the time bids were made. The first, and most important, prediction of theory, that $R^A > R^S > R^F$, then corresponds to the null:

$$\beta_1 + \beta_4 N_j > 0 > \beta_2 + \beta_5 N_j. \quad (8)$$

Likewise, the prediction that $dR^k/dN > 0$ for all k becomes the null $\beta_3, \beta_4, \beta_5 > 0$.

An increase in the return on charitable donations should also increase expected revenues under all three formats ($dR^k/d\gamma > 0$). However, the magnitude of this effect is difficult to order and therefore we only include the baseline effect in our analysis (i.e., $\beta_6 > 0$).

Our revenue results are summarised in Table 3. Robust standard errors are corrected for non-independence of the error terms within auctions. Column (1) presents a basic revenue model that explains 54% of the variation in revenue. Column (2) extends the basic model by incorporating interactions between auction type and the average expected number of bidders, as well as controls for the demographic characteristics of the bidders.⁶ The more elaborate specification explains 60% of the variation in revenue.

The key result is that when one considers mechanism only, the first price auction revenue dominates the second price auction and weakly dominates the all-pay ($p = 0.10$), with no significant difference between the all-pay and second price formats. Specifically, column (1) indicates that *ceteris paribus*, first price auctions generate about \$19 more revenue than second price auctions and about \$16.50 more revenue than all-pay auctions. However, in column (2) we see that the all-pay does worse than the first price because of the differential effect of anticipated competition. Each additional expected bidder in the all-pay lowers revenue by \$0.96 but has no significant effect on revenues in either the first or second price formats.

Not surprisingly, the results in the full model suggest a positive and significant relationship between revenue per item and retail value; a \$1 increase in retail value generates about \$1 in additional revenue for the seller. Collectively, the demographic

⁶ Due to the inclusion of demographic characteristics of the bidders in column (2) and the desire for comparability across the two models, the six items that earned zero revenue were excluded from both regressions. Note however, that when these six items are included in the model without demographic characteristics our results do not qualitatively differ from those reported in column (1).

Table 3
Ordinary Least Squares Estimation of Revenue by Item

	(1)	(2)
All-Pay	2.332 [6.863]	36.254 [14.776]*
First Price	18.809 [1.536]***	37.989 [16.043]*
Average Expected Bidders	0.235 [0.291]	1.251 [0.996]
Retail Value	0.916 [0.287]**	1.042 [0.277]**
Retail Value Squared	-0.002 [0.001]	-0.002 [0.001]
Gift Certificate	4.524 [13.368]	3.151 [14.356]
All-pay \times Average Expected Bidders		-2.210 [0.806]*
First Price \times Average Expected Bidders		-1.035 [0.857]
Average Preschool Donations		-0.004 [0.062]
Proportion of Employees or Board Members		-5.410 [6.861]
Proportion of Bidders who are Female		-3.059 [5.971]
Proportion with HH Income < \$75,000/year		-30.249 [17.873]
Average Future Child-Years		10.635 [2.593]**
Constant	-6.995 [8.096]	-23.891 [22.190]
Observations	74	74
R-squared	0.54	0.60

Notes. Robust standard errors corrected for non-independence within auctions in brackets. *significant at 10%; **significant at 5%; ***significant at 1%.

characteristics of bidders play only a minor role in revenue generation. However, average future child-years at the preschool, as a proxy for γ , does have a significant effect on revenue (and the effect is quite large); an increase by one in the bidders' average number of future child-years is associated with an additional \$11 in revenue. This supports our expectation that revenue increases when participants have stronger attachment to the charity.

Section 2 predicted that revenue would be ordered, $R^A > R^S > R^F$, if the auction attendees considered the revenues from our auction to be a public good. Instead, based on column (1) in Table 3, we find that $R^F > R^S = R^A$ indicating that charities raise the most revenue by using the first price format and not the all-pay format. We also see that the size of the bidding population may not matter in the way predicted by theory. Instead of the all-pay format taking advantage of bidder competition (i.e., our expectation was $dR^k/dN > 0$ for all k), we find that increasing the number of expected bidders does not significantly affect revenues in first and second price auctions and furthermore, additional expected bidders actually reduce the revenue collected in the

all-pay. Lastly, as mentioned in the previous paragraph, we do find limited support for the prediction that revenues will increase in bidders' attachment to the charity. Specifically, β_6 is greater than zero for one of our proxies, future child-years.

3.2. Efficiency

An advantage of our design is that we collected information on our participants' private values (proxied here by the maximum of either the amount one would pay for the item in a store or the amount one would bid for the item in a non-charity auction) and, therefore, we can discuss the efficiency properties of our three auction formats. A review of our auctions and items suggests that first price and all-pay auctions are generally more efficient than second price auctions. Controlling for the expected number of bidders, and the item's retail value and its square, a simple probit analysis of the determinants of efficiency confirms this pattern (Table 4). Specifically, column (1) suggests that compared to second price auctions, items are 9% more likely to be allocated efficiently in an all-pay auction and 32% more likely to be allocated efficiently in a first price auction. Furthermore, we can reject the null hypothesis that the coefficients on all-pay and first-price are equal ($p < 0.01$), suggesting that first price auctions are the most efficient format. These results are robust to the deletion of the six all-pay items that garnered no revenues. In this case, column (2) suggests that the relative efficiency of the all-pay mechanism increases but the all-pay is still significantly less efficient than the first price auction ($p < 0.05$). Interestingly, an increase in the average number of expected bidders decreases the probability that the winner is also the individual with the greatest private value; specifically, each additional (expected) bidder decreases the probability of an efficient auction outcome by between two and three per cent.

While the standard definition of efficiency is of allocative interest, an alternative measure, based on the proportion of the retail value of the items that is recovered,

Table 4
Probit Analysis of Efficiency by Item

	(1)	(2)
All-pay	0.094 [0.045]**	0.188 [0.046]***
First Price	0.315 [0.033]***	0.335 [0.025]***
Average Expected Bidders	-0.021 [0.007]***	-0.027 [0.006]***
Retail Value	0.002 [0.004]	0.001 [0.004]
Retail Value Squared	-0.00001 [0.00002]	-0.000007 [0.00002]
Observations	80 (all)	74 (positive only)
Pseudo R-squared	0.09	0.14

Notes. Marginal effects reported. Robust standard errors corrected for non-independence within auction in brackets. *significant at 10%; **significant at 5%; ***significant at 1%.

might be more important to charities.⁷ Returning to Table 1, we see that the first price auction recovered 98% of the retail value of the items we auctioned, while the other three auctions recovered only 66% in the second price, 72% in the first all-pay and 52% in the second all-pay. The first price auction is also more efficient using this more practical measure.

3.3. Bid Functions

The close relationship between auction participation and bid value suggests that bidders may not be a random sample of all auction attendees. Researchers must, therefore, be aware of the potential for sample selection bias when estimating the determinants of bid value. To understand better how selection bias can affect the analysis of bid behaviour, begin by letting $P_{i,j}^*$ be a latent random variable for bidder i which is some measure of the individual's desire to bid for item j . Assume that $P_{i,j}^*$ is a linear function of a set of non-stochastic independent variables and an error term. These covariates include information on the auction mechanism (AP_j, FP_j), individual i 's estimate of the total number of bidders on item j ($N_{i,j}$), a set of interactions designed to test whether the effect on participation of expected bidders differs by auction type (e.g., $AP_j \times N_{i,j}$), individual i 's attachment to the charity (γ_i) and other demographic information. The participation process can then be estimated as follows:

$$P_{i,j}^* = \eta_0 + \eta_1 AP_j + \eta_2 FP_j + \eta_3 N_{i,j} + \eta_4 (AP_j \times N_{i,j}) + \eta_5 (FP_j \times N_{i,j}) + \eta_6 \gamma_i + \dots + \epsilon_{i,j}, \quad (9)$$

where $\epsilon_{i,j}$ is iid $\sim N(0,1)$.

In fact, $P_{i,j}^*$, a measure of the individual's willingness to bid on the item, is not observed; only the sign of $P_{i,j}^*$ is known. If an individual submits a bid, then $P_{i,j}^*$ is assumed to be positive and $P_{i,j}$ takes the value of 1. If an individual does not submit a bid, then $P_{i,j}^*$ is assumed to be negative and we observe $P_{i,j} = 0$.

Let $B_{i,j}$ be the bid on item j submitted for individual i (observed only when $P_{i,j} = 1$). Assume that $B_{i,j}$ is also a linear function of the set of non-stochastic independent variables and an error term. The bid function can thus be estimated as follows:

$$(B_{i,j} | P_{i,j} = 1) = \tau_0 + \tau_1 AP_j + \tau_2 FP_j + \tau_3 N_{i,j} + \tau_4 (AP_j \times N_{i,j}) + \tau_5 (FP_j \times N_{i,j}) + \tau_6 \gamma_i + \dots + e_{i,j}, \quad (10)$$

where $e_{i,j}$ is iid $\sim N(0,1)$.

Sample selection bias arises if there exists some correlation among the errors, $\epsilon_{i,j}$ and $e_{i,j}$ in our two equations. For example, if we assume that $(\epsilon_{i,j}, e_{i,j})$ is distributed bivariate normal $(0,0,1,\sigma_e,\rho)$ then ρ is a measure of the correlation among the errors. The correlation between the two errors will be positive if the unobserved determinant increases both the probability of participation and bid value. Furthermore, the conditional mean bid will be higher than the unconditional mean bid if ρ is positive, and lower if ρ is negative. If correction is not made, then the estimates of the coefficients in the bid equation will be biased and inconsistent.

⁷ We thank Rob Moir for making this suggestion.

The Heckman selection model (Heckman, 1979) is the appropriate empirical tool in this situation; it corrects for the fact that the sample of individuals who submit bids may be systematically different from those who do not and allows us to use information from non-bidders to obtain consistent parameter estimates of the determinants of bid value. To identify the selection equation, we use an indicator for employee or board members (rather than relying on functional form assumptions). Employees and board members (i.e., event organisers) are likely to face external pressure to participate in the auction since participation is publicly observed. However, since bids are sealed, employee or board member status should have no additional impact on bids confidentially submitted.

Although the theoretical literature is silent on the effects of auction format on participation, Section 2 highlighted several hypotheses on bidding behaviour. The first prediction (that bids are ordered $B^S(v) > B^F(v) > B^A(v)$) now corresponds to the null:

$$0 > \tau_2 + \tau_5 N_{i,j} > \tau_1 + \tau_4 N_{i,j}, \quad (11)$$

and the second that $(dB^A(v)/dN < dB^S(v)/dN = 0 < dB^F(v)/dN)$, on the other hand, translates into $\tau_3 = 0$, $\tau_3 + \tau_4 < 0$ and $\tau_3 + \tau_5 > 0$ and the third ($dB^k/d\gamma > 0$) implies $\tau_6 > 0$.

Table 5 reports the Heckman two-step results. Model (1), the basic specification, includes information on auction-type, expected number of bidders, retail value, whether the item is a gift certificate and demographic characteristics of bidders. Model (2) adds interactions between auction-type and expected number of bidders.

The first important result is that selection clearly matters (i.e., the inverse Mills ratios are significant in both models); in other words, both laboratory and field experiments that fail to account for endogenous participation are susceptible to selection bias in their bid estimates. Furthermore, the positive value for ρ suggests that unobservable determinants tend to increase both the probability of participation and bid value, resulting in a conditional mean bid that is higher than the unconditional mean bid.

The participation results in column (1) of Model (1) reveal that auction type has a significant effect on the decision to submit a bid; that is, *ceteris paribus* and relative to second price auctions, bidders are 14% more likely to participate in first-price auctions and 24% less likely to participate in all-pay auctions. We attribute much of this to the relative familiarity of the first price mechanism and the uncertainty associated with the less common second price and all-pay formats. Furthermore, inclusion of the interaction terms in column (1) of Model (2) reveal a differential effect of expected bidders by auction type; as the expected number of bidders increases, individuals are more likely to participate, but this effect is dampened in both the all-pay and first price formats. In particular, we find that the expectation of one additional bidder increases the probability of submitting a bid by 1% in the second price but only by 0.4% in the first price and 0.6% in the all-pay.

Most of the other potential determinants of participation behave as expected.⁸ For example, higher retail priced items generate significantly higher participation rates, although the magnitude is small. At the same time, the likelihood of participation increases by about 14% for gift certificates. We suspect that gift certificates are more

⁸ The remaining coefficients are essentially the same across the two specifications.

Table 5
Heckman Estimates of Participation and Bidding

	Model (1)		Model (2)	
	Participation	Bid	Participation	Bid
All-Pay	-0.242 [0.026]***	-18.478 [3.753]***	-0.180 [0.039]***	-9.144 [4.205]**
First Price	0.141 [0.031]***	2.245 [2.008]	0.249 [0.043]***	8.847 [3.227]***
Expected Number of Bidders	0.005 [0.001]***	0.084 [0.046]*	0.010 [0.001]***	0.392 [0.113]***
Expected Number of Bidders Missing	-0.097 [0.032]***	3.206 [2.860]	-0.096 [0.033]***	3.631 [2.773]
Retail Value	0.001 [0.001]*	0.493 [0.044]***	0.001 [0.001]*	0.498 [0.043]***
Retail Value Squared	-0.000005 [0.000]***	-0.001 [0.0002]***	-0.000005 [0.000]***	-0.001 [0.0002]***
Gift Certificate	0.139 [0.023]***	4.733 [2.078]**	0.135 [0.023]***	4.130 [2.010]**
Female	0.107 [0.025]***	-1.649 [1.865]	0.118 [0.025]***	-0.966 [1.885]
HH Income < \$75000	-0.081 [0.033]***	-12.227 [2.267]***	-0.070 [0.033]**	-11.071 [2.232]***
\$75000<=HH Income<=\$125000	-0.066 [0.034]**	-8.366 [2.565]***	-0.054 [0.035]	-7.663 [2.493]***
Missing Income	0.040 [0.057]	2.384 [3.219]	0.061 [0.058]	3.765 [3.199]
Future Child-Years at Preschool	0.016 [0.010]	-0.107 [0.641]	0.015 [0.010]	-0.341 [0.639]
Preschool Donations (last 6 months)	-0.0003 [0.0001]***	0.029 [0.006]***	-0.0003 [0.0001]***	0.030 [0.005]***
Employee or Board Member	0.198 [0.028]***		0.205 [0.029]***	
All-Pay × Expected Number of Bidders			-0.004 [0.002]**	-0.509 [0.149]***
First Price × Expected Number of Bidders			-0.006 [0.002]***	-0.346 [0.114]***
Lambda (inverse Mills Ratio), p-value	9.803, 0.048		9.051, 0.062	
rho	0.489		0.460	
Observations	1,840	1,192	1,840	1,192
Wald Chi-squared, p-value	753, < 0.01		783, < 0.01	

Notes. Marginal effects reported. *significant at 10%; **significant at 5%; ***significant at 1%.

valuable than physical goods since they allow winners greater choice over both timing of receipt and product selection.⁹ Employees and board members are 20% more likely to participate than their non-affiliated counterparts and bidders with annual household incomes less than \$75,000 are 7–8% less likely to participate than those with incomes greater than \$125,000. Lastly, we find evidence that attachment to the public good plays an important role in the participation decision. In particular, females are 12% more likely than either males or couples to bid and we speculate that this reflects a

⁹ For example, we auctioned off a \$15 fruit tart from the local bakery that had to be eaten that day. If, instead, we had auctioned off a \$15 gift certificate to the same bakery, the winner could have redeemed the gift certificate for a different baked good on a more convenient occasion.

stronger attachment (due perhaps to greater exposure) to the preschool. While a bidder's previous money donations to the preschool significantly decrease the probability of participation, the small size of the coefficient calls into question the economic significance of this (perhaps) counterintuitive result.¹⁰

Table 5 also presents the results of the selection-corrected determinants of bid value. Perhaps the most important finding in Column (2) of Model (1) is that bids in the all-pay are significantly less than those in second price and first price auctions ($p < 0.01$); *ceteris paribus*, all-pay bids are approximately \$18.50 less, while first price bids are \$2.25 more than second-price bids for the same item. However, as Column (2) in Model (2) suggests, the inclusion of an interaction between auction format and expected number of bidders reveals that the negative relationship between all-pay format and bid value is primarily due to the strong negative effect that perceived competition has on one's bid. Taking the baseline and interaction terms together in Model (2), we see that each additional expected bidder is associated with a reduction in one's bid of \$0.12 in the all-pay and \$0.04 in the first-price but an increase in one's bid of \$0.39 in the second price format. Retail value has a positive effect on bids (although the relationship is non-linear) suggesting that an increase in retail value by \$1 is associated with an approximate \$0.50 increase in a second price bid. Furthermore, participants are willing to bid \$4 more for gift certificates than physical goods of equal retail value; again, this likely reflects a 'choice premium'. As expected, socioeconomic status has a significant effect on bid value; members of households with less than \$75,000 income submit bids that are about \$11 lower than otherwise similar bidders from households that earn more than \$125,000 yearly (the omitted category). To the extent that income proxies private value, those with greater values do bid more. Lastly, each previous dollar donated to the preschool is associated with a \$0.03 increase in bid. This supports the hypothesis that attachment to the charity, here proxied by previous donations, increases one's bid value.

Reconciling the results with our econometric specification, we find more support for theory, although not all the hypotheses are supported. Recall that our null hypothesis is that $B^S(v) > B^F(v) > B^A(v)$. We do find that bids are higher in the first price auction than in the all-pay auction ($\tau_2 > \tau_1$) and that all-pay bids are less than second price bids (i.e., $\tau_1 < 0$). However, only if there are 26 or more bidders (i.e., almost twice the average amount of competition) do first price bids exceed second price bids. In addition, only the all-pay bidders and first price bidders react as predicted when considering the size of the bidding population. All-pay bidders react rationally and reduce their bids as the expected number of bidders increases and the likelihood that their bids will be forfeited increases (i.e., $\tau_3 + \tau_4 < 0$). First price bidders also behave as predicted and increase their bids when more bidders are expected (i.e., $\tau_3 + \tau_5 > 0$). However, although second price bidders are expected to ignore the size of the bidding population, we find that they actually increase their bids when more competition is expected ($\tau_3 > 0$) and presumably become more vulnerable to the winner's curse. Lastly, we do find that bids are increasing with attachment to the charity ($\tau_6 > 0$); that is, those who provided greater monetary support in the past bid more.

¹⁰ An alternative interpretation is that previously generous bidders feel 'tapped out' and are less likely to participate in the auction. However, as we will see, those who are not 'tapped out' bid more.

Table 6
Robustness Checks for Participation and Bidding Estimates

	Model (A1)		Model (A2)	
	Participation	Bid	Participation	Bid
All-Pay	-0.180 [0.039]***	-9.021 [4.212]**	-0.178 [0.049]***	-9.215 [4.895]*
First Price	0.250 [0.044]***	8.921 [3.237]***	0.252 [0.073]***	8.644 [3.914]**
Expected Number of Bidders	0.010 [0.001]***	0.396 [0.114]***	0.010 [0.002]***	0.392 [0.120]***
Expected Number of Bidders Missing	-0.096 [0.033]***	3.681 [2.778]	-0.098 [0.060]*	3.751 [3.644]
Retail Value	0.001 [0.001]*	0.498 [0.043]***	0.001 [0.001]**	0.494 [0.053]***
Retail Value Squared	-0.000005 [0.000]***	-0.001 [0.0002]***	-0.000005 [0.000]**	-0.001 [0.0002]***
Gift Certificate	0.135 [0.023]***	4.130 [2.011]**	0.136 [0.025]***	4.080 [1.540]***
Female	0.117 [0.025]***	-0.932 [1.889]	0.112 [0.041]***	-0.816 [3.315]
HH Income < \$75,000	-0.071 [0.033]**	-11.013 [2.240]***	-0.069 [0.055]	-10.994 [3.068]***
\$75,000<=HH Income<=\$125,000	-0.054 [0.035] ⁺	-7.628 [2.498]***	-0.058 [0.055]	-7.532 [3.369]**
Missing Income	0.060 [0.058]	3.801 [3.211]	0.069 [0.065]	3.756 [5.843]
Future Child-Years at Preschool	0.014 [0.010]	-0.344 [0.640]	0.013 [0.017]	-0.308 [1.133]
Preschool Donations (last 6 ms)	-0.0003 [0.0001]***	0.030 [0.006]***	-0.0002 [0.0001]**	0.029 [0.015]*
Employee or Board Member	0.206 [0.029]***		0.202 [0.055]***	
All-Pay × Expected Number of Bidders	-0.004 [0.002]*	-0.512 [0.150]***	-0.004 [0.003] ⁺	-0.503 [0.143]***
First Price × Expected Number of Bidders	-0.006 [0.002]***	-0.348 [0.114]***	-0.006 [0.003]**	-0.342 [0.122]***
Another Bid	-0.019 [0.081]	2.853 [6.887]		
Lambda (inverse Mills Ratio), p-value	9.310, 0.056 0.472		8.975, - 0.460	
Errors clustered on Individual Observations	No		Yes	
Wald Chi-squared, p-value	1840	1192	1840	1192
	782, < 0.01		231, < 0.01	

Notes. Marginal effects reported. ⁺ significant at 15%, *at 10%, **at 5%, ***at 1%.

3.4. Robustness

The fact that individuals could bid on several items at each site prompts us to report the results of two robustness checks for our model.¹¹ The first views possible misspecification as an omitted variables problem. In particular, the first two columns of Table 6 list the estimates for an expanded model in which the variable *Another Bid*, which assumes the value 1 when individuals have bid on at least one other item and 0

¹¹ Although the median number of bids submitted by an individual is six (out of 20), 25% of participants submit three or fewer bids and less than 1% submit more than 18 bids.

otherwise, is added to both the participation and bid equations. In neither case is the estimated coefficient statistically significant at the 50, let alone 10%, level. Furthermore, the presence of *Another Bid* has little effect on the other coefficient estimates or their significance, results that support our choice of specification.

The second considers the effects of multiple bids on the joint distribution of errors, and asks if the same coefficients would still be significant if errors were clustered at the level of the bidder. The estimation of a clustered selection model required the use of maximum likelihood (ML) methods, however, which introduce complications of their own. The two-step estimates reported in Table 5, for example, do not assume that the joint distribution is normal and limit the ‘contamination effects’ associated with other possible misspecification problems. In addition, as Nawata (1994) and others have documented, ML algorithms can sometimes fail to converge, or converge to local rather than global maxima, even in well-specified models. Because our own estimates did not always converge, the third and fourth columns of Table 6 contain the ML estimates and corrected standard errors when the correlation coefficient ρ is set equal to its two-step value, 0.460.¹²

The results provide further support for our choice of specification. In the bid equation, all of the estimated coefficients that were significant at the 10% level or better in Table 5, in which the errors are not clustered, are still significant. In the participation equation, only one of the coefficients, that on the interaction between all-pay format and the expected number of bidders, loses significance and, even in this case, the p-value increases to just 0.123. At worst, then, we are a little less confident that the participation differential increases with the number of bidders, but nevertheless satisfied that all of our basic results are robust.

4. Discussion

To summarise, we find limited support for the standard models of charity auctions offered by Engers and McManus (2002) and Goeree *et al.* (2005) and our field results are contrary to those generated in the laboratory with induced altruistic preferences (Goeree and Schram, 2003). Instead of generating the most revenue, our all-pay auction was revenue dominated by our first price auction. Why might our field results differ from theory and the laboratory? We feel that the most important aspect of charity auction theory that has been neglected to this point is participation. In both theory and the laboratory, participation is essentially guaranteed.¹³ As Table 5 indicates, in the real world of fund-raising, participation is not guaranteed. Based on our casual debriefings after the auctions, the results reported in Table 5 make sense. Most participants had never heard of the all-pay auction format and only a few (those with some internet bidding experience) had experience in second price auctions. Furthermore, some potential bidders seemed to object, on principle, to the all-pay auction. While this is bound to be true of subjects in the laboratory, our field participants were much more likely to respond naturally by not participating when the rules seemed too unfamiliar.

¹² As a further check, the model was also estimated for other values of ρ between 0.1 and 0.9, and we found that the results were robust in this sense, too.

¹³ To be sure, laboratory participants may choose to bid \$0, but this sort of non-participation is almost unheard of.

To get a sense of the cost imposed by the unfamiliarity of the all-pay format, in terms of reduced participation, consider the following thought experiment. Imagine that everyone who was given a bid kit participated in every auction (i.e., they bid on all 20 items). Under these circumstances, how much revenue would be generated in each of our four auctions? We can use our bid estimates generated by the sub-sample of positive bids to predict, out of sample, the bids of non-participants. Based on the bids from the entire population of attendees, we can re-evaluate the winning bids in the first price and second price auctions and sum the revenue over all the possible bids in the all-pay auctions. When we do this we find that the first price auction would generate \$1,317.62, the second price auction would generate \$923.75, and the two all-pay auctions would generate \$3,521.27 and \$5,630.92, respectively. Notice now that the order of revenues would be $R^A > R^F > R^S$, which is much closer to what theory offers. Also notice that the difference between the actual revenue and our full-participation revenue is an estimate of the cost of reduced participation. The cost is negligible in the first price auction (\$92) and the second price auction (\$99) but it is quite substantial in the all-pay auctions (\$2,617.27 and \$4,974.92, respectively).

At first blush it may seem as if the participation differences across mechanisms reflect differences in the incentive to free ride. In particular, the all-pay auction resembles a public goods game in which the individual who contributes the most wins a prize, an analogy that seems consistent with its low(er) participation rate. We do not think that this can explain the differences, however. If it did, then, even in the absence of participation costs, some would find it optimal to submit bids of zero but we know (Goeree *et al.* 2005) that under these conditions, even those who do not value the prize much should submit positive bids. Furthermore, the observation that under the same conditions, the all-pay is predicted to revenue dominate both winner-pay mechanisms is a reminder that the incentive to free ride is not limited to the former.

The data, we believe, also do not support the differential free riding hypothesis. Taken seriously, one would predict, on the basis of the free riding analogy, that those who expected to use the same childcare provider in the future would actually have *more* of an incentive to free ride. In fact, the event will probably resemble a for-profit, as much as a charity, auction for the attendee whose last child is close to leaving the preschool. At the same time, the benefit accruing to the parents and the school of a contribution is much larger for the attendee who faces a lengthy interaction with the school because either she has a young child who has just entered the programme or multiple children at the school. In formal terms, if $\Delta\bar{P}_{AP}$ and $\Delta\bar{P}_{FS}$ are the differences in mean participation rates between those who are well-vested and those who are not in the all-pay and combined first and second price auctions, one would expect $\Delta\bar{P}_{AP}$, $\Delta\bar{P}_{FS}$ and, perhaps most important, the difference in difference $\Delta\bar{P}_{AP} - \Delta\bar{P}_{FS}$ to be significantly negative. If we define 'vested' to mean *Future Child-Years* ≥ 1 , however, the simple differences are $\Delta\bar{P}_{AP} = 0.004$ and $\Delta\bar{P}_{FS} = -0.048$, so that $\Delta\bar{P}_{AP} - \Delta\bar{P}_{FS} = 0.051$, a positive, if insignificant, number. In other words, neither theory nor our data suggest that differential free riding explains the differences in participation that we find.

In separate work (Carpenter *et al.*, 2004) we use the current empirical participation result to motivate a theory of charity auctions with endogenous participation. Adding participation costs can change the ordering of expected revenues so that they correspond to what we see in the field. With this theoretical support for our empirical

results, we are more confident that our identification of endogenous participation as the source of revenue differentials in real world charity auctions is the correct one. Further, from our estimation of bids, it also appears that the choice of gift certificates over other items is also of practical concern. On average, participants bid \$4.13 more for gift certificates, perhaps the implied value of their flexibility. In sum, charities with unsophisticated or inexperienced bidders should be reluctant to use the all-pay format, despite conventional wisdom, because its costs of participation are high. For such charities, the more familiar first price format and the use of gift certificates is the sensible choice.

Appendix: Experimental Instructions and Our Survey

Instructions

This is a sealed bid auction. You will receive no information about the bids of the other participants and they will receive no information about your bids. [*First Price*: The person who places the highest bid will receive the item and, in turn, make a contribution to this preschool center for the amount of the bid.] [*Second Price*: The person who places the highest bid will receive the item and, in turn, make a contribution to this preschool centre for the amount of the second highest bid. That is, the highest bidder wins but only has to pay the second highest bid.] [*All-pay*: The person who places the highest bid will receive the item. However, this is an All-pay Auction which means that everyone must pay their bids whether or not they are the highest bidder.] Bids will be accepted until 6:30pm and we will announce the winning bids at 7:00pm. [*First and Second Price*: If you make the highest bid on an item, you must pay with cash or write out a cheque to this preschool centre.] [*All-pay*: You must pay for each bid with cash or a cheque made out to this preschool.] If you have to leave before 7:00pm, place bids on items and we will call you only if you make the winning bid on an item. Please remember that all bids will go directly and entirely to this preschool. You may direct any questions about the items being auctioned off or the procedures of the auction to one of the auctioneers.

BID KIT SAMPLE

Bidder Number: _____

Panasonic DVD Player (retail value: \$100)

Would you buy this item in a store? Yes No

If Yes, what is the most you would pay for this item in a store? \$ _____

How much would you bid in a similar auction not conducted for charity? \$ _____

Sex of bidder: Male Female Joint Decision

How many people do you think will bid on this item? _____

Your bid for this item: \$ _____ (There is no minimum bid)

Survey

Please fill in the following information about the adult members of your family.

	Sex	Age	Marital Status	Schooling: Please check one box					Occupation
				Less than high school	High school degree	Some college	College degree	Advanced degree	
Adult 1									
Adult 2									
Adult 3									
Adult 4									

Please fill in the following information about the children in your family. We are interested in how much contact your family has had, and will have, with this preschool centre.

	How many years has (or did) child attend this preschool?	How many more years will child attend this preschool (include infants not yet enrolled)?
Child 1		
Child 2		
Child 3		
Child 4		
Child 5		
Child 6		

Is your family happy with the service provided by this preschool (please circle one)?

Very Unhappy 1 2 3 4 5 Very Happy

Is anyone in your family currently on the advisory board of this preschool? Yes No

Has anyone in your family been on the advisory board of this preschool? Yes No

Is anyone in your family currently employed by this preschool? Yes No

Estimate how much your family has already donated to this preschool since January 1, 2003 (not including any donations in the auction).\$ ____

Estimate how many total hours of service your family has donated to this preschool since January 1, 2003? ____ total hours

Town of residence:

- Addison ■ Bridport ■ Bristol ■ Cornwall ■ Ferrisburgh ■ Goshen ■ Granville ■ Leicester
- Lincoln ■ Middlebury ■ Monkton ■ New Haven ■ Orwell ■ Panton ■ Ripton ■ Salisbury
- Shoreham ■ Starksboro ■ Sudbury ■ Vergennes ■ Waltham ■ Weybridge ■ Whiting

How long has your family lived in this area: ____ years.

Annual Household Income (please circle one):

- (a) \$0-\$25,000
- (b) \$25,001-\$50,000
- (c) \$50,001-\$75,000
- (d) \$75,001-\$100,000
- (e) \$100,001-\$125,000
- (f) \$125,001-\$150,000
- (g) \$150,001-\$175,000
- (h) more than \$175,000

Estimated annual charitable giving: \$ _____

Do you have any past experience participating in charity auctions? Yes No

Do you have any past experience participating in non-charity auctions? Yes No

Your Phone Number (we will only use this if you need to leave before the end of the auction and you win an item):

Middlebury College

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References

- Andreoni, J. (1989). 'Giving with impure altruism: applications to charity and ricardian equivalence', *Journal of Political Economy*, vol. 97(6), pp. 1447–58.
- Andreoni, J. (1998). 'Toward a theory of charitable fund-raising', *Journal of Political Economy*, vol. 106, pp. 1186–213.
- Andreoni, J. (2004). 'Philanthropy', in (L.-A. Gérard-Varet, S.-C. Kolm and J. Mercier-Ythier, eds.), *Handbook of Giving, Reciprocity and Altruism*, Amsterdam: Elsevier/North-Holland.
- Carpenter, J., Holmes, J. and Matthews, P. (2004). 'Charity auctions: a field experimental investigation', IZA Working Paper No. 1330.
- Carpenter, J., Harrison, G. and List, J. (2005a). 'Field experiments in economics: an introduction', in (J. Carpenter, G. Harrison and J. A. List, eds.), *Field Experiments in Economics*, pp. 1–16, Greenwich, Conn, and London: JAI/Elsevier.
- Carpenter, J., Liati, A. and Vickery, B. (2005b). 'They come to play: supply effects in an economic experiment', *Department of Economics, Middlebury College Working Paper 0602*.
- Davis, D., Razzolini, L., Reilly, R. and Wilson, B. (2006). 'Raising revenues for charity: auctions versus lotteries', in (D. Davis and R. M. Isaac, eds.), *Research in Experimental Economics*, pp. 49–95, New York: JAI Press.
- Engers, M. and McManus, B. (2002). 'Charity auctions', Department of Economics, University of Virginia Working Paper.
- Goeree, J. K., Maasland, E., Onderstal, S. and Turner, J. (2005). 'How (not) to raise money', *Journal of Political Economy*, vol. 113(4), pp. 897–918.
- Goeree, J. K. and Schram, A. (2003). 'Bidding to give: an experimental comparison of auctions for charity', CREED, University of Amsterdam, Working Paper.
- Heckman, J. (1979). 'Sample selection bias as a specification error', *Econometrica*, vol. 47, pp. 153–61.
- Isaac, R. M., Salmon, T. and Zillante, A. (2007). 'A theory of jump bidding in ascending auctions', *Journal of Economic Behavior & Organization*, vol. 62(1), pp. 144–64.
- Isaac, R. M. and Schneir, K. (2003). 'Run silent, run cheap? A study of a charity auction mechanism', Department of Economics, Florida State University Working Paper.
- Karlan, D. and List, J. (2006). 'Does price matter in charitable giving? Evidence from a large-scale natural field experiment', NBER working paper 12338.
- Landry, C., Lange, A., List, J., Price, M. and Rupp, N. (2006). 'Toward an understanding of the economics of charity: evidence from a field experiment', *Quarterly Journal of Economics*, vol. 121, pp. 747–82.
- List, J. A. and Lucking-Reiley, D. (2000). 'Demand reduction in multiunit auctions: evidence from a sports-card field experiment', *American Economic Review*, vol. 90(4), pp. 961–72.

- List, J. A. and Lucking-Reiley, D. (2002). 'The effects of seed money and refunds on charitable giving: experimental evidence from a university capital campaign', *Journal of Political Economy*, vol. 110(1), pp. 215–33.
- Lucking-Reiley, D. (1999). 'Using field experiments to test equivalence between auction formats: magic on the internet', *American Economic Review*, vol. 89(5), pp. 1063–80.
- Morgan, J. and Sefton, M. (2000). 'Funding public goods with lotteries: experimental evidence', *Review of Economic Studies*, vol. 67(4), pp. 785–810.
- Nawata, K. (1994). 'Estimation of sample selection bias models by the maximum likelihood estimator and Heckman's two-step estimator', *Economic Letters*, vol. 45, pp. 33–40.
- Orzen, H. (2003). 'Fundraising through competition: theory and experiments', University of Nottingham Working Paper.
- Vickrey, W. (1961). 'Counterspeculation, auctions, and competitive sealed bid tenders', *Journal of Finance*, vol. 16, pp. 8–37.