Last Minute Bidding in eBay Charity Auctions

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Abstract

Relative to typical eBay auctions, bidding in eBay charity auctions occurs earlier and also less frequently in the auctions' final seconds. This suggests that some charity bidders benefit from driving-up others' payments, as when auction revenue is a public good.

Keywords: charity auctions; bid timing; bid sniping; preferences for giving; online auctions

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1. Introduction

Consumers are frequently presented opportunities to purchase products that are linked to charitable causes, green production, or fair trade practices. In Elfenbein and McManus (forthcoming) we demonstrate that consumers are willing to pay a premium for these items by analyzing a hand-matched data set of identical items sold in charity and non-charity auctions on eBay. This premium may occur because consumers receive a private benefit from winning a charity auction, such as egotistical "warm glow" (Andreoni 1989), because bidders value charity auction revenue as a public good, or both.[1] Models of bid timing in online consumer auctions suggest that bid times may reveal some aspects of bidder preferences, specifically, whether bidders view charity auction revenue as a public good. In particular, sophisticated bidders who value overall auction revenue will be less likely to bid at the last minute ("snipe") and may be inclined to bid earlier to elicit more bidding from naïve bidders.

While the data in Elfenbein and McManus (forthcoming) allow some coarse measurement of bid timing, they are insufficient to examine truly last-minute bidding, as sniping is generally described. For the present paper we construct a new data set specifically designed for this purpose.

2. Background

Last-minute bidding is widespread in online consumer auctions. Leading explanations for late bidding include: delaying the release of private information in common value auctions (Bajari and Hortacsu 2003), efforts to avoid price wars among strategic bidders (Roth and Ockenfels 2002), and attempts to avoid having naïve bidders drive up the price (Ockenfels and Roth 2006, Ariely et al. 2005, Ely and Hossain 2009). Ely and Hossain (2009) compare "sniping" (submitting one bid very late) to "squatting" (submitting one bid very early) in eBay auctions. They consider the optimal action of a strategic ("sophisticated") bidder facing naïve bidders who, rather than bidding their willingness-to-pay first, follow "incremental" bidding strategies, starting at the current price and submitting a series of bids, each slightly higher than the last, until they either lead the bidding or learn that the current price exceeds their

[1] See Engers and McManus (2007) for a model of equilibrium bidding in charity auctions.

willingness-to-pay.[2] By sniping, sophisticated bidders avoid giving naïve bidders a high hurdle to clear when they choose to end their bidding, thereby reducing the price at which the sniping bidder can win the auction. Squatting, on the other hand, can benefit a bidder if it deters some other bidders from participating in the auction. Ely and Hossain show that an individual's private net benefit from sniping and squatting are nearly equal; however squatting is associated with greater overall auction revenue and expected payments from other bidders. For bidders who care about auction revenue as a public good, these differences may then affect bid timing choices.

3. Data

We examine eBay charity listings ending in September and October 2006. We identified the 48 eBay-defined product categories in which charity auctions were most common, and then collected auction details and bidding histories for all charity listings in these categories. We then downloaded the same information for up to 2,000 non-charity auctions in each category during the same months. We restrict our analysis to true auctions. We exclude all listings that did not result in a sale, "buy-it-now" listings, and all auctions that ended with prices below $2 or which lasted more than 10 days. Our data set contains about 26,000 completed auctions.[3]

Selected summary statistics on these data are presented in Table 1. Average and median prices of the charity and non-charity samples are similar. Completed auctions in the charity sub-sample received slightly more bids on average than those in the non-charity sub-sample. Seller attributes in the two groups are also similar, although charity auctions' sellers are slightly more experienced and slightly less likely to be a "Power seller," an eBay designation for sellers with both high feedback scores and percentages of positive feedback. The median auction length for the two sub-samples is identical,

[2] See Elfenbein and McManus (forthcoming) for institutional details about the eBay bidding system which support this practice.

[3] By contrast, the data in Elfenbein and McManus (forthcoming) contain 2,433 auctions, organized around 723 distinct groups of auctions for identical products. The frequency of within-group variation in last-minute bidding is too low to permit analysis of true sniping within those data.

although the average charity auction length is about three-quarters of a day longer than the mean non-charity auction.

Between sub-samples there are clear differences in the timing of bidders' final (i.e. highest) bids. The fractions of winning bids submitted in the last 30 seconds and 1 minute are lower in the charity sub-sample (13.6% and 17.1%, respectively vs. 14.2% and 17.9% in the non-charity sub-sample), and bidders' final bids occur earlier on average (2.34 days vs. 1.79 days, representing 33.2% and 28.5% of time remaining in the auction). Additionally, bidders are more likely to bid multiple times in charity auctions, despite being more experienced, on average, than bidders in non-charity auctions.

Finally, we note that more than 90% of observed charity auctions donate 100% of revenue to charity. About 7% of charity auctions donate 10%, and fewer than 3% dedicate a share of revenue between 15% and 95%, inclusive, to charity.

4. Analyses

4.1 Days between bid and auction close

We begin by estimating the lapsed time (in days) between a bidder's final bid and an auction's closing. The econometric model is:

$$days_{ij} = \alpha_c + CHARITY_j\beta + AUCTION_j\gamma + SELLER_j\delta + BIDDER_i\phi + \varepsilon_{ij} \qquad (1)$$

The dependent variable $days_{ij}$ is the number of days between bidder i's final bid in auction j and the auction closing time. $CHARITY_j$ is a vector of indicator variables for whether an auction donates 10%, 100%, or some share strictly between 10% and 100%. These dummy variables are, respectively, *10%-SHARE*, *100%-SHARE*, and *MID-SHARE*. $AUCTION_j$ is a vector of auction characteristics including dummy variables for the scheduled duration,[4] ending time of day (in four-hour blocks), and ending day of the week. $SELLER_j$ describes the seller's percentage positive rating, logged feedback score, and "Power seller" status. The vector $BIDDER_i$ includes quadratic terms for bidder i's feedback score to control for

[4] We employ dummies indicating whether the auction ran for 1-3, 3-5, 5-7, or 7-10 days, with single-day auctions as the excluded category.

prior experience in eBay auctions. The model includes a set of category-level dummy variables in α_c to account for differences in bidding practices across product classes. Finally, we cluster the error term, ε_{ij}, on auction identifier (j) because multiple bidders (i) are observed for each auction.

We estimate equation (1) with OLS and report the results in Table 2. We suppress the coefficient estimates for *AUCTION*, *SELLER*, and *BIDDER* in this and all subsequent tables, focusing exclusively on the three variables in *CHARITY*. When we include the final bids of all bidders in our sample (Column 1), we find that bidders in each class of charity auction submit bids significantly earlier than in non-charity auctions. We repeat the analysis in Column 2 after dropping bidders who bid more than once. The retained bidders may be more likely to be sophisticated and aware of the strategic value of shifting bid timing. While the magnitudes of our coefficient estimates change between Columns 1 and 2, we again find that bidding is substantially earlier in charity auctions.

4.2 Discrete measures of sniping

For each bidder, we create an indicator variable equal to 1 if his or her highest bid was placed in the final 60 seconds of the auction, and the variable takes a value of 0 otherwise. We also create an indicator for whether a bidder's highest bid was in the final 30 seconds. We use a probit model to estimate the probability that bidders' indicators for last-minute bids (and, separately, last half-minute bids) are equal to 1. The explanatory variables mirror the structure of equation (1), including the set of category dummies (α_c), our descriptors of charity status (*CHARITY*), and other controls for the auction, seller, and bidder attributes.

The results, presented in Table 3, demonstrate that charity auction bidders snipe significantly less frequently than bidders in non-charity auctions. We focus on the choices of bidders who bid only once in an auction. Across charity auctions, we observe a significant reduction in sniping behavior when a large share of revenue is donated to charity and thus the public goods value of an auction is as strong as possible. The results in Column 1 indicate that last-minute bids are about 9% less common in auctions with *100% SHARE* = 1 (a change of -.0082 on the sample average of .0947). Bids in the last 30 seconds decline by a similar proportion (10%) in charity auctions with all revenue donated. In unreported regressions we examine the highest bids of *all* bidders and find coefficients that are very similar and exhibit substantially larger t-statistics.

4.3 Timing shifts and incremental bidding

For a shift in bid timing to affect revenue, a sophisticated bidder's earlier bidding must result in more "aggressive" bidding by naïve bidders. We investigate this possibility and present the results in Table 4. We retain the full set of product, auction, seller, and bidder controls in equation (1) in addition to the vector *CHARITY* for the empirical analysis. In Columns 1 and 2 we show that charity auctions with *100%-SHARE* = 1 are significantly more likely to include a bidder who bids multiple times. The 5.2 percentage point increase in Column 1 represents a 16% increase over the average for all auctions in the sample. In terms of number of bids per bidder, we find that bidders in full charity auctions submit, on average, an extra .09 bids. Finally, in Column 3 we examine whether bidders who bid multiple times are more likely to win charity auctions. Indeed, if the shifted bid timing of sophisticated bidders did not result in more frequent sales to bidders who were induced to bid aggressively, then it would likely be improper to infer that the public goods nature of auction revenue is causing timing shifts. The results in Column 3 show that bidders in auctions with *100%-SHARE* = 1 are 26% more likely to be won by a bidder who has bid more than once.

5. Conclusions

Our results, taken together, are consistent with the theory that consumers view the charity component of an auction as a public good, and they will adjust their actions to increase the size of other bidders' payments. The difference in bid timing results between 100%-share and 10%-share auctions is also consistent with this view. Bidding earlier in 100%-share auctions may be more likely to generate an extra dollar in revenue for a charity than bidding earlier in a 10%-share auction, where the final price would have to rise by $10 to achieve the same result.

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Table 1: Summary Statistics on Charity Auctions

	Charity Auctions				Non-Charity Auctions			
	Obs.	*Avg.*	*Median*	*Std. Dev.*	*Obs.*	*Avg.*	*Median*	*Std. Dev.*
Auction Level Data:								
Price ($)	7654	76.45	15.50	354.64	18347	78.25	15.82	893.68
Donation (%)	7654	92.1	100	24.8	18347	0	0	0
Number of bids	7654	5.67	3	6.56	18347	5.19	3	5.88
Seller rating (/1000)	7654	5.54	.85	19.85	18347	4.77	.737	18.443
Percent positive rating (%)	7654	99.5	99.7	.8	18347	99.5	99.9	1.6
Power seller (dummy)	7654	.330	0	.470	18347	.347	0	.476
Length (days)	7654	7.04	7	1.26	18347	6.26	7	1.69
High bid came in last …								
… 30 seconds (dummy)	7654	.136	0	.343	18347	.142	0	.349
… 1 minute (dummy)	7654	.171	0	.376	18347	.179	0	.383
Bidder-Level Data:								
Time of highest bid before end of auction (days)	21298	2.34	.978	2.67	50629	1.79	.639	2.27
Incremental bidder (dummy)	21298	.188	0	.390	50629	.168	0	.373
Bidder Rating (/1000)	20831	.290	.077	.765	49584	.239	.067	.619

Table 2: Timing of a Bidder's Final Bid

Dependent Variable:	Days before Auction Close	
Included bidders	All	Bid once
Column:	(1)	(2)
Charity Variables		
10%-SHARE	***.346 [.099]	†.187 [.107]
100%-SHARE	***.260 [.030]	***.372 [.034]
MID-SHARE	***.472 [.139]	***.617 [.148]
R^2	0.124	0.141
N	70,216	46,715

Notes: *** = significant at p ≤ 0.001; ** = significant at p ≤ 0.01; * = significant at p ≤ 0.05; † = significant at p ≤ 0.10. Standard errors, clustered on the auction identifier, are in brackets. The models include (unreported) controls for: Day of week for auction close (six dummies), time of day for auction close (four dummies), seller rating, seller percentage positive rating, length of auction in days (four dummies), bidder feedback rating (quadratic), and 47 category-level dummies. Coefficient estimates for these unreported variables are available on request.

Table 3: Discrete Measures of Sniping

Dependent Variable:	Bidders' only bid occurs in last 60 seconds (Y*es* = 1)	Bidders' only bid occurs in last 30 seconds (Y*es* = 1)
Column:	(1)	(2)
Charity Variables		
10%-SHARE	-.0065 [.0094]	.0022 [.0091]
100%-SHARE	**-.0082 [.0033]	*-.0077 [.0030]
MID-SHARE	†-.0187 [.0128]	†-.0207 [.0111]
Sample average	.0947	.0780
N	46,715	46,715

Notes: *** = significant at $p \leq 0.001$; ** = significant at $p \leq 0.01$; * = significant at $p \leq 0.05$; † = significant at $p \leq 0.10$. Results are given as marginal effects. Standard errors, clustered on the auction identifier, are in brackets. See notes for Table 2 for additional details.

Table 4: Incremental Bidding

Dependent Variable:	Incremental bidder present? (Yes = 1)	Bids per bidder	Incremental bidder wins? (Yes = 1)
Estimation method	Probit	OLS	Probit
Column:	(1)	(2)	(3)
Charity Variables			
10%-SHARE	-.021 [.023]	-.036 [.051]	-.004 [.016]
100%-SHARE	***.052 [.008]	***.090 [.018]	***.038 [.006]
MID-SHARE	.049 [.035]	†.134 [.097]	.037 [.026]
Sample average	.323	--	.146
R^2	--	.031	--
N	25,898	70,216	25,898

Notes: *** = significant at p ≤ 0.001; ** = significant at p ≤ 0.01; * = significant at p ≤ 0.05; † = significant at p ≤ 0.10. Standard errors, clustered on the auction identifier, are in brackets. Results in columns 1 and 3 are marginal effects. See notes for Table 2 for additional details.