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## A random $n$ th-price auction

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### Abstract

Second-price auctions are designed to induce people to reveal their private preferences for a good. Laboratory evidence suggests that while these auctions do a reasonable job on aggregate, they fall short at the individual level, especially for bidders who are off-margin of the market-clearing price. Herein we introduce and explore whether a random  $n$ th-price auction can engage all bidders to bid sincerely. Our results first show that the random  $n$ th-price auction can induce sincere bidding in theory and practice. We then compare the random  $n$ th-price to the second-price auction. We find that the second-price auction works better on-margin, and the random  $n$ th-price auction works better off-margin. © 2001 Elsevier Science B.V. All rights reserved.

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### 1. Introduction

Over the last decade, Vickrey's (1961) second-price auction has been a popular mechanism in laboratory valuation experiments. These experiments use the auction to induce people to reveal private preferences for new goods and services.<sup>1</sup> The popularity is largely due to the mechanism being demand revealing in theory, relatively simple to explain, and it has an endogenous market-clearing price. People have an incentive to tell the truth because the auction separates what they say from what they pay: the highest-bidder buys one unit of

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<sup>1</sup> See, for example, Coursey et al. (1987); Hoffman et al. (1993); Buhr et al. (1993); Shogren et al. (1994); Melton et al. (1996); Fox et al. (1998); and Shogren et al. (2000a).

a good and pays the second highest bid. Sincere bidding is the weakly dominant strategy. Underbidding risks foregoing a profitable purchase, whereas overbidding risks making an unprofitable purchase. Furthermore, evidence from induced value experiments suggests the auction can produce efficient outcomes in the aggregate (see Kagel, 1995).

But the second-price auction has its problems at the individual level. People often bid insincerely, especially those bidders who are off-margin, i.e. bidders whose value is far below or above the market-clearing price. Such uncontrolled bidding suggests the auction is unreliable if one is trying to measure the entire demand curve for a real-world good (e.g. irradiated meat). For instance, based on bidding behavior in second-price and ninth-price auctions, Knetsch et al. (1998) conclude that “contrary to common understanding the Vickrey auction may not be demand revealing.”<sup>2</sup> They contend the auction is problematic if it fails to engage off-margin bidders. A second-price auction might not engage low-value bidders who believe they will never win. Similarly, a ninth-price auction might bore high value bidders who think they will never lose. Laboratory evidence does not contradict their conjecture — off-margin bidders often do not reveal their lab-induced private values (e.g. Miller and Plott, 1985; Franciosi et al., 1993). Insincere bidding can be sustained if such behavior remains undetected and unpunished by the mechanism (see, for example, Cherry et al., 2000).

This paper introduces a mechanism — the random  $n$ th-price auction — designed to engage otherwise disengaged off-margin bidders. The auction combines elements of two classic demand-revealing mechanisms: the Vickrey auction and the Becker–DeGroot–Marschak (BDM) mechanism.<sup>3</sup> The key characteristic of the random  $n$ th-price auction is a random but endogenously determined market-clearing price. Randomness is used to engage all bidders, and to reduce any incentive to fixate on a stable market-clearing price. The endogenous price guarantees that the market-clearing price retains some relation to bidders’ private values. Each bidder should bid sincerely because he cannot use a random market-clearing price as a marker, and they all should be engaged because everyone has a chance to buy a unit of the good.<sup>4</sup>

The random  $n$ th-price auction works as follows: each bidder submits a bid; each bid is rank-ordered from highest to lowest; the monitor selects a random number — the  $n$  in the

<sup>2</sup> Knetsch et al. ran their experiments in part to address the debate over whether the so-called endowment effect — people sell a good in their possession at a substantially higher rate than they will pay for the identical good not in their possession — is a fundamental behavioral phenomenon or an artifact of the mechanism used to reveal preferences. Recall theory says that with small income effects and many substitutes, the willingness to pay (WTP) for a good and the willingness to accept (WTA) compensation to sell the same good should be about equal (Hanemann, 1991). Kahneman et al. (1990) reject this theory given observed bidding behavior within the incentive-compatible Becker et al. (1964) (BDM) mechanism, whereas Shogren et al. (1994) do not reject the theory based on behavior in the second-price auction. Knetsch et al. (1998) reject the theory with their two uniform-price auctions. In contrast, Shogren et al. (2000b) cannot reject the theory with the second-price auction and the random  $n$ th-price auction. These results suggest that more work to understand why different mechanism fail to induce sincere bids would be useful (also see Grether, 1994).

<sup>3</sup> In the Becker–DeGroot–Marschak mechanism each subject states his or her maximum buying price to purchase a good. A selling price is randomly selected from some distribution known to the subjects. If the selling price is less than or equal to the buying price, the buyer pays the selling price and gets the good; otherwise no sale is made. See, for example, Grether and Plott (1979) and Bohm et al. (1995).

<sup>4</sup> Fox et al. (1998), List and Shogren (1998), and Shogren et al. (2000b) have used the random  $n$ th-price auction to reveal individual values for irradiated meat, Christmas gifts, candy bars and coffee mugs.

Table 1  
Payoffs from off-equilibrium strategies

Bids	Price		
	$\beta < \beta^n$	$\beta = \beta^n$	$\beta > \beta^n$
Underbid ( $b_k < v_k$ )	0	$\hat{\pi}_k$	Impossible
Overbid ( $b_k > v_k$ )	Impossible	$\hat{\pi}_k$	$v_k - \beta < v_k - \beta^n < 0$

$n$ th-price auction, uniformly-distributed between 2 and  $k$  ( $k$  bidders); and the monitor sells one unit of the good to each of the  $(n-1)$  highest bidders at the  $n$ th-price. For instance, if the monitor randomly selected  $n = 5$ , the four highest bidders each purchase one unit priced at the fifth-highest bid. Ex ante, bidders with low or moderate valuation now have a non-trivial chance to buy the good since the price is determined randomly. The auction ups the odds that insincere bidding will lead to a loss. Each bidder, on-margin or off-margin, should have more incentive to bid his private value.

We first show the random  $n$ th-price auction can induce sincere bidding behavior in theory and practice. We then compare bidding behavior across the random  $n$ th-price and second-price auctions. The results suggest the second-price auction works better on-margin, while the random  $n$ th-price auction works better off-margin. The two auctions perform similarly when we pool the data from the on-margin and off-margin bidders.

## 2. A random $n$ th-price auction

Recognizing the truth-revealing properties in the random  $n$ th-price auction is straightforward given the intuition of Vickrey’s classic second-price auction.<sup>5</sup> To see this, assume nature selects independent private values  $v_k$  for each of  $k$  bidders. Also let nature select the random integer,  $n \in \{2, 3, \dots, k\}$ , which determines the random  $n$ th-price. Bidders submit sealed bids,  $b_k$ , and their payoffs,  $\pi_k$ , are determined as follows. Let  $\beta$  denote the  $n$ th-highest bid. If  $b_k > \beta$ , bidder  $k$  receives  $v_k$  and pays  $\beta$ ; if  $b_k \leq \beta$ , the bidder receives 0.

$$\pi_k = \begin{cases} v_k - \beta & \text{if } b_k > \beta \\ 0 & \text{if } b_k \leq \beta \end{cases} \tag{1}$$

The dominant strategy is for each bidder to bid his private value,  $b_k = v_k$ . To see why, first let  $\beta^n$  denote the  $n$ th-highest bid under the proposed dominant strategy, i.e. if  $b_k = v_k$ , then  $\beta = \beta^n$ . Let  $\hat{\pi}_k$  be the payoff from this strategy, given the moves of the other  $k - 1$  bidders and nature. Inspection of the payoff formula reveals  $\hat{\pi}_k = \max\{0, v_k - \beta^n\}$ , since if  $v_k < \beta^n$ , then  $b_k < \beta$ .

Table 1 shows the payoffs from off-equilibrium bidding strategies. Consider first a bid less than private value (row 1). Underbidding may reduce  $\beta$  such that  $\beta < \beta^n$ , but only if it causes the bidder’s bid to be unsuccessful, thus, the zero payoff. If  $\beta = \beta^n$ , a bid wins if

<sup>5</sup> An alternative demonstration can be developed following Forsythe and Isaac (1982).

and only if the private value bid would have won and the payoff is  $\hat{\pi}_k$ . The case of  $\beta > \beta^n$  is impossible because no bidder can increase the value of the  $n$ th-highest bid by lowering his own bid.

Now consider overbidding (row 2). If bidder  $k$  overbids,  $\beta < \beta^n$  is impossible and  $\beta = \beta^n$  offers  $\hat{\pi}_k$ , as before. The only circumstance in which his payoff differs from that given by bidding  $v_k$  occurs when his bid is successful where  $v_k$  would not have been, and this payoff is always negative. This payoff is negative because private value would have been an unsuccessful bid,  $v_k < \beta^n$ ; add to this  $\beta > \beta^n$ , and it follows that the payoff,  $v_k - \beta$ , is less than zero. No possible outcome from bids other than private value offers a payoff above  $\hat{\pi}_k$ . Since this argument does not appeal to any particular assumption about the distribution of other bids, bidding private value is a dominant strategy in a random  $n$ th-price auction.

### 3. Experimental design I: does the random $n$ th-price auction work?

We begin by considering whether the random  $n$ th-price auction works — do people bid sincerely in an induced value experiment? Subjects were recruited and informed they would participate in a multi-round auction in which they would submit a bid to purchase one unit of a good they could resell to the monitor. We did not inform subjects that the optimal strategy was to bid their induced value, but we did explain the basics of how the auction mechanism worked.<sup>6</sup> For example, they knew before bidding that if the monitor randomly selected, say, bidder #5's bid of \$ 4.50 as the cut-off bid, the market-clearing price was \$ 4.50.

Each auction round had nine steps. Step 1: each bidder received a recording sheet that listed his or her set of induced private resale values for the experiment. The resale value was the price the monitor paid a bidder to buy back the token purchased in the auction. The sets of private values were randomly drawn from a uniform distribution of [\$ 0.10, \$ 10.00] in 10 cents increments: [0.4, 1.8, 3.2, 5.3, 6.1, 6.5, 6.8, 7.1, 7.6, 8.4]. Each subject was assigned each value twice during the experiment. An example-recording sheet was provided to the subjects.

Step 2: each bidder submitted a bid, private and sealed, to buy one unit of the good. Step 3: the monitor ranked the bids from highest to lowest. Step 4: the monitor selected the cut-off bidder at random to determine the market price. There was a uniform chance the cut-off bidder was either the 2nd, 3rd, . . . , or 10th highest bidder. Step 5: the market-clearing price (i.e. the bid of the cut-off bidder) was announced. Step 6: each bidder who bid above the market price purchased one unit at the market price. In our example, the four highest bidders (#1–4) would each buy one unit and each would pay \$ 4.50.

Step 7: each buyer then sold the unit back to the monitor at his or her assigned resale value for that trial. The difference between the resale value and the market price was the bidder's profits for that round: profits = resalevalue – marketprice. Subjects knew they could have negative profits. Step 8: all bidders at or below the market price did not buy anything, and made zero profit for that round. In our example, these are bidders #5 through #10.

<sup>6</sup> All instructions are available on request from the authors.

Step 9: the round ended and the next round began by going back to step 1, in which subjects received a new resale value.

Ten subjects participated in 20 rounds. Pooling all results, the mean bid of \$ 5.14 (S.D. = \$ 3.82) is not significantly different from mean induced value of \$ 5.32 (S.D. = \$ 2.52). Mean actual bids ranged from a high of \$ 9.50 (S.D. = \$ 11.99) in trial two to a low of \$ 4.04 (S.D. = \$ 2.85) in trial 20. The pooled median bid of \$ 5.25 was lower than the median induced value of \$ 6.23.

If all subjects maximized their personal payoff, each bid should equal the induced value. We test this hypothesis by nesting it within the general structure

$$\text{bid}_{it} = \phi \text{IN}_{it} + \alpha_i + \varphi_t + \varepsilon_{it} \quad (2)$$

where  $\text{bid}_{it}$  denotes subject  $i$ 's bid in trial  $t$ ;  $\text{IN}_{it}$  denotes subject  $i$ 's induced value in trial  $t$ ;  $\alpha_i$  represents subject-specific characteristics;  $\varphi_t$  represents trial-specific effects, including learning or other trends in bidding behavior; and  $\varepsilon_{it}$  is bid error. In Eq. (2), data points along a 45° ray from the origin in bid–IN space ( $\phi = 1$ ;  $\alpha_i = 0 \forall i$ ;  $\varphi_t = 0 \forall t$ ) are perfectly demand revealing bids.

Under the maintained hypothesis that the  $\alpha_i$  and the  $\varphi_t$  are drawn from a bivariate normal distribution (two-way random effects) the estimated equation is<sup>7</sup>

$$\text{bid}_{it} = \underset{(0.62)}{0.43} + \underset{(0.08)}{0.89} \text{IN}_{it}$$

(standard errors in parentheses). We see the regression line is flatter than the perfect-revelation line, with positive intercept and slope below one. The discrepancy is insignificant — we cannot reject the joint hypothesis that the mean of  $\alpha = 0$  and  $\phi = 1$  ( $F_{2,170} = 1.43$ ;  $P = 0.24$ ). The random  $n$ th-price auction seemed to induce people to bid sincerely without being told that truth-telling was the weakly dominant strategy.

#### 4. Experimental design II: comparing off-margin and on-margin bidders

Having evidence suggesting the random  $n$ th-price auction can work in practice, we now take the next step to consider whether the random  $n$ th-price auction outperforms the standard second-price auction in engaging off-margin bidders. There is one important difference in design from the first experiment: the experimental instructions explicitly told subjects it was in their best interest to bid their private value. This was done for two reasons. First, revealing the best strategy is a standard experimental procedure in lab valuation auctions because the goal is to elicit meaningful values, not to test the theory of incentive compatibility (see Hoffman et al., 1993; Fox et al., 1998). We maintain consistency with this procedure because we are ultimately interested in understanding the role of auction mechanisms in eliciting real preferences for new goods. Second, by revealing the best strategy in both the

<sup>7</sup> We do not report the details of less restricted models, which would be less likely to reject the null, and which in fact do not. Given that the LM statistic and the Hausman (1978) test both suggest that the random effects model is appropriate for our data, we focus on estimates from the more efficient error components model. Note that results from the two-way covariance model are qualitatively similar.

Table 2  
Summary of experimental design

Experimental variable	Actual parameter
Actual good	A redeemable token
Value measure	Willingness to pay (WTP)
Auction institutions	Sealed bid second-price auction and sealed bid random $n$ th-price
Three stage ABA auction design	Groups 1 and 2: $A$ = second-price auction, and $B$ = random $n$ th-price auction; for groups 3 and 4: $A$ = random $n$ th-price, and $B$ = second-price
Monetary endowment	\$ 5 per stage = \$ 15 total plus flat participation fee
Trials	5 per stage = 15 total trials
Number of subjects	8–10 per group
Private values	Stage 1: [1.1, 1.2, 1.3, 2.9, 3.5, 5.5, 5.7, 6.7, 6.9, 9.6]; stage 2: [0.8, 2.4, 2.5, 3.4, 4.9, 5.1, 6.0, 6.9, 7.1, 9.5]; stage 3: [0.5, 1.0, 2.1, 2.2, 2.7, 3.3, 3.6, 5.6, 6.6, 7.7]

second-price and the random  $n$ th-price auctions we can explore whether the random auction actually does a better job of enticing low value bidders to bid truthfully. As researchers have found (see, for example, Kagel and Levine, 1997), telling people their best strategy does not guarantee they bid accordingly.

Table 2 summarizes our three stage experimental design. Four groups of 8–10 subjects (37 in total) participated in an ABA format to control for order effects, and to allow a within-subject comparison of bidding behavior. For groups 1 and 2:  $A$  = second-price auction, and  $B$  = random  $n$ th-price auction; for groups 3 and 4:  $A$  = random  $n$ th-price, and  $B$  = second-price.

In stage 1, subjects in a group entered the laboratory. Subjects did not communicate, either orally or by gestures. The monitor distributed a folder with the experimental instructions, a \$ 10 endowment, a private identification number, and an induced private resale value,  $v_k(1)$ . Table 2 shows the set of private values, which were randomly drawn from a uniform distribution of [\$ 0.10, \$ 10.00] in 10 cents increments. A subject knew only his or her own private value. Each participant's private value was changed at the end of each stage. The monitor varied private values by stage so subjects with a low private value in stage 1 had a high value in stages 2 or 3.

After the monitor read the instructions aloud and answered all relevant questions, the auction began. Following two practice rounds to introduce the first auction, the subjects completed a quiz checking for confusion or misunderstanding. The monitor then ran the first five trials. In each trial, a subject wrote his or her bid on a card. We posted the market-clearing price and the identification number(s) of the winner(s) after each trial. After all five trials were completed, the monitor selected one of the five trials as binding. The winner(s) of the binding trial bought the token at the market price. The monitor then repurchased the token from the winner(s) at a price equal to his or her private value. A winner earned positive profits if his or her private value exceeded the market price; otherwise he broke even or lost money. After this money transfer, and before moving to stage 2, the monitor gave each bidder a new private value,  $v_k(2)$  and the winner(s) a new identification number.

Stage 2 began with two additional practice rounds and a second quiz to introduce the next auction institution. The monitor ran five trials of the new auction. Again, after announcement

of the binding trial, the winner’s profits were determined and money was transferred. The winner received a new identification number and private values,  $v_k(3)$ , were assigned for stage 3. Stage 3 used the same auction and followed identical procedures as in stage 1, except that we eliminated the practice rounds and quiz. After stage 3, the subjects left the lab with their take-home earnings.

**5. Results and discussion of experimental design II**

Tables 3 and 4 provides summary statistics of the experimental data. The results suggest that both auctions were demand revealing in aggregate. Mean bids were less than mean induced values in the second-price auction by \$ 0.20 (S.D. = \$0.84); the mean bids exceeded mean induced values in the random  $n$ th-price auction by \$ 0.003 (S.D. = \$ 1.27). Examining Fig. 1 and Tables 3 and 4 suggests the second-price auction performed reasonably well — over 55% of bids were perfectly demand revealing, and 65% of bids were within \$ 0.10 of induced value. Insincere bidders usually shaved bids (33% of all bids) rather than inflating them (11%). The ratio of bid to private value was 0.96. These findings contrast with recent studies that found overbidding in the second-price auction (see Kagel et al., 1987; Kagel and Levine, 1997). Fig. 2 suggests that the random  $n$ th-price auction also performs credibly. Although, a greater bid variance exists, as revealed by the spread in bid-value

Table 3  
Descriptive statistics

	Second-price mean (S.D.)	Random $n$ th-price mean (S.D.)
Bid (\$)	4.14 (2.59)	4.063 (2.51)
Private value (\$)	4.34 (2.61)	4.06 (2.53)
Bid–private value (\$)	–0.20 (0.84)	0.003 (1.28)
Bid-to-private value	0.96 (0.45)	1.06 (0.68)

Table 4  
Frequency of actual bids relative to private value

Bids			Bids $\pm$ 10 cents <sup>b</sup>		
Notation <sup>a</sup>	Number	Percentage	Notation <sup>a</sup>	Number	Percentage
Second-price auction $N = 280$					
=	155	55.4	=	187	65.0
<	93	33.2	<	71	26.8
>	32	11.4	>	22	8.2
Random $n$ th-price auction ( $N = 275$ )					
=	159	57.8	=	174	63.3
<	72	26.2	<	67	24.4
>	44	16.0	>	34	12.3

<sup>a</sup> Notation: =, bid equals private value; <, bid is less than private value; and >, bid exceeds private value.

<sup>b</sup>  $\pm$ 10 cents: an individual’s bid is within 10 cents of his or her private value.

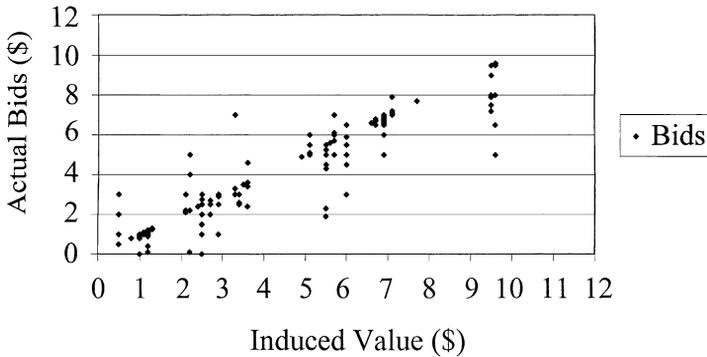


Fig. 1. Bids in second-price auction.

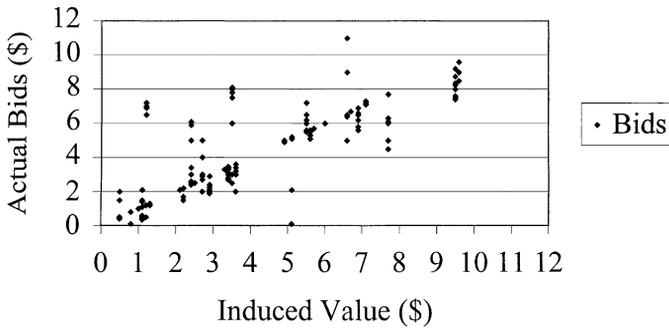


Fig. 2. Bids in random *n*th-price auction.

space in Fig. 2, 58% of the bids were perfectly demand revealing, and 63% were within \$ 0.10 of value.

One way to compare the two auction mechanisms is to ask which results in greater deviation of bids from the induced private value. Table 5 presents the mean and standard errors of the squared deviations and absolute deviations, broken down by auction type and by whether the bidder was off-margin in the previous trial. Formally, we define a bidder as off-margin in trial *t* when his trial *t* – 1 bid was at least one dollar below the market-clearing price.<sup>8</sup>

The results in Table 5 provide weak evidence that the two auction types perform differently. We can make the strongest case by examining the fourth column of statistics — the Mann–Whitney non-parametric tests of the null hypothesis that the second-price and random *n*th-price squared deviations are distributed equally. We cannot reject the null in the aggregate. We do reject the null, however, for each sub-sample when off-margin bidders

<sup>8</sup> We experimented with \$ 0.25 as the cut-off point for off-margin bidders and results were unchanged. Since we used the *ABA* experimental design format, three observations are lost for each bidder since there is no variable for off in trial 1 of each experiment type. Approximately 69% of bidders were off-margin in the Vickrey auctions and 55% were off-margin in the random *n*th price auctions.

Table 5  
Deviations of bid from value induced (\$) <sup>a</sup>

Random <i>n</i> th-price	Second-price	Aggregate	Mann–Whitney ( <i>P</i> -value)	Mann–Whitney on subject means
On-margin				
2.45 (6.90)	0.593 (2.56)	1.67 (5.56)	2.236 (0.0254)	−0.327 (0.7433)
0.746 (1.39)	0.280 (0.722)	0.547 (0.175)		
Off-margin				
0.051 (4.15)	0.805 (2.12)	0.914 (3.18)	−1.711 (0.0870)	−1.123 (0.2614)
0.412 (0.942)	0.459 (0.773)	0.438 (0.851)		
Aggregate				
1.63 (5.44)	0.741 (2.32)	1.18 (4.19)	0.112 (0.9108)	−1.094 (0.2739)
0.554 (1.15)	0.400 (0.763)	0.476 (0.977)		

<sup>a</sup> Except for the last column, each cell gives mean squared deviation on the top line, with S.D. in parentheses; then mean (S.D.) absolute deviation on the bottom line.

are considered separately ( $P < 0.10$ ), and we reject the null for on-margin bidders ( $P < 0.05$ ).<sup>9</sup>

These results suggest a straightforward interpretation: the random *n*th-price auction could be more confusing, so its performance is inferior for on-margin bidders — the mean squared deviation is significantly greater. For off-margin bidders, however, this confusion appears less severe relative to their tendency to become disengaged from the second-price auction. In the second-price auction, off-margin bidders are fairly confident their bids will be less than the market-clearing price. But these off-margin bidders are not so confident in the random *n*th-price auction, since a large *n* in the next round could make their bid meaningful. Among off-margin bidders, therefore, the random *n*th-price auction results in significantly lower mean squared deviations from private value.

Given each subject offered multiple bids, the Mann–Whitney tests are probably vulnerable since they presume independent observations. A person who was especially prone to underbid in second-price auctions, for example, would be given too much weight in the statistical test. An alternative that does not share this flaw — but which is inefficient — is to compare subject-specific means. This test indicates no significant differences (see the last column of Table 5). The test performed separately for each round of bidding (not presented) also fails to reveal any significant differences.

A second way to compare the two mechanisms is to explore whether the random *n*th-price auction produces meaningfully different results. In bid–private value space, recall from design I that sincere bids fall on the line through the origin with unit slope. We estimate the following equation to examine how each mechanism compares to this ideal bidding line

$$\begin{aligned}
 \text{bid}_{it} = & \alpha_i + \phi_1 \text{PV}_{it} + \phi_2 (\text{Auc}_{it}) + \phi_3 (\text{PV}_{it} \times \text{Auc}_{it}) + \phi_4 (\text{off}_{it-1}) + \phi_5 (\text{off}_{it-1} \\
 & \times \text{PV}_{it}) + \phi_6 (\text{off}_{it-1} \times \text{Auc}_{it}) + \phi_7 (\text{off}_{it-1} \times \text{PV}_{it} \times \text{Auc}_{it}) + \varepsilon_{it}, \quad (3)
 \end{aligned}$$

<sup>9</sup> In contrast to the off-margin and on-margin results in Table 5, the results for aggregate bidders include all observations because we are pooling all the data. Excluding first trial observations does not change our results appreciably.

Table 6  
Panel data estimation results<sup>a, b</sup>

Variable	Random effects	Fixed effects	Random effects AR(1)	Fixed effects AR(1)
Constant	2.03* (0.50)	2.10 <sup>*,c</sup> (0.52)	1.47 (0.29)	–
PV	0.66* (0.05)	0.62* (0.09)	0.71* (0.05)	0.70* (0.05)
Auc	–0.52 (1.3)	–0.04 (1.4)	–1.29 (0.79)	–1.40 (0.81)
PV × Auc	0.11 (0.18)	0.08 (0.20)	0.20 (0.11)	0.21 (0.11)
off <sub><i>it</i>–1</sub>	–1.86* (0.62)	–1.97* (0.67)	–1.23* (0.31)	–1.28* (0.32)
off <sub><i>it</i>–1</sub> × PV	0.29* (0.12)	0.38* (0.15)	0.21* (0.07)	0.24* (0.08)
off <sub><i>it</i>–1</sub> × Auc	0.82 (1.4)	0.80 (1.5)	1.47 (0.82)	1.69* (0.84)
off <sub><i>it</i>–1</sub> × PV × Auc	–0.24 (0.24)	–0.39 (0.26)	–0.29* (.13)	–0.34* (0.14)
$F(\alpha_i = 0)$ (d.f.)	–	2.27* (36, 67)	–	3.3* (36, 364)
Breusch–Pagan <sup>d</sup>	$\chi^2(1) = 7.67$	–	$\chi^2(1) = 54.28^*$	–
Hausman <sup>e</sup>	$\chi^2(7) = 9.21$	–	$\chi^2(7) = 5.31$	–
Auctions equal <sup>f</sup>	$\chi^2(4) = 1.44$	$F(4, 67) = 1.18$	$\chi^2(4) = 0.19$	$F(4, 364) = 0.17$
R <sup>2</sup>	0.81	0.85	0.78	0.84
<i>n</i>	111	111	444	444

<sup>a</sup> Dependent variable is bid; PV is induced private value; Auc = 1 for second-price auction, 0 otherwise; off<sub>*it*–1</sub> = 1 for off-margin bidders, 0 otherwise.

<sup>b</sup> Standard errors in parentheses under coefficient estimates.

<sup>c</sup> Average of subject-specific intercepts.

<sup>d</sup> Test of zero variance in random effects.

<sup>e</sup> Test of maintained hypothesis in random effects.

<sup>f</sup> Test joint null that coefficient on Auc and all interaction terms including Auc are zero.

\* Significant at 0.05.

where the dependent variable, bid<sub>*it*</sub>, is subject *i*'s bid in trial *t*,  $\alpha_i$  is a subject specific fixed/random effect that accounts for systematic differences in bidding patterns and controls for ordering of the experiment types; PV<sub>*it*</sub> is subject *i*'s induced private value in trial *t*; Auc<sub>*it*</sub> = 1 for second-price auction, 0 otherwise; and off<sub>*it*–1</sub> = 1 for bidder *i* in trial *t* if he was off-margin in trial *t* – 1, 0 otherwise. The remaining variables PV<sub>*it*</sub> × Auc<sub>*it*</sub>, off<sub>*it*–1</sub> × PV<sub>*it*</sub>, off<sub>*it*–1</sub> × Auc<sub>*it*</sub>, and off<sub>*it*–1</sub> × PV<sub>*it*</sub> × Auc<sub>*it*</sub> are interaction terms and allow slope and intercept heterogeneity across auction and bidder type (off-margin or on-margin bidders).

Estimation of Eq. (3) using pooled data suffers from a potential problem. A subject who has decided, for example, to place a particularly low bid in the first trial of any stage might choose to retain the same bid in the next trial. Each subsequent trial is less a fresh decision than a decision of whether to change one's mind under essentially unchanged circumstances from the previous round. In fact, 48% of the bids in trials 2–5 are exactly equal to the previous bid. This pattern generates a correlation between  $\varepsilon_{it}$  and  $\varepsilon_{it-1}$ , of a sort that seems unlikely to be sufficiently captured by conventional autocorrelation-corrected models.<sup>10</sup>

The estimates in the first two columns of Table 6 sidestep this problem by using only the last observation in each stage.<sup>11</sup> Table 7 presents Wald test statistics for the joint hy-

<sup>10</sup> These models are designed to deal with unobserved impacts that die out at a steady rate.

<sup>11</sup> For completeness, we also present estimates from models of panel data that correct for the non-spherical disturbance using an AR1 correction. These estimates are presented in columns 3 and 4 of Table 6 and are largely consistent with the less efficient estimates in columns 1 and 2. We should note one additional shortcoming of these regression estimates: the random effects results are from generalized least squares models and therefore may be inconsistent due to the inclusion of a regressor which is a function of the lagged endogenous variable, off<sub>*t*–1</sub>.

Table 7  
Tests of the joint hypothesis of zero intercept, unit slope

Auction type	
Random <i>n</i> th	Second-price
Off-margin	
RE: $\chi^2(2) = 18.13^{**}$	RE: $\chi^2(2) = 2.55$
FE: $F(2, 67) = 9.61^{**}$	FE: $F(2, 67) = 1.65$
On-margin	
RE: $\chi^2(2) = 0.24$	RE: $\chi^2(2) = 3.34$
FE: $F(2, 67) = 0.18$	FE: $F(2, 67) = 3.98^*$

\* Significant at 0.05.

\*\* Significant at 0.01.

pothesis of zero intercept and unit slope (i.e. perfectly demand revealing bids) based on these estimates. The hypothesis is strongly rejected for the random *n*th-price mechanism with on-margin bidders. For the second-price auction, perfect demand revelation is rejected at the  $P < 0.05$  level using the fixed-effects specification, but cannot be rejected by random effects. In the other two cells, the null hypothesis appears quite close to being satisfied.

These results confirm the picture suggested by inspecting the deviations from true values — the second-price auction works better on-margin, while the random *n*th-price auction works better off-margin. Also consistent with the deviations story is that the two auctions appear to perform similarly when we pool the data for on-margin and off-margin bidders; we cannot reject the null hypothesis that the auctions are equal (Table 6, line “auctions equal”).<sup>12</sup>

Again we observe regression lines flatter than the perfect-revelation line, with positive intercepts and slopes below one. In the case of the random *n*th-price auction for off-margin bidders, this flattening is statistically significant (see top left cell of Table 7). This behavior could represent a tendency of bidders who do not fully understand the mechanism to offer bids near the middle of the range. This pattern could also emerge if our parameter estimates are biased by the classic attenuation of least squares (Greene, 1997, p. 437), which occurs when an independent variable is measured with error.<sup>13</sup> In the present context, this would mean our induced value is transformed inside the subject by some noisy and unobserved process, e.g. a belief that the experience of redeeming tokens will be occasion for social display or embarrassment. If the mean error is zero and no correlation exists between induced value and the error with which we measure it, the slope coefficient is biased downward and the constant term biased upward.

<sup>12</sup> One could also argue that the results could be an artifact of the particular distribution of off-margin and on-margin bidders.

<sup>13</sup> Attenuation is guaranteed, however, if and only if, one exogenous variable is measured with error. With more than one error in variables, anything could happen (see, for example, Leamer and Leonard, 1983).

## 6. Conclusion

Previous studies suggest people with relatively low or moderate preferences for a good can become disengaged from an auction they cannot profitably win. These off-margin bidders often bid insincerely even if the auction is demand revealing in theory. They have little to lose if their insincere bid always falls below the market-clearing price. The random  $n$ th-price auction we consider herein attempts to reengage these bidders, while preserving the property that the market-clearing price comes from the bidders.

Our results indicate the random  $n$ th-price mechanism does regain the off-margin bidders. The auction, however, does not generate more truthful bids from the on-margin bidders; here the second-price auction performs better. This combination suggests that there might be an effective mix between the number of subjects ( $k$ ) and the number of units of an auctioned good ( $n$ ) that would engage both on-margin and off-margin bidders. Exploring this mix might help us better understand why auctions that are demand-revealing in theory can fail in practice. In addition, comparing the random  $n$ th-price auction with other mechanisms such as the English clock auction, in which bidders opt out as the price rises, also seems a worthwhile direction for laboratory valuation experiments.

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