Supplement to "Why are open ascending auctions popular? The role of information aggregation and behavioral biases"

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Appendix A: "Why are open ascending auctions popular?"

The Appendix is intended for online publication. We start with an analysis of information effects on eBay. Then we discuss revenue predictions for different parameterizations, and we present behavioral models. We present cursed equilibrium for the JEA and show the results for a horse race between different models in the AV and the JEA. We also present some robustness checks of the analyses in the main paper.

A.1 *Information usage on eBay*

eBay gives bidders access to a detailed bidding history during an auction. To investigate the effects of information use on eBay, we collected data from eBay-auctions between August 8 and September 27, 2019. We chose one of the most frequently auctioned cell phones in that moment, the Apple iPhone X, 64GB, with a total of 1194 phones. These phones vary considerably in the condition they are sold, with buyers potentially making inference on the phone's value, for example, based on pictures, descriptions, or the sellers' reviews. Crucially, the interested bidders can study others' bids, which may allow them to learn about a specific phone's value.

To explore this endogenous learning, we perform median splits of the data on a number of dimensions, which might convey information during the auction, such as the interim price, the number of bids per bidder and the average increments between consecutive bids. We then study if median splits along these variables explain variation in the final price. Before performing the median splits, we regress the final price on a number of observable characteristics, such as the (exogenously set) length of the auction, the reserve price, the number of bids, and the number of bidders, as well as the review count

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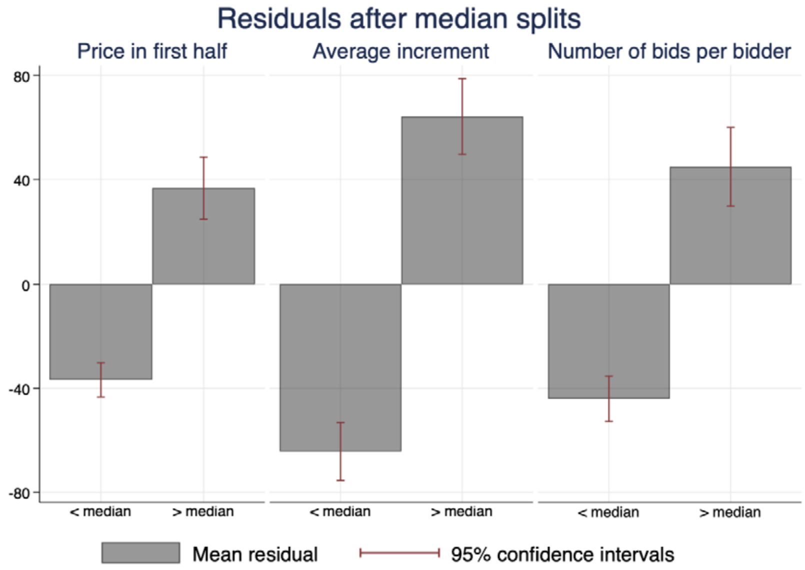


FIGURE 6. Residuals obtained from regressions of final price.

of the seller. By extracting the residuals obtained from these regressions, we factor out all variation that can be explained by these observable exogenous characteristics.[1]

In Figure 6, we plot the average residual for cellphones above and below the median for each of the three different splits of the data. First, we split the auctions based on the price of the cell phone when half of the total length of the auction elapsed. Second, we perform a split based on the average increment per bidder (given by the price at the end less the reserve price, divided by the number of bids submitted). This captures the degree of jump bidding observed. Third, we split on the number of bids per bidder.[2]

We observe that the average residuals of the iPhones are different depending on which half of the data they are categorized in. The effects are also quite sizable, as the average price of the phones is $425.8, standard deviation of $175.8. This implies that there is systematic variation in the prices of these phones, which cannot be explained by the observable exogenous characteristics. Instead, this residual variation can be explained by the categories we perform the median split by, and these variables may capture information generated endogenously in the auction. This indicates that information revelation might matter.

Crucially, this type of observational data cannot be used to establish unambiguously that information revelation is taking place and what effect revealing information has. First of all, the direction of causality is not clear (e.g., are expensive phones attracting many bids, or do many bids increase the price?). More importantly, we cannot evaluate what information is processed without observing bidders' information sets and the

[1]The described pattern is also found when directly comparing prices across the same median splits.

[2]As we perform the median split on these characteristics, we do not residualize the reserve price when performing the split on the price in the first-half, and we do not residualize the number of bids and the number of bidders when performing the split on the number of bids per bidder.

TABLE 7. Revenue Nash predictions with varying parameters.

$(\mu, \sigma_V, \sigma_\epsilon)$		R_{AV}	R_{JEA}
(50, 10, 12)	Mean	48.3555	48.7510
	Standard deviation	(8.3056)	(8.6844)
(100, 10, 12)	Mean	98.3877	98.7540
	Standard deviation	(8.4207)	(8.8667)
(100, 10, 30)	Mean	98.3874	98.5852
	Standard deviation	(5.3808)	(6.0436)
(100, 20, 20)	Mean	96.9314	97.6790
	Standard deviation	(17.6035)	(18.2750)
(100, 20, 30)	Mean	96.5708	97.4156
	Standard deviation	(15.1637)	(6.0436)
(100, 20, 40)	Mean	96.1720	97.2063
	Standard deviation	(12.7600)	(12.4809)
(100, 30, 20)	Mean	96.6016	97.5939
	Standard deviation	(26.8225)	(27.2350)
(100, 30, 30)	Mean	95.4797	96.9314
	Standard deviation	(23.5650)	(24.1363)
(100, 40, 40)	Mean	92.9095	95.5161
	Standard deviation	(26.4453)	(26.4859)
(200, 40, 40)	Mean	194.1535	195.6345
	Standard deviation	(35.1111)	(36.3651)

underlying value of the good to be sold. Also, we are unable to determine the impact of information without providing a control condition where no information is being revealed. However, this is possible in our laboratory experiment.

A.2 *Revenue predictions for different parameterizations*

In the choice of parameterizing the mean and variances of the values and signals for this experiment, we simulated revenues of the AV and the JEA to generate predictions of the symmetric Nash equilibrium. In Table 7, we report results of these simulations. For each parameterization, we draw 50,000 sets of signals according to the procedures of the draws for the experiment, then calculate average revenues based on all simulated bids. In Table 7, R_{AV} are revenues in the AV, R_{JEA} are revenues in the JEA. We simulate different parameterizations, for the full set of parameters $(\mu, \sigma_V, \sigma_\epsilon)$, which is the mean μ and standard deviation σ_V of the value distribution as well as the standard deviation σ_ϵ of the error distribution. Within each parameterization, we give mean revenues in the first row, and the standard deviation of the revenue in the second row. From the table, it is clear that revenue differences of the Nash equilibrium are quite small across specifications. Theoretical revenue differences for uniformly distributed values and errors are similarly low, the case studied by the previous literature.

Additionally, we calculated revenue differences for varying numbers of bidders. In Table 8, for the paramaterization used in this experiment, $(\mu, \sigma_V, \sigma_\epsilon) = (100, 25, 35)$, we state Nash equilibrium revenue differences for different numbers of bidders. Evidently,

TABLE 8. Revenue predictions varying number of bidders, $(\mu, \sigma_V, \sigma_\epsilon) = (100, 25, 35)$.

Number of Bidders		R_{AV}	R_{JEA}
3	Mean	93.4861	94.2020
	SD	(18.0011)	(18.2828)
5	Mean	95.6073	96.9290
	SD	(18.2036)	(18.9653)
7	Mean	96.1953	97.7570
	SD	(18.1058)	(19.0956)
9	Mean	96.6706	98.4264
	SD	(17.7684)	(18.8915)
11	Mean	96.6956	98.5875
	SD	(17.6533)	(18.7593)

theoretical revenue differences between treatments are not driven by the size of our auctions.

A.3 *Naïve models*

In this section, we discuss some behavioral models that have been discussed in the literature, to explain observed behavior in the AV and the JEA. In the AV, there are two principal behavioral models, which might capture bidding behavior. First is the "bid signal"-heuristic, according to which bidders might just enter a bid equal to their own signal:

$$b(x_i) = x_i.$$

In expectation, this will result in overbidding of the winning bidder, as the bidder neither includes information on the distribution of signals and values nor considers the informativeness of winning.

Second, somewhat more sophisticated bidders will incorporate information about the prior distribution of the value. In the "Bayesian bid signal"-heuristic, bidders still suffer from the Winner's curse, but bid the expected value of the good for sale, conditional on one's signal, as in Goeree and Offerman (2003):[3]

$$b(x_i) = \mathbb{E}[V|x_i] = x_i - \mathbb{E}[\epsilon_i|x_i].$$

To explain behavior in the JEA, Levin, Kagel, and Richard (1996) propose a "signal averaging rule," according to which bidders bid an equally weighted average of their own signal and the signals of their fellow bidders, revealed from the previous dropouts. This rule incorporates revealed information in a natural way.

Close to the bid-signal heuristic is the "symmetric signal averaging rule," introduced by Levin, Kagel, and Richard (1996). Here, all bidders assume that all other bidders follow

[3] Within the setup of our experiment, we can use that $\epsilon_i|x_i \sim \mathcal{N}(\frac{\sigma_\epsilon^2(x_i-\mu)}{\sigma_\epsilon^2+\sigma_V^2}, \frac{\sigma_\epsilon^2\sigma_V^2}{\sigma_\epsilon^2+\sigma_V^2})$. As derived in Goeree and Offerman (2003): $b(x_i) = \frac{\sigma_V^2 x_i+\sigma_\epsilon^2\mu}{\sigma_V^2+\sigma_\epsilon^2}$

this rule as well. After k bidders dropped out, with the vector of revealed signals being $\mathbf{Y}_i$, this implies the following bid:

$$b_j(x_i, \mathbf{Y}_i) = \frac{1}{j} x_i + \frac{1}{j} \sum_{k=1}^{j-1} Y_{i}, (k).$$

This formulation can be rewritten to only depend on the last dropout price, for the vector of previous dropout prices $\mathbf{p}_{j-1}$, p_{j-1} being the $j-1$-th observed dropout:

$$b_j(x_i, \mathbf{p}_{j-1}) = x_i + \frac{j-1}{j} p_{j-1}.$$

A variant of this rule is the "asymmetric signal averaging rule," according to which bidders assume that other dropouts are based on the heuristic of bidding equal to signal. This would enable bidders to more easily include others' information. Additionally, it appears to be an intuitive rule given the information salient in the auction process. If bidders follow the asymmetric signal averaging rule, with p_{j-1} being the $j-1$-th dropout, bids are given by

$$b_j(x_i, \mathbf{p}_{j-1}) = \frac{1}{j} x_i + \frac{1}{j} \sum_{k=1}^{j-1} p_k.$$

Similar to the "Bayesian bid signal" heuristic, signal averaging rules can also incorporate information about the prior. According to the "Bayesian signal averaging rule," bidders apply Bayes rule in combination with the symmetric signal averaging rule. In this case, after $j-1$ observed dropouts, bidder i calculates the average of available signals $\bar{x}_i = \frac{1}{j} x_i + \frac{1}{j} \sum_{k=1}^{k-1} Y_{i,(5-k)}$:

$$b(\bar{x}_i) = \frac{\sigma_V^2 \bar{x}_i + \sigma_\epsilon^2 \mu}{\sigma_V^2 + \sigma_\epsilon^2}.$$

While it is unlikely that a bidder that is sophisticated enough to apply Bayes rule correctly would rely on a signal averaging rule, Bayesian signal averaging is most of all useful in anchoring bidding to the prior, compared to standard signal averaging. Even if Bayes rule in itself is too sophisticated, it is also unlikely that bidders rely purely on averaging available signals and fully ignoring all information on the prior distribution of values.

A.4 *Cursed equilibrium in the JEA*

As shown by Eyster and Rabin (2005), the expected payoffs from winning in the χ-virtual common value auction is given by

$$\pi(V, p) = (1-\chi)V + \chi \mathbb{E}[V | X_i = x_i] - p$$

for price p, compared to winners' payoff in Nash equilibrium of $\pi(V, p) = V - p$. We continue to analyze a game where χ is homogeneous across participants, as well as during the auction. This implies bidder's cursedness is not affected by observing other's bids. From Milgrom and Weber (1982), we know that a symmetric Bayes Nash equilibrium in the JEA is given by

$$b_j(x_i) = \mathbb{E}\big[V|X_i = x_i, Y_{i,(1)} = x_i, \ldots, Y_{i,(5-j)} = x_i, p_1 = b_1(Y_{i,(4)}), \\ \ldots, p_{j-1} = b_{j-1}(Y_{i,(5-j+1)})\big].$$

This conditional expected value in a χ-virtual game is equal to

$$\begin{aligned}
&\mathbb{E}\big[(1-\chi)V + \chi\mathbb{E}[V|X_i = x_i]|X_i = x_i, Y_{i,(1)} = x_i, \ldots, Y_{i,(5-j-1)} = x_i, p_1 = b_1(Y_{i,(4)}), \ldots \\
&\quad \ldots, p_{j-1} = b_{j-1}(Y_{i,(5-j+1)})\big] \\
&= (1-\chi)\mathbb{E}\big[V|X_i = x_i, Y_{i,(1)} = x_i, \ldots, Y_{i,(5-j-1)} = x_i, \\
&\quad p_1 = b_1(Y_{i,(4)}), \ldots, p_{j-1} = b_{j-1}(Y_{i,(5-j+1)})\big] + \chi\mathbb{E}[V|X_i = x_i].
\end{aligned}$$

As Milgrom and Weber (1982) have shown that $b_j(x_i)$ is a Nash equilibrium in the original game, the expression above is a symmetric cursed equilibrium in a χ-virtual game, for $\chi \in [0, 1]$.

To employ cursed equilibrium, we need to estimate the additional parameter χ. This also provides a measure of the cursedness of our subjects.

We estimate for the AV:

$$b(x_i) = \underbrace{\left(x_i - \frac{\int_{-\infty}^{\infty} \epsilon\phi_V(x_i-\epsilon)\phi_\epsilon^2(\epsilon)\Phi_\epsilon^3(\epsilon)\,\mathrm{d}\epsilon}{\int_{-\infty}^{\infty} \phi_V(x_i-\epsilon)\phi_\epsilon^2(\epsilon)\Phi_\epsilon^3(\epsilon)\,\mathrm{d}\epsilon}\right)}_{=w_i} \\
+ \chi \underbrace{\left(\frac{\sigma_\epsilon^2 x_i + \sigma_\epsilon^2\mu}{\sigma_V^2 + \sigma_\epsilon^2} + \frac{\int_{-\infty}^{\infty} \epsilon\phi_V(x_i-\epsilon)\phi_\epsilon^2(\epsilon)\Phi_\epsilon^3(\epsilon)\,\mathrm{d}\epsilon}{\int_{-\infty}^{\infty} \phi_V(x_i-\epsilon)\phi_\epsilon^2(\epsilon)\Phi_\epsilon^3(\epsilon)\,\mathrm{d}\epsilon}\right)}_{=z_i}.$$

We simulate all terms using bidders' signals and then regress bids using OLS:

$$b(x_i) = \beta_1 w_i + \beta_2 z_i.$$

In a constrained regression, we impose no constant and $\beta_1 = 1$. Then $\beta_2 = \chi$. For the JEA, we proceed similarly. We first simulate Nash equilibrium bids, based on the inference of observed dropouts.[4] We also use OLS to estimate χ in the following equation:

$$b_k(x_i, \bar{x}_i) = \underbrace{\frac{5\bar{x}_i\sigma_V^2 + \mu\sigma_\epsilon^2}{5\sigma_V^2 + \sigma_\epsilon^2}}_{=w_i} + \chi \underbrace{\left(\frac{\sigma_V^2 x_i + \sigma_\epsilon^2\mu}{\sigma_V^2 + \sigma_\epsilon^2} - \frac{5\bar{x}_i\sigma_V^2 + \mu\sigma_\epsilon^2}{5\sigma_V^2 + \sigma_\epsilon^2}\right)}_{=z_i}.$$

[4]Note that we do not use the theoretical, unobserved signals other bidders hold for simulations. These predictions differ from the Nash equilibrium predictions by not incorporating realized dropout prices, but these do require inferences bidders are not able to make given the observed dropouts in the laboratory.

TABLE 9. Estimating χ.

	(1) AV	(2) AV, d_4	(3) JEA	(4) JEA, d_4
w_i	1.000	1.000	1.000	1.000
	(·)	(·)	(·)	(·)
z_i (for $\hat{\chi}$)	0.058	0.985	−0.137	0.186
	(0.058)	(0.072)	(0.059)	(0.041)
Observations	2417	598	2453	599
Estimation	OLS	OLS	OLS	OLS

Note: Standard errors in parentheses and clustered at the matching group level.

We regress dropout prices on x_1, x_2:

$$b_k(x_i, \bar{x}_i) = \beta_1 w_i + \beta_2 z_i.$$

Again using constrained regression with no constant and $\beta_1 = 1$, we obtain $\beta_2 = \chi$. In Table 9, we summarize the regression results. We estimate χ once for all pooled data and once for the fourth dropouts in (2) and (4), respectively.

The coefficient on z_i is $\hat{\chi}$, which turns out to be low in our sample. Recall that $\chi = 0$ corresponds to Nash equilibrium bidding, thus our bidding behavior appears to be close to this benchmark judged by the cursedness of the participant pool.

A.5 *Horse race between models*

To understand how bidding behavior can be characterized, we analyze how well individual bids can be predicted by the available models. For each bid in each round and based on the available information, such as the signals and observed dropouts, we simulate all models described previously. Then we calculate the distance between each of the bids and all theoretical predictions, using the squared difference. Denote $\delta_{i,t,m}$ the distance of the bid by bidder i in round t, compared to model m. $b_{j;i,t}$ is the observed dropout price of bidder i in round t, dropping out at order j.[5] $b^m_{j;i,t}$ is the theoretically predicted dropout price by model m for this bid. The distance $\delta_{i,t,m}$ is given by

$$\delta_{i,t,m} = \left(b_{j;i,t} - b^m_{j;i,t}\right)^2.$$

After calculating each of the distances for all bids and models, we can determine which model fits individual bids best. Then we calculate the average distance of all models across all bids. In other words, as a measure-of-fit, we state the mean squared error in predicting bids for each model.

To allow for a comparison of the size of the error, we also provide a benchmark linear rule.[6] For this, we run regressions which use the identical available information as the models, which is the bidder's signal and dropouts in case they are observable. We

[5] Here, we only consider bidders who actively choose to drop out.

[6] Note that all models are in fact linear models. Derivations are available on request.

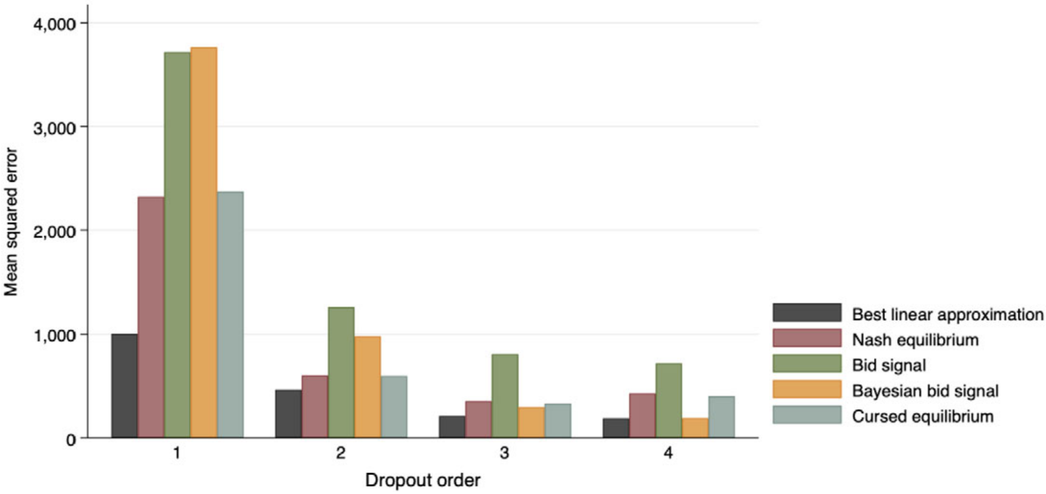


FIGURE 7. Mean squared error of model predictions in the AV.

then state the mean squared error of this prediction. By design, this minimizes this error within the class of linear models, which nests all models which are competing in this analysis.

In our analysis, we distinguish bids by dropout order. The first dropout order are all bidders who drop out first in an auction, and so forth. Note that the fourth dropout order is the most interesting, as these determine revenue.

Horse race for the AV We start by comparing bidding behavior in the AV to the benchmarks. At this stage, we consider four models. In Figure 7, we compare the Nash equilibrium benchmark and three naïve models: (i) bidders exactly bid their signal, (ii) Bayesian bid signal, where bidders suffer from the winner's curse, but do take the base rate into account, as in Goeree and Offerman (2003), and (iii) bidders in cursed equilibrium as proposed by Eyster and Rabin (2005), with an estimated $\hat{\chi} = 0.0578$. Next to it, we provide the mean squared error of the linear benchmark at each dropout order, where only the private information signal is observable by bidders.

The first key insight is the fact that bidding behavior at early dropout orders is substantially less well predicted, as the mean squared error of the benchmark is much larger for early dropout orders than for late dropout orders. This decrease in the error in dropout orders also holds for most other models considered. Second, especially for the later dropouts, Bayesian bid signal shows the lowest error, and comes very close to the benchmark prediction error.

Horse race for the JEA We now continue this analysis for the JEA, using the identical classification procedure. We incorporate all models tested above.[7] Additionally, information revelation allows us to evaluate naïve models where bidders incorporate others' bids. For this, we test three signal averaging rules. In these rules, bidders are bidding

[7]For this auction format, we estimate $\hat{\chi} = -0.137$.

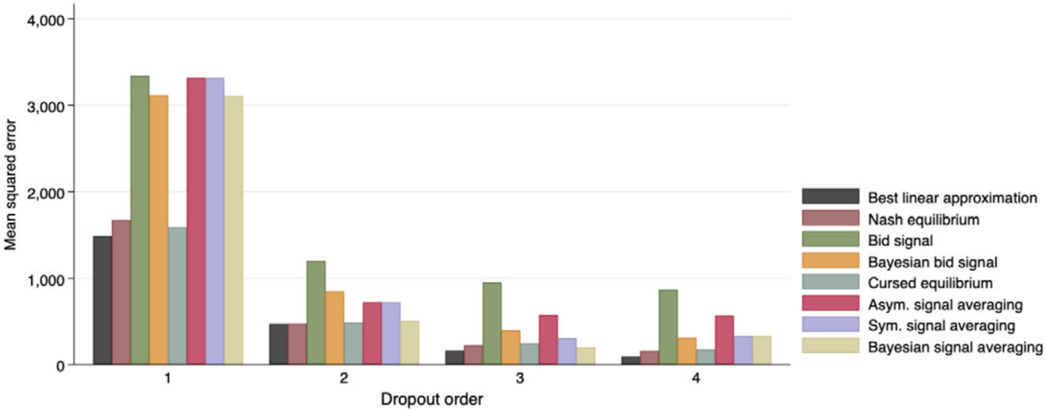


FIGURE 8. Mean squared error of model predictions in the JEA.

the average of all signals available, both the private information signal as well as signals inferred from opponents' bidding behavior. The symmetric signal averaging rule, originally introduced by Levin, Kagel, and Richard (1996), uses that bidders assume that also their opponents apply such a signal averaging rule. The Bayesian signal averaging rule is additionally applying information on the prior, similar to the difference between bid signal and Bayesian bid signal-rules for second-price auctions. The asymmetric signal averaging rule assumes that other bidders bid their signal, thus allows for straightforward computations. For the JEA, the best linear approximation incorporates all bids at earlier dropout orders, as these are observable when deciding on a bid. In Figure 8, we present the results of this analysis.

The main pattern observed in the AV carries over to the JEA: later bids can and in fact are predicted more precisely. Compared to the AV, the prediction error is much lower in the JEA at late dropout orders, suggesting that bidding behavior is more predictable at this point (e.g., the best linear approximation for the fourth dropout shows a mean squared error of 189.5 in the AV and 96.1 in the JEA). At early dropout orders, there is however more noise in the JEA than in the AV. This might complicate matters for remaining bidders trying to estimate the value based on this revealed information in the JEA.

Interestingly, Nash equilibrium fits bidding behavior quite well, when comparing the mean squared error to the benchmark error of the regression.[8] Within the signal averaging rules, the Bayesian signal averaging rule performs best. Note that all signal averaging rules imply low intercepts in the linear bidding model, and we have presented evidence for substantial intercepts in the main text. This contributes to the high errors found for all signal-averaging rules.

Table 10 reports distances to predictions based on observed bidding.

[8]Note that the simulated Nash equilibrium bids, as well as all other models incorporating observed dropouts, are based on inverting observed bids to retrieve the underlying signal. To do so, these rules make assumptions about how other bidders form their bids. This often leads to inferences about other bidders' signals, which are incorrect, as other bidders did not, in fact, bid exactly as predicted by these models.

TABLE 10. Classifying bids into models.

	AV	JEA		AV	JEA
	First dropout			Third dropout	
Nash	**2321.8**	*1675.4*	Nash	356.3	225.8
Bid signal	3718.3	3339.3	Bid signal	807.5	952.6
Bayesian bid signal	3763.3	3114.3	Bayesian bid signal	**298.1**	398.6
χ cursed	*2372.2*	**1590.5**	χ cursed	333.3	248.1
Sym. signal average		3316.7	Sym. signal average		307.8
Asym. signal average		3316.7	Asym. signal average		575.2
Bay. signal average		3106.6	Bay. signal average		**200.3**
Best linear approx.	1004.0	1489.3	Best linear approx.	212.2	163.9
	Second dropout			Fourth dropout	
Nash	*602.3*	**474.7**	Nash	431.5	**159.3**
Bid signal	1261.3	1202.6	Bid signal	717.7	869.7
Bayesian bid signal	978.8	850.3	Bayesian bid signal	**190.3**	313.5
χ cursed	**597.6**	*488.2*	χ cursed	404.0	*176.4*
Sym. signal average		722.3	Sym. signal average		331.6
Asym. signal average		722.9	Asym. signal average		567.4
Bay. signal average		505.6	Bay. signal average		335.6
Best linear approx.	465.9	473.5	Best linear approx.	189.5	96.1

Note: Average distance of observed bids to all considered models, by auction format and dropout order. Distances are squared distance from observed bid to bid predicted by each model. The best fitting model's distance is in bold, models within 10% of the best model's fit are italicized.

A.6 *Learning effects*

Information revelation in auctions potentially affects how bidders learn over time. In open auctions, this learning might also take place during the auction itself, and before information is revealed in sealed bid auctions, at the end of an auction.

In Figure 9, we plot the evolution of the winning bidders' profits over rounds, by auction format. There is learning in the sense that profits increase over rounds. However, there are no meaningful differences in the evolution of profits between the JEA and the AV, learning in the OO is strongest in the sense of increases in profits over time. As we discuss in the main text, our results on revenue continue to hold in our auction data separately both in the first and last 15 rounds.

A.7 *Estimations with experienced bidders*

In the following, we present results of repeating estimations we report in the main text when only using the second half of our data, rounds 16 to 30.

In Table 3 in the main text, we study how available information correlates with bids. Table 11 repeats this analysis for rounds 16–30.

Across dropout orders, bidders appear to rely relatively less on public dropouts, and relatively more on their own private signal in late rounds. (8) shows that observed bids are more informative in late rounds than in the full data set. However, bidders still rely too strongly on the observed dropouts than what the empirical best response in (9) suggests.

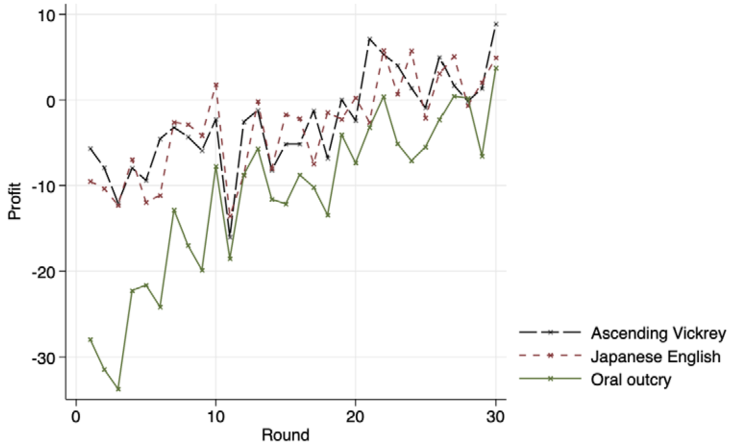


FIGURE 9. Evolution of profits over rounds by auction format.

TABLE 11. Bidders' use of information in JEA.

	(1) b_1	(2) b_2	(3) b_3	(4)	(5) b_4	(6)	(7)	(8) V	(9) $\widehat{BR}$
	Observed	Observed	Observed	Observed	Nash	SA	BSA		
x	0.329	0.274	0.179	0.149	0.287	0.250	0.168	0.232	0.290
	(0.078)	(0.057)	(0.047)	(0.035)	(0.000)	(0.000)	(0.000)	(0.040)	(0.001)
b_1		0.341	0.038	0.029	0.100	0	0	−0.010	0.017
		(0.063)	(0.026)	(0.015)	(·)	(·)	(·)	(0.035)	(0.005)
b_2			0.537	−0.010	0.167	0	0	−0.011	0.047
			(0.089)	(0.019)	(·)	(·)	(·)	(0.057)	(0.008)
b_3				0.641	0.333	0.750	0.832	0.302	0.143
				(0.088)	(·)	(·)	(·)	(0.085)	(0.009)
t	−0.592	0.201	0.288	−0.063				0.379	−0.041
	(0.522)	(0.423)	(0.163)	(0.140)				(0.187)	(0.007)
Constant	35.745	34.694	23.235	26.580	11.265	0	0	41.700	50.207
	(17.143)	(10.104)	(5.317)	(4.495)	(·)	(·)	(·)	(6.651)	(0.597)
Observations	300	300	300	300				300	300
Adj. R^2	0.167	0.394	0.751	0.833				0.370	0.988
Rounds	16–30	16–30	16–30	16–30				16–30	16–30
Estimation	FE	FE	FE	FE				OLS	OLS

Note: b_j: dropout price at order j; V: common value; x: own signal. (1) to (4) are fixed effects estimates (within estimation) of information use. Dependent variables (in columns) are dropout prices at each order, for example, (1) are all bidders dropping out first in an auction. Regressors (in rows) are the available information at each dropout order, that is, the signal x and the preceding dropout prices $\mathbf{b}_{j-1}$. (5) to (7) show how information is used in three canonical models, only for the fourth dropout. SA refers to the signal averaging-rule, BSA to the Bayesian signal averaging-rule. Note that these show how bids respond to earlier bids, where these bids are also calculated to follow the theoretical models. (8) shows how the price-setting bidder would have to use information to predict the common value after observing three dropouts. (9) shows how the bidder dropping out fourth would weigh information in an empirical best response. We provide adjusted R^2 of the original within-estimated model, as well as from estimating standard OLS where we include subject-specific absorbing indicators. The latter also includes fit obtained from subject fixed effects. Standard errors in parentheses, clustered at the matching group level.

TABLE 12. Comparing information use in the AV and the JEA, rounds 16–30.

	b_2	b_3	b_4
b_{j-1}	0.316	0.268	0.325
	(0.050)	(0.026)	(0.039)
JEA × b_{j-1}	0.026	0.269	0.316
	(0.079)	(0.091)	(0.094)
Observations	599	599	599
Adjusted R^2	0.432	0.733	0.784

Note: b_{j-1} denotes the just preceding dropout, for example, is b_1 for b_2. JEA is a dummy equal one for JEA auctions. Other variables in regression omitted from table: all regressions include signal x, round t, all preceding dropouts (b_{j-k} for all $k \in \{1, \ldots, j-1\}$), as well as all these variables interacted with the JEA-dummy and a constant. Standard errors in parentheses and clustered at the matching group level.

In Table 4, we show that bids are more strongly correlated in the JEA than in the AV. Table 12 repeats this analysis for rounds 16–30. Results are in line with results in the full data set, apart from the coefficient on the interaction term of b_1 and JEA in the regression of b_2.

In Table 5, we study whether separately elicited characteristics of subjects correlate with the fixed effect we estimate from bidders' information use. Table 13 repeats this with experienced bidders.

Point estimates are mostly comparable to the analysis with the full data set in the main text. There are some estimates with larger standard errors, for example, Imitator is no longer significant in (1). Point estimates for Imitator in the JEA in (2) turn negative, but remain not significant. The coefficient on SVO in the AV in (3) and the JEA in (4) turns positive and significant, comparable to the coefficient for early bids in (1). Note however that by restricting the data set to the last 15 rounds, we will estimate the fixed effects much less precisely, as we on average only have 3 observations per individual to

TABLE 13. Bidder fixed effects and their characteristics, rounds 16 to 30.

	(1)	(2)	(3)	(4)
	Average Bidder Fixed Effect			
	b_1 & b_2		b_3 & b_4	
	AV	JEA	AV	JEA
SVO	0.110	−0.222	0.100	0.117
	(0.043)	(0.213)	(0.034)	(0.030)
Imitator	4.469	−1.086	3.014	3.179
	(3.668)	(7.912)	(2.023)	(2.032)
Constant	0.894	7.993	−4.797	−3.264
	(1.847)	(3.317)	(1.295)	(1.949)
Observations	50	39	47	38
Adjusted R^2	−0.006	−0.013	0.035	0.141

Note: Average fixed effects from regressing bids on available information for first and second versus third and fourth dropout. SVO is a subject's social value orientation, in degrees. Imitator is a dummy variable equal one if a subject chose to retrieve social information when this contains no valuable information on the true state. Standard errors in parentheses, clustered at the matching group level.

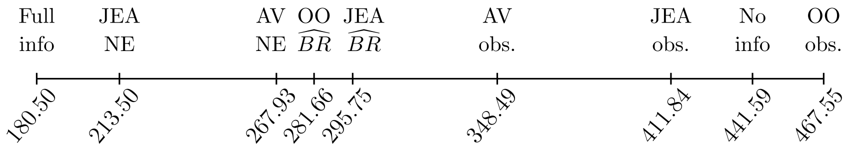


FIGURE 10. Squared distance to common value, rounds 16 to 30.

estimate those. In addition, for one bidder for b_1 and b_2, as well as for five bidders for b_3 and b_4, we cannot obtain a fixed effect any longer, as we do not have observations at these dropout orders for these bidders.

In Figure 5 in the main text, we plot squared distances from the value to the prices in the auction and to some benchmarks, respectively. In Figure 10, we show this based on auction rounds 16 to 30. We observe some learning, as distances decrease compared to the analysis in the main text. This is strongest for the OO, where distances move closer to the no information benchmark, and bids in the empirical best response reveal more information than they do in the JEA.

In Table 6 in the main text, we investigate the effect of jump bids. In Table 14, we repeat this analysis for rounds 16 to 30, also constructing instruments only from experienced bids. Effects of jump bidding appear to be somewhat less pronounced in the second half of the data, but broadly similar.

TABLE 14. Effect of jump bids in the OO, rounds 16–30.

	(1) Jump Bid	(2) Pr (Win)	(3) Profits	(4) Winners' Profits
Total jump bid (IV)		0.341	−0.106	−0.232
		(0.097)	(0.054)	(0.067)
x	0.283	0.178	−0.118	−0.095
	(0.029)	(0.043)	(0.014)	(0.025)
t	−0.043		0.471	0.434
	(0.185)		(0.130)	(0.175)
V			0.587	0.630
			(0.059)	(0.071)
Constant	27.738	−14.532	−57.356	−49.753
	(7.274)	(2.465)	(4.318)	(8.201)
Observations	1309	1309	1309	300
Adjusted R^2	0.072	0.097	0.304	0.283
Estimation	OLS	2SLS	2SLS	2SLS
First-stage F-statistic		490.25	500.05	188.05
Hansen J-statistic, p-value		0.800	0.249	0.620

Note: Jump bid is the increment of a bid beyond the current price at the moment the bid was submitted. In 2SLS, we instrument the total jump bids and the maximum bid increment in other rounds. x is the submitting bidder's signal in round t. V represents the common value. Standard errors in parentheses, clustered at the matching group level.

Table 15. Predicting signals with observed bids.

	(1) x_1	(2) x_2	(3) x_3
d_j	0.205	0.567	1.009
	(0.064)	(0.089)	(0.087)
$\widehat{x_1}$		0.048	0.081
		(0.191)	(0.226)
$\widehat{x_2}$			−0.147
			(0.140)
t	0.270	0.177	0.166
	(0.202)	(0.175)	(0.140)
Constant	68.089	33.977	5.797
	(4.111)	(11.964)	(13.079)
Observations	600	600	600
Adjusted R^2	0.031	0.213	0.342
Rounds	1–30	1–30	1–30
Estimation	OLS	OLS	OLS
Session FE	Yes	Yes	Yes

Note: Standard errors in parentheses and clustered at the matching group level.

A.8 *Information usage in the AV and the JEA*

In Section 6.2, we describe an empirical best response $\widehat{BR}$ in the JEA. It relies on estimated signals. Table 15 shows results of regressing signals on bids, which we in turn use to predict signals based on observable bids, where x_j refers to the signal of the bidder dropping out in jth order in round t, and $\widehat{x_j}$ refers to the predicted signal of the bidder dropping out in jth order.

In Table 4, we show that bids are more strongly correlated in the JEA than in the AV, suggesting that information is actively used in the open format. Doing so controls for the correlation of unobservable dropouts in the AV, which arise as in these regressions bids are ordered. Table 16 shows the full regression results.

A.9 *Informational impact of dropouts*

In this section, we investigate the informational impact of earlier bids on subsequent bids. To do so, we first regress bids, by dropout order, on public information, and then predict residuals. As this estimation by design excludes all private information, for example, a bidder's signal or bidders' idiosyncratic characteristics, this variation will be captured in the residual. In Table 17, we reproduce the estimation used to predict residuals, we do use matching group fixed effects in this estimation.

We then regress dropouts at later dropout orders on these residuals, results are reported in Table 18. Doing so, we can estimate the impact of information revealed in earlier bids on later bids, where we isolate the information contribution of each observed

TABLE 16. Comparing information use in the AV and the JEA.

	b_1	b_2	b_3	b_4
x	0.247	0.297	0.242	0.227
	(0.0457)	(0.0216)	(0.0224)	(0.0298)
b_1		0.285	−0.00113	−0.0141
		(0.0309)	(0.0172)	(0.0209)
b_2			0.357	−0.0114
			(0.0319)	(0.0317)
b_3				0.465
				(0.0440)
t	−0.498	−0.0381	−0.126	−0.174
	(0.155)	(0.0872)	(0.0596)	(0.0341)
JEA × x	0.0464	−0.0296	−0.0704	−0.109
	(0.0718)	(0.0398)	(0.0342)	(0.0336)
JEA × b_1		0.0871	0.0244	0.0392
		(0.0463)	(0.0243)	(0.0253)
JEA × b_2			0.195	−0.0271
			(0.0533)	(0.0479)
JEA × b_3				0.244
				(0.0827)
JEA × t	0.181	−0.0844	0.0433	0.0991
	(0.315)	(0.141)	(0.0937)	(0.0455)
Constant	32.09	38.94	37.14	33.30
	(4.573)	(1.653)	(1.969)	(2.440)
Observations	1199	1199	1199	1199
Adjusted R^2	0.135	0.502	0.732	0.777
Estimation	FE	FE	FE	FE

Note: Standard errors in parentheses and clustered at the matching group level.

TABLE 17. Residual estimations.

	b_1	b_2	b_3
b_1		0.477	0.0221
		(0.0385)	(0.00955)
b_2			0.665
			(0.0435)
t	−0.555	−0.148	−0.0479
	(0.318)	(0.108)	(0.0949)
Constant	77.19	60.20	36.93
	(4.930)	(2.747)	(4.435)
Observations	600	600	600
Adjusted R^2	0.113	0.419	0.698
Fixed effects	matching group	matching group	matching group
Estimation	OLS	OLS	OLS

Note: Standard errors in parentheses and clustered at the matching group level.

TABLE 18. Information effects captured by residuals.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
	Observed			Nash Equilibrium			Bayesian Signal-Averaging		
	b_2	b_3	b_4	b_2	b_3	b_4	b_2	b_3	b_4
x	0.272	0.168	0.120	0.575	0.431	0.287	0.253	0.202	0.168
	(0.0220)	(0.0211)	(0.0180)	(0.00000261)	(0.00000411)	(0.00000549)	(0.00000220)	(0.00000475)	(0.00000568)
e_1	0.401	0.286	0.250	0.200	0.354	0.491	0.747	1.057	1.220
	(0.0392)	(0.0186)	(0.0134)	(0.00000342)	(0.00000524)	(0.00000515)	(0.00000366)	(0.0000154)	(0.0000112)
e_2		0.566	0.429		0.250	0.458		0.798	1.218
		(0.0455)	(0.0328)		(0.0000102)	(0.00000744)		(0.0000198)	(0.0000204)
e_3			0.719			0.333			0.832
			(0.0710)			(0.0000234)			(0.0000370)
Constant	60.04	78.92	90.86	37.08	49.18	63.64	65.16	69.01	74.32
	(2.940)	(2.711)	(2.151)	(0.000190)	(0.000386)	(0.000619)	(0.000157)	(0.000484)	(0.000610)
Observations	600	600	600	600	600	600	600	600	600
Adjusted R^2	0.439	0.713	0.772	1.000	1.000	1.000	1.000	1.000	1.000
Estimation	OLS	OLS	OLS	OLS	OLS	OLS	OLS	OLS	OLS

Note: Standard errors in parentheses and clustered on matching group level.

TABLE 19. Bidder fixed effects and their characteristics.

	(1)	(2)	(3)	(4)
	Average Bidder Fixed Effect			
	b_1 and b_2		b_3 and b_4	
	AV	JEA	AV	JEA
SVO	0.118	−0.231	0.037	0.045
	(0.024)	(0.037)	(0.024)	(0.037)
Imitator	5.364	4.840	5.606	1.080
	(1.030)	(1.695)	(1.030)	(1.695)
Constant	0.492	7.681	−3.719	−0.615
	(0.716)	(1.092)	(0.716)	(1.092)
Observations	50	40	50	40
Estimation	WLS	WLS	WLS	WLS

Note: Average fixed effects from regressing bids on available information for first and second versus third and fourth dropout; pooling data from the AV and the JEA. SVO is a subject's social value orientation, in degrees. Imitator is a dummy variable equal one if a subject chose to retrieve social information when this contains no valuable information on the true state. We use weighted least squares, with the weight given by the inverse average variance of the estimate of the bidder fixed effect, averaged at d_1 and d_2, and at d_3 and d_4. Standard errors in parentheses.

bid. For comparison, we repeat this exercise for Nash equilibrium and the Bayesian signal-averaging rule.[9]

In (1) to (3), we observe that the effect of a bidder's private information, captured by x is less than the public information, revealed through the dropouts. As in the analysis in the main text, we see that the just preceding dropout carries most weight in explaining bidding behavior. This does not lend support to bidders suffering from a strong correlation neglect, as we would expect higher coefficients on the impact of earlier residuals in that case (e.g., on e_1). Similarly, bidders' private information, x, is weighted less than in the benchmarks.

A.10 *Explaining heterogeneity in bidding*

In Section 6.3, we study correlations of bidders' fixed effect with their separately elicited characteristics. A potential concern of this analysis is that these fixed effects are themselves estimated, and some might be more noisily estimated than others. To account for this, we study whether the results presented in the main text are robust to using weighted least squares instead of OLS, where the weights are given by the inverse of the average variance of the estimate of each bidders' (averaged) fixed effect. This procedure ensures that particularly noisy fixed effects receive less weight in the regression. We present results in Table 19.

We observe that the point estimates presented in the main text carry over. In addition, some coefficients which are not significant in the main text are highly significant in this specification, for example, the coefficient on SVO in JEA in (2).

[9] In predicting corresponding residuals, we do not use matching group fixed effects nor do we control for round. For this estimation, note that the residuals are obtained from regressing simulated bids on simulated bids.

Table 20. First stage for 2SLS estimation.

	(2)	(3)	(4)
	Dependent Variable: Total Jump Bid		
Maximum increment in other rounds	0.163	0.163	0.151
	(0.032)	(0.032)	(0.060)
Mean total jump bid in other rounds	0.582	0.584	0.699
	(0.069)	(0.071)	(0.079)
x	0.279	0.302	0.175
	(0.028)	(0.029)	(0.046)
V		−0.076	0.106
		(0.018)	(0.046)
t		−0.163	−0.528
		(0.122)	(0.201)
Constant	−26.761	−19.123	−9.381
	(5.742)	(7.061)	(8.876)
Observations	2687	2687	600
F-statistic	96.4	98.7	143.3
Hansen J-test	0.584	0.582	0.948

Note: The dependent variable across all first-stage regressions is the total jump bid, given by the sum of bid increments beyond the current price within a round. As instruments, we use the maximum bid increment and the mean total jump bid for each bidder in all but the current round. x is the submitting bidder's signal in round t. V represents the common value. Standard errors in parentheses, clustered at the matching group level.

A.11 *Further results on jump bidding*

In the main text, we report 2SLS estimations, where we instrument for the total jump bid with the maximum bid increment and average total jump bid of each bidder obtained in all other rounds.

In Table 20, we report results of the first stage. In addition, we report the Kleibergen–Paap F-statistic, which suggests that the instruments are relevant, and p-values for the Hansen J-statistic, which do not reject that the chosen instruments are valid. Columns (2), (3), and (4) show first-stage results for each of the corresponding second-stages in Table 6 in the main text.

For robustness, we repeat the analysis in Table 6 using only the mean total jump bid in other rounds, and show results in Table 21.

A.12 *Questionnaire results*

In the questionnaire, we offered several reasons why bidders behaved as they did, asking participants how much they agree to a statement on a 7-point Likert scale.

In Table 22, we present the mean and standard deviation of how much people agree with a given statement. The scale is from 1 to 7, where 7 is fully agreeing, 4 is undecided.

A.13 *Circle test*

We also elicited subjects' social value orientation. It is given as an angle. 0° is purely selfish (6 self, 0 other), whereas 45° is splitting equally between self and other (minimizing inequality and maximizing efficiency). Figure 11 gives a histogram of observed choices.

TABLE 21. Effect of jump bids in the OO, one instrument.

	(1) Jump Bid	(2) Pr (Win)	(3) Profits	(4) Winners' Profits
Total jump bid (IV)		0.343	−0.274	−0.315
		(0.087)	(0.134)	(0.151)
x	0.274	0.146	−0.064	−0.031
	(0.032)	(0.039)	(0.043)	(0.044)
t	−0.137		0.875	0.779
	(0.125)		(0.166)	(0.151)
V			0.624	0.634
			(0.046)	(0.066)
Constant	30.525	−12.128	−66.217	−58.989
	(5.937)	(2.756)	(6.987)	(10.231)
Observations	2687	2687	2687	600
Adjusted R^2	0.069	0.103	0.284	0.286
Estimation	OLS	2SLS	2SLS	2SLS
F-statistic		86.9	85.7	325.2

Note: Jump bid is the increment of a bid beyond the current price at the moment the bid was submitted. In (1), we regress total jump bid on bidders' signals and round t. In (2) to (4), we use 2SLS, where we instrument using the average total jump bid in other rounds. (2) is the ex post probability of winning, which is a dummy equal to one if a bidder wins the auction, 0 otherwise. Mean earnings are a participants' average earning across all auctions, winners' profits are the earnings for the auctions which a participant won. x is the submitting bidder's signal in round t. V represents the common value. Standard errors in parentheses, clustered at the matching group level.

A.14 *Histograms of auction revenues*

In Figure 12, we plot histograms of the revenues in all three auction formats as well as a histogram of the common values drawn.

APPENDIX B: INSTRUCTIONS AND SCREENSHOTS OF THE EXPERIMENTAL INTERFACE

In the following, we reproduce the instructions for participants as well as examples of the auction screens.

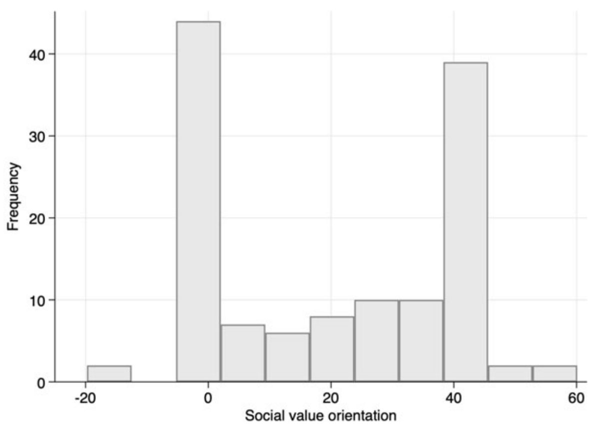


FIGURE 11. Angle in circle test.

Table 22. Questionnaire results.

Treatment	Statement	Mean	SD
AV	In auctions where I did not expect to win, I stayed in the auction longer to increase the price paid by the winner.	2.72	1.96
JEA	In auctions where I did not expect to win, I stayed in the auction longer to increase the price paid by the winner.	3.64	2.03
AV	In auction where I did not expect to win, I quit the auction sooner to decrease the price paid by the winner	2.98	2.00
JEA	In auction where I did not expect to win, I quit the auction sooner to decrease the price paid by the winner	3.08	1.83
JEA	When I observed other bidders leaving, I formed a more precise guess of the value of the item.	4.82	1.76
JEA	When I observed other bidders leaving, I also immediately left the auction, as I relied on the other bidders' guess of the value.	3.79	1.85
OO	All else being equal, I was more likely to enter a new bid if I have been the standing bidder for longer.	3.21	1.76
OO	All else being equal, I was willing to pay more for the item if I have been the standing bidder for longer.	3.26	1.82
OO	I tried to deter other bidders from bidding by entering a bid much higher than the current price.	4	2.12
OO	I tried to prevent other bidders from entering their desired bid by entering a bid much higher than the current price.	4.36	1.94
OO	I entered bids much higher than the current price because I thought this would allow me to pay a lower price for the item.	3.21	2.04
OO	I entered bids much higher than the current price because I was feeling impatient and wanted the auction to finish sooner.	3.15	1.95
OO	I entered bids much higher than the current price because I was becoming annoyed by being overbid by other participants.	3.26	2.11
OO	I entered bids much higher than the current price because it felt costly to decide on and enter new bids.	2.92	1.75

B.1 *Experimental instructions*

Page 1 Welcome!

Welcome to this experiment. Please read the following instructions carefully. You will also receive a handout with a summary. There is a pen and paper on your table, you can use these during the experiment. We ask that you do not communicate with other people during the experiment. Please refrain from verbally reacting to events that occur during the experiment. The use of mobile phones is not allowed. If you have any questions, or need assistance of any kind, at any time, please notify the experimenter with the CALL button on the wall to your left, the experimenter will then assist you privately.

Your earnings will depend on your decisions and may depend on other participants' decisions. Your earnings will be paid to you privately in cash at the end of today's session. All your earnings will be denoted in points. At the end of the experiment, each point that you earned will be exchanged for 25 eurocents.

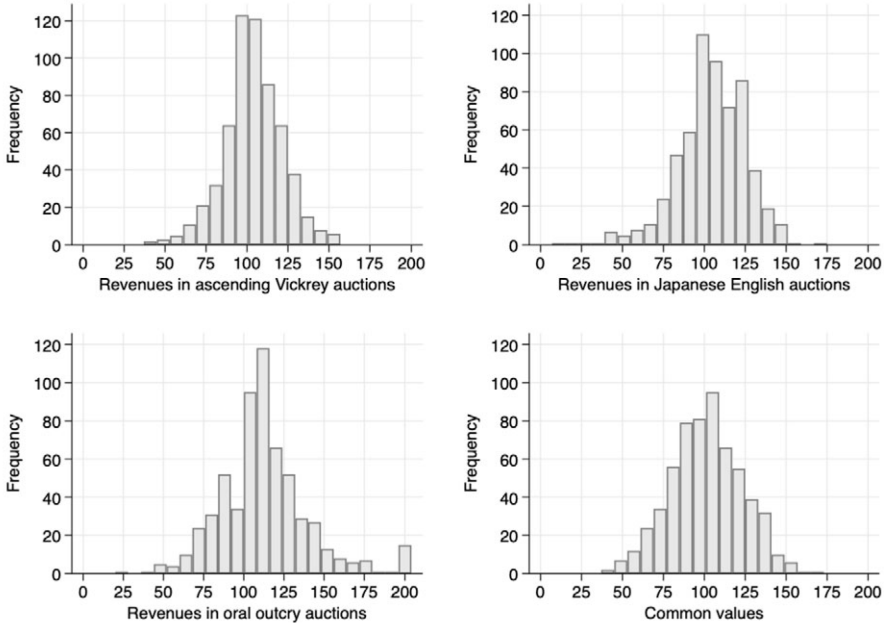


FIGURE 12. Histograms of the drawn common values and revenues.

Page 2 Decision and payoffs

This experiment consists of 30 periods. In each period, you will be allocated randomly to a new group of five participants. Therefore, in each period you will be in a group with (most likely) different participants. You will never learn with whom you are in a group. At the end of the experiment, five periods will be randomly selected for payment. Your earnings will be the sum of the earnings in these five periods.

Description of the situation and possible earnings

In each period, an auction will take place. In each auction, a product of unknown value will be sold. In each period, you will be given a capital of 20 points. Any profits or losses you make in this period will be added to or subtracted from this capital.

Procedures

In each auction, each of the five participants (including you) can obtain the product. First, every participant indicates that he or she is ready, and, as soon as all participants indicate so, there will be a countdown of three seconds, after which the auction starts.

{JEA/AV: In the auction itself, the price will rise in increments of one point, starting at a price of 0. This will be indicated with a thermometer, where the level of the thermometer indicates the current price.

At any point while the price rises, you can decide to leave the auction. You do so by clicking on the "EXIT" button, indicating that you are not willing to buy the item and leave the auction for this period. For all remaining participants, the auction continues.

The auction stops after four of the five participants have pushed the "EXIT" button. The winner of the auction is the last participant remaining in the auction. The price the winner has to pay to buy the product is determined by the level of the thermometer when the fourth bidder has pushed the “EXIT” button. The price level at this point is called SELLING PRICE. The winner obtains the product and pays the SELLING PRICE. The earnings for the winner in the period are given by the value of the product minus the SELLING PRICE. These earnings are added to the capital of 20 points in this period. More details about how the value of the product is determined will follow. All participants who exited the auction will not obtain the product and will earn an amount equal to the capital of 20 points in this period.

{AV ONLY: During the auction, you will not observe how many participants remain in the auction. The price continues to rise as long as there are at least two participants in the auction including yourself.}{JEA ONLY: During the auction, you will be notified as soon as any other participant exits the auction. You will be shown at which price this other bidder left the auction, and there will be a pause of 4 seconds, in which the price will not be increasing. Afterwards, as long as there are at least two participants remaining in the auction, the price rises again.}

In the unlikely case in which multiple participants quit at the same moment and there is no bidder remaining in the auction afterwards, the program will randomly choose the person buying the item from all participants who were the last to exit and did so at the same time. The SELLING PRICE is then the level of the thermometer where these participants simultaneously pressed the button.

At the end of each period, the SELLING PRICE paid by the buyer will be shown to all participants within a group. The buyer will not literally receive a product. In addition to the capital for the period, he or she will receive an amount equal to the value of the product minus the selling price of the product (in points). The previously unknown value of the good will then be revealed to all bidders, as well as their earnings in points in this period. Afterwards, you will be matched with a new group of bidders and a new auction starts, with the same procedure.

Example: Suppose that the first 4 bidders who exit the auction do so at prices 40, 50, 70, 80. Further assume that the product’s value is 90 points. Then the last remaining bidder in the auction will receive the product and pay 80 points. His or her earnings from the auction will be 90–80=10, and the total earnings for the period will be 10 + 20, where 20 is the capital of the period. All other bidders will each earn the capital of 20 in that period.}

{OO: In the auction itself, participants will have the opportunity to enter maximum bids. A maximum bid tells the computer how much you maximally want to pay for the good. The computer will try to obtain the good as cheap as possible on your behalf, and at a price that is no higher than your maximum bid. If your maximum bid is the highest at some moment, then you are the current standing bidder. The standing bidder at the end of the auction obtains the product. This auction proceeds in bidding rounds in the following manner:

As soon as the auction starts, a 15 seconds countdown is initiated. Within these 15 seconds, each bidder can submit a maximum bid that is zero or higher. Whenever a maximum bid is submitted, the auction will be momentarily paused. The bidder who submitted the highest maximum bid so far will be recognized as the standing bidder. At the same time, the second highest maximum bid submitted up to this point will be the CURRENT PRICE for the good. The CURRENT PRICE will be displayed to all participants and a new bidding round immediately starts. Again, a countdown of 15 seconds is initiated, and bidders can submit new maximum bids. Any new maximum bid has to be higher than the CURRENT PRICE. The current standing bidder is notified that he is the standing bidder. He/she will only be able to submit a new maximum bid when he/she is no longer the standing bidder.

This procedure will then be repeated. As soon as new maximum bids above the CURRENT PRICE are submitted, there will be a brief pause, and afterwards a new CURRENT PRICE and standing bidder will be declared. During the bidding procedure, you will be able to see the last submitted maximum bid of each bidder (if a bidder submitted at least one maximum bid). Only the maximum bid of the current standing bidder is not revealed. Note that the bidder numbers do not enable you to identify bidders, as groups change over periods and these numbers are randomly reallocated.

Bidding will continue until no bidder in your group is willing to submit a maximum bid higher than the CURRENT PRICE, and the countdown elapses.

At the end of each period, so when a countdown elapses before any new bid is submitted, the earnings of the bidders are calculated as follows: The winner of the auction is the bidder who submitted the highest maximum bid, and he or she will pay a price equal to the CURRENT PRICE when bidding stopped. The buyer will not literally receive a product. He or she will receive an amount equal to the value of the product minus the CURRENT PRICE of the product (in points). This amount is added to the capital of 20 points in this period. All other bidders earn an amount equal to the capital of 20 points. The previously unknown value of the good will then be revealed to all bidders, as well as their earnings in points in this period. Afterwards, you will be matched with a new group of bidders and a new auction starts, with the same procedure. Notice that the winner of an auction can make a gain or a loss. A loss occurs if the price paid is higher than the value. Even though the final standing bidder pays a price equal to the second highest maximum bid, such bid may be high and result in a high price.}

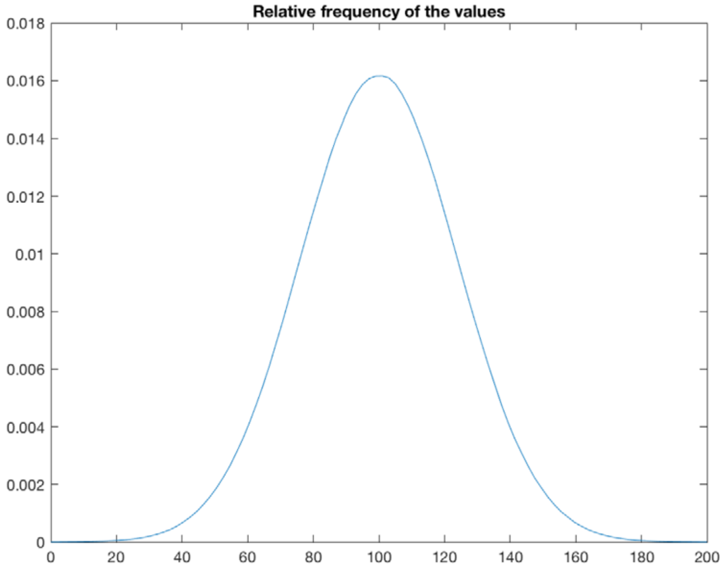
In total, there will be 30 periods, and five randomly determined periods will be chosen to be paid out. Your earnings for the experiment will be equal to the sum of your earnings in these 5 periods.

Page 3 Value of the product and signals

The value of the product is a random number which changes in each period. You cannot learn anything about subsequent value draws from previously observed values. Within the period the value is identical for all participants in the group. At the time of bidding, this value is unknown to all participants. Instead, each participant receives a signal which provides an imprecise indication of what the value may be. In the following, we will describe how the values and signals are determined in each period.

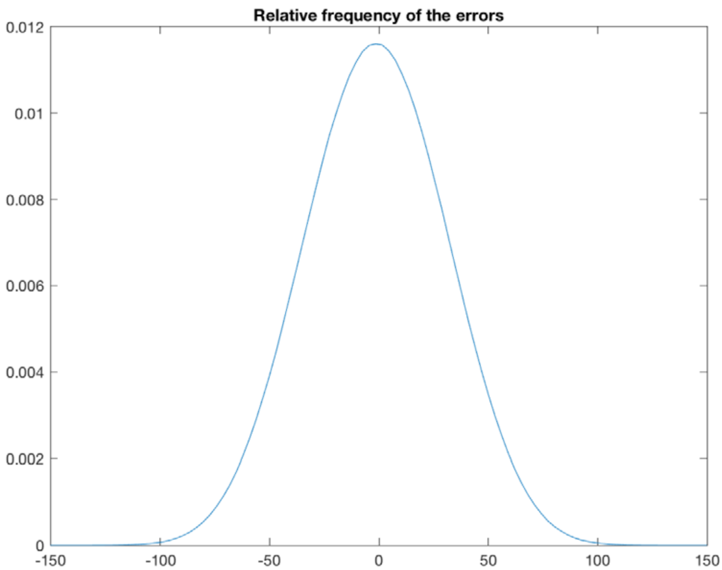
In each period, the value of the product will be randomly determined. The value can be any round number between 0 and 200. The figure below clarifies how frequently different values occur. You can see that values close to 100 occur most often (the frequency is highest when the value on the horizontals axis equals 100). Values below 100 occur as frequently as values above 100. Also, values below 50 occur as often as values above 150.

You do not need to be familiar with such a distribution to participate in this experiment, and you will see some typical value draws on the next page.



The signals

Each participant will receive a (different) signal of the value. This signal gives a first indication of the value of the product in that period, although this is only imprecise information. In particular, the signal is the sum of the value and an error. The figure below shows how frequently different errors occur. You can see that errors close to 0 occur most often, and that errors below 0 occur as frequently as errors above 0.



The error (most likely) differs for every participant. Therefore, each participant in your group will (most likely) obtain a different signal of the value, even though the value of the product is the same for everyone. Signals higher than the value occur as frequently as signals lower than the value. Signals closer to the value are more likely than signals further away from the value. In this experiment, you will encounter only values and signals between 0 and 200.

Notice that each signal in a group is informative about the value of the product. If other bidders let their bidding depend on their signal, then their bidding will be informative about the value of the product.

Note that the signals will be newly determined in each period, therefore only the signals of this period are helpful for you to determine the value of the product for sale.

Payment

As mentioned before, out of the 30 periods, 5 will be randomly selected. You will receive the sum of the points that you earned in each of the 5 selected periods. In each period, every bidder receives a capital of 20 points. Then, any gains or losses a participant made in this period's auction are added to or subtracted from the capital. Notice that the buyer in a period can make a gain but also a loss. If the buyer pays a price higher than the value of the product, he or she makes a loss. Just like a profit is automatically added to the capital, a loss will automatically be subtracted.

Page 4 We will now illustrate in one particular example how the auction process works. We emphasize that this is only an example, and that these numbers are not relevant for the real auctions in which you will participate afterwards.

Example

First, a value of the product is randomly determined, but not revealed to the participants. In our example, this value will be 121. Then, based on the value of 121, the signal for each participant will be drawn. The following signals are drawn: one bidder receives a signal of 60, one bidder a signal of 87, one bidder a signal of 126, one bidder a signal of 144 and the last bidder a signal of 175. Now the auction starts. {JEA/AV: The thermometer starts at 0, and rises continuously as soon as every participant indicated that he or she is ready and the countdown is initiated.

As the thermometer rises, bidders may decide to press the "EXIT" button and leave the auction. Imagine that the first participant exits at a price of 52, the second participant at a price of 77 and the third participant quits at a price of 109. Now, there still remain two bidders in the auction. {IN JEA: Each time a participant quits, all remaining participants will be notified about this, and will receive information about the price at which this participant chose to exit.} The thermometer will keep rising up to the point where the fourth bidder presses the "EXIT" button, for example at a price of 115. Then, the last remaining bidder buys the product at the selling price of 115. In this example, the product's value was 121 points. Therefore, the winner will earn $121 - 115 = 6$ points in addition to his or her capital in this period, hence $6 + 20 = 26$ points in total, if the period is selected for payment.} {OO: The countdown starts at 15 seconds, and is initiated as soon as every participant indicated that he or she is ready. Then, imagine that the first participant to enter a bid submits a maximum bid of 52. This bidder becomes

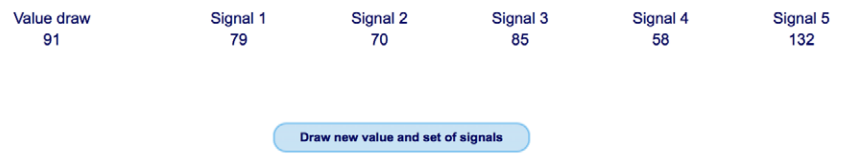


FIGURE 13. Screenshot of the practice draws from the instructions.

the new standing bidder. As so far only one maximum bid has been submitted, the CURRENT PRICE will be 0, and this is shown to all bidders as soon as the next bidding round commences. The countdown is reset and starts immediately. Then imagine a new maximum bid of 77 is submitted. As this is the current highest maximum bid, this bidder becomes the new standing bidder. The second highest maximum bid at this point is 52, and therefore 52 is the new CURRENT PRICE. Bidding continues in this fashion until the countdown elapses. For example, imagine that in the next rounds maximum bids of 109, 115, and 120 are, and in the next bidding round the countdown elapses. Then the bidder who submitted the highest maximum bid (i.e. the bidder who bid 120) will win the auction. This bidder will pay the last CURRENT PRICE, which equals the second highest maximum bid (115 in this example). In this example, the product's value was 121 points. Therefore, the winner will earn $121 - 115 = 6$ points in addition of his or her capital in this period, if the period will be selected for payment.}

Page 6   Practice draws

Now, you have the opportunity to see how typically values and corresponding signals are drawn. You can click on a button to draw new values and signals. Then, you will be shown a value and set of signals drawn according to the same procedure as those in the experiment. In the experiment, you will not be able to observe the value draw, but instead you receive one of the imprecise signals of the value. Five signals corresponding to this value are shown to you next to the value draw. When you click on the button again, a new value and corresponding set of signals will be drawn, you can repeat this as often as you like. Note that these example values and signals are not informative about the draws you will actually face in the experiment. (Figure 13 provides a screenshot of the practice draws.)

When you have tried a number of times, please continue to the practice questions on the next page.

B.2 *Additional elicitations*

For the last 14 sessions, we added two additional measures, elicited after the auctions concluded. Below are instructions for both tasks.

B.2.1 *Imitation, adapted from Goeree and Yariv (2015)*

Part 2

In this part of the experiment, you make an individual decision. The amount you earn depends only on your choices and your choices do not affect the earnings of other participants.

Guessing the urn

In this task, you have to guess which one of two possible urns has been selected. It is equally likely that you face a red or a blue urn. These urns contain red and blue balls as follows:

- Red urn: 7 red balls and 3 blue balls
- Blue urn: 7 blue balls and 3 red balls

Information

For your decision, you have to choose to receive one of two types of information:

- Draw: The color of one randomly selected ball drawn from your urn will be shown to you.
- History: The choices of three participants from previous sessions of this experiment will be revealed to you. These three participants faced the same urn as you do, but did not receive any of the two types of information you can choose between (neither Draw nor History).

Task

After you receive this information, you have to guess which of the two urns has been selected.

Payoff

You will earn 4 points if you guess correctly which urn has been chosen.

When you continue, it will be randomly determined whether you face the red or the blue urn. In the next screen, you first choose the type of information you would like to receive, then you have to enter your guess which urn you are facing.

B.2.2 *Circle test, adapted from Linde and Sonnemans (2012)*

Part 3

For this part of the experiment, you have been matched with one other randomly selected participant, called OTHER. Your subsequent decision will be anonymous, no participant will know with whom they have been matched. In the end, either your or OTHER's decision will be implemented.

Choice

In this part you have to choose between combinations of earnings for yourself and the OTHER. All possible combinations are represented on a circle. You can click on any point on the circle. Which point you choose determines how much money you and the OTHER earn. You can enter this choice on the next page.

Earnings

The axes in the circle represent how much money you and the OTHER earn when you choose a certain point on the circle. The horizontal axis shows how much you earn: the more to the right, the more you will earn. The vertical axis shows how much the OTHER will earn: the more to the top, the more the OTHER earns. The distribution can also imply negative earnings for you and/or the OTHER. Points on the circle left of the middle imply negative earnings for you, points below the middle imply negative earnings for the OTHER. When you click on a point on the circle the corresponding combination

FIGURE 14. Screenshot from a ascending Vickrey auction.

of earnings, in cents, will be displayed in the table to the right of the circle. You can try different points by clicking on the circle using your mouse. Your choice will only become final when you click on the "send" button.

Payoff

The OTHER is presented with the same choice situation. At the end of the experiment, either your decision or the decision of the OTHER will be paid. This will be determined by a random draw, your decision is as likely to be chosen as the decision of the OTHER. This draw is not affected by the choices you or others make.

B.3 *Screenshots of the interface*

Figure 14, Figure 15 and Figure 16 present screenshots of the screens of auction participants for all three treatments.

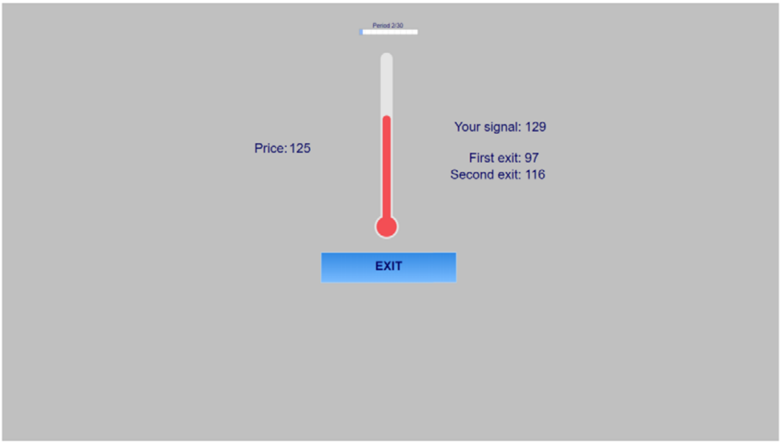


FIGURE 15. Screenshot from a Japanese–English auction.

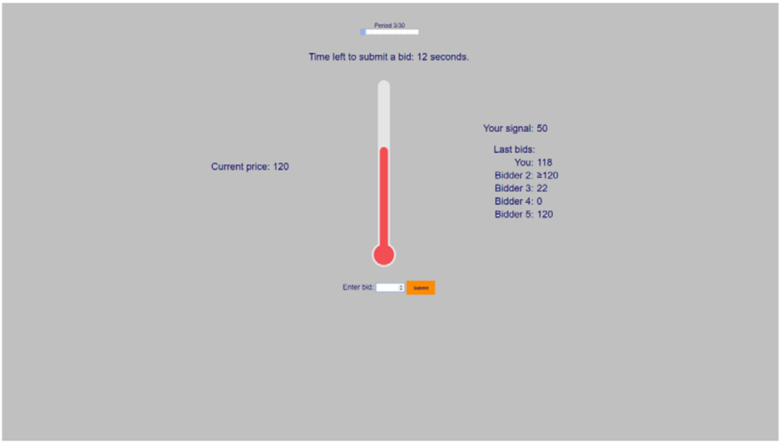


FIGURE 16. Screenshot from an Oral Outcry auction.

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