Online Appendixes

Round Bidding in Auctions

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This document contains three online appendixes supplementing the article. Appendix A1 provides details on the grid search used to estimate the structural parameters. Appendix A2 provides supplementary exhibits.

A1. Grid Search for Structural Estimates

This appendix describes the adaptive grid-search procedure we developed to locate the structural parameters minimizing the method of simulated moments (MSM) criterion function (14). Judicious design is needed to thoroughly explore the parameter space while honing in on precise parameter estimates. The "curse of dimensionality" is a real threat since the grid search is over six parameters, and each grid point requires extensive computations since some types' bidding strategies need to be computed via simulation within each Monte Carlo run.

For purposes of this discussion, we partition the parameter vector $\theta_i = (\mu_i, \alpha_i, \beta_i, \rho_i, \pi_{1i}, \pi_{2i})$ as $\theta_i = (\theta_{ai}, \theta_{bi})$, where $\theta_{ai} \equiv (\mu_i, \alpha_i, \beta_i)$ is the subvector of basic auction parameters and $\theta_{bi} \equiv (\rho_i, \pi_{1i}, \pi_{2i})$ is the subvector of behavioral parameters. The grid search proceeds in two stages. Stage 1 focuses on iterating toward a precise estimate of θ_{ai} for values of θ_{bi} on a fairly coarse grid. Stage 2 works on refining the grid over which θ_{bi} is searched, fixing the estimate of θ_{ai} from stage 1.

Stage 1: Refined Estimation of Basic Auction Parameters

This stage adaptively hones in on precise estimates of θ_{ai} for each point in a coarse grid covering the entire parameter space of θ_{bi}. We construct the grid over θ_{bi} one parameter at a time. For ρ_i, we use an empirical fact to narrow down its range. Specifically, the empirically observed share of $5\mathbb{N}$ winning bids—label it $\check{\rho}_i$—provides an upper bound on the proportion of round bidders since some non-round bidders may opt for a round bid. We take the grid for ρ_i to be the five evenly spaced points from 0 to $\check{\rho}_i$:

$$\{0, 0.25\check{\rho}_i, 0.5\check{\rho}_i, 0.75\check{\rho}_i, \check{\rho}_i\}. \tag{A1}$$

We base the contruction of grids for π_{1i} and π_{2i} on the conjecture that the proportion of bidders with higher levels of reasoning weakly declines with each level:

$$\pi_{0i} \geq \pi_{1i} \geq \pi_{2i}. \tag{A2}$$

While other work (see, e.g., Crawford and Iriberri, 2007) finds that the proportion of level-0 reasoners is small compared to the proportion of level-1 reasoners, reasoning levels have different meaning in our setting. Our level-0 reasoners do not make random decisions as in other settings; aside from their ignorance of rival's round bidding, they are fully rational optimizers. It is plausible that a substantial proportion of bidders reason at this level, justifying conjecture (A2), which implies

$$\pi_{1i}, \pi_{2i} \leq 1/3. \tag{A3}$$

Lacking observational evidence on bidders' reasoning levels beyond inequality (A3), we take the five-point, evenly spaced grid for π_{1i} and π_{2i} encompassing (A3):

$$\{0, 0.1, 0.2, 0.3, 0.4\}. \tag{A4}$$

It turns out that conjecture (A2) was correct for all 100 items in our structural sample; the corner 0.4 never emerged as a solution for π_{1i} or π_{2i}. Had a corner solution materialized, the stage-2 procedure is designed to adapt and look for higher values of these parameters, as we will discuss.

For each of the $5^3 = 125$ grid points for θ_{bi}, we perform an adaptive grid search over θ_{ai} over three iterations substages, described next.

Iteration 1.1 In this iteration, we construct a relatively coarse grid for each of the basic auction parameters that are centered on empirically supported values and sufficiently wide that they are likely to encompass the true parameter values. If corner solutions emerge, subsequent iterations will expand to look for values outside the initially selected ranges.

For μ_i, the mean of the χ^2 distribution of number of bidders, we take the center the grid, denoted $\mu_i^{\langle 1.0 \rangle}$, to be the average number of bids submitted across final-stage auctions for item i. We take a five-point grid of evenly spaced values from 0.5 to 1.5 times $\mu_i^{\langle 1.0 \rangle}$:

$$\{0.5\mu_i^{\langle 1.0 \rangle}, 0.75\mu_i^{\langle 1.0 \rangle}, \mu_i^{\langle 1.0 \rangle}, 1.25\mu_i^{\langle 1.0 \rangle}, 1.5\mu_i^{\langle 1.0 \rangle}\}. \tag{A5}$$

For β_i, the mean of the Γ distribution of item values, we take the center the grid, denoted on $\beta_i^{\langle 1.0 \rangle}$, to be the average winning bid across auctions for item i. We take a five-point grid of evenly spaced values from 0.5 to 1.5 times $\beta_i^{\langle 1.0 \rangle}$:

$$\{0.5\beta_i^{\langle 1.0 \rangle}, 0.75\beta_i^{\langle 1.0 \rangle}, \beta_i^{\langle 1.0 \rangle}, 1.25\beta_i^{\langle 1.0 \rangle}, 1.5\beta_i^{\langle 1.0 \rangle}\}. \tag{A6}$$

For α_i, the shape parameter of the Γ distribution of item values, we centered the grid on $\alpha_i^{\langle 1.0 \rangle} = \beta_i^{\langle 1.0 \rangle}/2$, the value that, as one can show, makes the variance of the Γ distribution twice the mean, which is close to the 1.6 ratio of the variance to the mean of winning bids averaged across items in our structural sample. We take a five-point grid of evenly spaced values from 0.5 to 1.5 times $\alpha_i^{\langle 1.0 \rangle}$:

$$\{0.5\alpha_i^{\langle 1.0 \rangle}, 0.75\alpha_i^{\langle 1.0 \rangle}, \alpha_i^{\langle 1.0 \rangle}, 1.25\alpha_i^{\langle 1.0 \rangle}, 1.5\alpha_i^{\langle 1.0 \rangle}\}. \tag{A7}$$

In total, the grid searched in iteration 1.1 involves 5^3 combinations of θ_{bi} parameters for each of the 5^3 combinations of θ_{ai}, for a total of $5^6 = 15,625$ grid points for θ_i. Each grid-point evaluation requires one run through the procedure described in Section 6.2. As this passage indicates, the procedure constructs a population of $M = 1,000$ bidders with valuations given by the Γ distribution with the grid-point parameters from which the bidders for $J = 1,000$ auctions are drawn, where the number of participants is a random draw of n_j from the χ^2 distribution with the grid-point mean.

Let $\theta_i^{\langle 1.1\rangle} = (\theta_{ia}^{\langle 1.1\rangle}, \theta_{ib}^{\langle 1.1\rangle})$ denote the grid point emerging from this iteration that minimizes the MSM criterion (14). We check whether any of the elements of $\theta_{ia}^{\langle 1.1\rangle}$ are corners, i.e., whether any of the following equalities hold:

$$\mu_i^{\langle 1.1\rangle} = 0.5\mu_i^{\langle 1.0\rangle} \tag{A8}$$
$$\mu_i^{\langle 1.1\rangle} = 1.5\mu_i^{\langle 1.0\rangle} \tag{A9}$$
$$\alpha_i^{\langle 1.1\rangle} = 0.5\alpha_i^{\langle 1.0\rangle} \tag{A10}$$
$$\alpha_i^{\langle 1.1\rangle} = 1.5\alpha_i^{\langle 1.0\rangle} \tag{A11}$$
$$\beta_i^{\langle 1.1\rangle} = 0.5\beta_i^{\langle 1.0\rangle} \tag{A12}$$
$$\beta_i^{\langle 1.1\rangle} = 1.5\beta_i^{\langle 1.0\rangle}. \tag{A13}$$

If not, the vector of parameters $\theta_{ia}^{\langle 1.1\rangle}$ is passed directly to the next iteration stage. If so, we re-run iteration 1.1 centering the grids in equations (A5)–(A7) on, respectively, $\mu_i^{\langle 1.1\rangle}$, $\beta_i^{\langle 1.1\rangle}$, and $\alpha_i^{\langle 1.1\rangle}$ rather than $\mu_i^{\langle 1.0\rangle}$, $\beta_i^{\langle 1.0\rangle}$, and $\alpha_i^{\langle 1.0\rangle}$. We iterate in this way until the solution involves no corners. The procedure passes the resulting non-corner parameter values in the vector $\theta_{ia}^{\langle 1.1\rangle}$ to the next iteration.

Iteration 1.2 This iteration is identical to the previous except that it centers the grids on the subvector $\theta_{ia}^{\langle 1.1\rangle}$ passed by the previous iteration in place of $\theta_{ia}^{\langle 1.0\rangle}$. The other difference is that it refines the grid search by cutting the step-size proportion in half. Thus, the grids in (A5)–(A7) are replaced by

$$\{0.75\mu_i^{\langle 1.1\rangle}, 0.875\mu_i^{\langle 1.1\rangle}, \mu_i^{\langle 1.1\rangle}, 1.125\mu_i^{\langle 1.1\rangle}, 1.25\mu_i^{\langle 1.1\rangle}\} \tag{A14}$$
$$\{0.75\beta_i^{\langle 1.1\rangle}, 0.875\beta_i^{\langle 1.1\rangle}, \beta_i^{\langle 1.1\rangle}, 1.125\beta_i^{\langle 1.1\rangle}, 1.25\beta_i^{\langle 1.1\rangle}\} \tag{A15}$$
$$\{0.75\alpha_i^{\langle 1.1\rangle}, 0.875\alpha_i^{\langle 1.1\rangle}, \alpha_i^{\langle 1.1\rangle}, 1.125\alpha_i^{\langle 1.1\rangle}, 1.25\alpha_i^{\langle 1.1\rangle}\}. \tag{A16}$$

This iteration uses the same grid of 5^3 points for the behavioral parameters θ_{ib} as iteration 1.1. The combination of these with the 5^3 grid points entailed by equations (A14)–(A16) yields $5^6 = 15,625$ total grid points to explore in this iteration. Let $\theta_i^{\langle 1.2\rangle} = (\theta_{ia}^{\langle 1.2\rangle}, \theta_{ib}^{\langle 1.2\rangle})$ denote the grid point emerging from this iteration that minimizes the MSM criterion (14). As in the previous iteration, we check whether any of the elements of $\theta_{ia}^{\langle 1.2\rangle}$ are corners. If not, the vector of parameters $\theta_{ia}^{\langle 1.2\rangle}$ is passed directly to the next iteration stage. If so, we re-run iteration 1.2 centering the grids in equations (A14)–(A16) on, respectively, $\mu_i^{\langle 1.2\rangle}$, $\beta_i^{\langle 1.2\rangle}$, and $\alpha_i^{\langle 1.2\rangle}$ rather than $\mu_i^{\langle 1.1\rangle}$, $\beta_i^{\langle 1.1\rangle}$, and $\alpha_i^{\langle 1.1\rangle}$. We iterate in this way until the solution involves no corners. The procedure passes the resulting non-corner parameter values in the vector $\theta_{ia}^{\langle 1.2\rangle}$ to the next iteration.

Iteration 1.3 The third and last step in the stage-1 refined estimation of basic auction parameters is identical to iteration 1.2 except that it centers the grids on the subvector $\theta_{ia}^{\langle 1.2\rangle}$ passed by the previous iteration in place of $\theta_{ia}^{\langle 1.1\rangle}$. The other difference is that it refines the grid search by cutting the step-size proportion again in half. Thus, the grids in (A14)–(A16) are replaced by

$$\{0.875\mu_i^{\langle 1.2\rangle}, 0.9375\mu_i^{\langle 1.2\rangle}, \mu_i^{\langle 1.2\rangle}, 1.0625\mu_i^{\langle 1.2\rangle}, 1.125\mu_i^{\langle 1.2\rangle}\} \tag{A17}$$

$$\{0.875\beta_i^{\langle 1.2\rangle}, 0.9375\beta_i^{\langle 1.2\rangle}, \beta_i^{\langle 1.2\rangle}, 1.0625\beta_i^{\langle 1.2\rangle}, 1.125\beta_i^{\langle 1.2\rangle}\} \tag{A18}$$

$$\{0.875\alpha_i^{\langle 1.2\rangle}, 0.9375\alpha_i^{\langle 1.2\rangle}, \alpha_i^{\langle 1.2\rangle}, 1.0625\alpha_i^{\langle 1.2\rangle}, 1.125\alpha_i^{\langle 1.2\rangle}\}. \tag{A19}$$

Let $\theta_i^{\langle 1.3\rangle} = (\theta_{ia}^{\langle 1.3\rangle}, \theta_{ib}^{\langle 1.3\rangle})$ denote the grid point emerging from this iteration that minimizes the MSM criterion (14). As before, we check whether any of the elements of $\theta_{ia}^{\langle 1.3\rangle}$ are corners. If not, the vector of parameters $\theta_{ia}^{\langle 1.3\rangle}$ is passed directly to stage 2. If so, we re-run iteration 1.3 centering the grids in equations (A17)–(A19) on, respectively, $\mu_i^{\langle 1.3\rangle}$, $\beta_i^{\langle 1.3\rangle}$, and $\alpha_i^{\langle 1.3\rangle}$ rather than $\mu_i^{\langle 1.2\rangle}$, $\beta_i^{\langle 1.2\rangle}$, and $\alpha_i^{\langle 1.2\rangle}$. We recursively iterate in this way until the solution involves no corners. The procedure passes the resulting non-corner parameter values in the vector $\theta_{ia}^{\langle 1.3\rangle}$ to the next stage.

Stage 2: Refined Estimation of Behavioral Parameters

This stage fixes the basic auction parameters at $\theta_{ia}^{\langle 1.3\rangle}$ and refines the estimates of the behavioral parameters θ_{ib}. Stage 2 is similar to stage 1. Both are adaptive grid searches involving three iterations. The differences are subtle. One, just mentioned, is that we do not perform a grid search over the subvector of parameters that are not the focus of the stage, θ_{ia} in this case, but fix them at the result from the previous stage $\theta_{ia}^{\langle 1.3\rangle}$ for the entire stage.

Another difference is that we increase the number of simulations by a factor of 10, drawing bidders from a population of $M = 10,000$ and simulating $J = 10,000$ auctions. We do this for two reasons. First, fixing the vector of other parameters at $\theta_{ia}^{\langle 1.3\rangle}$ rather than performing a grid search over them reduces the number of computations compared to the previous stage by more than two orders of magnitude, allowing leeway for more simulation precision. Second, estimating the prevalence of different reasoning levels is with observational as opposed to experimental data has been found to be delicate (Gillen, 2010), introducing simulation error that can be reduced by using a large simulation sample.

Iteration 2.1 The parameter vector passed by stage 1, $\theta_{ia}^{\langle 1.3\rangle}$, becomes the starting point for this iteration, reflected in the notation by writing $\theta_{ia}^{\langle 2.0\rangle} = \theta_{ia}^{\langle 1.3\rangle}$. For each of the behavioral parameters, we take a five-point grid with a step size of 0.25 centered at the components of $\theta_{ia}^{\langle 2.0\rangle}$. For ρ_i, π_{1i}, and π_{2i}, the grids are, respectively,

$$\{0.5\rho_i^{\langle 2.0\rangle}, 0.75\rho_i^{\langle 2.0\rangle}, \rho_i^{\langle 2.0\rangle}, 1.25\rho_i^{\langle 2.0\rangle}, 1.5\rho_i^{\langle 2.0\rangle}\} \tag{A20}$$

$$\{0.5\pi_{1i}^{\langle 2.0\rangle}, 0.75\pi_{1i}^{\langle 2.0\rangle}, \pi_{1i}^{\langle 2.0\rangle}, 1.25\pi_{1i}^{\langle 2.0\rangle}, 1.5\pi_{1i}^{\langle 2.0\rangle}\} \tag{A21}$$

$$\{0.5\pi_{2i}^{\langle 2.0\rangle}, 0.75\pi_{2i}^{\langle 2.0\rangle}, \pi_{2i}^{\langle 2.0\rangle}, 1.25\pi_{2i}^{\langle 2.0\rangle}, 1.5\pi_{2i}^{\langle 2.0\rangle}\}. \tag{A22}$$

Let $\theta_{ib}^{\langle 2.1\rangle}$ denote the grid point emerging from this iteration that minimizes the MSM criterion (14) (recall, the other parameters are fixed at $\theta_{ia}^{\langle 1.3\rangle}$ throughout stage 2). As before, we check whether any of the elements of $\theta_{ib}^{\langle 2.1\rangle}$ are corners. If not, the vector of parameters $\theta_{ia}^{\langle 2.1\rangle}$ is passed directly to the next iteration. If so, we re-run iteration 2.1 centering the grids in equations (A20)–(A22) on, respectively, $\rho_i^{\langle 2.1\rangle}$, $\pi_{1i}^{\langle 2.1\rangle}$, and $\pi_{2i}^{\langle 2.1\rangle}$ rather than $\rho_i^{\langle 2.0\rangle}$, $\pi_{1i}^{\langle 2.0\rangle}$, and $\pi_{2i}^{\langle 2.0\rangle}$. We iterate in this way until the solution involves no corners.

The description of iteration 2.1 has abstracted from one modification introduced in stage 2 that is of practical relevance in this stage will apply throughout, which was irrelevant in stage 1. Since the associated χ^2 and Γ distributions involve positive parameters, there was no practical reason to accommodate zero values for components of θ_{ia}. On the other hand, zero values for the proportions of behavioral types in θ_{ib} are practically relevant and empirically interesting. However, it is mathematically impossible for the procedure for forming the grids and recursively iterating when corners are hit to return a zero value. Indeed, the procedure could iterate endlessly as it approaches but never reaches a true value of zero.

To adderess this issue, in forming any grid in iteration 2.1, we overlay a minimum absolute step size of 0.05. If several steps of this size from the grid's center would entail a negative grid point for that parameter, we replace that grid point with 0.

For example, suppose $\rho_i^{\langle 2.0\rangle} = 0.3$. The grid prescribed by equation (A20) is

$$\{0.15, 0.225, 0.3, 0.375, 0.45\}. \tag{A23}$$

Since the smallest absolute step in this grid is $0.075 > 0.05$, our restriction on absolute step size is satisfied by (A23), and that grid can be used as is. Suppose instead that $\rho_i^{\langle 2.0\rangle} = 0.08$. Then the grid prescribed by equation (A20) would be

$$\{0.04, 0.06, 0.08, 0.1, 0.12\}, \tag{A24}$$

with step sizes of $0.02 < 0.05$, violating our restriction on absolute step size. The modification substitutes the following grid instead:

$$\{0, 0.03, 0.08, 0.13, 0.18\}. \tag{A25}$$

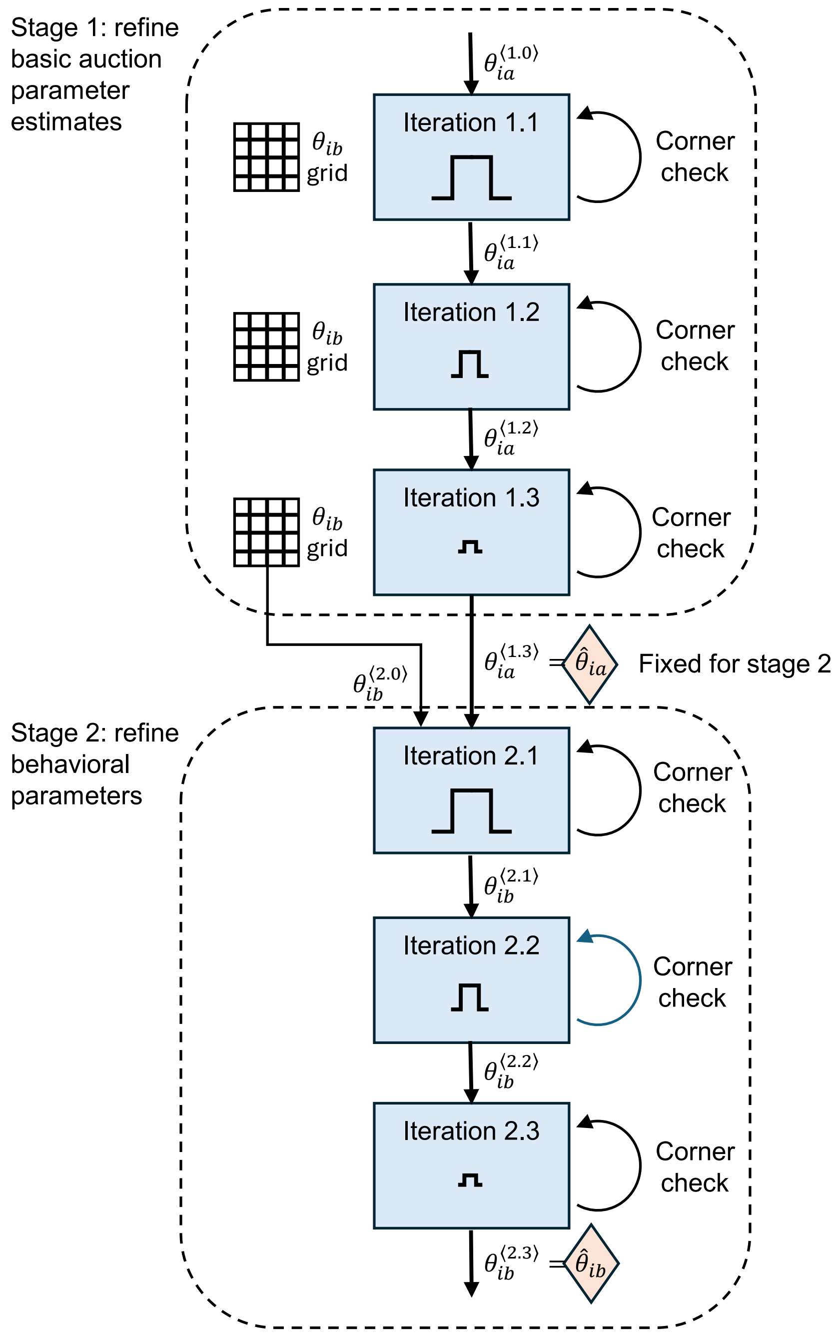
The grid continues to be centered at $\rho_i^{\langle 2.0\rangle} = 0.08$ but replaces steps of absolute size 0.02 with steps that are of the constrained absolute size. A negative value is not allowed for the smallest grid point, so it is rounded up to 0. The overlay of a minimum absolute step size leads to the construction of grids having 0 as a candidate point in the grid search.

To avoid infinite iterations, a 0 parameter value has special status in the check for corner solutions. If the solution to the minimization problem hits the smallest grid point, and this grid point is positive, further iteration is triggered centered on this grid point as usual. However, if the solution hits 0, further iteration is not triggered.

Iteration 2.2 This iteration is identical to the previous except that it centers the grids on the subvector $\theta_{ia}^{\langle 2.1\rangle}$ passed by the previous iteration in place of $\theta_{ia}^{\langle 2.0\rangle}$. The other difference is that it refines the grid search by cutting the step-size proportion in half (to 0.125) and cutting the minimum absolute step size to 0.02.

Iteration 2.3 This iteration is identical to the previous except that it centers the grids on the subvector $\theta_{ia}^{\langle 2.2\rangle}$ passed by the previous iteration in place of $\theta_{ia}^{\langle 2.1\rangle}$. The other difference is that it refines the grid search by cutting the step-size proportion in half (to 0.0625) and cutting the minimum absolute step size to 0.01.

Figure A1: Schematic Diagram of Adaptive Grid Search



Notes: Reduction in step size in lower boxes in each stage indicative of more refined grid used in that iteration. Arc to the right of each box indicates iterative checking whether the solution is at a corner and re-estimating with a grid around that corner if so until the solution is not a corner.

A2. Supplementary Exhibits

The rest of the online appendix provides supplementary exhibits in the order referenced in the text.

Figure A2: Relative Frequency of Bid Values in Various Subsamples

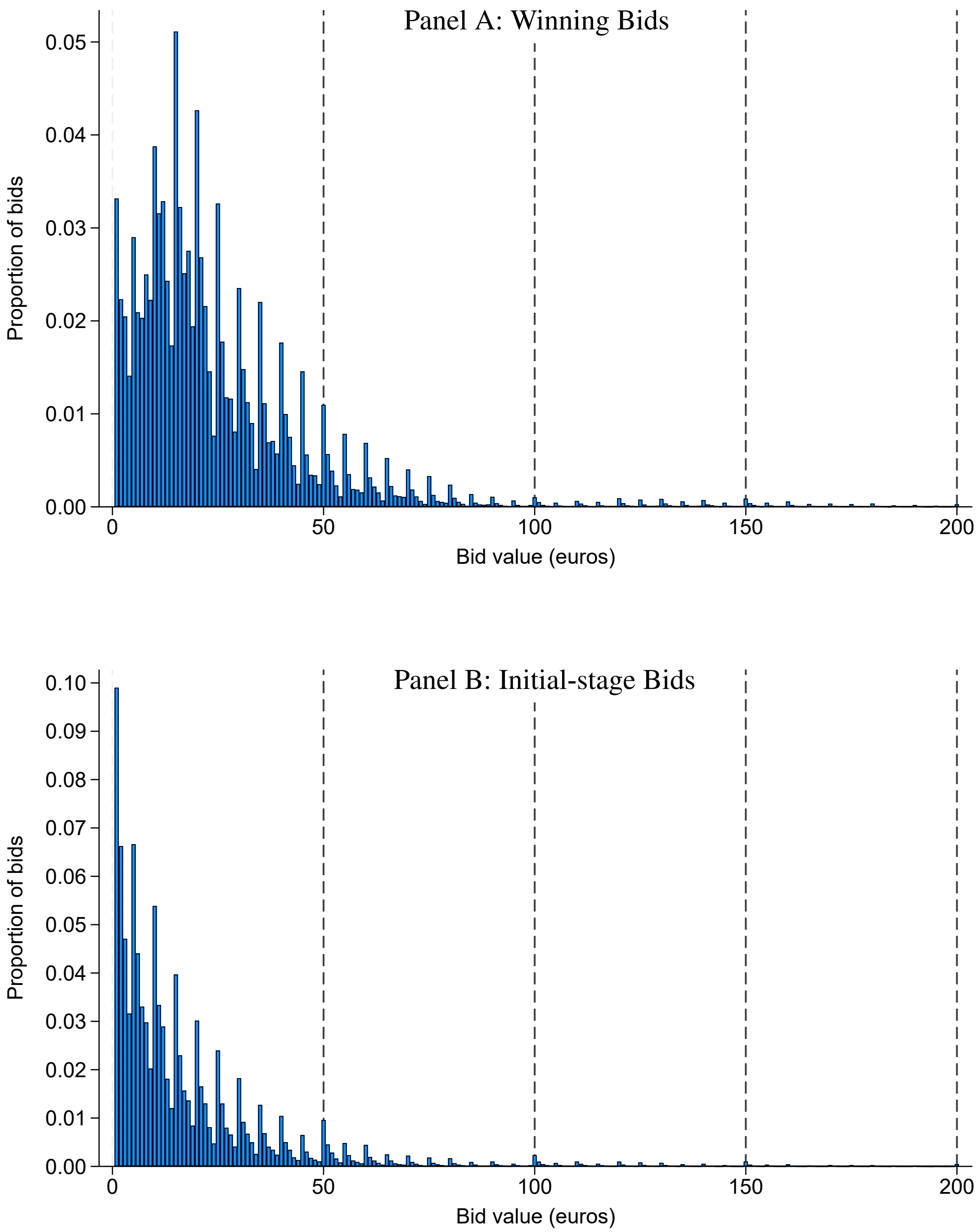
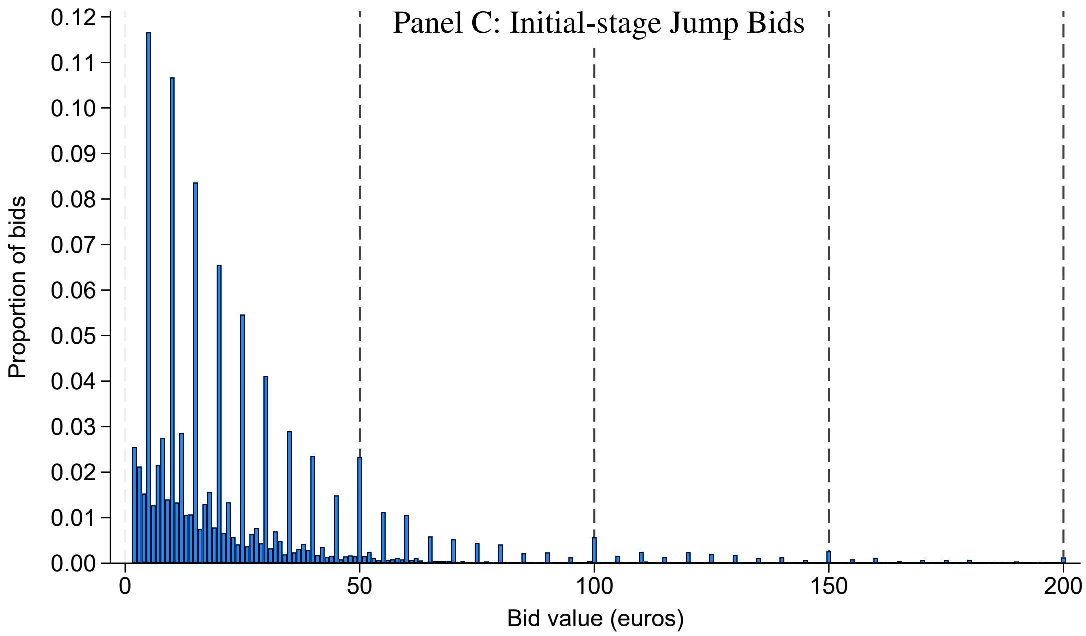
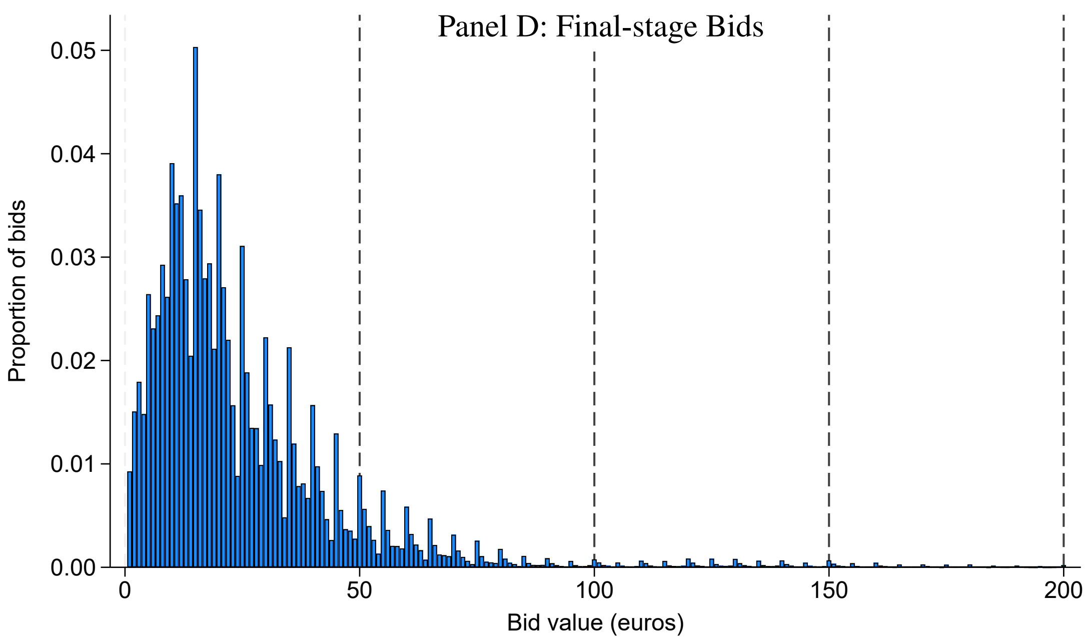


Figure A2 (continued)





Notes: Reprises the exercise in Figure 1 for various subsamples of bids. See that figure for additional notes.

Figure A3: Departure of Bid Counts from Predictions of Various-Degree Polynomials

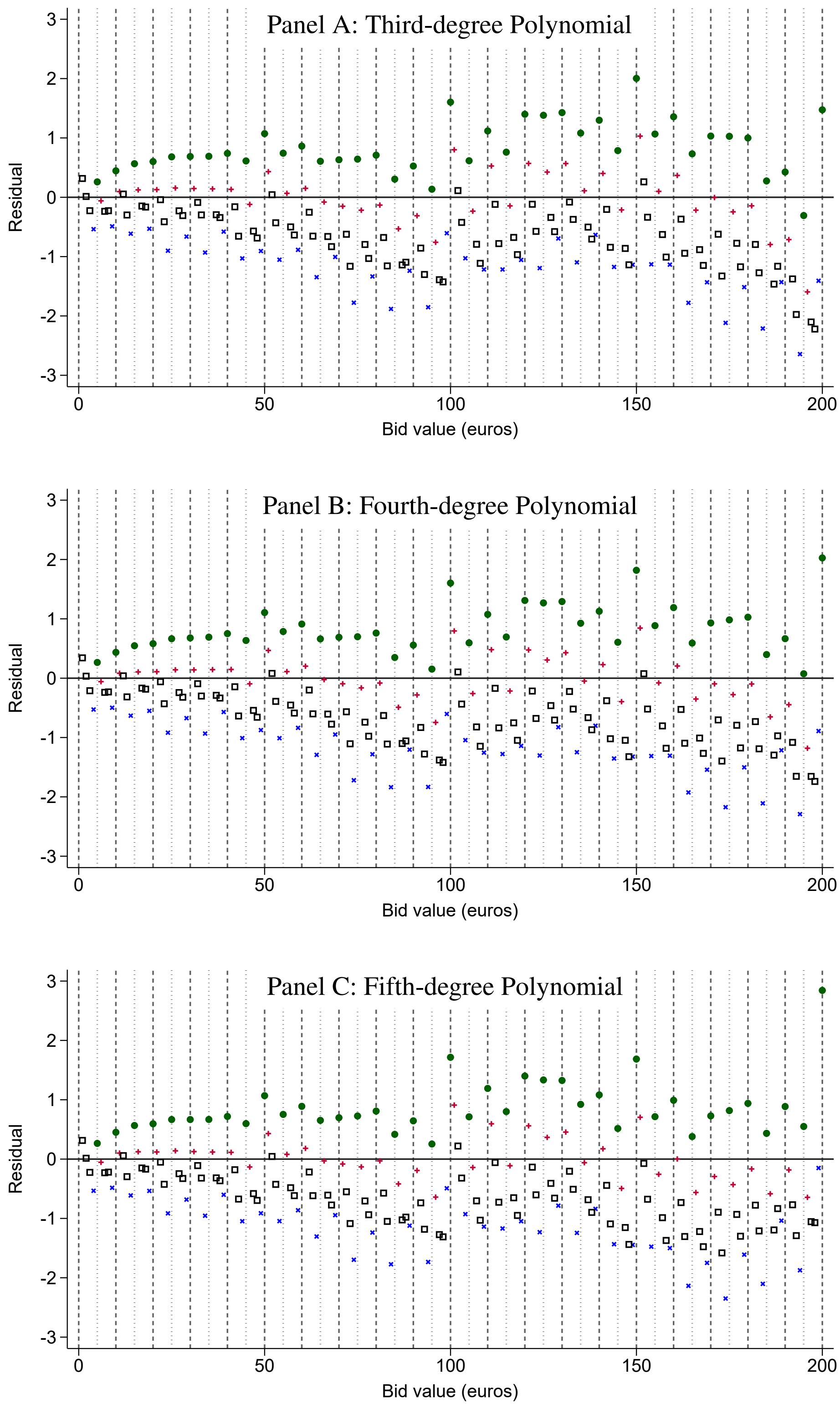
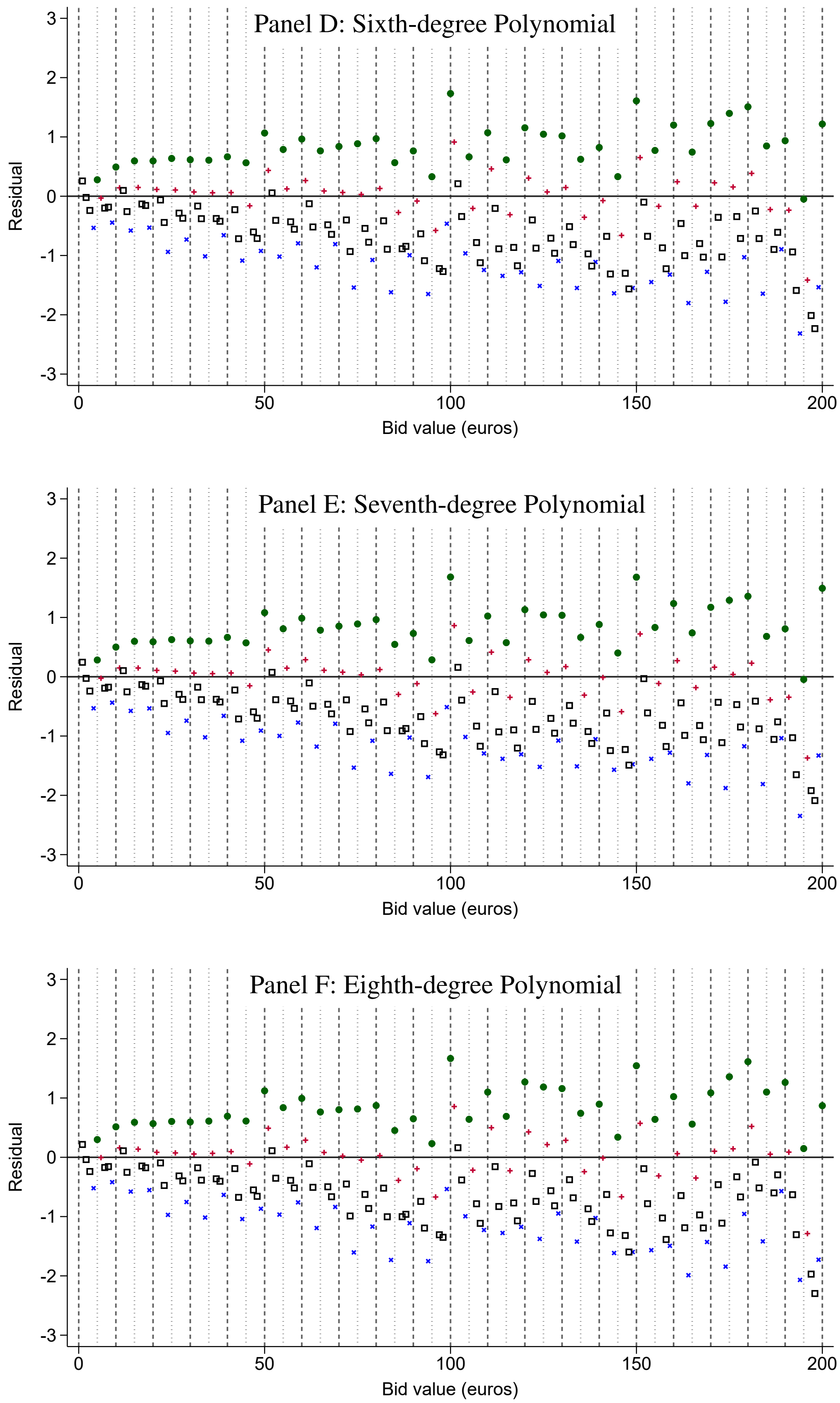


Figure A3 (continued)



Notes: Reprises the exercise in Figure 3 for various-degree polynomials. The specification with a seventh-degree polynomial from that figure is repeated here for reference. See that figure for the legend identifying the shapes of plotted points and additional notes.

Table A1: Reprising Table 3 Regressions—Quantifying Extent of Round Bidding—Using Method Inspired by Bunching Literature

	Bid sample				
Regressor	All bids	Winning bids	Initial-stage bids	Initial-stage jump bids	Final-stage bids
$5\mathbb{N}$ indicator	1.31***	1.39***	1.33***	2.36***	1.28***
	(0.10)	(0.12)	(0.10)	(0.16)	(0.15)
$10\mathbb{N}$ indicator	0.50*	0.33	0.58*	0.39	0.10
	(0.23)	(0.20)	(0.25)	(0.23)	(0.221)
$5\mathbb{N}^+$ indicator	0.66***	0.61***	0.70***	−0.31*	0.56***
	(0.07)	(0.07)	(0.07)	(0.12)	(0.10)
$5\mathbb{N}^-$ indicator	−0.48***	−0.41***	−0.53***	−0.39**	−0.37***
	(0.09)	(0.10)	(0.10)	(0.13)	(0.10)
Dependent variable (second stage)	$\ln(CB_n/\widehat{CB}_n)$	$\ln(CB_n/\widehat{CB}_n)$	$\ln(CB_n/\widehat{CB}_n)$	$\ln(CB_n/\widehat{CB}_n)$	$\ln(CB_n/\widehat{CB}_n)$
Functional form (second stage)	Linear	Linear	Linear	Linear	Linear
Observations	200	200	200	199	200
R^2 (second stage)	0.70	0.69	0.68	0.75	0.56

Notes: In a first stage, we perform a Poisson regression of CB_n on a seventh-degree polynomial in n, as specified in equation (7), but here using bid values excluding those in $5\mathbb{N}$, $5\mathbb{N}^+$, and $5\mathbb{N}^-$. For example, in the interval $[10, 15]$, we exclude bid values 10, 11, 14, and 15, and use 12 and 13 in the estimation of the polynomail. As in Table 3, the regression sample is formed by starting with subsample indicated in column heading and collapsing to bid counts, generating one observation per n. The regression sample is truncated at $n \leq 200$ for reasons explained in Figure 3. In a second stage, the fitted values $\widehat{CB}_n$ are computed for each n using the estimated coefficients β_τ from the first-stage polynomial. The difference $\ln CB_n - \ln \widehat{CB}_n = \ln(CB_n/\widehat{CB}_n)$ is regressed on $5\mathbb{N}$, $10\mathbb{N}$, $5\mathbb{N}^+$, and $5\mathbb{N}^-$ indicators. The table shows the estimated coefficients from this second-stage linear regression for various subsamples of the data. Huber-White heteroskedasticity-robust standard errors reported in parentheses. Statistically significantly different from zero in a two-tailed test at the *5% level, **1% level, ***0.1% level.

Table A2: Reprising Table 5 Regressions—Analyzing Bidding Propensities by Experience Quartile—for Alternative Subsamples

	Regressor				
Dep. var.	XQ_2	XQ_3	XQ_4	Observations	R^2
		Panel A: Sample of all bids			
$\mathbf{1}(b_{ijk} \in 5\mathbb{N})$	0.002^{*}	-0.008^{***}	-0.042^{***}	5,304,211	0.04
	(0.001)	(0.001)	(0.002)		
$\mathbf{1}(b_{ijk} \in 10\mathbb{N})$	0.000	-0.006^{***}	-0.027^{***}	5,304,211	0.04
	(0.001)	(0.001)	(0.001)		
$\mathbf{1}(b_{ijk} \in 5\mathbb{N}^{+})$	-0.007^{***}	-0.007^{***}	-0.003^{**}	5,304,211	0.01
	(0.001)	(0.001)	(0.001)		
$\mathbf{1}(b_{ijk} \in 5\mathbb{N}^{-})$	-0.003^{***}	-0.003^{***}	-0.000	5,304,211	0.01
	(0.000)	(0.001)	(0.001)		
		Panel B: Subsample of initial-stage bids			
$\mathbf{1}(b_{ijk} \in 5\mathbb{N})$	0.011^{***}	0.003^{**}	-0.032^{***}	4,288,608	0.04
	(0.001)	(0.001)	(0.002)		
$\mathbf{1}(b_{ijk} \in 10\mathbb{N})$	0.006^{**}	0.001	-0.020^{**}	4,288,608	0.04
	(0.001)	(0.001)	(0.001)		
$\mathbf{1}(b_{ijk} \in 5\mathbb{N}^{+})$	-0.008^{**}	-0.007^{***}	0.001	4,288,608	0.01
	(0.001)	(0.001)	(0.001)		
$\mathbf{1}(b_{ijk} \in 5\mathbb{N}^{-})$	-0.005^{***}	-0.004^{***}	0.002^{*}	4,288,608	0.01
	(0.000)	(0.001)	(0.001)		
		Panel C: Subsample of initial-stage jump bids			
$\mathbf{1}(b_{ijk} \in 5\mathbb{N})$	0.005^{***}	-0.001	-0.041^{***}	1,671,307	0.06
	(0.001)	(0.001)	(0.002)		
$\mathbf{1}(b_{ijk} \in 10\mathbb{N})$	0.004^{**}	-0.003^{*}	-0.030^{***}	1,671,307	0.06
	(0.001)	(0.001)	(0.002)		
$\mathbf{1}(b_{ijk} \in 5\mathbb{N}^{+})$	0.000	0.003^{***}	0.014^{***}	1,671,307	0.01
	(0.001)	(0.001)	(0.001)		
$\mathbf{1}(b_{ijk} \in 5\mathbb{N}^{-})$	0.001	-0.005^{***}	0.021^{***}	1,671,307	0.01
	(0.000)	(0.001)	(0.001)		
		Panel D: Subsample of final-stage bids			
$\mathbf{1}(b_{ijk} \in 5\mathbb{N})$	-0.022^{***}	-0.043^{***}	-0.071^{***}	1,015,569	0.03
	(0.002)	(0.002)	(0.003)		
$\mathbf{1}(b_{ijk} \in 10\mathbb{N})$	-0.015^{**}	-0.028^{**}	-0.043^{**}	1,015,569	0.02
	(0.001)	(0.002)	(0.002)		
$\mathbf{1}(b_{ijk} \in 5\mathbb{N}^{+})$	0.004^{**}	0.012^{***}	0.014^{***}	1,015,569	0.01
	(0.001)	(0.002)	(0.002)		
$\mathbf{1}(b_{ijk} \in 5\mathbb{N}^{-})$	0.008^{***}	0.014^{***}	0.024^{***}	1,015,569	0.01
	(0.001)	(0.001)	(0.002)		

Notes: Reports coefficients from the same regressions as in Table 5 run on alternative subsamples than the subsample of winning bids. Remaining notes from Table 5 apply.

Table A3: Reprising Table 6—Adding Bidder Fixed Effects to Analysis Regressions Analyzing Bidding Propensities by Experience Quartile —for Alternative Subsamples

	Regressor				
Dep. var.	XQ_2	XQ_3	XQ_4	Observations	R^2
Panel A: Sample of all bids					
$\mathbf{1}(b_{ijk} \in 5\mathbb{N})$	0.016***	0.021***	0.020***	5,158,787	0.23
	(0.001)	(0.001)	(0.001)		
$\mathbf{1}(b_{ijk} \in 10\mathbb{N})$	0.009***	0.011***	0.010***	5,158,787	0.18
	(0.001)	(0.001)	(0.001)		
$\mathbf{1}(b_{ijk} \in 5\mathbb{N}^+)$	−0.009***	−0.011***	−0.012***	5,158,787	0.12
	(0.001)	(0.001)	(0.001)		
$\mathbf{1}(b_{ijk} \in 5\mathbb{N}^-)$	−0.003***	−0.004***	−0.004***	5,158,787	0.11
	(0.000)	(0.001)	(0.001)		
Panel B: Subsample of initial-stage bids					
$\mathbf{1}(b_{ijk} \in 5\mathbb{N})$	0.020***	0.026***	0.026***	4,149,223	0.24
	(0.001)	(0.001)	(0.002)		
$\mathbf{1}(b_{ijk} \in 10\mathbb{N})$	0.011***	0.015***	0.013***	4,149,223	0.19
	(0.001)	(0.001)	(0.001)		
$\mathbf{1}(b_{ijk} \in 5\mathbb{N}^+)$	−0.013***	−0.018***	−0.019***	4,149,223	0.11
	(0.001)	(0.001)	(0.001)		
$\mathbf{1}(b_{ijk} \in 5\mathbb{N}^-)$	−0.006***	−0.007***	−0.008***	4,149,223	0.10
	(0.001)	(0.001)	(0.001)		
Panel C: Subsample of initial-stage jump bids					
$\mathbf{1}(b_{ijk} \in 5\mathbb{N})$	−0.001	−0.006***	−0.018***	1,552,198	0.33
	(0.001)	(0.001)	(0.002)		
$\mathbf{1}(b_{ijk} \in 10\mathbb{N})$	0.003	0.001	−0.007*	1,552,198	0.25
	(0.002)	(0.002)	(0.003)		
$\mathbf{1}(b_{ijk} \in 5\mathbb{N}^+)$	0.004***	0.007***	0.012***	1,552,198	0.21
	(0.001)	(0.001)	(0.001)		
$\mathbf{1}(b_{ijk} \in 5\mathbb{N}^-)$	0.001	0.004***	0.009***	1,552,198	0.22
	(0.000)	(0.001)	(0.001)		
Panel D: Subsample of final-stage bids					
$\mathbf{1}(b_{ijk} \in 5\mathbb{N})$	−0.005**	−0.013***	−0.018***	860,567	0.35
	(0.002)	(0.002)	(0.003)		
$\mathbf{1}(b_{ijk} \in 10\mathbb{N})$	−0.005***	−0.011***	−0.017***	860,567	0.31
	(0.001)	(0.002)	(0.002)		
$\mathbf{1}(b_{ijk} \in 5\mathbb{N}^+)$	0.002	0.007***	0.009**	860,567	0.27
	(0.001)	(0.002)	(0.003)		
$\mathbf{1}(b_{ijk} \in 5\mathbb{N}^-)$	0.003*	0.005**	0.004	860,567	0.26
	(0.001)	(0.002)	(0.003)		

Notes: Reports coefficients from the same regressions as in Table 6 run on alternatives to the subsample of winning bids. Remaining notes from Table 6 apply.

Table A4: Reprising Table 6—Adding Buyer Fixed Effects to Regressions Analyzing Winning-Bid Propensities by Experience Quartile—for Subsample of Eventually Experienced Bidders

	Bidding strategy analyzed			
Regressor	$5\mathbb{N}$	$10\mathbb{N}$	$5\mathbb{N}^+$	$5\mathbb{N}^-$
XQ_2	−0.011	−0.006	−0.004	0.001
	(0.006)	(0.005)	(0.006)	(0.005)
XQ_3	−0.024***	−0.009*	−0.001	0.005
	(0.006)	(0.004)	(0.005)	(0.004)
XQ_4	−0.032***	−0.015**	−0.001	0.006
	(0.006)	(0.005)	(0.005)	(0.004)
Dependent variable	$\mathbf{1}(p_{ij} \in 5\mathbb{N})$	$\mathbf{1}(p_{ij} \in 10\mathbb{N})$	$\mathbf{1}(p_{ij} \in 5\mathbb{N}^+)$	$\mathbf{1}(p_{ij} \in 5\mathbb{N}^-)$
Functional form	OLS	OLS	OLS	OLS
Bid subsample	Winning	Winning	Winning	Winning
Bidder subsample	Eventually in XQ_4	Eventually in XQ_4	Eventually in XQ_4	Eventually in XQ_4
Item fixed effects	Yes	Yes	Yes	Yes
Bidder fixed effects	Yes	Yes	Yes	Yes
Observations	143,000	143,000	143,000	143,000
R^2	0.26	0.23	0.20	0.18

Notes: Reports coefficients from the same regressions as in Table 6 but for restricted sample of bidders who enter experience quartile XQ_4 by the end of the sample. Remaining notes from Table 6 apply.

Table A5: Reprising Table 7—Regressions Analyzing the Effect of Experience on Winning-Bid Levels—for Subsample of Eventually Experienced Bidders

	Without bidder fixed effects		With bidder fixed effects	
Regressor	(1)	(2)	(3)	(4)
XQ_2	-0.40^{***}	-0.49^{***}	-0.47^{***}	-0.55^{***}
	(0.08)	(0.08)	(0.09)	(0.09)
XQ_3	-0.76^{***}	-0.85^{***}	-0.83^{***}	-0.89^{***}
	(0.08)	(0.09)	(0.09)	(0.09)
XQ_4	-1.44^{***}	-1.49^{***}	-1.28^{***}	-1.22^{***}
	(0.10)	(0.10)	(0.12)	(0.10)
Dependent variable	p_{ij}	p_{ij}	p_{ij}	p_{ij}
Functional form	OLS	OLS	OLS	OLS
Bid subsample	Winning	Winning	Winning	Winning
Bidder subsample	Eventually in XQ_4	Eventually in XQ_4	Eventually in XQ_4	Eventually in XQ_4
Item fixed effects	Yes	Yes	Yes	Yes
Bidder fixed effects	No	No	Yes	Yes
Auction controls	No	Yes	No	Yes
Observations	146,159	146,159	143,000	143,000
R^2	0.96	0.97	0.97	0.97

Notes: Reports coefficients from the same regressions as in Table 7 but for restricted sample of bidders who enter experience quartile XQ_4 by the end of the sample. Remaining notes from Table 7 apply.

Table A6: Effect of Experience on Winning Bids Using Round and Non-round Bidding Strategies

	Without bidder fixed effects		With bidder fixed effects	
Regressor	(1)	(2)	(3)	(4)
$5\mathbb{N} \times XQ_2$	-0.90^{***}	-0.90^{***}	-0.59^{***}	-0.52^{***}
	(0.08)	(0.07)	(0.08)	(0.07)
$5\mathbb{N} \times XQ_3$	-1.42^{***}	-1.43^{***}	-0.91^{***}	-0.79^{***}
	(0.10)	(0.10)	(0.10)	(0.09)
$5\mathbb{N} \times XQ_4$	-2.24^{***}	-2.25^{***}	-1.27^{***}	-1.07^{***}
	(0.12)	(0.12)	(0.13)	(0.11)
$10\mathbb{N} \times XQ_2$	-0.11	-0.12	-0.05	-0.06
	(0.12)	(0.12)	(0.11)	(0.11)
$10\mathbb{N} \times XQ_3$	-0.12	-0.14	0.09	0.08
	(0.15)	(0.14)	(0.13)	(0.13)
$10\mathbb{N} \times XQ_4$	0.05	0.01	0.18	0.15
	(0.18)	(0.17)	(0.15)	(0.15)
$5\mathbb{N}^+ \times XQ_2$	-0.84^{***}	-0.84^{***}	-0.46^{***}	-0.40^{***}
	(0.05)	(0.05)	(0.07)	(0.07)
$5\mathbb{N}^+ \times XQ_3$	-1.39^{***}	-1.40^{***}	-0.78^{***}	-0.67^{***}
	(0.07)	(0.07)	(0.08)	(0.07)
$5\mathbb{N}^+ \times XQ_4$	-1.93^{***}	-1.93^{***}	-0.90^{***}	-0.70^{***}
	(0.09)	(0.08)	(0.10)	(0.08)
$5\mathbb{N}^- \times XQ_2$	-0.56^{***}	-0.56^{***}	-0.30^{***}	0.25^{***}
	(0.05)	(0.05)	(0.07)	(0.07)
$5\mathbb{N}^- \times XQ_3$	-1.07^{***}	-1.07^{***}	-0.55^{***}	-0.44^{***}
	(0.07)	(0.07)	(0.08)	(0.08)
$5\mathbb{N}^- \times XQ_4$	-1.54^{***}	-1.53^{***}	-0.68^{***}	-0.50^{***}
	(0.09)	(0.08)	(0.10)	(0.09)
Dependent variable	p_{ij}	p_{ij}	p_{ij}	p_{ij}
Functional form	OLS	OLS	OLS	OLS
Bid subsample	Winning	Winning	Winning	Winning
Item fixed effects	Yes	Yes	Yes	Yes
Bidder fixed effects	No	No	Yes	Yes
Auction controls	No	Yes	No	Yes
Observations	677,086	677,086	484,902	484,902
R^2	0.96	0.96	0.98	0.98

Notes: Reports results from OLS regressions that are the same as in Table 7 except experience-quartile indicators XQ_2–XQ_4 are interacted with bidding strategies $5\mathbb{N}$, $10\mathbb{N}$, $5\mathbb{N}^+$, and $5\mathbb{N}^-$. A suite of other indicators is included to faciliate interpretation of reported coefficients as differences from the baseline given by the lowest quartile indicator XQ_1 interacted with the relevant bidding strategy. Remaining notes from Table 7 apply.