Round Bidding in Auctions

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Abstract: Our analysis of novel data from hundreds of thousands of online auctions on a large platform operating in the Netherlands uncovers a tendency to bid round numbers. Round winning bids are higher than average for a given item and are eschewed by bidders as they gain experience. These findings lead us to hypothesize that, rather than delivering a strategic benefit (say, adding salience to a jump bid), round bidding is a symptom of a behavioral bias. We construct a structural model of behavioral bidding in auctions, estimated for each of a subsample of the most frequently auctioned items. Our median estimate is that 21% of bidders are prone to round-number bias, reducing their expected surplus by nearly 10%.

Journal of Economic Literature codes: D44, D83, D91, L11

Keywords: auction, behavioral bias, round number, overbidding, jump bidding, reference points, limited attention

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1. Introduction

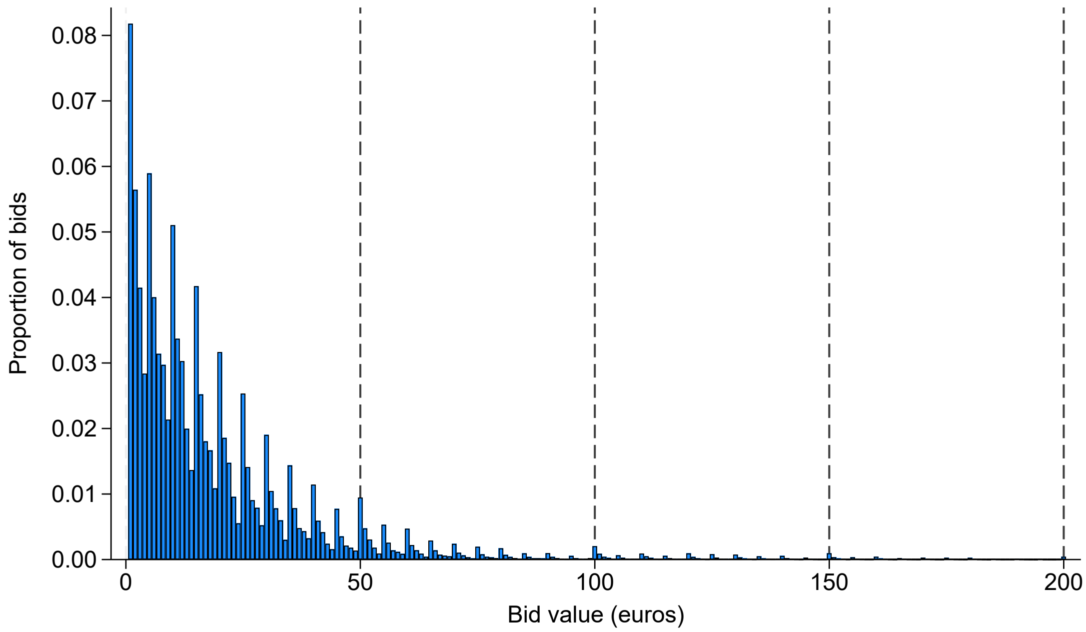
In perhaps the most notorious example in auction history, after murdering the emperor in 193 CE, pretorian soldiers offered the entire Roman Empire to the highest bidder. Commentators since Klemperer and Temin (2001) have found Julianus' winning bid of 25,000 sesterces per soldier remarkable for various reasons: its sheer size (exceeding one billion current dollars), its enormous jump over the previous bid (20,000 offered by Sulpicianus), its ultimate futility (Julianus only reigned as emperor for two months before being murdered himself). What has gone unremarked is that both Sulpicianus' and Julianus' bids are round numbers.

In this paper, we analyze novel data from hundreds of thousands of online auctions on Vakantie Veilingen (VV), a large platform operating in the Netherlands. We uncover a propensity to bid round numbers, which, as in the historical example, has gone unnoticed in the auction literature. The bids on this platform, which are constrained to be natural numbers, are concentrated at multiples of five. Although multiples of five represent only 20% of natural numbers, they constitute 31% of bids in our sample. Figure 1 shows a consistent pattern of spikes in the relative frequency of bids at each multiple of five. The spikes at multiples of 50 stand out even more.

The existing auction literature is silent on the issue of round numbers, so we look to marketing and related literatures for hypotheses explaining the prevalence of round prices. Most of these hypotheses posit a behavioral bias exhibited by buyers, perhaps compounded by an attempt by sellers to exploit this bias: left-digit bias (Lacetera et al., 2012; Busse et al., 2013; Repetto and Solís, 2020), round mental budgeting (Argyle et al., 2020), round reference or focal points (Pope and Simonsohn, 2011; Pope et al., 2015; Allen et al., 2017), a preference for making round payments (Lynn et al., 2013), a reflection of imprecise private values (Manski and Molinari, 2010; Butler and Loomes, 2007), sloth or satisficing (Herrmann and Thomas, 2005; Gideon et al., 2017). Backus et al. (2019) take an alternative approach, suggesting that round prices can have special signaling value. In their bargaining setting, they find that round posted prices signal that the seller is willing to offer concessions to make a quick deal.

Some work is required to tailor hypotheses developed for posted-price settings to our auction setting in which prices are determined by buyers. We focus on their implications for whether round bids are under- or overbids on average. On the one hand, round bids may be lower than average if they reflect round budgets that bidders commit to prevent themselves from overbidding in the heat of the moment or if they scare away competitors by signaling a high valuation. On the other

Figure 1: Relative Frequency of Bid Values



Notes: For legibility, the horizontal axis has been truncated at €200. Relative frequencies are computed using the number of observations above and below the truncation threshold in the denominator. Only 0.6% of bids exceed the €200 threshold and are thus truncated. The pattern of spikes at multiples of five continues for bids above the threshold. Figure A2 in the online appendix shows a similar pattern for the subsamples of winning bids, initial-stage bids, initial-stage jump bids, and final-stage bids.

hand, round bids may be higher than average if they result from a lack of effort or attention. Our reduced-form evidence supports the set of hypotheses associating round bidding with overbidding. The most convincing support leverages repeated auctions of the same item observed in our rich dataset, allowing us to compare winning bids that are multiples of five to other winning bids, holding the value of the item constant. Our regression results indicate that winning bids that are multiples of five average a euro or more higher than others controlling for item fixed effects and a rich set of auction-specific characteristics. We uncover suggestive evidence that overbids are greater for higher-value items.

Further reduced-form evidence supports the hypothesis that round bidding arises from a behavioral bias that can be dispelled with experience. The user IDs in our dataset allow us to track the same bidder over multiple auctions. Looking at the subsample of bidders who participate in at least ten auctions, as they gain experience by participating in subsequent auctions, we find that they submit fewer round-number bids and lower winning bids.

The last part of the paper turns to structural analysis to estimate the proportion of bidders subject to round-number bias and the surplus they lose from this bias. Structural analysis allows us to circumvent the difficulty in inferring the latent proportion of biased bidders from reduced-form estimates of the excess proportion of round bids. Auctions may amplify the impact of behavioral biases for several reasons. Since auctions are won by the highest bidder, the population of winners is adversely selected toward bidders with an overbidding bias, a phenomenon Malmendier and Lee (2011) call the "bidder's curse." A relatively small fraction of biased bidders can suffice for a large fraction of auctions to end with overbidding (Malmendier and Lee, 2011; Malmendier and Szeidl, 2020). A countervailing force is that sophisticated bidders could exploit rivals' round bidding by outbidding round numbers by a euro. For these reasons, the observed proportion of round bids may not provide an accurate measurement of the latent proportion of biased bidders.

Our structural model posits that a proportion of the population are round-number bidders, constrained to round their equilibrium bid to the nearest multiple of five. We allow bidders to vary in the extent to which they incorporate the presence of other round bidders in their equilibrium strategies, building on Crawford and Iriberri (2007), who characterize equilibrium in auctions when bids are formed using level-k reasoning. In our reformulation, level-0 reasoners submit bids that would be rational in the absence of round bidders. Level-1 bidders take into account the rounding some level-0 bidders are constrained to do. Level-2 bidders recognize that rivals will try to exploit others' rounding. The proportion of round bidders and level-0, 1, and 2 reasoners are parameters to be estimated.

Our structural model focuses on the last five seconds of the auction, when most winning bids are submitted and no time is left for rivals to respond. This final stage of the auction is isomorphic to a first-price, sealed-bid auction, simplifying the analysis. Using the method of simulated moments, we estimate the model separately for each of the 100 items that are most frequently auctioned on the platform. Each of these items is auctioned thousands of times on our platform, providing a wealth of observations to precisely estimate the distribution of consumer values and behavioral parameters even when these are allowed to differ across items.

Our median estimate is that 21% of bidders are susceptible to round-number bias, reducing their expected surplus from participating in the auction by about 10% compared to unbiased bidders. A substantial majority (median estimate 68%) are level-0 reasoners, who do not consider their rivals' round-number bias when constructing their own bidding strategy. A smaller proportion (median estimate 21%) are level-1 bidders, and a yet smaller proportion (median estimate 8%) are level-2 bidders.

The remainder of this paper is structured as follows. Section 2 reviews relevant literatures. Section 3 describes the auction platform and the data we derive from it. Section 4 outlines a series of hypotheses behind round bidding and drawing out further empirical implications of those hypotheses. Section 5 provides formal evidence of the extent of round bidding and reduced-form evidence for behavioral explanations. Section 6 provides the structural model and estimation. Section 7 concludes. An online appendix provides supplementary exhibits and further details on the structural estimation.

2. Literature Review

Our paper contributes to several literatures. The introduction already described the connection between our work and the marketing literature on round-number biases. We contribute to this literature by identifying a new setting—auctions—in which this phenomenon arises and provide a detailed reduced-form and structural analysis tailored to that setting. A recent economics paper (Dube et al., 2025) documents round wages in the labor market, attributing it to misoptimization by employers having substantial monopsony power in wage setting.

Our paper adds to a large literature on behavioral biases exhibited by bidders in auctions. Closest are those papers those providing a behavioral explanation for overbidding in private-value auctions, including joy of winning (Cooper and Fang, 2008), auction fever (Heyman et al., 2004; Ku et al., 2005), social comparisons (Ariely and Simonson, 2003), spite (Morgan et al., 2003), herding (Dholakia and Soltysinski, 2001), loss aversion (Engelbrecht-Wiggans and Katok, 2007; Kim and Ratan, 2022; Graddy et al., 2023), probability errors (Armantier and Treich, 2009), self projection (Breitmoser, 2019), and limited attention (Malmendier and Lee, 2011). The evidence for behavioral biases in auctions is not uncontested (Podwol and Schneider, 2016; Schneider, 2016). The round bidding we identify provides support for the behavioral view. The explanation of round bidding that appears to fit our setting best—bidders economize on cognition costs by guessing round numbers rather than computing optimal bids—is a close cousin of the explanation offered by Malmendier and Lee (2011). Our suggestive evidence that round bidders overbid more for higher-value items is explained by the behavioral theories of Thaler (1980) and Bordalo et al. (2013), contending that the salience of add-on prices depends on their level relative to the product's reference price.

Our analysis of a structural auction model incorporating round-number bias and level-k reasoning among bidders continues a long line of work providing structural estimates of auction models in increasingly rich environments (see, e.g., Gentry et al., 2018, for a survey). Only a small subset of these allow for behavioral biases among bidders: Bajari and Hortaçsu (2005) compare the performance of quantal response equilibrium (QRE) versus a fully Baysian bidders who are risk averse, Crawford and Iriberri (2007) compare QRE to a model of level-k reasoning, Banerji and Gupta (2014) test for loss aversion. All three papers estimate their models on datasets from relatively small experiments, whereas we provide estimates using observational data on thousands of auctions for each of 100 items. In an unpublished dissertation, Gillen (2010) estimates a semiparametric model using observational data from timber auctions allowing pre-specified proportions of bidders to be level-1 reasoners, level-2 reasoners, or fully Bayesian. We have the more ambitious goal of estimating the proportion of biased bidders as well as the proportion of bidders with the extra sophistication to exploit rivals' bias. Furthermore, we focus on a bias that is new to the auction literature and has complex equilibrium properties. To make progress on these difficult goals, we default to parametric methods, recognizing this compromises the ambition in the structural literature to develop nonparametric methods that work in increasingly rich auction environments (Athey and Haile, 2007).

Our paper has several connections to the literature on jump bidding. Echoing Easley and Tenorio (2004), we document extensive jump bidding in online consumer auctions. Our findings also contribute to the theoretical literature by providing a new motive for jump bidding. To date, the theoretical literature has offered two main motives: forestalling rival entry by signaling a high private value (Avery, 1998; Easley and Tenorio, 2004; Daniel and Hirshleifer, 2018) and accelerating the auction process (Isaac et al., 2007; Plott and Salmon, 2004). The preference for round numbers that we uncover provides another motive for jump bidding: bidders may jump over non-round numbers to the round numbers they prefer. While this is an admittedly mundane motive for jump bidding, we conjecture that round bidding has an underappreciated connection to the more intriguing motives offered by the literature to date. Jumping to a non-round amount may provide the wrong signal to rivals, suggesting that they have arrived at a carefully calculated maximum bid rather than a convenient round number well short of their willingness to pay. Someone trying to accelerate the auction process would likely resort to coarse rather than precisely calculated amounts.

Some of our subsidiary findings are in line with standard results in the empirical auction literature. Our finding that experience can reduce but perhaps not eliminate behavioral biases in auctions echoes Wilcox (2000), List (2003), Pownall and Wolk (2013), and others. Our finding that most auctions are won in the last few seconds echoes work on sniping dating back to Roth and Ockenfels (2002) seminal work, also including Bajari and Hortaçsu (2003), Ockenfels and Roth (2006), Hickman et al. (2017), and Bodoh-Creed et al. (2021).

Our paper uses one of the largest datasets on business-to-consumer auctions in the literature, involving thousands of unique items and hundreds of thousands of auctions, approaching the scale of Einav et al. (2015) and Einav et al. (2018). Those and scores of others mostly focus on eBay data; we are the first to study the VV platform and have collected novel data to do so. Our structural analysis follows Bajari and Hortaçsu (2003) and a line of subsequent papers that collect data on hundreds or thousands of auctions for the same product or narrow product class. Our large dataset allows us to repeat the structural estimation for 100 distinct items for which we observe thousands of auctions.

3. Backgound and Data

Our data come from Vakantie Veilingen (VV), a large platform which has been conducting online business-to-consumer auctions in the Netherlands for over two decades.[1] The auctioned items include tickets to events like concerts and holiday revues, services like car waxing and beauty treatments, and consumer goods like headphones and watches. Hundreds of parallel auctions for different items continuously run day and night. Auctions have specified end times. Durations vary across items but are all much shorter than eBay auctions. While auctions typically last at least three days on eBay, most auctions on the platform last less than an hour and can be as short as one minute. The identical item may be sold in a repeated series of auctions, one starting right after the other. Like eBay, VV does not supply the items itself but serves as an intermediary between buyers and sellers. Unlike on eBay, no used items are auctioned; all items are supplied by businesses, not individuals; and, importantly, the platform does not offer automated bidding. The winning bidder pays their bid, a shipping fee of around €5 for physical items, and an administrative fee of around €5.

The platform conducts open-outcry, ascending-price auctions. Bids are denominated in whole euros (no cents) with a minimum increment of €1. The webpage for each auction displays a glossy picture and detailed description of the item, suggested retail price, active bid, user ID of the active bidder, cumulative number of different bidders, and countdown clock.

[1] We identify VV as operating in the Netherlands since it is headquartered there, uses the Dutch language for its website, and only ships to customers in the Netherlands and Belgium. We avoid calling it a Dutch platform because its auctions use an English format.

We collected our data by scraping VV's website and recording item and bid information for all auctions conducted on the platform between November 2016 and April 2017. After some modest cleaning of the raw data, we obtained the final sample analyzed in the paper covering 2,502 different items.[2] The same item was auctioned repeatedly (median 90 auctions per item), leading to a total of 678,449 auctions in the sample. Multiple bids are submitted in an auction (median 7 bids per auction), leading to a total of 5,304,211 bids in the sample. The sample includes 552,900 unique user IDs identifying the participants.

Table 1 contains summary statistics at the bidder, item, auction, and bid level. Most items are fairly low value. The mean winning bid is about €27, and 99% of winning bids in our sample are below €150. The median auction duration is 33 minutes, and 28% of auctions last ten minutes or less. Looking at the descriptive statistics by bidder, the median bidder bid in three auctions and placed three bids in total. Some bidders were extensively engaged in the platform—over 2,000 auctions and nearly 3,000 bids at a maximum—right-skewing the per-bidder distributions.

Certain features of the platform's design and auction rules facilitate our analysis. The wide range of items auctioned on the platform will help bolster the generality of results that hold consistently across items. The large number of total auctions will enable us to detect even small differences in rates of bidding between round numbers and neighboring values. The substantial number of auctions per item will allow us to benchmark the item's mean value and thus gauge whether round bids are under- or overbids. We track user IDs across auctions to determine whether within-bidder strategy evolves with their experience. The platform constrains participants to submit whole-number bids and cap the bid increments to €50, leading to a finite, discrete strategy space, which simplifies the structural analysis.

As shown in Figure 2, most bids (81%) are submitted before the last five seconds. However, hardly any of these bids (3%) end up winning the auction. Most auctions (81%) are won in the last five seconds. Prior to the last five seconds, the arrival rate of winning bids flatlines in the figure. Very few winning bids arrive from five to ten seconds before the auction's end, from ten to 15 seconds before, or any earlier five-second interval, underscoring the pivotalness of the last five seconds, which we will label the final stage. The pivotalness of the final stage is not limited to

[2] We dropped 12,228 auctions (1.3% of auctions in the raw sample) for which a start time was not recorded. We next dropped 1,335 auctions (0.1% of auctions in the raw sample) lasting longer than a day. We next dropped 166 auctions (0.02% of auctions in the raw sample) for which the first bid exceeded €50. We suspect that this bid reflects a data-scraping error because the first bid should not exceed the maximum bid increment of €50. Finally, we dropped 77 items (3.0% of items in the raw sample) for which more than 70% of the auctions generated no competition, registering either zero or one bid. Our motive was to exclude items generating so little consumer interest that they typically sold for the minimum price of €1.

Table 1: Sample Statistics

Variable	Min.	Max.	Mean	Median	Observations
Bidder level					
• Items bid on (count)	1	390	3.8	2	552,900
• Auctions bid in (count)	1	2,155	7.4	3	552,900
• Bids submitted (count)	1	2,810	9.6	3	552,900
Item level					
• Auctions per item (count)	1	13,480	271.2	90	2,502
• Average winning bid per item (€)	1.8	2,533.7	40.8	21.5	2,502
• Event ticket (indicator)	0	1	0.41	0	2,502
• Consumer product (indicator)	0	1	0.59	1	2,502
Auction level					
• Bids per auction (count)	1	118	7.8	7	678,449
• Amount of winning bid (€)	1	4,814	26.6	19.0	678,449
• Duration (minutes)	1	1,440	115.8	33	678,449
Bid level					
• Submitted in final stage (indicator)	0	1	0.19	0	5,304,211
• Bid wins auction (indicator)	0	1	0.13	0	5,304,211
• Jump bid (indicator)	0	1	0.43	0	5,304,211
• Bid increment (€)	1	50	3.4	1	5,304,211

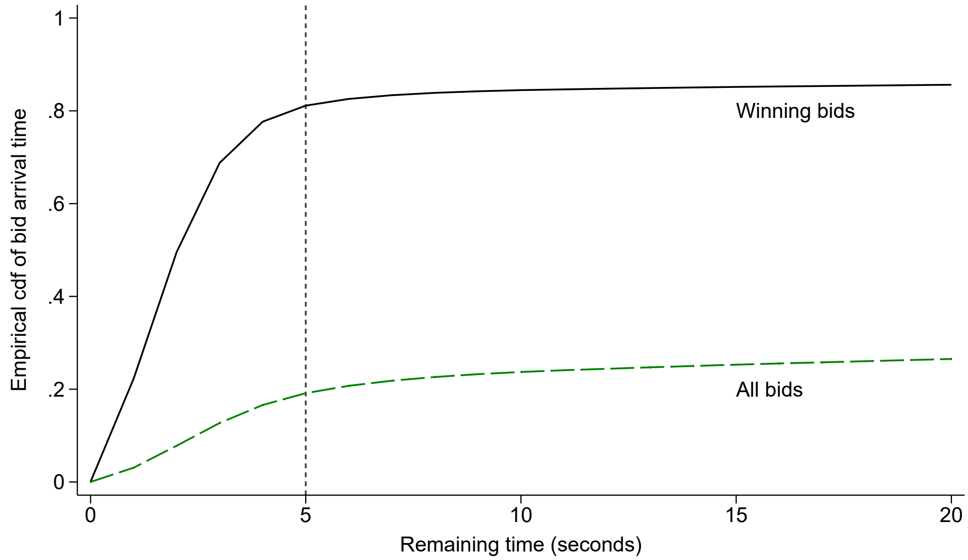
Notes: The first set of rows collapse the summary statistics down to the 552,900 bidders in the sample, the second set to the 2,502 unique items in the sample, and the third to the 678,449 auctions in the sample. The last set provide summary statistics for all bids across all auctions.

short auctions. In the 39% of auctions that last an hour or more, 74% of winning bids are placed in the final stage.

The hard closing rule combined with latency in the user interface prevent bidders from responding to each other in the last five seconds. What begins as an ascending-price auction is in effect transformed into a first-price, sealed-bid auction in the final stage, with the standing bid going into this stage functioning as a reserve price. Throughout the paper, we will separate the analysis of the initial stage from the final stage. Bajari and Hortaçsu (2003), Ockenfels and Roth (2006), Hickman et al. (2017), and Bodoh-Creed et al. (2021), make a similar distinction in their studies of late bidding on eBay and Amazon.[3]

[3] Our final stage is much shorter than in previous work. For example, Hickman et al. (2017) takes the final stage to be the last 30 minutes of the auction; Bodoh-Creed et al. (2021) take it to be last 60 minutes. What is consistent between our study and previous work is the proportion of winning bids submitted in the final stage. For example, the 81% of winning bids placed in the final five seconds in our sample is comparable to the 85% of winning bids placed in the final 60 minutes of eBay auctions analyzed by Bodoh-Creed et al. (2021). If anything, specifying a shorter final stage provides more justification for modeling the auction as sealed bid in that stage.

Figure 2: Bid Arrival Near Auction End



Notes: The empirical cumulative distribution function (cdf) measures the proportion of bids arriving within that many seconds of the auction's end. The vertical line at five seconds remaining demarcates the auction's initial and final stages.

4. Hypotheses

This section draws from the marketing, behavioral-economics, and other literatures for hypotheses to explain the prevalence of round bidding hinted at so far in the descriptive statistics, to be quantified more formally below. The literatures have posed their hypotheses in posted-price markets, so some work is required to tailor the hypotheses to an auction setting.

To provide a benchmark and introduce some useful notation, we begin with a model of rational bidding in the final stage. We then investigate a sequence of seven alternative hypotheses for round bidding in sequence. In each case, we analyze how a bidder's strategy might change if they are subject to a behavioral or preference factor outside of the neoclassical model and how neoclassical rivals might respond to non-neoclassical bids.

4.1. Neoclassical Benchmark

To establish a neoclassical benchmark and introduce some useful notation, we present a stylized model of bidding in the final stage of an auction on our platform. The final stage is effectively a first-price, sealed-bid auction because time is too short for bidders to respond to each other before the auction's hard close.

Let b_s be the highest bid from the initial stage, which becomes the standing bid entering the final stage. The bidder chooses their bid b in the final stage to maximize their expected surplus

$$P(b)(v-b), \tag{1}$$

where where $P(b)$ denotes the probability of winning the auction with bid b and v denotes the bidder's private value for the item.[4] The bidder maximizes equation (1) subject to constraints

$$b \in \mathbb{N} \tag{2}$$

$$b \leq B \tag{3}$$

$$b \geq b_s. \tag{4}$$

Equation (2) reflects the constraint that bids on the platform be natural numbers. Equation (3) requires the bidder to stay within their budget, B. Equation (4) requires bidders to weakly exceed the standing bid b_s. The bidder who submitted b_s may win if they stand pat at that bid (if no one outbids them), but other bidders can only win if they submit a new bid that increments b_s by one or more euros.

The strictly highest bidder in the final stage wins the auction and pays their bid. When multiple bidders tie for the highest (intended) bid, in practice one who was first to register their intended bid is the winner and others would be blocked from entering the same number. We will capture this outcome in the model by assuming that the winner is randomly selected among those with the highest (intended) bids, each given an equal chance of winning.

The distribution of equilibrium bids need not be uniform across natural numbers since the distribution of underlying values v need not be uniform and, even if it were, bidding strategies need not preserve the uniformity of values. Still, given regularity conditions on the distribution of values, it would be difficult to explain systematic spikes of mass at round numbers in a neoclassical model.

A different model would apply to bids submitted in the initial stage. Since bidders have time to respond to each other then, the auction has an open-outcry, ascending-price form. In neoclassical models, the standard result is that jump bidding is dominated by incremental bidding in ascending auctions (Isaac et al., 2007). Incremental bidding in the initial stage should generate a smooth

[4] Model variables b, v, and others should be understood to vary across bidders, but the bidder index has been suppressed to streamline the notation.

distribution of bids over natural numbers rather than spikes of mass at round bids.

4.2. Hypothesis: Preference for Round Payments

We next turn to a series of hypotheses drawn from the literature to explain the prevalence of round prices, which we extend to round bidding.

We begin with a somewhat tautological explanation: consumers dislike paying non-round prices (Lynn et al., 2013). One could speculate on a number of reasons behind this general dislike, whether non-round numbers entail a greater cognitive load, the nuisance of making change, or the appearance of penury. Formally, the disutility of non-round bids can be modeled by writing the payoff from winning as $v - b - \xi$, where ξ is the extra cost when b is not round. The higher is ξ, the more likely the bidder is to submit a round bid, exclusively submitting round bids when ξ is sufficiently high.

The extra cost of non-round bidding would lead bidders with this behavioral bias to clump at $5\mathbb{N}$, causing jumps in the probability of winning $P(b)$ for $b \in 5\mathbb{N}^+$, a euro above round numbers. Equilibrium forces would not totally eliminate these jumps: while biased bidders would gain a discrete increase in $P(b)$ by adding a euro to their round bid, they would experience a discrete utility loss ξ from so doing. The discrete jumps create strategic incentives for bidders without this behavioral bias to place $5\mathbb{N}^+$ bids in the final stage.

4.3. Hypothesis: Cognitive Load

The previous subsection offered several specific explanations for the generic dislike of non-round prices. This subsection fleshes one of them out in more detail: non-round prices may entail a greater cognitive load. Meticulously calculating an optimal bid may take considerable effort. Bidders may not even know their own private value without burdensome introspection. They may only have a vague notion of the range in which their preferences lie, an "imprecision interval" (Butler and Loomes, 2007). Faced with an effortful decision, individuals may engage in satisficing behavior, economizing on effort by settling on a strategy that is "good enough" (Gideon et al., 2017). Round numbers may be suitable candidates for satisficing strategies assuming they are salient or cognitively easy to access (Herrmann and Thomas, 2005). Studies have found that subjects resort to rounding when they are more uncertain about a target variable (Ruud et al., 2014) and when they are asked to think in terms of probabilities (Manski and Molinari, 2010).

Bidders may be particularly inclined to avoid calculation costs in the initial stage of the auctions we study. Bids in this stage are often inconsequential, very unlikely to win, moreso the earlier in the stage they are submitted. Bidders may decide to economize on calculation costs in the initial stage by picking a round number.

Bids are more consequential in the final stage, so we expect that there will be more incentive to carry out precise calculations, leading to fewer round bids. Still, incentives may not be powerful enough to eliminate round bidding entirely in this stage. Bids in the final stage may be rounded up or down relative to the optimum. Assuming these errors are white noise, equally likely to be under- as overbids, the auction would adversely select a high bid as the winner. Thus, on average, we expect round bids stemming from this behavioral factor to be overbids, as in Malmendier and Lee (2011).

4.4. Hypothesis: Left-digit Bias

As in the previous subsection, the bias discussed in this subsection stems from a heuristic used to reduce cognitive load. The difference is that the left-digit bias discussed involves a very particular heuristic. Left-digit bias is the phenomenon whereby a price of €19 seems more than a euro lower than €20 because individuals tend to focus only on the left digit and to disregard the rest of the number. Left-digit bias has been identified in the market for used cars (Lacetera et al., 2012; Busse et al., 2013), stocks (Sonnemans, 2006), and apartments (Repetto and Solís, 2020).

According to the formalization by Lacetera et al. (2012), a number's subjective value is the weighted sum of its digits, downweighting digits to the right relative their base-10 values. Bid b is assigned subjective cost $c(b) = 10d_{10} + (1-\phi)d_1$, where $d_{10} \equiv 10\lfloor b/10 \rfloor$ is the quotient after dividing b by 10 (the left-most digit in a two-digit number), d_1 is the remainder (the right-most digit), and $\phi \in [0,1]$ is an inattention parameter. For example, a bid of 19 would have subjective value $19 - 9\phi$, less than its 19 face value, while a bid of 20 would have subjective value equal to its face value.

In our data, not just multiples of ten but multiples of five are prevalent. A natural generalization of the model of Lacetera et al. (2012) that gives prominence to multiples of m assigns bid b the subjective cost

$$c(b) = md_m + (1-\phi)d_1, \tag{5}$$

where $d_m \equiv m\lfloor b/m \rfloor$ is the quotient after dividing b by m and $d_1 = b - d_m$ is the remainder. In this extension, taking $m = 5$ to give prominence to multiples of five, a bid of 19, for example, would have subjective cost $19 - 4\phi$.

In auction settings, this generalization of left-digit bias could alter bidding strategies through two channels: changing the perceived probability of winning the auction from $P(b)$ to $P(c(b))$ or changing the perceived payoff conditional on winning from $v - b$ to $v - c(b)$. The second channel would tend to reduce the perceived benefit of winning by making round bids discretely more expensive than an increment below. Hence this channel would lead round bids to be less prevalent in the data, not more.

For this generalization of left-digit bias to explain prevalent round bidding, it must operate through the first channel, by discretely increasing the perceived probability of winning by bidding a round number with a discretely higher subjective value. However, this channel has a difficulty in generating atoms of mass at round bids. If a bidder deviates to a minimum increment over a round bid, they would not perceive this as reducing their subjective payoff from winning much because they would underweight the increment. But this deviation would discretely increase their probability of winning by beating the bids massed at the round number.

4.5. Hypothesis: Round Budgets

Another possibility is that people use mental accounting, imposing round budgets on themselves when bidding. Thaler (1985) found that consumers tend to group expenditures into categories (entertainment, groceries) and impose category-specific budget constraints. Mental category budgets have been documented for purchases of groceries (Milkman and Beshears, 2009), gasoline (Hastings and Shapiro, 2013), and restaurant meals (Abeler and Marklein, 2017). Argyle et al. (2020) find that consumers' monthly payments on auto loans tend to be round numbers, consistent with a round mental budget for that expense.

In the model, a round mental budget would show up as an integer constraint on B in equation (3). Mental budgeters for whom this constraint bids would end up bidding round numbers in the final stage. Whether they end up under- or overbidding on average is ambigous, depending on why their budget constraint binds. If it binds because their mental budgets are low, round bids could be lower than average. If it binds because competition forced bids up to the constraint, round bids could be higher than average.

Bidders with this behavioral bias would disproportionately clump at $5\mathbb{N}$, causing jumps in the probability of winning $P(b)$ for $b \in 5\mathbb{N}^+$, a euro above round numbers. Equilibrium forces would not totally eliminate these jumps: bidders who have hit their round budget constraint cannot deviate to a higher bid. The discrete jumps create strategic incentives for bidders without this behavioral bias to place $5\mathbb{N}^+$ bids in the final stage.

4.6. Hypothesis: Round Reference Prices

Behavioral bidders may care not just about their expected surplus but also about getting a bargain relative to some reference price. Lange and Ratan (2010) model this effect by introducing loss aversion (á la Kahneman and Tversky, 1979) into the bidder's payoff conditional on winning:

$$(v-b)-\lambda \max\{0, b-r\}, \tag{6}$$

where λ is the utility weight on overpaying relative to reference price r and the max operator captures the asymmetry in losses versus gains relative to the reference price. A growing auction literature (e.g., Dholakia and Simonson, 2005; Banerji and Gupta, 2014; Rosato and Tymula, 2019; Balzer and Rosato, 2021; von Wangenheim, 2021) analyzes how this aversion to paying more than a reference price affects bidding and revenue. Various candidates for reference points have been posited, including reserve prices (Rosenkranz and Schmitz, 2007), previous auction outcomes (Backus et al., 2017), and endogenous price expectations (Ahmad, 2015). Bidders who are loss averse in this way would have a kink in their objective functions at their reference price, tending to concentrate equilibrium bids at these kinks.

In other contexts, round numbers have often been found to serve as important reference points or goals for individuals, for example when running a marathon (Allen et al., 2017; Soetevent, 2022), trading stocks (Bhattacharya et al., 2012), or bargaining over a house (Pope et al., 2015). If it is likewise true that reference prices in auctions tend to be round numbers, equilibrium bids concentrated on these reference prices would tend to be round as well.

Round reference prices would have similar implications for bidding behavior as did the round budgets analyzed in the previous subsection. The reference price provides a soft constraint, costly but not impossible to exceed, which otherwise functions similarly to a hard budget constraint.

4.7. Hypothesis: Round Valuations

Another potential hypothesis is that round bidding stems from bidders' round valuations for the items. There are a number of reasons to discount this hypothesis in our setting.

First, while it would not be surprising that, after binning by integer, a continuous distribution of values has a mode falling on a round number; it would be surprising to have modes systematically at every round number, as seen in Figure 1. Furthermore, our sample combines thousands of disparate items with disparate value distributions. It is even more unlikely that a random combination of disparate value distributions would have modes systematically at every round number. Perhaps most importantly, in the first-price auctions in our sample, bidding one's valuation is weakly dominated. Round valuations would only lead to round bids if the equilibrium amount of shading also happens to be round, which there is little reason to expect.

4.8. Hypothesis: Strategic Signaling

The theoretical literature has hypothesized that jump bidding may function as a signal of the bidder's high private value for the item to forestall rivals' entry or prompt their exit from ascending-bid auctions (Avery, 1998; Easley and Tenorio, 2004; Daniel and Hirshleifer, 2018). Although this literature is silent on round bids, a plausible speculation is that round numbers amplify the signal sent by a jump bid. A jump to a precise non-round number could be interpreted as having been chosen for good reason, perhaps tied to the bidder's valuation, perhaps suggesting a limit the bidder is unwilling to go beyond. On the other hand, a round jump bid could signal that their precise value is unimportant, perhaps suggesting that additional precision is rounding error compared to the bidder's much higher valuation.

The signaling value of round numbers has been recognized in settings outside of auctions. Backus et al. (2019) find evidence for a cheap-talk signaling equilibrium in negotiated sales of collectibles conducted on eBay. They find that when sellers post a round number (multiple of $100) as a list price prior to bargaining, this signals a weak bargaining position, reducing the price received but leading the deal to close more quickly.

A signaling explanation cannot explain round bidding in the final stage of auctions in our sample. We argued that the final stage resembles a sealed-bid auction since there is no time to respond to bids submitted in the last five seconds, precluding signaling.

Bids submitted in the initial stage, before the last five seconds, may have signaling value in our setting, but if they do it is subtle. Very few (3.4%) of round jump bids in the initial stage end up being the last bid in the auction as envisioned in equilibrium in the jump-bidding literature. In fact, only 12.5% of initial stage round jump bids go as standing bid into the final stage. If there is any signaling value to a jump bid in the initial stage, it is not chiefly in forestalling all further rival bidding but manipulating their behavior in the final stage. Observing a round jump bid in the initial stage may scare off some participants, reducing competition in the final stage, but may

Table 2: Summary of Theoretical Implications for Biased and Unbiased Bidding Behavior

	Bidding tendencies					
	Initial auction stage		Final auction stage			
Hypothesis	Biased bidder	Unbiased bidder	Biased bidder	Unbiased bidder	Round bidding in final vs. initial stage	Round vs. non-round winning-bid levels
Prefer round payments	$5\mathbb{N}$	$5\mathbb{N}$	$5\mathbb{N}$	$5\mathbb{N}^+$	More	Overbid
Cognitive load	$5\mathbb{N}$	$5\mathbb{N}$	$5\mathbb{N}$	$5\mathbb{N}^+$	Less	Overbid
Round budgets	$5\mathbb{N}$	$5\mathbb{N}$	$5\mathbb{N}$	$5\mathbb{N}^+$	More	Underbid
Round reference prices	$5\mathbb{N}$	$5\mathbb{N}$	$5\mathbb{N}$	$5\mathbb{N}^+$	More	Underbid

Notes: First column lists hypotheses remaining after ruling out those not fitting our setting on a priori grounds, as discussed in the text. The notation $5\mathbb{N}$ indicates bidding multiples of five and $5\mathbb{N}^+$ indicates a euro above that.

lead the remaining rivals to bid more aggressively, conjecturing that they are bidding against a high-value rival.

The bulk of our subsequent analysis will focus on the final-stage auction, in which signaling is precluded, leading us to discount the strategic signaling hypothesis.

4.9. Summary of Hypotheses

After culling hypotheses that the preceding subsections argued do not fit our setting on a priori grounds, we are left with the four behavioral biases listed in Table 2. The table summarizes the empirical implications of these remaining hypotheses for the behavior of biased and unbiased bidders.

By construction—since we only considered hypotheses positing a behavioral bias toward round bidding—the $5\mathbb{N}$ designation appears down the column for biased bidders in both auction stages, indicating a tendency toward round bidding. Regardless of which bias leads behavioral bidders to submit round bids, their unbiased rivals may strategically respond by submitting round bids themselves in initial stages, perhaps to occupy those standing bids preemptively, and by sniping in the final stage by slightly overbidding round numbers.

The hypotheses differ regarding whether round winning bids would tend to be overbids or underbids. According to Bayes rule, auctions won with a round bid are more likely to have been won by a behavioral bidder and thus the winning bid is more likely to have been driven by the hypothesized behavioral bias. If round bidding provides positive utility, bidders with that bias would bid higher on average than those without, and winning round bids would be higher on average than winning non-round bids. If round bidding results from errors in calculation, the auction mechanism would tend to select bidders who made positive errors for the winner; negative errors produce low bids that typically lose. Hence, the hypothesis of cognitive load generating errors in calculation would lead round winning bids to be higher on average than non-round winning bids. The last two hypotheses posit that round bidding stems from a constraint, whether imposed by a fixed budget or a reference price, leading bidders with this bias to underbid relative to those without. Auctions won with a round bid are more likely to have been won by a constrained bidder and thus with a lower than average bid than those won with a non-round bid.

The table provides a fairly subtle comparative-static prediction that we have not discussed so far, regarding whether behavioral bidders "indulge" their bias more in the initial versus the final auction stage. If the round bias is due to errors in calculation as in the second hypothesis, it is reasonable to expect that the bidder puts in more effort to compute an accurate bid when it is more consequential, in the final stage when that bid is more likely to win. We predict behavioral bidders would exhibit less rounding in the final stage according to this hypothesis. The other hypotheses would likely lead to the opposite prediction. If a preference for round payments drives round bids, the behavioral bidder would be more concerned about submitting a round bid the more likely the bid is to win, so later in the auction. A round budget or round reference price is more likely to bind as bids rise over the course of the auction, and so more round bids would be expected in the final stage.

5. Reduced-Form Analysis

This section begins by formally quantifying the extent of round bidding on the auction platform. The section then turns to a series of other reduced-form statistical analyses, looking for evidence that bidders strategically respond to round bids by bidding a euro above, determining whether round bids tend to be overbids, and estimating the effect of experience on bidding strategies.

The reduced-form analysis will focus on winning bids for several reasons. First, these are the bids with the greatest payoff relevance. Second, winning bids constitute a well-defined subsample with no missing latent observations. Broader subsamples have the potential of omitting bids in the final stage that bidders intended to submit but were sniped by an equal or higher bid submitted a moment earlier. The exclusion of such sniped bids might distort inferences about latent bidding behavior from these subsamples. While bids lower than the winning bid can be censored in this way, the winning bid cannot.

Some notation will aid our discussion of various empirical specifications. Let $i = 1, \dots, I$ index items auctioned on the site; let $j = 1,\dots,J_i$ index the multiple auctions run for item i; and let $k = 1,\dots,K_{ij}$ index the sequence of bids in auction j for item i. Denote the kth bid submitted in auction j for item i by b_{ijk}. The winning bid according to this notation is $b_{ijK_{ij}}$. We will adopt the more compact notation p_{ij} for the winning bid, the mnemonic being that this is the "price" the item sells for on the auction.

5.1. Prevalence of Round Bidding

To characterize the unexplained excess of round bids in our sample, we borrow an approach from Pope et al. (2015). For each natural number of euros n, we counted the number of bids equal to n in the relevant subsample, $CB_n = \sum_{i=1}^{I}\sum_{j=1}^{J_i}\mathbf{1}(b_{ijk} = n)$, where $\mathbf{1}(\cdot)$ denotes the indicator for the event in parentheses. We ran a Poisson regression of CB_n on a seventh-degree polynomial:[5]

$$CB_n = \exp\left(\sum_{\tau=0}^{7}\beta_\tau n^\tau\right) + \varepsilon_n. \tag{7}$$

The Poisson specification accommodates the fact that the outcome variable is in the form of count data. Inclusion of the high-dimensional polynomial in n partials out a smooth distribution of underlying item values, leaving the residuals ε_n to quantify the unexplained mass of bids at each n.

Figure 3 plots the residuals from regression (7) run on the sample of all bids. The round bids in $5\mathbb{N}$ stand out, having positive residuals in not just a few but in every case, confirming the excess mass at these values. Bids in $5\mathbb{N}^+$ (a euro above round numbers) also have positive residuals in nearly every case, though the residuals are considerably less than in $5\mathbb{N}$. Those in $5\mathbb{N}^-$ (a euro below round numbers) have negative residuals in almost all cases, suggesting missing mass due to bidders rounding up to the next round number or outbidding that round number by a euro.

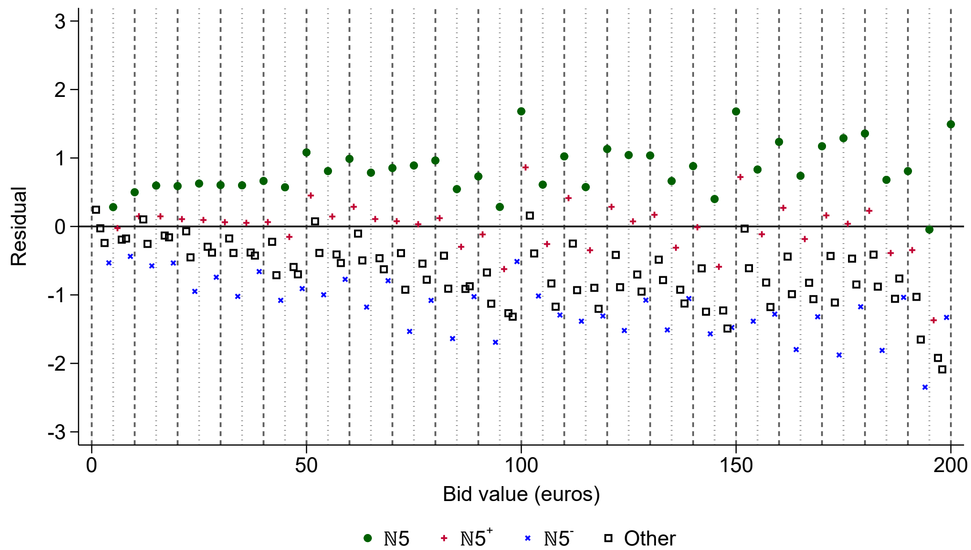
To quantify the average excess mass on round bids, we re-ran the Poisson regression in (7) adding indicators for $5\mathbb{N}$, $10\mathbb{N}$, $5\mathbb{N}^+$ and $5\mathbb{N}^-$:

$$CB_n = \exp\left(\sum_{s\in\{5\mathbb{N},10\mathbb{N},5\mathbb{N}^+,5\mathbb{N}^-\}}\gamma_s\cdot\mathbf{1}(b_{ijk}\in s) + \sum_{\tau=0}^{7}\beta_\tau n^\tau\right) + \varepsilon_n. \tag{8}$$

Table 3 reports the results for the sample of all bids in the first column; results for various other subsamples are reported in subsequent colums. Consistent with the large, positive residuals seen in

[5]The specific choice of a seventh-degree polynomial follows Pope et al. (2015). As verified in Figure A3 in the online appendix, the results are virtually identical for third- to eigth-degree polynomials.

Figure 3: Departure of Bid Counts from Prediction of High-Dimensional Polynomial



Notes: Each point is a residual from Poisson regression of CB_n (count of bids at each natural number n) on seventh-order polynomial in n, as specified in equation (7). Regression sample formed by starting with the sample of all bids and collapsing to bid counts, generating one observation per n. The regression sample is truncated at $n \leq 200$. Truncating the regression sample inside the range of observed bids avoids biases to the polynomial that would arise if the truncation point were set at or above the highest observed bid. Our truncation point still captures virtually all (99.4%) of all bids.

Figure 3, the coefficient on the $5\mathbb{N}$ indicator is large and statistically significant across all columns. The 0.65 coefficient on the $5\mathbb{N}$ indicator in the regression for winning bids implies that multiples of five are $e^{0.65} - 1 = 92\%$ more common than numbers in the baseline category (any natural number that is not $5\mathbb{N}$, $5\mathbb{N}^+$ or $5\mathbb{N}^-$).

The results for the $5\mathbb{N}$ indicator for the subsamples in the other columns have similar magnitudes to that for all bids in the first column except for the subsample of jump bids. The notion of a jump bid is well-defined in an ascending-price auction—the format of the initial stage of VV auctions—but not in a simultaneous, sealed-bid auction—the effective format of the final stage of VV auctions. Thus, we restrict our analysis of jump bids to those submitted in the initial stage. The 1.79 coefficient on the $5\mathbb{N}$ indicator in that column implies that multiples of five are $e^{1.79} - 1 = 499\%$ more common than baseline numbers. Bidders seldom jump to non-round numbers in the initial stage.

Bids in $10\mathbb{N}$ are particularly round. Since we include the $10\mathbb{N}$ indicator along with the $5\mathbb{N}$ indicator in the regression specification, the coefficients on $10\mathbb{N}$ have the interpretation of the extra mass on multiples of ten compared to multiples of five. While the coefficients on $10\mathbb{N}$ are generally

Table 3: Regressions Quantifying Extent of Round Bidding

	Bid sample				
Regressor	All bids	Winning bids	Initial-stage bids	Initial-stage jump bids	Final-stage bids
$5\mathbb{N}$ indicator	0.65^{***}	0.67^{***}	0.69^{***}	1.79^{***}	0.60^{***}
	(0.12)	(0.12)	(0.13)	(0.10)	(0.08)
$10\mathbb{N}$ indicator	0.18	0.03	0.25	0.08	−0.06
	(0.13)	(0.13)	(0.13)	(0.08)	(0.09)
$5\mathbb{N}^+$ indicator	0.27^{***}	0.20^{**}	0.31^{***}	-0.54^{***}	0.20^{***}
	(0.07)	(0.06)	(0.04)	(0.11)	(0.07)
$5\mathbb{N}^-$ indicator	-0.46^{***}	-0.42^{***}	-0.49^{***}	-0.43^{***}	-0.32^{***}
	(0.07)	(0.10)	(0.07)	(0.11)	(0.09)
Dependent variable	CB_n	CB_n	CB_n	CB_n	CB_n
Functional form	Poisson	Poisson	Poisson	Poisson	Poisson
7^{th} order polynomial in n	Yes	Yes	Yes	Yes	Yes
Observations	200	200	200	200	200
Pseudo R^2	0.99	0.97	0.99	0.98	0.98

Notes: Poisson regressions of CB_n (count of bids at each natural number n) on seventh-order polynomial in n, as specified in equation (7). Also includes regressors listed in row headings. Regression sample 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. 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.

positive, suggesting there is slightly more mass at rounder multiples of five, the coefficients are small and not statistically significant.

Consistent with the pattern of positive residuals for $5\mathbb{N}^+$ bids in Figure 3, Table 3 shows that $5\mathbb{N}^+$ bids are significantly overrepresented in virtually all of the subsamples analyzed. In the subsample of all bids, for example, $5\mathbb{N}^+$ bids are $e^{0.27} - 1 = 31\%$ more common than baseline numbers. While round bidders may be biased against $5\mathbb{N}^+$ bids, those bids may be favored by sophisticated bidders who appreciate their strategic benefit.

The overrepresentation of $5\mathbb{N}^+$ bids holds for all subsamples except jump bids in the initial stage, where $5\mathbb{N}^+$ bids are significantly underrepresented, 42% less more common than baseline numbers ($e^{-0.54} - 1 = -42\%$). Comparing the results for all bids in the initial stage to jump bids in that stage, we conclude that it is common for bidders to advance the standing bid (whether round or not) by the minimum euro increment but rare to try to edge out a higher round number yet to be submitted by a euro. Nevertheless, bids in the initial stage, whether jump bids or not, are not particularly consequential. For the subsamples of the more consequential bids—final-stage bids or winning bids—we see positive and highly statistically significant coefficients on the $5\mathbb{N}^+$ indicator, supporting the possibility that $5\mathbb{N}^+$ bids have strategic importance beyond other non-round bids.

Consistent with the pattern of negative residuals for $5\mathbb{N}^-$ bids in Figure 3, Table 3 shows that $5\mathbb{N}^-$ bids are significantly underrepresented in the full sample of all bids and in all other subsamples as well. Round bidders have a bias against these non-round numbers, and unlike $5\mathbb{N}^+$ bids, they may have little strategic benefit because they would tend to lose to the nearest round number.

Table A1 in the online appendix reprises the results in Table 3 using an alternative methodology inspired by the applied-econometrics literature on bunching (Kleven, 2016; Allen et al., 2017; Dube et al., 2025). That literature suggests that excess bunching can be measured differencing out the predicted value of the outcome variable from a smooth curve estimated using data outside of a window in which bunching is thought to occur. Applying the idea here, instead of using all bid values n to estimate the polynomial partialled out of the Poisson regression in (8), we fit the polynomial in a first stage using only values outside of a window around each round number. In particular, we exclude bids in $5\mathbb{N}$, $5\mathbb{N}^+$, and $5\mathbb{N}^-$ and only use the other values. In a second stage, we regress $\ln CB_n$, after differencing out $\ln \widehat{CB}_n$, on the indicators of interest from equation (8), where $\widehat{CB}_n$ are fitted values from the first-stage polynomial. This method is designed to prevent the excess mass at round numbers from distorting the estimate of the smooth polynomial, which could bias the estimate of excess mass at round numbers downward. Indeed, virtually all of the results in Table A1 are substantially larger in magnitude than their analogs in Table 3.[6]

5.2. Round Overbidding

This subsection documents the extent of overpayment that round bidding entails. To provide some initial visual evidence, we compute the difference between the price p_{ij} that item i sold for in auction j and the average price $\bar{p}_i = \sum_{j=1}^{J_i} p_{ij}/J_i$ that item i sold for across auctions our sample. Denote this price difference by $\Delta p_{ij} = p_{ij} - \bar{p}_i$. For for each natural number n, we compute the average value of Δp_{ij} for auctions with a selling price of $p_{ij} = n$. To reduce the impact of extreme outliers, indicative of data-scraping errors, all of the analysis in this subsection is undertaken after

[6]We chose to report the more conservative results because one cannot be sure that bunching at round numbers did not pull mass from the intervals used to estimate the smooth polynomial. This problem of a "contaminated counterfactual," arising when the bunching window is not precisely known, can bias the bunching estimate (Dekker and Schweikert, 2021).

modestly winsorizing winning bids.[7]

Figure 4 provides a binscatter plot of Δp_{ij}, plotting of the mean of Δp_{ij} for each bin n for all winning bids $p_{ij} = n$. The figure is split in three panels to aid legibility: different bid ranges require different vertical scales to be able to detect the finer details of the relative position of the plotted points. In the top panel, we see that winning with a bid of less than €20 tends to be a good deal for the average item, suggested by the fact that the mean of Δp_{ij} is negative for $n < 20$. However, round winning bids in this interval generate less of a good deal than neighboring, non-round bids, indicated by fact that the green dots associated with $5\mathbb{N}$ bids lie above neighboring points.

The same pattern occurs over all the other intervals in the first panel. Whether the winning bids in the interval tend to produce good deals for the bidder (as in the interval 1–20 euros), about an average deal (as in the interval 20–40), or tend to be overbids relative to average (as in the interval 40–60), the green dots representing $5\mathbb{N}$ bids stand above neighboring points in virtually every case, not only in the first panel but across all three panels. The overpayment relative to neighboring bids is particularly stark for the roundest of bids, at 50 and 100. For example, winning bids of 50 involve a €3.20 average overpayment. Despite being a euro higher, winning bids for the next natural number, 51, involve a smaller average overpayment of €1.48. Winning bids of 100 involve a €9.29 average overpayment, which drops to €1.65 for winning bids of the next natural number, 101.

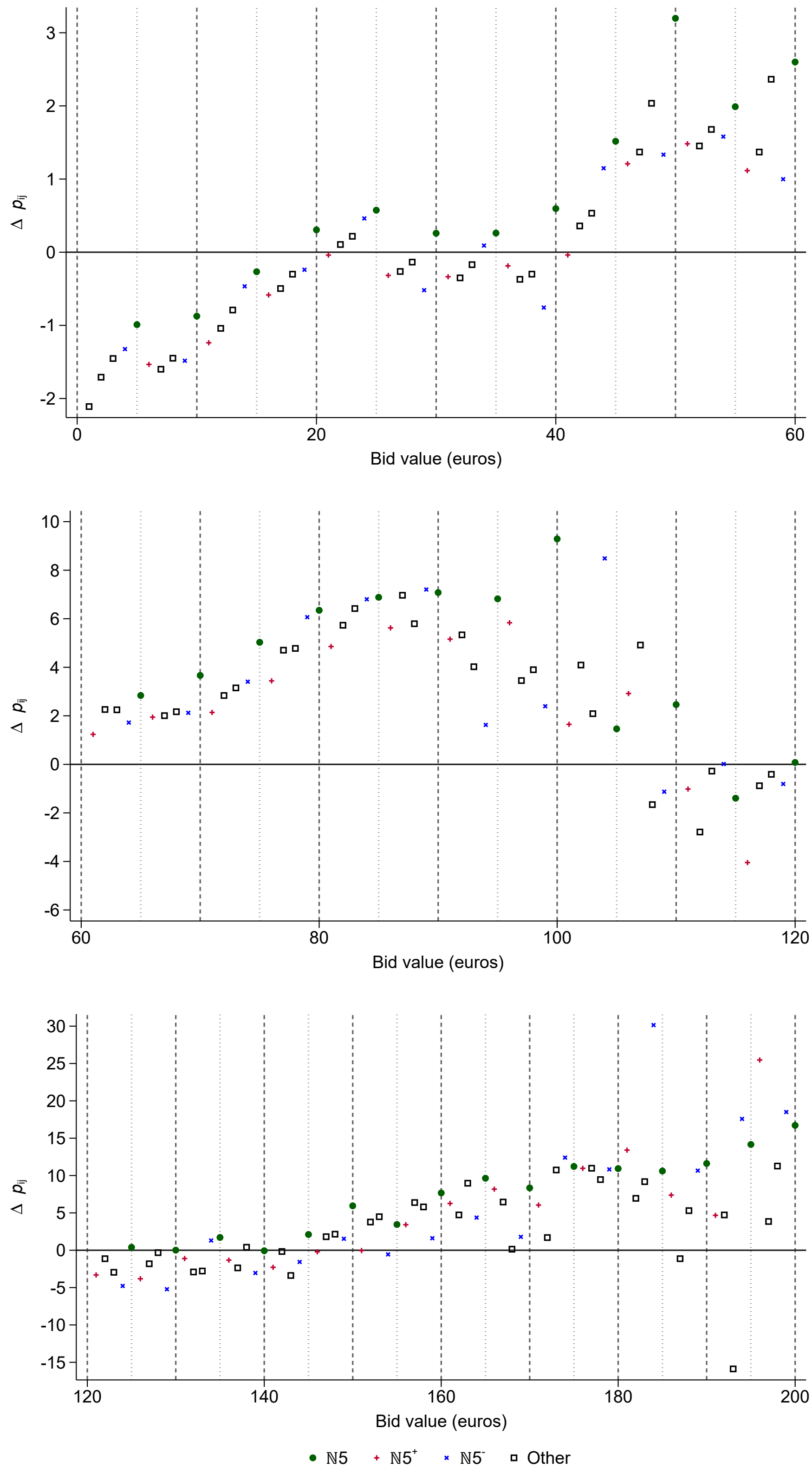
To quantify the average overbidding across round bids and judge the robustness of the results across subsamples, we ran the following linear regression for the sample of winning bids:

$$p_{ij} = \sum_{s \in \{5\mathbb{N}, 10\mathbb{N}, 5\mathbb{N}^+, 5\mathbb{N}^-\}} \gamma_s \cdot \mathbf{1}(p_{ij} \in s) + z_j \beta + \alpha_i + \varepsilon_{ij}, \tag{9}$$

where γ_s are the coefficients of interest on indicators for various multiples, z_j is a vector of auction controls, β their associated coefficients, α_i is an item fixed effect, and ε_{ij} is an error term. Estimates of γ_s measure the amount of over- or underbidding at multiples of five, ten, or a euro above or below multiples of five relative to the comparison category (any natural number that is not $5\mathbb{N}$, $5\mathbb{N}^+$ or $5\mathbb{N}^-$). The auction controls z_j includes fixed effects for deciles of the auction's duration, a count of the number of bids in the auction, a suite of fixed effects for each day over the five months over which we collected data, and separate suites of fixed effects (one for weekdays, one for weekends)

[7] We drop winning bids that are more than five standard deviations away from the average winning bid for that item. This reduced the number of observations by 1,363 (0.2% of the sample of winning bids).

Figure 4: Binscatter Plot Documenting Overbidding for Round Winning Bids



Notes: Each point in this binscatter plot graphs the mean of Δp_{ij} for all winning bids p_{ij} equal to bin value n. For legibility, the figure has been split in three panels to allow different vertical scales for different bid ranges.

for each hour during a day the auction ends.[8]

Table 4 reports results from estimating regression (9) on five separate subsamples of items i, divided according to the intervals in which the item's average winning bid $\bar{p}_i$ falls. Performing separate regressions for different bid levels serves several purposes. First, Figure 4 suggests that the variance of winnnig bids for an item appears to increase in item value. We could try to account for this by running regression (9) using $\ln p_{ij}$ rather than p_{ij} as the dependent variable, but a log specification would force round numbers to have a proportional rather than a level effect on overbidding. Running separate regressions allows the effect of round bidding to freely vary across item-value bins. Second, small winning bids present an integer problem for the specification in equation (9). It is mathematically impossible for a winning bid of €1 to be an overbid since €1 is the lowest possible bid on the platform. Bids of €2 and €3 are also very likely to be underbids because few items had average selling prices that low. It is hard to know how high the value of an item has to be for this integer problem to disappear. Running separate regressions for bins of lower-value items will allow us to see when the integer problem starts to wash out and to keep these bins from polluting the rest of the results if the integer problem is present.

The estimated coefficient on the $5\mathbb{N}$ indicator in the first row of Table 4 is positive and highly statistically significant across the columns. The magnitude of the coefficient, ranging from 0.93 to 1.90, implies that $5\mathbb{N}$ winning bids are from one to two euros higher than bids in the baseline category (any natural number that is not $5\mathbb{N}$, $5\mathbb{N}^+$, or $5\mathbb{N}^-$).

The results for the other indicators, $10\mathbb{N}$, $5\mathbb{N}^+$, and $5\mathbb{N}^-$, are not as consistent across subsamples. Their pattern is consistent with the presence of an integer problem in bin $[1,20)$ containing the lowest-value items, which appears to mostly wash out in the next, $[20,40)$, bin.

The table offers suggestive evidence that round bidders overbid more for higher-value items. Over the last three columns, the coefficient on the $5\mathbb{N}$ indicator increases from 0.93 to 1.06 to 1.90, and the coefficient on the $10\mathbb{N}$ indicator increases from 0.29 to 1.33 to 1.62. On average for the highest value items, $5\mathbb{N}$ bids are overbids by €1.90 compared to baseline numbers, and $10\mathbb{N}$ bids are overbids by $1.90 + 1.62 = 3.52$ euros compared to baseline numbers. By contrast, the $5\mathbb{N}^+$ and $5\mathbb{N}^-$ indicators do not reveal more overbidding at these non-round numbers compared to the other non-round numbers in the baseline category.

Our survey of explanations for round overbidding offered in Section 4 was silent on the relationship between round bidding and an item's value. In their simplest form, the hypotheses posited

[8]The estimates are identical to those that would be obtained if the price difference Δp_{ij} were used for the outcome variable and item fixed effects α_i omitted.

Table 4: Regressions Quantifying Overbidding Among Round Winning Bids

	Subsample of items k with average winning bid $\bar{p}_i$ in indicated interval				
Regressor	$\bar{p}_i \in [1,20)$	$\bar{p}_i \in [20,40)$	$\bar{p}_i \in [40,60)$	$\bar{p}_i \in [60,80)$	$\bar{p}_i \in [80,200]$
$5\mathbb{N}$ indicator	1.18***	1.01***	0.93***	1.06***	1.90***
	(0.13)	(0.07)	(0.13)	(0.19)	(0.42)
$10\mathbb{N}$ indicator	0.43*	−0.06	0.29*	1.33***	1.62*
	(0.19)	(0.14)	(0.15)	(0.24)	(0.74)
$5\mathbb{N}^+$ indicator	0.75***	0.13***	0.07	−0.15	−0.41
	(0.11)	(0.03)	(0.10)	(0.20)	(0.42)
$5\mathbb{N}^-$ indicator	0.38***	−0.07	−0.29*	0.16	0.52
	(0.09)	(0.05)	(0.12)	(0.27)	(0.57)
Dependent variable	p_{ij}	p_{ij}	p_{ij}	p_{ij}	p_{ij}
Functional form	OLS	OLS	OLS	OLS	OLS
Bid subsample	Winning	Winning	Winning	Winning	Winning
Item fixed effects	Yes	Yes	Yes	Yes	Yes
Auction controls	Yes	Yes	Yes	Yes	Yes
Observations	350,539	205,924	73,860	26,694	16,886
R^2	0.72	0.56	0.38	0.22	0.74

Notes: OLS regressions specified in equation (9) in which dependent variable is winning bid, p_{ij}. Regressions include bid indicators listed in row headings, an item fixed effect α_i, and a vector of auction controls z_j described in the text. Huber-White heteroskedasticity-robust standard errors clustered at the item level reported in parentheses. Statistically significantly different from zero in a two-tailed test at the *5% level, **1% level, ***0.1% level.

a fixed utility benefit from round bidding, entailing a fixed level of round overbidding, independent of item value. To explain why round overbidding increases in item value requires additional theory. One possibility goes back to the behavioral theory of Thaler (1980), which builds on Weber's law of psychophysics, holding that the minimal detectable stimulus is proportional to the mean level of the stimulus (Fechner, 1966). Applying this idea to prices, Thaler (1980) suggests that price differences are overlooked unless they exceed a certain percentage of a reference price. Bordalo et al. (2013) formalize and extend the theory, invoking the salience of prices and other product attributes compared to items in the consumer's choice set. Applied to round bidding in our setting, the theory could explain, for example, why a bidder would be willing to round up by €3 for convenience for an item that typically sells for €100 but only by €1 for an item that typically sells for €33—in both cases the "fee" for the convenience of a round bid is about the same 3% of the reference price.

In sum, the evidence suggests that round bids tend to be overbids. This finding is consistent with the first two hypotheses summarized in Table 2, identifying round bids with a preference for round payments or to lessen cognitive load. The finding is not consistent with hypotheses that tie round bidding to underbidding. There is no suggestion that round bids provide some strategic advantage, say providing a signal that drives rivals out of the market, reducing the price the round bidder ends up paying. Round winning bids are higher than average, not lower. We uncovered suggestive evidence that round bidders overbid more for higher-value items. The evidence is only suggestive since the number of observations for items in the $[80, 200]$ interval is too small to allow a finer partition to be estimated with reasonable confidence.

5.3. Bidder Experience

This subsection explores whether more experienced bidders engage in less round bidding and less overbidding. We measure auction experience following Lacetera et al. (2012). For each bid b_{ijk}, we compute the experience of the bidder who submitted it, measured by the number of auctions in which the bidder participated from the start of our dataset up to and including the current auction.[9] Next, we convert the experience measure from a count into a percentile ranking from 0 to 100, denoted x_{ijk}. To allow the estimated effect of experience to vary flexibly over its support, we estimate effects by quartile. Denote the indicator for experience lying in the first quartile interval by $XQ_{1,ijk} \equiv \mathbf{1}(x_{ijk} \in [0, 25])$, the second by $XQ_{2,ijk} \equiv \mathbf{1}(x_{ijk} \in (25, 50])$, the third by $XQ_{3,ijk} \equiv \mathbf{1}(x_{ijk} \in (50, 75])$, and the highest by $XQ_{4,ijk} \equiv \mathbf{1}(x_{ijk} \in (75, 100])$.

A caveat that will apply to the analysis throughout this subsection is that we do not observe subjects' full bidding history but only the bids they submit within our data-collection window. Some bidders may be labeled as inexperienced who have participated in many auctions before our data start. Bidders who switched user ID during our sample period will be construed as new subjects and have their experience undercounted. We are also unable to observe experience gained from watching auctions in which the subject does not bid. These errors in measurement are likely to bias the estimated impact of experience toward zero.

We ran the following linear probability model to analyze the effect of experience on round bidding:

$$\mathbf{1}(b_{ijk} \in 5\mathbb{N}) = \sum_{s \in \{2,3,4\}} \gamma_s \cdot XQ_{s,ijk} + \alpha_i + \varepsilon_{ijk}, \tag{10}$$

where the dependent variable is an indicator for $5\mathbb{N}$ bidding, γ_s are coefficients of interest on experience-quartile indicators, α_i is an item fixed effect, and ε_{ijk} is an error term. The omitted indicator XQ_1 for the lowest quartile provides the baseline for comparison.

[9] For example, in the subsample of winning bids—the focus of much of the analysis in this subsection—mean experience is 36.2.

Table 5: Regressions Analyzing Winning-Bid Propensities by Experience Quartile

	Bidding strategy analyzed			
Regressor	$5\mathbb{N}$	$10\mathbb{N}$	$5\mathbb{N}^+$	$5\mathbb{N}^-$
XQ_2	-0.021^{***}	-0.011^{***}	0.003	0.005^{***}
	(0.002)	(0.001)	(0.002)	(0.001)
XQ_3	-0.040^{***}	-0.022^{***}	0.011^{***}	0.011^{***}
	(0.002)	(0.002)	(0.002)	(0.001)
XQ_4	-0.067^{***}	-0.034^{***}	0.020^{***}	0.017^{***}
	(0.003)	(0.002)	(0.002)	(0.002)
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
Item fixed effects	Yes	Yes	Yes	Yes
Bidder fixed effects	No	No	No	No
Observations	678,417	678,417	678,417	678,417
R^2	0.04	0.04	0.02	0.02

Notes: Linear probability model given by equation (10) regressing indicator for round or non-round bidding strategy listed in column heading on experience-quartile indicators XQ_2–XQ_4. Lowest quartile indicator XQ_1 omitted, forming the comparison group. Regressions also include item fixed effects α_i. 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.

The results for $5\mathbb{N}$ bidding as well as other round and non-round bidding strategies are reported in Table 5. For parsimony, the text focuses on reporting results for the subsample of winning bids; the results for other bid subsamples are quite similar, as reported in Table A2 in the online appendix.

The first column of results in Table 5 suggest that each increment to the next higher experience quartile leads the probability of $5\mathbb{N}$ bidding to fall by about two percentage points. Bidders in the top experience quartile are 6.7 percentage points less likely to engage in $5\mathbb{N}$ bidding compared to the bottom quartile. The second column suggests that increasingly more experienced bidders are also increasingly less likely to engage in $10\mathbb{N}$ bidding. The coefficients are half the size of those in the first column, but the mean of the dependent variable is about half that in the first column (as there are only half as many $10\mathbb{N}$ as $5\mathbb{N}$ integers in our sample), implying that the percentage (rather than percentage-point) effect on the dependent variable is about the same in the first two columns.

Experienced bidders who shift away from round bids must shift their strategy to something else. Indeed, we see from the table that they engage in more $5\mathbb{N}^+$ and $5\mathbb{N}^-$ bidding. There is no evidence in the table to suggest that experienced bidders privilege a certain non-round number, seeming about equally likely to shift to a euro above or below multiples of five. In fact, about an

Table 6: Adding Buyer Fixed Effects to Regressions Analyzing Winning-Bid Propensities by Experience Quartile

Regressor	Bidding strategy analyzed: $5\mathbb{N}$	$10\mathbb{N}$	$5\mathbb{N}^+$	$5\mathbb{N}^-$
XQ_2	-0.017^{***}	-0.008^{***}	-0.001	0.004^{*}
	(0.002)	(0.002)	(0.002)	(0.002)
XQ_3	-0.029^{***}	-0.016^{***}	0.002	0.010^{***}
	(0.003)	(0.002)	(0.002)	(0.002)
XQ_4	-0.038^{***}	-0.020^{***}	0.004	0.011^{***}
	(0.005)	(0.003)	(0.004)	(0.003)
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
Item fixed effects	Yes	Yes	Yes	Yes
Bidder fixed effects	Yes	Yes	Yes	Yes
Observations	486,037	486,037	486,037	486,037
R^2	0.40	0.37	0.33	0.31

Notes: Reports coefficients from the same regressions as in Table 5 with the addition of bidder fixed effects. Fewer observations than in that table since fixed-effects procedure drops bidders with fewer than two winning bids. Remaining notes from Table 5 apply.

equal residual chance is left of shifting to non-round numbers more than a euro away.

The estimates in Table 5 derive from a regression without bidder fixed effects, implying that they pick up the combination of within-bidder effects of experience and between-bidder heterogeneity. Within-bidder effects of experience relate to how a bidder's strategy changes as that individual gains experience over time by participating in multiple auctions, perhaps learning what strategies are more successful. Table 5 picks up not only learning effects but also possible between-bidder heterogeneity—inherent differences between bidders who only participate in a few auctions and bidders who consistently interact with the VV platform, who might be more tech- or auction-savvy.

Having detected the presence of an experience effect in Table 5—stemming from some combination of within-bidder learning and between-bidder heterogeneity—we take the further step in Table 6 of extracting pure effect of an increase in experience for a given bidder. The table reports estimates from the regression specified in equation (10) with the addition of bidder fixed effects.

The coefficients on the experience quartiles in the $5\mathbb{N}$ regression fall by about a third from Table 5 to 6. This suggests that about a third of the originally estimated experience effect stemmed from inherent bidder heterogeneity. The remaining two thirds can be attributed to bidders learning to submit fewer round bids as they gain experience. For example, a bidder who gains the experience to move them from the lowest to the highest experience quartile during the sample period reduces their probability of $5\mathbb{N}$ bidding by an estimated 3.8 percentage points. In sum, bidders who participate in many VV auctions—call them power users—seem less drawn to round numbers than others from the start, perhaps because they are more sophisticated. These bidders learn over time to lean even further away from round numbers.

The biggest qualitative change from Table 5 to 6 is that the coefficients in the $5\mathbb{N}^+$ column are no longer significantly positive but are close to zero. These results suggest that it may be difficult to learn that bidding a euro above round numbers can be an effective strategy. Rather, it is just something that power users intuit.

We next turn to the question of whether experienced bidders get better or worse deals than average. To analyze this question, we ran a similar regression to (10), substituting the winning bid for the outcome variable:

$$p_{ij} = \sum_{s \in \{2,3,4\}} \gamma_s \cdot XQ_{s,ijk} + \alpha_i + \varepsilon_{ijk}. \tag{11}$$

The inclusion of item fixed effects α_i, means that the coefficients of interest γ_s on the experience quartiles capture underbidding or overbidding relative to average for the items. We will present a series of specifications adding further controls to the right-hand side. We do not start with a specification including auction controls z_j as we did in equation (9), later adding them to allow us to study whether experienced bidders obtain better prices by choosing to participate in a different set of auctions, perhaps at less competitive times. We also start with a specification without bidder fixed effects, later adding them to allow us to decompose the price effect of experience into within-bidder learning or between-buyer heterogeneity.

The results reported in Table 7 indicate that more experienced bidders obtain better auction deals. The price discount that experienced bidders receive monotonically improves with each experience quartile. For example, looking at the least-controlled specification in column (1), bidders in the highest experience quartile pay an estimated €1.88 less than bidders in the lowest quartile.

Since the specification in column (1) omits bidder fixed effects, the results can be interpreted as the combination of within-bidder learning and between-bidder heterogeneity. These results can be compared to the analogous ones in column (3), which includes bidder fixed effects. The addition of bidder fixed effects purges between-bidder heterogeneity, estimating the pure effect of increases in individual bidder experience. The magnitude of the coefficients in column (3) is lower than that

Table 7: Regressions Analyzing the Effect of Experience on Winning-Bid Levels

	Without bidder fixed effects		With bidder fixed effects	
Regressor	(1)	(2)	(3)	(4)
XQ_2	-0.77^{***}	-0.78^{***}	-0.51^{***}	-0.46^{***}
	(0.04)	(0.04)	(0.04)	(0.04)
XQ_3	-1.27^{***}	-1.29^{***}	-0.91^{***}	-0.81^{***}
	(0.05)	(0.05)	(0.08)	(0.05)
XQ_4	-1.88^{***}	-1.91^{***}	-1.32^{***}	-1.10^{***}
	(0.07)	(0.07)	(0.13)	(0.07)
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 regression specified in equation (11) regressing winning bid on experience-quartile indicators XQ_2–XQ_4. Lowest quartile indicator XQ_1 omitted, forming the comparison group. Regressions also include item fixed effects α_i. Certain specifications add auction controls z_j and/or bidder fixed effects as noted in table. 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.

in column (1). For example, the magnitude of the coefficient on the top quartile indicator XQ_4 falls by 30%, suggesting that 30% of the combined discount obtained by the most experienced bidders is due to between-bidder heterogeneity and 70% is due to bidders' experience gains during our sample period.

The discount obtained by power users can be interpreted as a reward for their inherent sophistication. An alternative interpretation is that power users have a lower value of time, so are more willing to bid low at the risk of losing the item since they can always try for the item in a future auction. Since much of the price discount is explained by within-bidder gains in experience, which is hard to interpret as other than gains in sophistication, it is reasonable to think that some of the between-bidder variation in the price discount is accounted for by variation in their sophistication, not just variation in their value of time.

Comparing results with and without auction controls (which primarily measure auction duration and timing) allows for another informative decomposition of the experience effect. Specifications that control for auction timing purge the benefit experienced bidders might gain from participating in favorable auctions—perhaps those likely to involve less competition—isolating the effect of their experience on differences in the bidding strategy used in a given auction. Specifications without auction controls estimate the combined effect of experience on choice of time slot and bidding strategy. The results hardly change when auction controls are added to the specification without bidder fixed effects, as can be seen by comparing the results in column (1) and (2). On the other hand, adding auction controls to the specification with bidder fixed effects has a more substantial effect on the results, as can be seen by comparing the results in column (3) and (4). For example, the magnitude of the coefficient on XQ_4 falls by 21%, suggesting that 21% of the price discount obtained by experienced bidders can be attributed to the choice of the right auction to participate in and the remaining 79% to engaging in more bid shading in a given auction. The fact that including auction controls only affects the results with bidder fixed effects suggests that bidders learn with experience which are the right auctions to participate in, not that sophisticated bidders enter the market endowed with that insight.

We ran a variety of additional specifications aiming to uncover heterogeneity in the effect of experience on bidding. We ultimately found more homogeneity than interesting heterogeneity, so relegated the results to the online appendix. For example, we repeated the regressions in Tables 6 and 7 for the subset of bidders who will eventually enter the XQ_4 experience quartile—power users, in effect. The results are similar to those above with bidder fixed effects. This suggests that even if power users enter the market with more sophistication than others, they still have something to learn about eschewing round numbers and overbidding, and do so at about the same rate as others (see Tables A4 and A5 in the online appendix).

We reprised the regressions in Table 7 but interacting experience quartiles with indicators for different round and non-round bidding strategies. The idea was to see whether experienced bidders end up getting a good deal by avoiding round bids or whether they are able to obtain a good deal even when making round bids, perhaps because of a savvier strategy—say being the fastest to jump to the round number above the standing bid or avoiding jumping to a bid of say €35 when €30 would have sufficed to win. The results in Table A6 in the online appendix show that experienced bidders pay lower prices whether they win with an $5\mathbb{N}$ bid, an $5\mathbb{N}^+$ bid, or an $5\mathbb{N}^-$ bid. Indeed, their price discount is if anything larger with the $5\mathbb{N}$ strategy than the others. Apparently, when experienced bidders submit round bids, they choose them carefully.

6. Structural Analysis

This section constructs and estimates a structural model of an auction in which behaviorally biased and rational bidders compete. The structural analysis provides two advances over the reduced-form analysis. First, it allows estimation of the latent proportion of bidders with a round-bidding bias. This proportion cannot be gleaned from the observed proportion of winning bids that are round. According to the "bidder's curse" phenomenon (Malmendier and Lee, 2011), a small proportion of bidders with an overbidding bias can account for a disproportionate share of winning bids. The strategic response of rational rivals to these round bids further complicates inferences from the observed distribution of winning bids. Second, the structural approach allows inferences to be made about welfare. In particular, we will be able estimate the expected surplus loss attributable to round-number bias.

6.1. Structural Model

This subsection describes the auction model involving behavioral bidders used in the structural analysis. Each item i in the set of 100 most frequently auctioned will be analyzed separately using data on the sequence of auctions indexed by $j = 1, \ldots, J_i$ conducted for that item. The model focuses on the last stage of auction j, modeled as a simultaneous, first-price, sealed bid auction. The number of bidders n_{ij} in this auction is a draw from a $\chi^2(\mu_i)$ distribution, chosen because it is a parsimonius (one-parameter) distribution having the desirable properties of being positive and bell-shaped. The parameter μ_i is mean of the distribution.[10,11] We assume bidders observe n_{ij} before submitting their final-stage bids. While bidders do not directly observe this number in practice, they can likely infer the approximate number based on the time of day, week, and month and the competitiveness of the initial-stage auction.

Bidders' valuations are drawn from a gamma distribution parameterized as $\Gamma(\alpha_i, \beta_i/\alpha_i)$. Under this parameterization, α_i is interpreted as a shape parameter and β_i as the distribution's mean.

A proportion $\rho_i \in [0,1]$ of the population are subject to round-number bias. We model this

[10] We convert the continuous distribution into a discrete one by rounding to the nearest natural number. We also impose the floor $n_{ij} \geq 2$ to ensure competitive bidding in all simulated auctions.

[11] Our approach to modeling the number of bidders is less restrictive than Malmendier and Lee (2011) among other previous analyses of behavioral bidding that fix n_{ij} to the mean number of observed bidders across auctions for the item. Besides allowing for randomness in the number of bidders, our approach avoids the possibility that the number of unique bidder IDs observed in the final stage may understate the competitiveness of that auction. Some potential bids may go unregistered if a rival was slightly quicker to submit that or a higher bid. We presume the short span of the final stage leaves no time for the bidder to respond.

simply by assuming their choice set is restricted to bids in $5\mathbb{N}$, in effect facing an infinite cost of submitting non-round bids. The rest of the population can submit bids in $\mathbb{N}$.

Bidders are behavioral in another way, varying in the sophistication of their understanding of round bias in the population, captured by a model of level-k reasoning, building on Crawford and Iriberri (2007). Specifically, for $\ell = 0,1,2$, a proportion $\pi_{\ell i}$ are level-ℓ reasoners, where $\pi_{\ell i} \in [0,1]$ and $\pi_{0i} + \pi_{1i} + \pi_{2i} = 1$. Level-0 reasoners submit the equilibrium bid assuming no rivals are round bidders. Level-1 reasoners bid the best response to all rivals being level-0 reasoners, and level-2 reasoners bid the best respose to all rivals being level-1 reasoners.

While we borrow the basic structure of reasoning levels from Crawford and Iriberri (2007), the meaning of each level is quite different in our model. Level-0 bidders do not submit random bids—quite the opposite—they submit equilibrium bids, which may involve careful calculation. They are unsophisticated only in the narrow sense of ignoring the possibility that some rivals might round. Higher level reasoners are able to integrate an understanding of round bidding into their best responses. Thus, the criticism of existing empirical applications of level-k reasoning to auctions leveled by Rasooly (2023) does not directly apply to our model.

Let Bernoulli random variable $R_m \in \{0,1\}$ indicate whether bidder m is round-biased and categorical variable $L_m \in \{0,1,2\}$ indicate the reasoning level of bidder m. Then

$$\rho_i = \Pr(R_m = 1) \tag{12}$$

$$\pi_{\ell i} = \Pr(L_m = \ell), \quad \ell \in \{0,1,2\}. \tag{13}$$

Assume R_m and L_m are independent from each other for all m and independent across m for all items i and auctions j. Overall, bidder m can be one of six behavioral types, denoted $\tau_m \equiv (R_m, L_m)$.

6.2. Structural Methods

To obtain estimates of the parameters in the vector $\theta_i \equiv (\mu_i, \alpha_i, \beta_i, \rho_i, \pi_{1i}, \pi_{2i})$, we use the method of simulated moments. Specifically, we look for the $\hat{\theta}_i$ minimizing the distance between the vector of simulated bid frequencies $\hat{f}(p|\theta_i)$ and empirical frequencies $\phi_i(p)$:

$$\hat{\theta}_i = \underset{\theta_i}{\operatorname{argmin}} \sqrt{\sum_{p=1}^{p^{max}} \left[\hat{f}(p|\theta_i) - \phi_i(p)\right]^2} \tag{14}$$

Given the complicated structure of the model, with two dimensions of behavioral bias, discrete strategies, and rounding—there is no guarantee that objective function (14) is sufficiently well-behaved that descent methods would work well to minimize it. We thus resort to a grid search over θ_i. To avoid the "curse of dimensionality," we carefully designed an adaptive grid-search procedure described in in the online appendix. The adaptive grid search explores the whole parameter space before honing in on the most promising region.

For each grid point $\theta_g = (\mu_g, \alpha_g, \beta_g, \rho_g, \pi_{1g}, \pi_{2g})$ explored in the parameter space, we first construct a population of bidders $m = 1, \ldots, M$. For each bidder m, valuation v_m is drawn from the $\Gamma(\alpha_g, \beta_g/\alpha_g)$ distribution and behavioral type $\tau_m = (R_m, L_m)$ is drawn according to the probabilities ρ_g, π_{1g}, and π_{2g}. We then simulate J auctions $j = 1, \ldots, J$, by taking a random draw n_j from $\chi^2(\mu_g)$, randomly selecting n_j members of the simulated population M, and determining their bids. We initially set $M = J = 1,000$.

Bids in the simulated auction are computed as follows. Level-0, non-round bidders submit the equilibrium bid in a first-price, sealed-bid auction facing $n_j - 1$ rational rivals, which is given by a standard formula (see Klemperer, 1999):

$$b(v_m, n_j, \tau = (0,0)) = v_m - \int_0^{v_m} \left[\frac{F(v, \alpha_g, \beta_g)}{F(v_m, \alpha_g, \beta_g)} \right]^{n_j - 1} dv, \tag{15}$$

where $F(v, \alpha_g, \beta_g)$ is the cumulative distribution function associated with the $\Gamma(\alpha_g, \beta_g/\alpha_g)$ distribution. For non-round bidders, the result is rounded to the nearest number in $\mathbb{N}$ to reflect auction site rules. For round bidders, the result is rounded to the nearest number in $5\mathbb{N}$ below their valuation:

$$b(v_m, n_j, \tau = (1,0)) = \min \left\{ 5 \left\lfloor \frac{b(v_m, n_j, \tau = (0,0))}{5} + \frac{1}{2} \right\rfloor, 5 \left\lfloor \frac{v_m}{5} \right\rfloor \right\}. \tag{16}$$

Level-1 bidders best respond to their belief that their $n_j - 1$ rivals are level-0 reasoners having the population rate of round bias:

$$b(v_m, n_j, \tau = (0,1)) = \underset{x}{\operatorname{argmax}} \left[P(x, n_j, \theta_g, \tau = (0,1))(x - v_m) \right], \tag{17}$$

where $P(x, n_j, \theta_g, \tau = (0,1))$ is the level-1 bidder's subjective belief that they will win an auction against $n_j - 1$ level-0 rivals.

Due to the complicating presence of round bidders among those rivals, we are aware of no closed-form solution for this P, so we simulate it as follows. We generate J' auctions indexed by

$j' = 1, \ldots, J'$ involving $n_j - 1$ rivals who bid according to equation (15) with probability $1 - \rho_g$ and according to (16) with probability ρ_g, generating a vector of rival bids. Denote the highest of these rival bids by $b_{j'}^{[1]}$. A bid of x wins with probability 1 if $x > b_{j'}^{[1]}$ and probability 0 if $x < b_{j'}^{[1]}$. If $x = b_{j'}^{[1]}$, a bid of x results in a tie for the highest bid. We assume that the winner is equally likely to be any one of the tied bidders. Therefore, a bid of $x = b_{j'}^{[1]}$ wins with probability $1/(1 + t_{j'})$, where $t_{j'}$ denotes the number of rivals who tied for the highest bid in simulated auction j'. We compute $\hat{P}_1(x, n_j, \theta_g, \tau = (0,1))$ by averaging the probability of winning across the J' simulated auctions. Level-1 bidders round the result to the nearest $\mathbb{N}$ unless they have a round bias, in which case they round to the nearest $5\mathbb{N}$. An analogous procedure is used to simulate the bids of level-2 bidders.

In this way, we simulate bids in J auctions for grid point θ_g. We take the winning bid p_j from each auction and compute the frequencies $\hat{f}(p|\theta_g)$ substituted into objective (14). The structural estimate $\hat{\theta}_i$ is the grid point minimizing (14).

With $\hat{\theta}_i$ in hand, we simulate other relevant outcomes from the structural model, in particular, the expected surplus for various bidder types and the distribution of winning bids to compare to the empirical distribution to judge goodness of fit. Since this is the final step of the procedure that need only be run once rather than an intermediate step that must be iterated, it is computationally feasible to use a large population from which to draw bidders and to run more simulated auctions. We specify a population of $M = 100,000$ potential bidders and simulate $J = 100,000$ auctions. Expected surplus for a bidder type is the average surplus earned by bidders of that type across the simulated auctions in which they participate in this last step. The simulated distribution of winning bids is that for the 100,000 auctions simulated in this last step.

6.3. Structural Sample

We estimate the structural model separately for each of the 100 most frequently auctioned items in our dataset among those that sold for more than €10 on average. We excluded lower-value items to avoid cases in which the bidder's value for the item is below any round number, leaving round bidders with an empty strategy space in the model.

Table 8 provides descriptive statistics for the auctions for these 100 items. Even the item with the fewest auctions was auctioned nearly 1,000 times during the sample period. The most frequently auctioned item was auctioned over 10,000 times. Although these 100 items represent only 4% of the 2,502 items in the full study sample, their high auction frequency means they account for a much larger share (40%) of the auctions in the full study sample, yielding 221,000

Table 8: Descriptive Statistics for Items Used in Structural Estimation

Variable	Minimum	Median	Mean	Maximum
Number of auctions (count)	956	1,504	2,210	10,815
Number of final stage bids (mean)	1.25	1.75	1.76	2.15
Winning bid (mean, €)	10.1	22.8	27.2	67.7
Winning bids in 5ℕ (proportion)	0.25	0.34	0.35	0.54

Notes: Descriptive statistics for the 100 most frequently auctioned items in our sample selling for an average price of over €10, which forms our sample for structural estimation.

Table 9: Structural Parameter Estimates

Parameter	Definition	Median estimate	90% percentile band
μ	Mean of χ^2-distributed number bidders	2.4	[0.5, 3.1]
α	Shape of Γ distribution of item values	15.8	[3.7, 46.8]
β	Mean of Γ-distributed item values	24.8	[12.4, 54.7]
ρ	Proportion of round bidders	0.21	[0.10, 0.36]
π_1	Proportion of level-1 reasoners	0.21	[0.01, 0.53]
π_2	Proportion of level-2 reasoners	0.08	[0, 0.35]

Notes: Reports distribution of parameter estimates from separate estimation of structural model for 100 items described in Table 8. The 90% percentile band is formed by taking the interval from the 5th to 95th percentile structural estimates.

auction observations.

The lowest selling price is €10.1, just above the cutoff for inclusion in the structural sample. The highest is €67.7. The extent of round bidding varies substantially across items, from a quarter of winning bids for the item to more than half.

6.4. Structural Results

Table 9 presents the results for the structural parameter estimates, reporting the median estimate and the 90% percentile band, which we form by taking the interval from the 5th to the 95th percentile estimate.

The first three rows contain the estimates of the basic auction parameters, the mean for the distribution of the number of bidders and the parameters of the gamma distribution of bidder values. These parameter estimates are sensible and comport with the descriptive statistics in Table 8. The median estimate of the mean number of bidders is $\hat{\mu} = 2.4$, which is slightly larger than the analogous estimate of the observed number of final-stage bids. This finding is consistent with the presence of potential bidders who do not show up among final-stage bidders because their desired

Table 10: Structural Bidder Surplus Estimates

Surplus measured	Median estimate	90% percentile band
Mean surplus per participating bidder	2.47	[1.33, 4.75]
Mean surplus per participating round bidder	2.28	[1.11, 4.55]
Mean surplus per participating non-round bidder	2.51	[1.40, 4.80]
Mean percentage surplus lost to round bias	9.3	[4.2, 20.4]
Mean percentage surplus gained moving from level-0 to level-1	0.8	[0.1, 2.2]
Mean percentage surplus gained moving from level-1 to level-2	-0.3	[−1.5, 0.5]

Notes: Reports distribution of surplus estimates from separate estimation of structural model for 100 items described in Table 8. Mean surplus change moving between reasoning levels (level-1 to level-0 or level-2 to level-1) computed for nonround bidders. The 90% percentile band is formed by taking the interval from the 5th to 95th percentile structural estimates.

bids are preempted before they can be registered.[12] The median estimate $\hat{\beta} = 24.8$ for the mean item value is close to the median across items, 22.8, for the mean winning bid.

Of central interest are the behavioral parameters in the last three rows. The median estimate of the percentage of round bidders is $\hat{\rho} = 21\%$. The 90% percentile band ranges from 10% to 36%, suggesting the proportion of bidders with round bias is significantly greater than zero but significantly less than a majority. Echoing the "bidder's curse," by which behavioral bidders can be overrepresented among auction winners, we see that a median 21% share of round bidders can generate a 34% median share of round numbers among winning. A median $\hat{\pi}_1 = 21\%$ of bidders are estimated to be level-1 reasoners, capable of exploiting the presence of round bidders. Level-2 reasoning appears rare in the population: the median estimate is $\hat{\pi}_1 = 8\%$, and zero appears within the 90% percentile band.

Table 10 reports estimates of the expected surplus from participating for various bidder types. All reported surplus measures are conditional on participating rather than winning, so incorporate the chance of losing to a competitor and obtaining no surplus. The mean surplus conditional on winning (not reported) would of course be higher. The average participant in the final-stage auction obtains €2.42 surplus on average. Supposing effective participation requires 10 minutes of attention, the imputed wage would be around €15, perhaps reasonable for the low-value of time and which does not reflect the entertainment value from participating (nor any additional disutility). Assuming effective participation requires 30 minutes of attention reduces the imputed wage to around €5.

The last two rows of the table report estimates of the surplus gained if a nonround bidder moved

[12] In fact, the estimated $\hat{\mu}_i$ itself understates the simulated mean number of bidders because simulated draws from the $\chi^2(\hat{\mu}_i)$ distribution are rounded up to $n_{ij} \geq 2$.

to a higher reasoning level. The move from level-0 to level-1 reasoning captures the gain from being able to exploit round bidding among some rivals. The gain is small, the median estimate among the 100 items being slightly less than 1%. The move from level-1 to level-2 reasoning captures the gain from being able to exploit those who exploit round bidding. This additional sophistication appears not to be helpful: the tiny surplus change for the median item is in fact negative, but so small as to be negligible. In any event, this level of sophistication is estimated to be relatively uncommon.

We already provided some support for the goodness of the structural model's fit, noting that the estimates of the basic auction parameters and surpluses seemed sensible and in line with observed sample moments that were not targeted by the method of simulated moments procedure. Figure 5 provides additional support, comparing the observed to the simulated distribution of winning bids for the five most frequently auctioned items in the structural sample. In each case, the simulated distributions do a remarkably good job of reflecting the fine details of the irregular pattern of spikes, their individual heights, and the step down in mass for bids between the spikes. These irregular patterns are highly idiosyncratic across the five items, and the simulations are able to mirror those idiosyncracies.

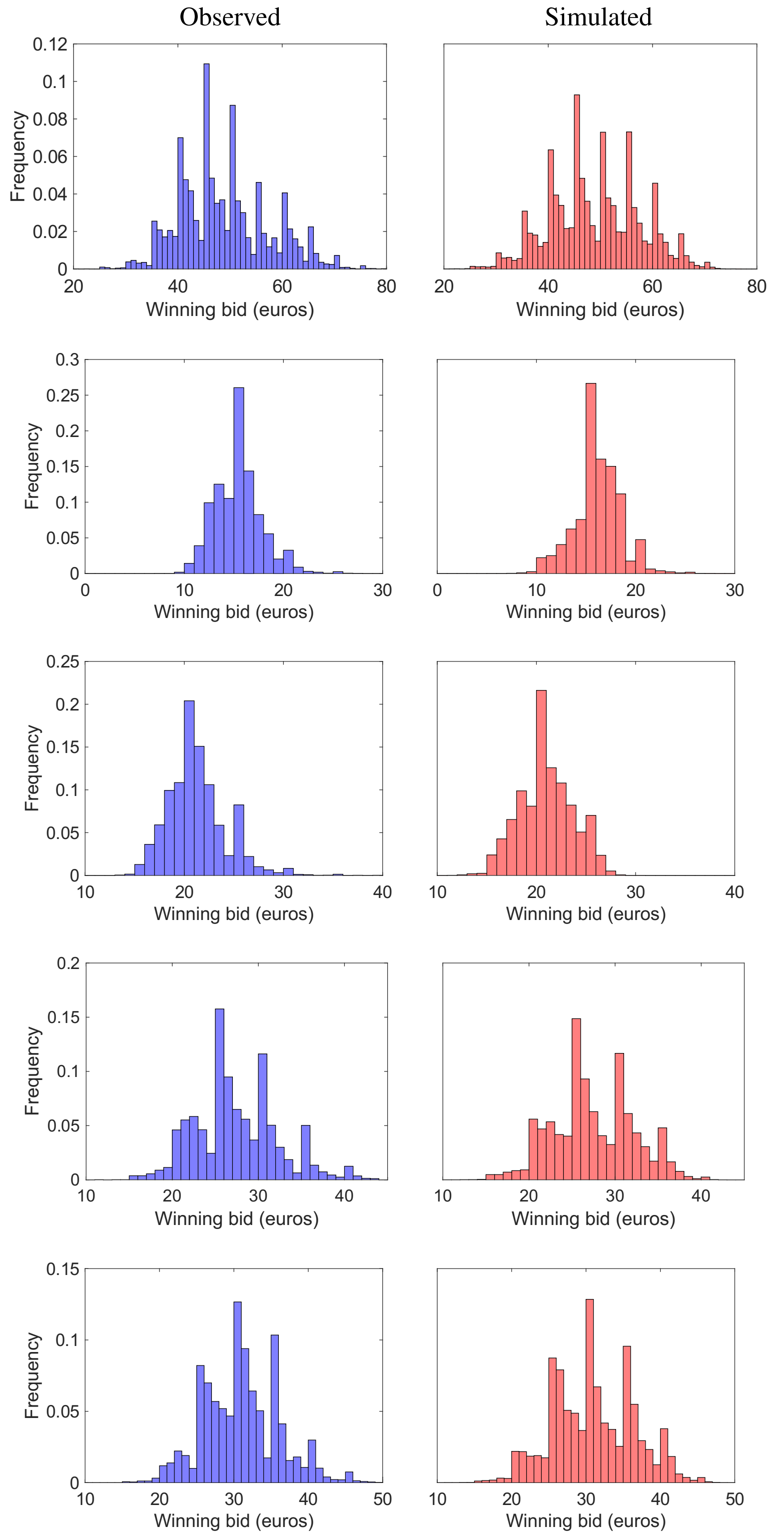
7. Conclusion

This paper applies reduced-form and structural methods to a large and novel dataset on business-to-consumer auctions. The analysis uncovers a disproportionate amont of round bidding consistent with a behavioral bias toward round numbers described in marketing and related literatures but as yet unnoticed in the auction literature.

In the subsample of winning bids, multiples of five are 95% more common than a smooth polynomial over natural numbers would predict. These round bids tend to be overbids, and the overbids tend to be larger for higher-value items. More experienced bidders engage in less round bidding and less overbidding. Roughly one third of the experience effect can be attributed to between-bidder heterogeneity and two thirds to within-bidder experience gains.

The heterogeneity between bidders may derive from inherent differences in their tech- or auction-savviness. Another explanation is that spending a lot of time on the platform reveals that the bidder has a low opportunity cost of time. They may be more willing to risk losing the current auction to get a better price since they are willing to participate in future auctions for the item. While differences in opportunity costs can explain differences in overbidding between bidders, it

Figure 5: Fit Between Observed and Simulated Distributions of Winning Bids for Top Five Items



Notes: Graphs comparing observed and simulated distribution of winning bids for the five most frequently auctioned items in our structural sample. In order from top to bottom, these are two tickets to a Toppers concert, tea for two in selected restaurants, dinner for two in selected restaurants, night stay in one set of hotels, and night stay in a different set of higher-end hotels.

does not explain differences in round bidding between bidders nor reductions in overbidding for individuals who gain experience. Differences in sophistication can explain the suite of experience effects—both between- and within-bidder effects of experience on both round bidding and overbidding.

Evidence from sniping in the auctions' final seconds suggests that some sophisticated bidders anticipate round bidding at the end of the auction and respond by submitting a $5\mathbb{N}^+$ bid. We find that $5\mathbb{N}^+$ bids are 22% more common than other non-round numbers in final stage. By contrast, $5\mathbb{N}^+$ bids are 42% less common than other non-round numbers among jump bids in the initial stage, a subsample which focuses on bids reflecting more tactical deliberation than mechanically raising the standing bid by the minimum increment. The difference in the rate of $5\mathbb{N}^+$ bidding between early and late stages of the auction supports the contention that $5\mathbb{N}^+$ bidding is a tactical decision by snipers, not an artifact of a law of anomalous integers à la Benford (1938).

Our structural analysis exploits a subsample of 100 items that were each auctioned a number of times stretching into the thousands, allowing precise estimation of valuation and behavioral parameters separately for each item. The median estimate suggests that about a fifth of bidders have round-number bias, and a fifth have some sophistication to exploit these round bidders. The average participant in a final-stage auction obtains an expected surplus of about €2.5 according to our median estimate, of which round bidders sacrifice around 10% due to their bias.

Overall, the evidence points to extensive round bidding, probably symptomatic of a bias affecting a substantial minority of bidders inclining them to avoid complex calculations. In our small-stakes setting of business-to-consumer auctions of items of moderate value, the bias only results in a modest surplus loss. Work remains to see if round bidding is a more general phenomenon, extending to higher stakes settings; and if so, whether the surplus loss remains modest there.

Our analysis has several limitations. We found a disproportionate amount of $5\mathbb{N}^+$ bidding in the final stage, which we suggested can be the result of sophisticated snipers exploiting round bidders. We did find a statistically significant shift in the mass of $5\mathbb{N}$ bids toward $5\mathbb{N}^+$ bids for more experienced bidders; however, this shift toward other non-round numbers was similar. In the absence of this nuanced evidence, our conclusions that round bidding and overbidding are connected to bidder sophistication must remain tentative. The complications involved in modeling round-number bias and other behavioral biases led us to simplify other dimensions of the structural model. In particular, we took a static approach that abstracted from dynamic strategies that can emerge in bidding across multi-unit auctions (see Hortaçsu and McAdams, 2018, for a survey).

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