Might as well jump? The role of round jump bids in auctions

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Abstract

The ubiquity of jump bidding in auctions presents a puzzle for auction theory. Commonly given explanations for this empirical phenomenon are that bidders want to speed up the bidding process or to signal their private valuation. Yet we present new data from a large business to consumer (B2C) first-price auction site where jump bidding is prevalent despite the fact that jump bids cannot speed up the auction process, and no successful signalling seems to be taking place. We argue that much of the observed jump bidding originates in round number biases, as we show a strong link between jump bidding and bidding round numbers. We estimate that around 15-30% of all bidders are prone to a round number bias which lowers their expected surplus by about 8%.

JEL classification: D44, D83, D91, L11.
Keywords: Auctions; Behavioral biases; Overbidding; Reference points; Limited attention

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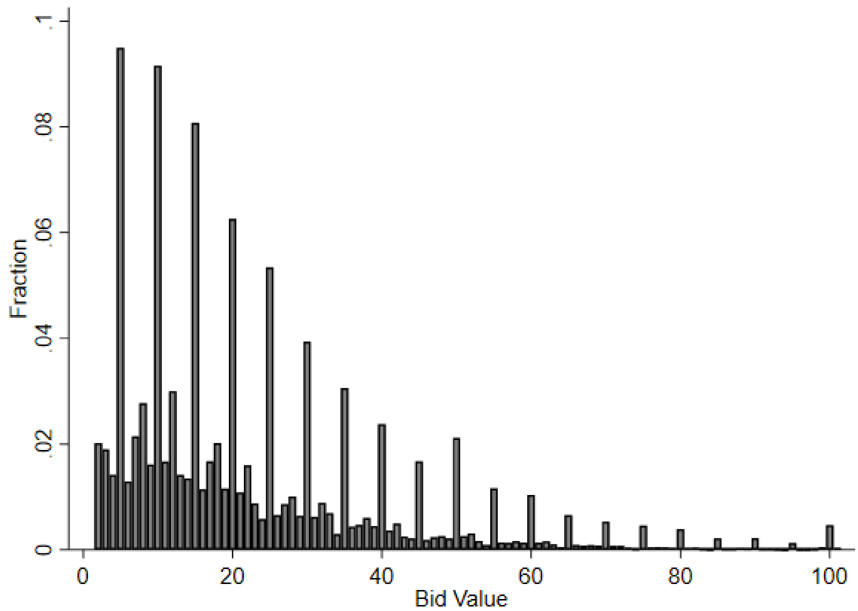
1 Introduction

Jump bidding, or increasing the bid with more than the minimum bid increment is observed in a wide range of auctions, from FCC wireless spectrum auctions (Cramton, 1997) to online auction settings (Easley and Tenorio, 2004) and has been called *"an endemic feature of real-world ascending auctions"* (Grether et al., 2015). This despite the fact that the opposite strategy of incremental bidding – increasing the bid with the minimum bid increment until your valuation is reached – is often thought to be the dominant strategy in these auctions (Isaac et al., 2007). Grether et al. (2015) hence conclude that the ubiquity of jump bidding presents a puzzle for standard auction theory. The literature to date offers two main explanations for the prevalence of jump bidding: a desire to speed up the auction process (Isaac et al., 2007; Plott and Salmon, 2004), and a motive to signal one's (high) private valuation for an item to prevent entry or bidding by others (Avery, 1998; Easley and Tenorio, 2004; Daniel and Hirshleifer, 2018).



Note: For expository clarity, the figure shows the bid distribution for jump bids in the range €1-101. This range covers 96.21% of all 2, 279, 212 jump bids in the data. Similar spikes at multiples of five occur at higher values.

Figure 1: Histogram of all jump bids in the range €1-101.

As a first main contribution we present new data from a large business to consumer (B2C) first-price auction platform in the Netherlands in which the aforementioned motives for jump bidding are by and large absent yet around 43% of all submitted bids are jump bids. This presents another puzzle because in the studied setting jump bids cannot speed up the auction process and no successful signalling seems to be going on. Furthermore, the data show that more than half of the jump bids (57.5%) are towards a multiple of five euro, see Figure 1. In fact, our data not only show an overrepresentation of multiples of five in the set of jump bids, but also in the set of all bids, the set of early bids, the set of last second bids, and in the set of winning bids.

Existing models of jump bidding do not explicitly link jump bids to round number biases.[1] We hypothesize that next to strategic motives, behavioural considerations that generate round number biases play an important role in explaining the prevalence of jump bidding. As a second main contribution, we examine and test the implications of different behaviorial theories on the decision to bid a round number. The literature suggests several reasons why round numbers play a role in markets: left-digit bias (Lacetera et al., 2012; Busse et al., 2013; Repetto and Solís, 2020), round (mental) budgets (Argyle et al., 2020), round reference points or goals (Pope and Simonsohn, 2011; Allen et al., 2017), a preference to pay round amounts (Lynn et al., 2013), round numbers reflecting uncertainty or being the salient choices from an imprecision interval (Manski and Molinari, 2010; Butler and Loomes, 2007), focal points in negotiation Pope et al. (2015), picking a round number may be associated with a lack of effort or a lack of knowledge (Herrmann and Thomas, 2005), clustering at round numbers may reflect satisficing behaviour where round numbers may be 'good enough' (Gideon et al., 2017) or round numbers may give a signal about someone's valuation (Backus et al., 2019). The strategic setting of the auctions could strengthen the impact of some of these explanations. For example, even if a person does not have a round budget, the person may jump toward a round number to drive others with round budgets out of the market.

A reduced form analysis provides strongly suggestive evidence that bidders who win an auction with a multiple of five bid tend to overbid. For example, when we simply split winning bids for every item into above and below average winning bids, multiples of five are more prominent in the set of above average winning bids. Also, regressing the winning bid in an auction on a rich set of auction and bid characteristics and plotting the residuals shows positive residuals at multiples of five, which is indicative of overbidding. The reduced form estimates indicate that multiple-5 bidders tend to overbid by on average 5%. This is more in line with an lack of knowledge or attention explanation for round

[1] For example, the bid with which Julianus won the auction of the Roman empire is an often-used example of a (naive) jump bid (Klemperer and Timin, 2001; Offerman et al., 2022) but the fact that this final bid of 20,000 sesterces is a round number bid has been ignored.

bidding than with a signaling or round budget explanation. Further evidence in line with a lack of knowledge explanation is that bidders get less likely to bid multiples of five with experience. Also, for a given item, experienced bidders win auctions with on average lower bids, suggesting that experience lowers the tendency to overbid.

An auction setting may amplify the impact of behavioral biases, because it 'fishes out the fools' who overbid (Malmendier and Szeidl, 2020). Malmendier and Lee (2011) and Malmendier and Szeidl (2020) show that a relatively small fraction of overbidders suffices for a large fraction of auctions to end with overbidding. So, a relatively small fraction of bidders with round number biases that cause them to overbid may have a large impact on auction outcomes. To identify the population share of biased and non-biased bidders, we construct a structural model that we apply to the empirical distribution of winning bids. This is the third main contribution we make. The structural estimates determine for a range of different auction items the fraction of multiple-5 bidders with round number bias in the population and to quantify the loss in expected surplus that these bidders experience compared to non-biased bidders with the same valuation for the item. This allows us to answer the question whether these bidders strike on average a better or worse deal than other bidders and to distinguish between several round number bias explanations. On the one hand, round number bidders may strike a good deal if bidders set a round budget to prevent themselves from overbidding in the heat of the moment, or if round bidders successfully scare away competitors by signalling a high valuation. On the other hand, if round bidding is the result of a lack of effort or attention or if round bids are placed by bidders who think that bidding a round number is 'good enough' instead of bidding more precise, round winning bidders may on average strike a bad deal. Hence, these explanations lead to different predictions regarding whether bidding round numbers leads to overbidding or not.

The remainder of this paper is structured as follows: in section 2 we discuss our data, in section 3 we discuss the extent of round and jump bidding in our data, in section 4 we discuss how different round number biases may impact bidding and derive hypotheses, and in section 5, we analyse multiple-5 bidding in more detail.

2 Data

The auction data in this paper comes from a large Dutch online Business-to-Consumer (B2C) auction platform and contains auctions and bids submitted between November 8th 2016 and April 6th 2017.[2]

The set up of the platform and the rules that govern the individual auctions have a number of attractive features for studying bidding behavior in general and for identifying behavioral motives to jump bid in particular. First, the site hosts auctions for a wide range of items, from overnight stays in hotels, to concert tickets, headphones, and watches. The empirical patterns we find are observed across items, which speaks for the generality of our findings. Second, all auctions have a fixed end time (hard closing rule).[3] This ensures that jump bids cannot speed up the auction process. The hard closing rule also makes signalling more difficult, because there always is a threat of a last-second bid that leaves the highest standing bidder without time to respond. Hence, early signalling is less effective in discouraging competition because competitors can simply wait until the last seconds to place a bid that cannot be challenged by the initial bidder. Our data show that most auctions are won by bids in the final seconds and not by bidders who place early (jump) bids, suggesting that signalling is indeed not successful.[4] Third, most items are auctioned repeatedly, resulting in many observations per item. This allows us to calculate a good benchmark for item value and to use a rich set of fixed effects in our analysis. Finally, bidders can only bid integer amounts and the maximum bid increment is €50.[5] This discretization of the strategy set simplifies the analysis.

Table 1 contains summary statistics at the item-, auction-, and bid-level. Our dataset contains 5,304,211 bids, spread over 678,449 auctions, for a total of 2,502 different items. Winning prices are typically relatively low, the mean winning bid is around €26.6, and 99.0% of winning bids are below €150. The average auction length is around 116 minutes, and around 28% of auctions last 10 minutes or less. The average bid increment is 3.40 euro, and 43% of bids is a jump bid.

[2]From our raw dataset, we exclude a small amount of items and auctions. We drop auctions which last longer than 1 day (1136 auctions, or 0.15%), and a small amount of auctions for which the first bid was recorded incorrectly (142 auctions, or 0.02%). Also, we exclude items for which less than 30% of the auctions has at least 2 bids. We do this to exclude items that are not that popular and have many of their auctions end with a winning bid at the lowest possible value of €1. This exclusion criterion results in us dropping 77 items (2.99% of items), which entails 118.922 auctions (14.91% of auctions) and 145.603 bids (2.67% of bids).

[3]The bidder who submitted the highest bid when the timer hits 0 wins the auction and pays her bid plus administration costs (around €5) and potentially shipping costs for items that need to be physically transported to the winner (also around €5).

[4]Around 81% all bids are placed before the final five seconds of an auction yet the winning bid is placed in the final 5 seconds in about 81% of all auctions.

[5]Bidders can observe the highest bid submitted so far and the bid history.

Table 1: Summary statistics

		Minimum	Maximum	Mean	Median	Total
Item level	Items					2,502
	Auctions per item	1	13480	271	90	-
	Bids per item	5	110999	2120	769	-
	Average Winning Bid (euro) per item	1.77	2533.67	40.76	21.50	-
Auction level	Auctions					678,449
	Bids per auction	1	118	7.83	7	-
	Winning Bid (euro)	1	4814	26.64	19	-
	Auction duration (minutes)	1	1440	115.76	33	-
Bid level	Bids					5,304,211
	Bid increment	1	50	3.4	1	-
	Jump bid (%)	-	-	42.97	-	-
	Bid placed in Final Stage (%)	-	-	19.15	-	-
	Winning Bid placed in Final Stage (%)	-	-	81.12	-	-

Notes: The entries denote summary statistics at three different levels: item level, auction level, and bid level.

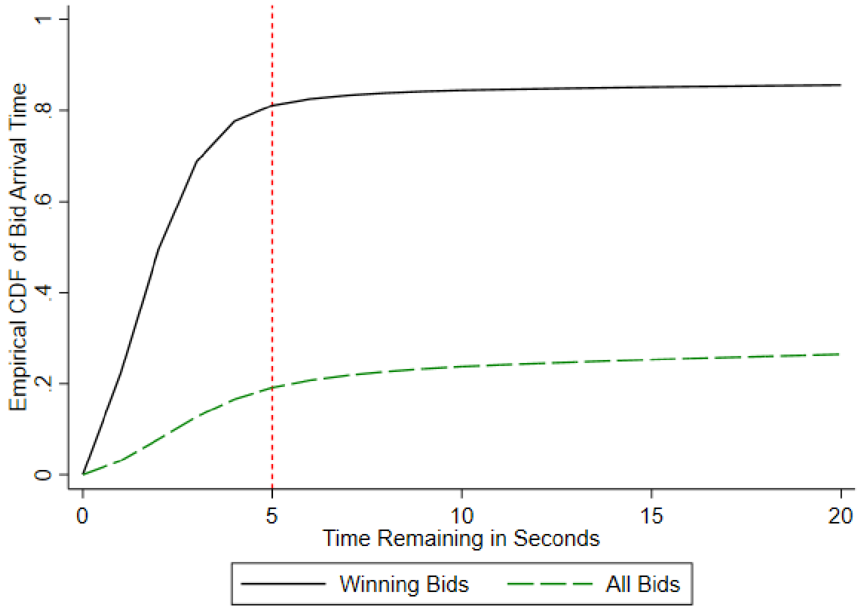
Throughout, we distinguish between what we call the "Early Stage" of an auction and the "Final Stage". In the Early Stage, bidding happens sequentially and bidders have time to observe and respond to bids placed by opponents. In the Final Stage, it is likely that bidders do not have sufficient time to respond to new bids because of the hard closing rule. Hence, the auction in these final seconds resembles a sealed-bid first price auction in which bidders need to take into account what others may do simultaneously. Ockenfels and Roth (2006) make a similar distinction between early sequential bidding and a final simultaneous bid phase.[6] We define the Final Stage as the final five seconds of an auction.[7] Figure 2 shows the empirical distribution of time remaining in seconds when bids are submitted, for winning bids and all bids separately.[8] Auctions are often won by bids placed in the final five seconds (about 81% of all auctions), despite the fact that the fast majority of bids (around 81%) is placed *before* these final seconds. The prominence of the final five seconds is not limited to short auctions. Also in one-hour, two-hour, and three-hour auctions, 81%, 78%, and 78% of winning bids, respectively, are placed in the final five seconds.

[6]TO DO: add something about empirical auction papers disregarding this early stage, hickman papers etc.

[7]TO DO: In Online Appendix Section XX we show that changing the cut-off from the final five seconds to the final $2, 3, \ldots, 10$ seconds leaves our results unaltered.

[8]Note that taking the final five seconds as the terminal sealed-bid period sets us apart from other papers. For example, in Bodoh-Creed et al. (2021) the final stage sealed-bid auction is specified as the last 60 *minutes* in an auction, and in Hickman et al. (2017) it is defined as the final 30 *minutes*. These five seconds suggests themself from our specific data: in our data, 81% of winning bids is placed in the final five seconds. Compare that with the eBay data in Bodoh-Creed et al. (2021), where 85% of winning bids is placed within the final 60 minutes. So, we choose a relatively comparable cut-off when looking at the amount of winning bids inside versus outside the Final Stage. Compared to taking the final 60 minutes, we feel that a sealed-bid assumption is more justified in our setting.

Figure 2: Empricial distribution of seconds remaining when bids are submitted



3 Round number bidding and jump bidding

Next, we discuss jump bids and round (multiple of five) bidding. Table 2 shows some selected statistics. Jump bids and multiples of five feature very prominently: 42.97% of bids are jump bids, 30.58% of bids are multiples of five, and 57.51% of jump bids is towards a multiple of 5. Out of all winning bids, 32.81% is a multiple-5 bid. If bids would be distributed uniformly, around 20% of bids would be a multiple of five. A simple binomial test clearly rejects the null that the actual percentage of 33% is equal to 20% ($p < 0.0001$). With 10% out of all bids, bids one euro below a multiple of 5 ($M5-$) are underrepresented (18% of all bids is one euro above a multiple of 5 ($M5+$)). If we classify all bids above two as $M5$, $M5+$, '$M5+2$',$M5-$, and '$M5-2$', and run a Pearson chi-square test, the null hypothesis of equal frequencies is firmly rejected ($p < 0.0001$).

To further visualize and quantify the prominence of $M5$ bids, we use an approach similar to Pope et al. (2015). First, we compute for each bid value the number of bids and the number of winning bids, and regress the log of these numbers on a high-order polynomial function of the bid value and next plot the residuals.[9] This allows us to eliminate a smooth, underlying distribution of bid values and to look at unexplained differences. Figure 3 plots these residuals. In this figure, the $M5$ bids clearly

[9]In these graphs and in the regression below, we focus on bids below 200 because of the limited amount of observations above this bid value, reported patterns are very similar without this restriction.

Table 2: Selected statistics on round and jump bids

	Percentage of all 5,304,211 bids.	Percentage that is: Multiple-5 Bid	Winning Bid	Jump Bid	Submitted in Final Stage
All bids	100.00	30.58	12.79	42.97	19.15
Multiple-5	30.58	100.00	13.72	80.81	19.09
Non Multiple-5	69.42	0.00	12.38	26.30	19.17
Winning bids	12.79	32.81	100.00	60.59	81.12
Non-winning bids	87.21	30.26	0.00	40.39	10.06
First bid in auction	12.79	22.00	4.82	36.42	2.00
Jump bids	42.97	57.51	18.03	100.00	26.67
Non-jump bids	57.03	10.29	8.84	0.00	13.48
Large jump bids (increase ≥ 5)	18.68	72.60	14.96	100.00	18.84
Early Stage (outside final 5 seconds)	80.85	30.61	2.99	38.97	0.00
Final Stage (final 5 seconds)	19.15	30.49	54.19	59.86	100.00

stand out, as well as the $M5-$ and $M5+$ bids. $M5$ bid values all have positive residuals, confirming the clustering of bids at multiples of five. $M5-$ bid values generally have negative residuals, and $M5+$ bid values tend to have positive residuals.

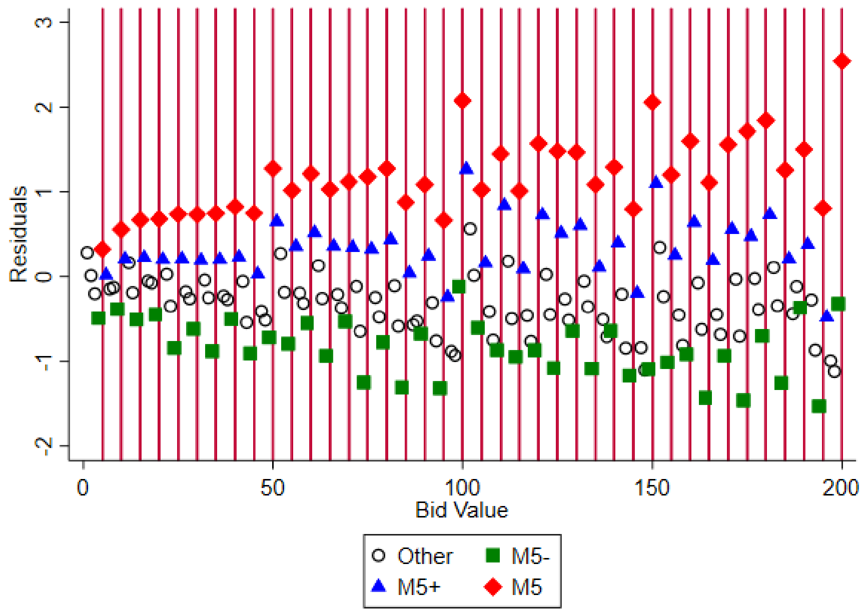
To quantify the clustering of multiple of 5 bids, we run a similar regression with multiple of 5 and 10 dummies. Specifically, we run the following regression specification:

$$Q_j = \theta F^7(b_j) + \beta_1 M_j^5 + \beta_2 M_j^{10} + \epsilon_j \tag{1}$$

The dependent variable Q_j is the (log) total number of bids at each bid value. The first term on the right hand side is the seventh-order polynomial in bid value. The M_j^m terms are indicator variables for bid values divisible by $m = 5$ and $m = 10$, respectively. These terms are additive: bid values that are divisible by 10 are by definition also divisible by 5.

Table 3 shows the regression results for winning bids and all bids separately. Since the unit of observation is the bid value and we focus on bids of 200 euro and below, we have 200 observations for these regressions. Consistent with the pattern revealed in Figure 3, the coefficient for $M5$ is significantly and strongly positive for both Winning Bids and All Bids. Multiples of ten stand out slightly in addition to multiples of five, but not significantly for winning bids. The Mult10 coefficient

Figure 3: Residual log number of bids for each bid value.



Notes: M5: Multiple of 5 bids, M5+: Bids one euro above a multiple of 5, M5-: Bids one euro below a multiple of 5.

also becomes insignificant for all bids when we exclude bids of 100, 150, 200, which stand out in particular in Figure 3.

3.1 Bid Paths

The prominence of multiples of five also shows up in the 'bid paths', i.e. how the standing bid develops throughout an auction. Table 4 shows for a given 'Current Bid' the percentage of bids that are equal

Table 3: Regression results

VARIABLES	(1) Log Winning Bids	(2) Log All Bids
Mult5	1.353***	1.269***
	(0.124)	(0.124)
Mult10	0.271	0.425**
	(0.166)	(0.166)
Observations	200	200
R-squared	0.950	0.948
Seventh order polynomial in price	YES	YES

Notes: Standard errors in parentheses, *** p<0.01, ** p<0.05, * p<0.1

to 'Next Bid'. For clarity, we limit attention to current bids and next bids in the range €1-15.[10] If we examine the jump bids, the multiples of five (5, 10, and 15) clearly stand out compared to the numbers around them. For example, for a current bid of 1, 12.21% of next bids is equal to 5, while only 1.73% and 0.81% of next bids are 4 or 6, respectively. Multiples of 5 also stand out diagonally: for example, when we focus on bids that advance the Current Bid by three, 3.37% of Next Bids are +3 if the Current Bid is 6, 16.54% if the Current Bid is 7, and 4.46% if the Current Bid is 8 (the red-colored number in Table 4). In short, bidders often forward the bid towards a (the next) multiple of five.

Table 4: Percentage of bids that is equal to Next Bid for given Current Bid

	Next Bid														
Current Bid	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15
0/first bid	63.58	6.53	1.76	0.81	9.41	0.50	0.53	0.65	0.43	4.82	0.50	0.50	0.20	0.19	2.27
1		61.95	7.22	1.73	12.21	0.81	0.69	0.85	0.52	4.52	0.57	0.50	0.21	0.19	2.05
2			62.75	6.51	15.35	1.31	0.93	1.09	0.57	4.41	0.49	0.50	0.18	0.16	1.57
3				57.94	24.99	2.64	1.70	1.49	0.73	4.51	0.54	0.46	0.18	0.14	1.42
4					**73.05**	8.92	3.29	2.89	0.99	5.43	0.67	0.51	0.18	0.15	1.35
5						62.78	10.25	5.23	1.79	10.15	1.07	0.83	0.29	0.21	2.44
6							60.20	13.88	3.37	13.25	1.53	1.19	0.33	0.26	2.39
7								63.21	9.12	16.54	2.48	1.81	0.53	0.36	2.66
8									55.42	28.42	4.46	3.35	0.98	0.57	3.46
9										**69.85**	11.40	7.05	1.91	1.04	5.09
10											58.17	15.69	3.14	1.69	11.79
11												60.07	9.20	3.55	17.09
12													54.03	9.71	23.27
13														47.87	34.96
14															**71.17**

Notes: Table denotes for a given Current Bid the percentage of bids that is equal to a certain Next Bid.

4 Hypotheses

In this section, we discuss what might motivate round number multiple-5 (jump) bidding in either the early stage or final seconds of an auction. To streamline thinking, we first present a stylized version of the auction that is the focus of this study. Next, we introduce a model of individual decision making that helps us to trace out the power of various motives for round number bidding in explaining the pattern of round number (jump) bidding that we observe in our data. We also discuss the strategic response to round number jump bidding by bidders not susceptible to round number biases.

In the auctions that we consider, bids need to be integer numbers $\{1, 2, \ldots\}$. Due to the hard closing

[10] Similar tables in appendix C for current bids in the range €45-55 and €95-105 show patterns very similar to the one in Table 4.

rule, and similar to Ockenfels and Roth (2006), we distinguish two stages in the bidding process. In the first stage ("Early Stage"), bidders can bid sequentially and have time to respond to each other. The highest bid at the end of this stage becomes the standing bid at which the second stage ("Final Stage") starts. In this stage, bidders have only time to place one more bid and do not have time to respond to new bids submitted by other bidders. This final stage resembles a sealed-bid first price auction. The highest bid at the end of the auction wins, and the highest bidder pays her bid. In case two highest bidders bid the same amount in this stage, chance will determine who wins.

Bidders in the final stage face a decision-problem that can be formulated in a very generic way as follows:

$$\max_{b_i} S_i(b_i) = \max_{b_i} P(b_i)(v_i - b_i) \tag{2}$$
$$s.t. \quad b_i \leq M,\ b_i > b_s, b_i \in \{b_s + 1, b_s + 2, \ldots\},$$

with M the bidder's budget, b_s the standing bid at the start of the final stage, and $\{b_s+1, b_s+2, \ldots\}$ the bidder's choice set. Bidders choose their bid b_i with the objective to maximize their expected surplus $S_i(b_i)$. For a given private valuation for the item v_i and without any round number biases, the expected surplus of placing a final stage bid b_i is given by $P(b_i)(v_i - b_i)$, where $P(b_i)$ reflects the probability to win the auction with bid b_i.

Early Stage bids determine the standing bid b_s with which the Final Stage starts and win the auction in case there are no Final Stage bids. The strategic considerations in the Early Stage differ from those in the Final Stage because if another bidder outbids a bid b_i in the Early Stage, bidder i can respond by submitting a higher bid in either the Early or Final Stage. Bidders are likely to take this option value of bidding again into account. This is why incremental bidding instead of jump bidding is often considered to be the dominant strategy in sequential auctions.

We examine the impact of different round-number biases on bidding strategies and bidding behavior by making explicit how each bias or motive alters the decision problem in (2). In particular we consider the explanatory power of each motive to explain the highly frequent round number (jump) bids that we empirically observe, both in the Early and Final Stage. To which extent does a motive generate an upward or downward shift in round-number winning bids compared to other winning bids? We explore the following explanations:

1. Left digit bias/inattention to non-round numbers
2. Round valuations
3. Round budgets
4. Round reference prices
5. Round signalling
6. Limited attention/effort and satisficing
7. Uncertainty or a selection from an imprecision interval
8. Preference to pay round amounts

The implications of each explanation for observed round number bidding are summarized in Table 5. The final column indicates whether bidders who win an auction with a multiple-5 bid are predicted to strike a relatively good (-) or bad (+) deal when compared to bidders who win the same item with a bid that is not a multiple of five.

1. Left digit bias/inattention to non-round numbers Left-digit bias is the phenomenon that a price of €19,99 seems much lower than a price of €20 because individuals tend to focus only on the left digit and to disregard the rest of the number. Left-digit bias has been shown to play a role on the market for used cars (Lacetera et al., 2012; Busse et al., 2013), on the stock market (Sonnemans, 2006), and on the market for apartments (Repetto and Solís, 2020). In auction settings, left-digit bias can feed into the decision in two ways: *i*) it can alter the (perceived) probability $P(b_i)$ to win the auction, and *ii*) it can alter the perceived pay-off $v_i - b_i$ in case of winning the auction. We work out both cases in turn, where we first focus on Final Stage bids and turn to Early Stage bids next.

If left-digit bias affects the (perceived) probability to win, bidders perceive the chances of winning with a bid of 30 as much higher than the chances of winning with a bid of 29. Following Chetty et al. (2009), and Lacetera et al. (2012) in particular, we deconstruct a bid as the sum of its assorted base-10 digits. If bidders have left-digit bias, they give more attention to the leftmost digit than to the other digits. Suppose bids have two digits, and that the value of the leftmost digit is given by d_2

and the value of the second digit by d_1. Then the perceived value of a bid $b_i \equiv d_2 d_1$, $\tilde{b_i}$, is given by:

$$\tilde{b_i}(b_i) = 10d_2 + (1-\phi)d_1,$$

where $\phi \in [0,1]$ is the inattention parameter.[11] A bid of 29 is then perceived as $\tilde{b_i}(29) = 20 + (1-\phi)9$, and a bid of 30 as $\tilde{b_i}(30) = 30$.

In this form, left-digit basis however cannot explain the prominence of numbers ending with a 5 that we observe in our data. Yet if bidders not necessarily pay differential attention to different digits, but instead think in round numbers or multiples of 5, they may perceive numbers to be considerably higher when they pass the next multiple of 5 but may be inattentive to the numbers that are in between. In that case, the perceived value of a bid b_i is given by:

$$\hat{b_i}(b_i) = 5\left\lfloor \frac{b_i}{5} \right\rfloor + (1-\phi)\left(b_i - 5\left\lfloor \frac{b_i}{5} \right\rfloor\right) \tag{3}$$

with again $\phi \in [0,1]$ the inattention parameter. For $\phi > 0$, $\hat{b_i}(b_i) \leq b_i$ with $\hat{b_i}(b_i) = b_i$ if and only if $b_i = 5\left\lfloor \frac{b_i}{5} \right\rfloor$. For example, a bid of 29 is processed as $\hat{b_i}(29) = 5 \cdot 5 + (1-\phi)(29-25) = 25 + (1-\phi)4$, and a bid of 30 as $\hat{b_i}(30) = 30$. The subjective expected surplus from bidding in (2) becomes $S_i(b_i) = P(\hat{b_i}(b_i))(v_i - b_i)$. The replacement of b_i by $\hat{b_i}(b_i)$ has the effect of creating discontinuous jumps in the perceived probability to win the auction at every multiple of 5.

As an example, consider a private-value auction with two risk neutral agents with i.i.d. valuation draws from a common uniform distribution with domain $[0, \bar{v}]$. Standard theory (see e.g. Klemperer, 2004, Appendix 1.A) shows that without left-digit bias, there is a symmetric equilibrium where a type v bidder bids $b(v) = \frac{1}{2}v$, $P(b_i) = 2b_i/\bar{v}$ with $b_i \in [0, \frac{1}{2}\bar{v}]$[12] and expected surplus $S(b(v)) = \frac{2b(v)}{\bar{v}}(v - b(v)) = v^2/2\bar{v}$. When the objective bid b_i in probability distribution $P()$ is replaced by the perceived bid $\hat{b_i}(b_i)$ from equation (3), the resulting probability distribution $P(\hat{b_i}(b_i)) = \frac{2\hat{b}_i}{\bar{v}}$ will jump upward discontinuously at bids that are multiples of 5. The expected surplus of bidding non multiple-5 values is lower than in the benchmark case, creating incentives to bid round numbers. The question is whether bidders who bid a non multiple-5 $b(v)$ in the benchmark case will jump towards

[11] Lacetera et al. (2012) work out the more general case that allows for more digits and also discusses the case where potentially a second digit gets more attention than a third digit etcetera. Adding more digits does not change the intuition. Moreover, 97% of all bids in our data are below 100 such that the two digit case captures most bids.

[12] $P(b_i) = P(b_i > b_j) = P(v_i/2 > v_j/2) = P(v_j < v_i) = v_i/\bar{v} = 2b_i/\bar{v}$, where the final step follows from inserting $b_i = v_i/2$.

the next multiple (increasing their chances of winning but decreasing the margin) or lower their bid to the previous multiple. It is easy to show that bidders will jump to the multiple-5 closest to $b(v)$. For example, a bidder who would bid 27 (28) without left digit bias, would bid 25 (30) with such a bias.[13]

If many bidders are inattentive to non-round numbers, Final Stage bids will cluster at round numbers, and also any Early Stage bids that bidders submit. This means that the 'true' $P(b_i)$ will also show discontinuous jumps at round numbers. For example, the presence of bidders who bid 25 instead of 23 because of inattention lowers the chance of winning with a bid of 24. This in turn gives bidders who do not suffer from inattention a strategic incentive to bid round numbers in order to be first. In the Final Stage, unbiased bidders may be induced to bid one above the round number ($M5+$) to reduce the chance to have one's bid tied with that of another bidder.

A second channel through which left digit bias, or an inattention to non-round bids, can influence the expected surplus is via the (perceived) net revenue $v_i - b_i$ in case a bid turns out to be the winning bid. In this case, bidders experience the incremental cost of bidding 30 instead of 29 to be considerably higher than 1. That is, the net revenue of winning with bid b_i is perceived as:

$$v_i - \hat{b}_i(b_i)$$

with $\hat{b}_i(b_i)$ as defined in (3). However, this is not a plausible explanation for the prominence of multiple-5 bids because inattention now generates a reluctance instead of an eagerness to bid the next round number. This logic holds for both Early Stage and Final Stage bidding. In addition, this also does not give non-biased bidders a strategic incentive bidders to jump to round numbers pre-emptively in the auction's Early Stage. If others' perceived revenue drops down at round numbers, these bidders may drop out once they are forced to bid the next round number. This creates a strategic incentive to force other bidders to do so by bidding one below the next round number (for example 29). This would force the next bidder to bid at least 30.

[13] A unilateral deviation from the equilibrium bid $b(v) = v/2$ by d gives an expected surplus of $S(b(v)+d) = S(b(v)-d) = 2(v/2 + d)(v/2 - d)/\bar{v}$. This number is decreasing in d. Together with the noting that $\hat{b}_i(b_i) = b_i$ for bids b_i that are a multiple of 5, this leads to the conclusion that the bidder maximizes expected surplus by choosing the multiple 5 bid closest to $b(v)$.

2. Round valuations Round valuations are another way that round numbers could influence the bidding process. People's valuations may be clustered at round numbers/multiples of 5 instead of being draws from a more continuous distribution function. A round number *valuation* however does not automatically translate into a round number *bid*. For example, if the standing bid is 23, a bidder with valuation $v = 25$ has nothing to gain from bidding 25 and should never jump bid towards her valuation. Hence, round valuations are not a plausible explanation for the round bidding in the Early Stage that we observe in the data. In our setting where only integer bids are admissible, a clustering of valuations around round numbers will induce biased bidders to bid just below a multiple of 5 in the Final Stage of the auction. This gives unbiased bidders an incentive to submit a round bid in the Final Stage because this helps them to outbid the round valuation competitors, increasing their chances of winning. Of course as a second order effect some unbiased bidders may anticipate this and bid just above the multiple-5 in order to outbid other unbiased bidders.

Whether round valuations lead to higher or lower bids is not a priori clear as this critically depends on the difference between the value distribution with and without clustering at round numbers.

3. Round budgets The bidding process can also be influenced by the fact that people have round mental budgets in mind when bidding. In the work on mental accounting by Thaler (1985), individuals group expenditures into categories (such as entertainment and groceries) and consider potential expenditures within their category, with category specific budget constraints. Evidence in line with such a mental accounting/budgeting approach has, for example, been found in online grocery shopping (Milkman and Beshears, 2009), gasoline spending (Hastings and Shapiro, 2013), and restaurant spending (Abeler and Marklein, 2017). Argyle et al. (2020) show that consumers' monthly payment amounts on auto loans tend to bunch at round numbers, which is consistent with a heuristic budgeting approach.

In the general statement of the decision problem, equation (2), a round budget would show up in the constraint M and create an upper-limit on what a bidder can bid. If this constraint is binding, many bidders end up bidding round numbers in the Final Stage. These bidders bid lower amounts than they would do without the constraint. This hurts their chances of winning but makes them likely to win with relatively low bids when they win. When it is common knowledge that some bidders have a round budget this creates for both bidders with and without a round budget a strategic incentive to jump to round numbers in the Early and Final Stage. For example, if many bidders have a budget capped at $M = 45$, the first bidder to bid 45 considerably increases her chance of winning the auction. So, round budgets also affect bidders without round budgets because they impact the $P(b_i)$ term. In the Final Stage, this can also create discontinuous upward jumps in the $P(b_i)$ function at one above the round numbers: if many bidders bid round numbers, either because of the constraint or because of strategic reasons, the probability of winning the auction may jump up if one bids just above these round numbers.

4. Round reference prices Bidders may not only derive utility from the difference between their valuation and their bid, but also from the value of the deal, or a comparison between the price they need to pay and some reference price. Reference prices (Thaler, 1985) can be round because round numbers often serve as important reference points or goals for individuals, for example when running a marathon (Allen et al., 2017) or when trading stocks (Bhattacharya et al., 2012). When placing a bid, bidders may have some target amount, or some 'reasonable' price for the item in mind. Bidding more than the reference price feels like a 'bad deal', which creates a reluctance to bid more than the reference price.

There is an active and growing auction literature looking at the impact of reference points and loss aversion on auctions and bidder behaviour (e.g. Dholakia and Simonson, 2005; Rosenkranz and Schmitz, 2007; Lange and Ratan, 2010; Banerji and Gupta, 2014; Ahmad, 2015; Backus et al., 2017; Rosato and Tymula, 2019; Balzer and Rosato, 2021; von Wangenheim, 2021). This literature has not yet considered the link between reference points and jump bidding. This literature has looked into reserve prices, previous auction outcomes, and endogenous (price) expectations as reference points, but not yet at round numbers.

In the extreme case, where bidders are completely unwilling to bid more than the reference price, the reference price essentially functions as an extra budget constraint, and the impact on the bidding process is similar as above. The impact is rather similar when the reference price creates a reluctance to bid more but does not impose a hard upper limit on every bidder's budget. For example, if bidders are reluctant to bid more than 25, bidding 25 becomes relatively attractive compared to other amounts. In that case, bids are clustered at round numbers in both auction stages. In addition, it creates an incentive to be the first bidder to bid 25. If sufficiently many people have the same reference price, the probability function of winning, $P(b_i)$, will again show discontinuous upward jumps at round numbers, which create incentives to jump bid towards these numbers. This explanation gives bidders without a reference point a strategic incentive to bid one above the round number in the Final Stage.

5. Round signalling Bidding round numbers may signal something different about a bidder's valuation than bidding non-round numbers. Backus et al. (2019) find evidence for a cheap-talk signalling equilibrium on eBay, where sellers signal a weak bargaining situation by setting a round (multiple of $100) list price. Within an auction context there is no seller-buyer dynamic but instead competition between bidders. Bidding a round number may indicate that a bidder can afford not bidding very precise, which signals that the bidder has a much higher valuation than her bid. A signalling explanation can explain the observed round number bids in the Early Stage but not in the Final Stage where the auction resembles a sealed-bid first price auction.

A signalling explanation for Early Stage round bids requires that the (perceived) probability to win the auction with a given bid depends on the standing bid, or previous bids placed by other bidders. If bidding round numbers is a successful signalling tool, competing bidders will upwardly revise their estimates of their competitors valuation and of the bids that their competitors will place, thus lowering their estimated probability to win with a given bid. This alone will however not prevent these bidders from placing Early or Final Stage bids up to their valuation. In order for signalling to be successful, we need to introduce an additional element that is typically present in jump bidding models of signalling, such as bidding costs (Daniel and Hirshleifer, 2018) or a transaction cost of entering the auction (Easley and Tenorio, 2004). With bidding costs c, the expected surplus is zero when not placing a bid, and

$$S_i(b_i) = P(b_i)(v_i - b_i) - c$$

when placing a bid.

In this situation, a bidder will only bid if $P(b_i)(v_i - b_i) - c \geq 0$. If round numbers successfully signal a high valuation, other bidders adjust their estimates of $P(b_i)$ downward, and more of them will decide to drop out of the market. This gives high valuation bidders an incentive to jump towards round numbers. It also creates incentives for mimicking behaviour, so the jump towards a round number should be large enough such that low valuation bidders are not willing to mimic. Yet signallers cannot conclude from the absence of any further bids in the Early Stage that their signalling has been successful. Due to the sealed-bid nature of the Final Stage, competitors may just wait for the Final Stage to place a bid. So, the scope for successful signalling may be limited in this setting.[14]

One can empirically test this explanation by investigating whether these early multiple-5 bids successfully signal different things than non-round bids. If so, round Early Stage bids should be more likely to win than Early Stage non-round bids, or Early Stage round bidders should be more likely to win the auction than Early Stage non-round bidders. If signalling is successful, this should allow the signallers to strike a relatively good deal. The empirical observation that around 80% of winning bids are placed in the final 5 seconds casts doubts on the success of Early Stage signalling.

6. Limited attention/effort or satisficing Bidding round numbers may also result from bidders paying limited attention to the exact bid they are placing. People who put in less effort may be more likely to pick round numbers (Herrmann and Thomas, 2005), or round numbers could be picked if bidders engage in satisficing behaviour and want to pick a number that is 'good enough' instead of calculating the optimal bid (Gideon et al., 2017). Round numbers are salient or cognitively easy to access. This channel could impact both (potentially irrelevant) Early Stage bids and Final Stage consequential bids.

Especially early in the auction, bids may be far removed from 'reasonable prices', and the chance that a given bid is going to win is quite low. If exerting effort to determine an optimal bid is costly, it may be optimal not to think too much about these bids. In this situation, the exact bid is likely to be inconsequential and bidders can pick the salient round number without too much risk. However, this does not explain why multiple-5 bids remain prominent in the Final Stage and in the set of winning bids. If bidders are generally inattentive, also to potentially consequential bids, round numbers may suggest themselves as reasonable bids. Instead of meticulously determining the optimal bid, bidders just pick a round number because they may deem a round number to be 'good enough'.

In terms of the decision process in (2), these bidders limit their choice set to multiples of 5. These bidders pick the multiple-5 bid which is best, or choose not to bid if the multiple-5 needed to become

[14]See Daniel and Hirshleifer (2018) for a more formal treatment of a signalling model with bidding costs that could lead to jump bids (without multiples of 5). It goes beyond the scope of this paper to develop such a model with round numbers.

the standing bidder is too high. Clearly, this is a possible explanation for the observed multiple-5 (jump-)bids observed in both stages of an auction. Compared to bidders bidding more 'precisely', these bidders may bid higher or lower. They risk bidding too low (resulting in not winning the auction), or too high (resulting in winning with an unnecessary high bid). This implies that within the set of winning bids, the multiple-5 wining bids should stand out as relatively high.

Additionally, this channel creates strategic incentives for others to pre-emptively bid multiples of 5 in the Early Stage. By bidding a round number, bidders can force bidders with this multiple-5 choice set to jump towards the next multiple of 5. Hence, similar as before, this creates a discontinuous jump in the $P(b_i)$ term at multiples of 5. In the Final Stage, it creates discontinuous jumps in the $P(b_i)$ function at multiples of 5, and potentially also just above these multiples.

7. Uncertainty/selection from imprecision interval Individuals may be uncertain about their valuation, or about the optimal bid to place. Instead of having a point valuation, subjects may only have a vague idea or an 'imprecision interval' (Butler and Loomes, 2007) of their valuation. Similarly, instead of being able to precisely calculate the optimal bid, bidders may only have a vague idea or some rough bounds on this. The salience of a round number can cause individuals to choose that round number from an imprecision interval (Pope et al., 2015).

The repeated nature of most auctions on the auction web site we study may reinforce the uncertainty to bidders. Both Zeithammer (2006) and Backus and Lewis (2016) provide models that involve such a sequential nature of auctions for the same or similar items. In these models, bidders shade down their bids below their valuation to account for this option value. To determine the optimal amount of bid shading in a current auction, a bidder needs to consider the potential entrance of new bidders, the amount of current bidders, time costs of attending at least one more auction, etcetera. Individuals may be uncertain about the optimal amount of bid shading. When people are uncertain, they often round. Ruud et al. (2014) for example show that an increase in subjects' uncertainty about a target variable translates into higher variance of the subjects' beliefs, which in turn results in more rounding. Manski and Molinari (2010) state that rounding may reflect uncertainty in probabilistic expectations.

In case of uncertain bids, the analysis is similar to the Limited attention/effort case and round bids could come from these uncertain bidders, or could be preemptive strategic responses by other

Table 5: Summary of implications of the various round number biases for the bidding behavior of bidders biased and unbiased by round number influences.

Auction stage:	Early		Final		Over/underbidding
Bidder type:	Biased	Unbiased	Biased	Unbiased	by M5 winning bidders
1. Left digit bias	M5	M5	M5	M5+	+
2. Round valuations	-	-	M5-	M5 (M5+)	?
3. Round budgets	M5	M5	M5	M5+	-
4. Round reference prices	M5	M5	M5	M5+	-
5. Round signalling	M5	-	-	-	-
6. Limited attention/effort	M5	M5	M5	M5+	+
7. Uncertainty/imprecision interval	M5	M5	M5	M5+	+
8. Preference to pay round amounts	M5	M5	M5	M5+	+

Notes: The entries denote the following predictions of the bias for the bidding behavior: $M5$: multiple-5 bids. $M5+$ ($M5-$): bids just above (below) a multiple of 5. The final column indicates whether bidders who win an auction with a multiple-5 bid are predicted to strike a relatively good ($-$) or bad ($+$) deal in the sense that they under- or overbid when compared with winning bids for the same item that are not multiples of 5.

bidders. In case of uncertain valuations, bidders may bid according to their perceived valuation $\hat{v}$. In that case, the analysis is similar to the Round valuation case.

8. Preference to pay round amounts Finally, people may have a preference to pay round numbers (Lynn et al., 2013). This can be incorporated in (2) by adding an extra cost to the surplus function when winning with a non-round bid, or a bonus when winning with a round bid. If this cost of winning with non-round bids is sufficiently high, bidders will submit no or fewer non-round bids. This works out quite similar to the Limited attention/effort case and hence potentially explains round bidding in both auction stages. Additionally, it creates discontinuous jumps in the $P(b_i)$-function at multiples of 5. This again may create strategic incentives for bidders without a preference to pay round numbers to bid one above a multiple in the Final Stage.

5 Reduced form analysis

This section presents a reduced form analysis of the hypotheses derived above. First, we analyse to what extent more $M5+$ bidding is present in the Final Stage than in the Early Stage, which would be consistent with strategic responses to $M5$ bidders. Next, we analyse whether $M5$ winning bids on average result in over- or underbidding. In terms of notation, we follow Table 5, and define multiple-5 bids as $M5$ bids, bids one euro below a multiple of five as $M5-$ bids, and bids one euro above a multiple of five as $M5+$ bids.

Table 5 suggests that we should observe less $M5$ bidding in the Final Stage than in the Early Stage due to strategic responses to biased bidders. The raw statistics in Table 2 above seem to suggest that $M5$ bidding is similar in the Early Stage and Final Stage (30.61% versus 30.49% of bids in these stages are $M5$). However, these statistics hide some patterns because many Early Stage bids are equal to one euro. When we limit attention to all bids of 5 and higher, 40% of Early Stage versus 32% of Final Stage bids are multiples of five. Also, 64% of Early Stage jump bids is a multiple of five versus 40% of Final Stage jump bids. So, $M5$ bidding indeed seems less prevalent in the Final Stage.

5.1 M5+ bidding

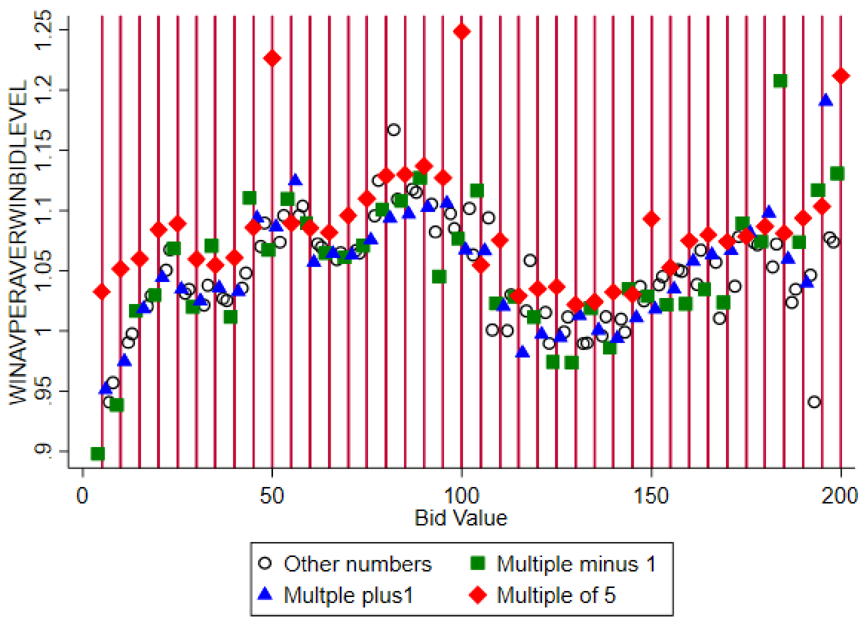
In the Final Stage, $M5+$ (jump) bidding features more prominently than in the Early Stage, consistent with a strategic response to $M5$ bidders. The raw statistics do not directly suggest this: out of all Final Stage bids, 20% is a $M5+$ bid, compared to 17% of Early Stage bids. While a Pearson's χ^2 test rejects the null of equal percentages ($p < 0.0001$), this raw statistic understates the importance of $M5+$ Final Stage bids, because it combines two offsetting phenomena. On the one hand, $M5+$ bids stand out among all Early Stage bids, because there are relatively many $M5$ bids and relatively many incremental bids in the Early Stage. 60% of Final Stage bids are jump bids, compared to 39% of Early Stage bids. A Pearson χ^2 test confirms that these are significantly different from each other ($p < 0.0001$). This means that this incremental channel for $M5+$ bidding is less strong in the Final Stage. On the other hand, there are more jump bids towards $M5+$ bid values in the Final Stage: 6% of Early Stage jump bids are $M5+$ bid values, compared to 15% of Final Stage bids. Again, a Pearson χ^2 confirms that these percentages are significantly different from each other ($p < 0.0001$).

To investigate whether this is consistent with a strategic response to $M5$ bidders, it is important to evaluate whether the increased amount of $M5+$ jump bids in the Final Stage really stands out or simply reflects that all non-multiple of 5 numbers are bid relatively more often. For example, 7% of Early Stage jump bids are towards $M5-$ values versus 12% of Final Stage jump bids, which is also significantly different from each other following a Pearson χ^2 test ($p < 0.0001$). Therefore, we compare non-multiple-5 jump bids in the Early versus the Final Stage. There are more non-multiple-5 Final Stage jump bids towards $M5+$ than in the Early Stage. Out of all non-multiple-5 Early Stage jump bids, 15.9% is a $M5+$ bid, compared to 25.0% of Final Stage non-multiple-5 bids ($p < 0.0001$ following a Pearson χ^2 test). In the Final Stage there are less non-multiple-5 '$M5-2$' and '$M5+2$' jump bids than in the Early Stage, and there are slightly more $M5-$ bids (19% in the Early Stage versus 20% in the Final Stage, which is significant following a Pearson χ^2 test $p < 0.0001$). In the Early Stage, there are significantly less $M5+$ jump bids than $M5-$ jump bids, while there are significantly more $M5+$ than $M5-$ jump bids in the Final stage. This suggests that jumping towards $M5+$ bid values is more common in the Final Stage, and that this effect is not only driven by the fact that there are less $M5$ jump bids.[15] This is consistent with a strategic response to $M5$ bidders in the Final Stage.

5.2 Over/under bidding

Next, we analyse to what extent bidders who win auctions with $M5$ bids tend to overbid or underbid. As a first, we express every winning bid as a percentage of the average winning bid for an item, and plot the average percentage of the average winning bid per bid value (the average of all winning bids of x) in Figure 4. Multiples of five winning bids are a higher percentage of the average winning bid than surrounding numbers. This is particularly true for winning bids of 50, 100, 150, and 200.

Figure 4: Multiple of 5 bidders tend to overbid



To analyse whether multiple-5 winning bids are on average higher or lower than other winning bids, we estimate the following regression equation:[16]

[15] To be done: Run some kind of dif-in-dif on these percentages, what test to do here?

[16] TO BE DONE: consider to what extent this approach is similar to what Reimers and Waldfogel (2021) do. In the

$$ln(b_{ij}) = \alpha + \beta_1 M_i^5 + \beta_2 M_i^{10} + \beta_3 M_i^{Int} + \boldsymbol{\beta X_i} + \eta_j + \epsilon_{ij} \tag{4}$$

The dependent variable $ln(b_{ij})$ denotes the log of the winning bid in auction i for item j. M_i^m are dummy variables indicating whether a given bid is a multiple of $m = 5$ or $m = 10$. The M_i^{Int} indicates whether a bid is within a €1 range from a multiple of five. This range variable absorbs all effects of bidding in the neighbourhood of multiples of 5, so that the estimated M_i^m coefficients only pick up the local effect of over- or under-payment within this range. In some regression specifications, we include indicator variables for each multiple range separately. The vector $\boldsymbol{X_i}$ contains a broad set of controls about auction characteristics: a dummy for the day on which an auction ends, a dummy for the hour an auction ends separately for weekdays and weekend days, auction length, and the number of bids. In some regression specifications, we also add some bid characteristics to this set of control variables. These include the time decile during which a bid was placed and whether a bid was placed in the Final Stage or within the final 10 seconds. η_j is an item fixed effect.

Our key coefficients of interest are β_1 and β_2. If bidders with winning multiples-5 bids do not overpay or underpay, these coefficients should equal 0. A positive estimate of β_1 would however indicate that multiple-5 winning bidders tend to overpay. Table 6 shows the estimated coefficients for different specifications of this regression equation. All specifications estimate the coefficient of the multiple-5 dummy to be around +5%, indicating overbidding. Multiple-10 winning bids do not seem to stand out strongly in addition to the multiple of 5, although this coefficient is significant in the final column.[17]

Next, we evaluate overbidding at every multiple of five separately. We replace the M_i^m dummies with separate dummies for every multiple of five in equation 4. Figure 5a shows the multiple-5 coefficients of this regression, using the same specification as in column (4) of Table 6. Almost all are positive, indicating that overbidding at multiples of five is a general phenomenon not limited to a few particular multiples of five. That said, bids of 50 and 100 definitely stand out. Winning bids of 100 tend to be more than 10% higher than can be explained by bid and auction characteristics and the

published version, I do not directly see something similar, in a working paper version I see they look at discontinuities at star-rating where they include a continuous measure of the rating plus dummies for values at which the star rating changes (for example at 3.8 the star rating changes from 3.5 stars to 4 stars).

[17]When we define MultRange as a bid withing a two euro range of a multiple of 5, the coefficients on Mult5 in the regressions above are around $3 - 4\%$

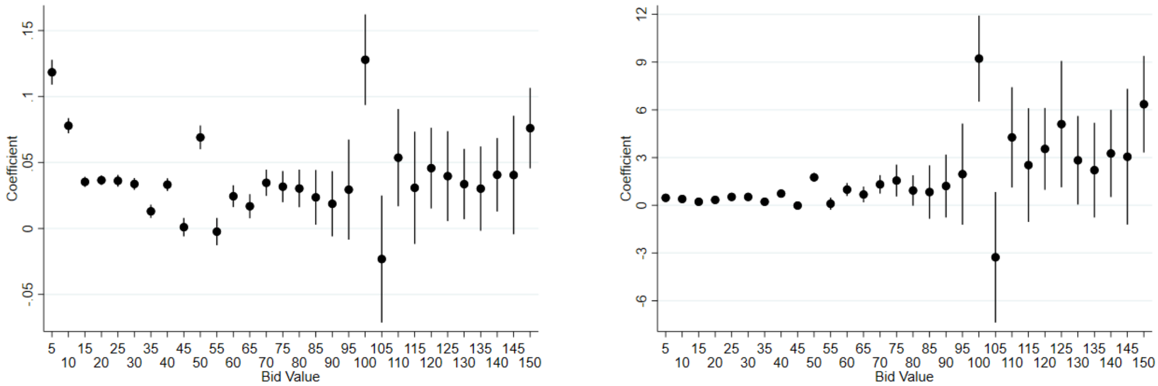
Table 6: Regression of the (log of) winning bid value on multiple of 5, 10, and range dummies

VARIABLES	(1) Log Bid Value	(2) Log Bid Value	(3) Log Bid Value	(4) Log Bid Value
Mult5	0.051***	0.052***	0.054***	0.047***
	(0.001)	(0.001)	(0.001)	(0.001)
Mult10	0.001	0.001	0.002*	0.007***
	(0.001)	(0.001)	(0.001)	(0.002)
MultRange	0.106***	0.104***	0.103***	
	(0.001)	(0.001)	(0.001)	
Constant	2.759***	2.670***	2.577***	2.570***
	(0.001)	(0.007)	(0.009)	(0.009)
Observations	678,449	678,449	678,449	678,449
R-squared	0.892	0.897	0.897	0.898
ItemFE	✓	✓	✓	✓
Auction Controls		✓	✓	✓
Bid Controls			✓	✓
Separate Range dummies				✓

Notes: Robust standard errors in parentheses, *** p<0.01, ** p<0.05, * p<0.1

fact that a bid is placed in the neighborhood of that multiple. In interpreting Figure 5a, one should

Figure 5: Coefficients on Multiples of 5.



(a) Dep. var: Log(Value Winning Bid)

(b) Dep. var: Value Winning Bid

realize that for low bid values an overbidding-percentage of 10% is not very meaningful in absolute sense. This makes it the more remarkable that for higher bid values the overbidding-percentage is not lower. Figure 5b takes the winning bid instead of the log of the winning bid as dependent variable. This figure shows that winning bidders with a bid of €100 on average seem to overpay by about €9.[18]

[18] As a robustness test, Appendix Figure B.1 presents the results of similar regressions where we define MultRange as a bid within a two instead of one euro range of a multiple of five. The pictures look similar, except that the multiple-5 coefficients for bid values below €100 are slightly less pronounced, and those above €100 slightly are more pronounced.

5.3 Experience

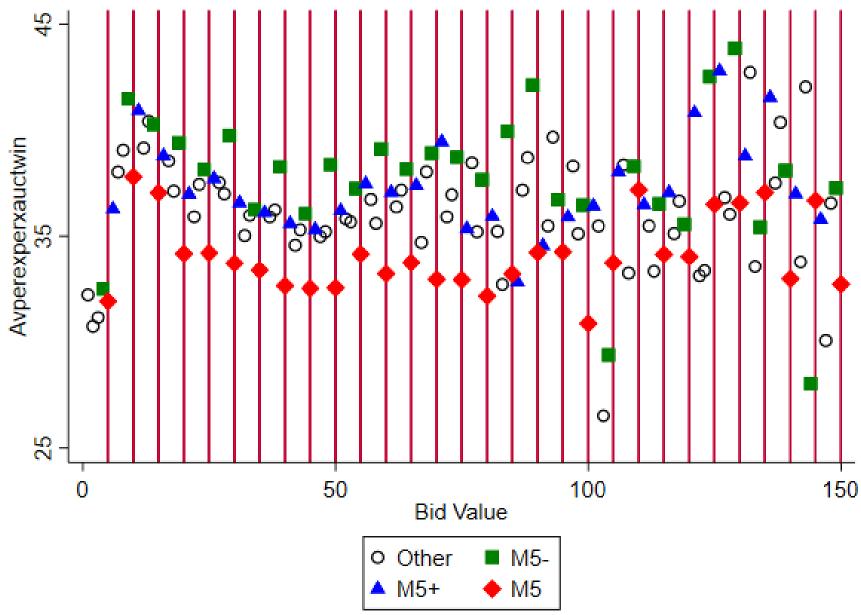
This subsection explores the role of bidder experience in the tendency to bid round numbers in the Early and Final Stage, to place $M5+$ bids in the Final Stage, and to overbid. One caveat is that we only observe bidders within our data collection window and not their full bid history. Hence, we may wrongly label some bidders as inexperienced, who in fact have participated in many auctions before our data collection window. Similarly, we do not observe if bidders first watch a couple of auctions before placing a bid. Assuming that learning is greatest in the first few auctions in which a bidder participates, our estimates are likely to be a lower bound on the impact of experience.

In our five month data collection window, we observe many bidders only one or a few times. From the $552,900$ unique bidders, we observe $144,936$ bidders only once (26.21%), and 80% ten times or less. So for many bidders we cannot say much meaningful about the role of (gaining) experience. On the other hand, out of all bids placed, 54% comes from a bidder that has placed at least 10 bids before.

First, we investigate for winning bids whether $M5$ winners are different in terms of experience compared to non-$M5$ winners. Therefore, we borrow an approach of Lacetera et al. (2012) and consider the average experience of winning bidders conditional on their bid level. For each bidder, we generate a variable equal to the number of auctions in which bidder has participated up to and including the moment of placing the current bid. Next, we attach to each bid an experience percentile ranking from 0 to 100, where 0 corresponds to a bid from a bidder who participates in her first auction, and 100 to the last bid of the bidder who participated in most auctions in our data collection window. Next, we generate the average experience percentile for winning bids of each bid value. These average experience percentiles for winning bids are plotted in Figure 6. Especially below 100, $M5$ winning bids stand out as coming from bidders with lower experience. In addition, $M5-$ stand out as coming from more experienced bidders. $M5+$ bids do not stand out strongly, if anything they come from relatively experienced bidders.

Next, we investigate how bid patterns change while a bidder gets experience. We assume that bidders gain experience by placing a bid in an auction, and that learning is strongest in the first few auctions. Because bidders who only place one bid may be quite different from bidders whom we observe a lot of times, we want to capture the experience effect using bidder fixed effects. Therefore, we focus on bidders whom in total bid in at least 10 auctions, and investigate how their bidding

Figure 6: Average experience percentile of winning bids per bid value



pattern changes over these first 10 auctions.

First, we investigate Final Stage $M5$ and $M5+$ bidding. If bidders learn to bid more strategically, they should be less likely to bid $M5$ with experience and more likely to bid $M5+$. We run a regression of a $M5$ and $M5+$ dummy on variable indicating the Xth auction in which a bidder participates with bidder fixed effects for the first 10 auctions, only considering bidders with a total of at least ten bids. Table 7 presents the results. More experienced bidders are significantly less likely to bid $M5$ in the Final Stage, but the effect is not very large (around 2 percentage points). Similarly, bidders get slightly more likely to bid $M5+$ in the Final Stage, but coefficients are not stably significant here. Overall, these findings suggests that bidders learn to bid more strategically, but not very strongly.

6 Structural model - UNDER CONSTRUCTION

The previous sections showed that many first stage jump bids are round number bids and a reduced form analysis showed that round number bids seems positively correlated with overbidding and negatively correlated with bidder experience. In this section we present and estimate a structural model. The model allows for an estimation of the share of biased round number bidders present in the population and the loss in expected surplus they experience compared to non-biased bidders with the same

Table 7: Regression of $M5$ and $M5+$ dummy on Xth auction in which a bidder participated for Final Stage bids

VARIABLES	(1) M5 bidding	(2) M5+ bidding
2.XthAuctionBidder	-0.004	0.000
	(0.005)	(0.005)
3.XthAuctionBidder	-0.014***	0.012**
	(0.005)	(0.005)
4.XthAuctionBidder	-0.010**	0.006
	(0.005)	(0.005)
5.XthAuctionBidder	-0.010**	0.005
	(0.005)	(0.005)
6.XthAuctionBidder	-0.017***	0.008*
	(0.005)	(0.005)
7.XthAuctionBidder	-0.023***	0.012***
	(0.005)	(0.005)
8.XthAuctionBidder	-0.015***	0.010**
	(0.005)	(0.005)
9.XthAuctionBidder	-0.018***	0.005
	(0.005)	(0.005)
10.XthAuctionBidder	-0.021***	0.017***
	(0.005)	(0.005)
Constant	0.309***	0.198***
	(0.004)	(0.003)
Observations	221,930	221,930
R-squared	0.411	0.346
Bidder FE	YES	YES

Notes: Robust standard errors in parentheses, *** p<0.01, ** p<0.05, * p<0.1

valuation.

6.1 Modeling assumptions

We consider $j =\in \{1, \ldots J\}$ auctions of an item m and model the final stage where the auction is a sealed bid first-price auction. Bidder valuations v are drawn from a χ^2-distribution with mean ν_m. The number of bidders is allowed to vary per auction were we assume that the number of bidders n_j in the final stage of auction j is a draw from a χ^2-distribution with mean μ.[19] We assume that bidders, knowing the time of day and observing the early stage outcomes, know the number of opponents they face in the final stage of a given auction.

In addition, we assume that a fraction $\lambda \in [0, 1]$ of the population is a round number bidder, for lack of a better term we refer to them as "behavioral bidders." The choice set of these bidders is $\{5, 10, \ldots\}$. Note that besides this share λ population that bids multiples of five for behaviorial reasons, there may in addition be bidders who bid multiples of five for strategic reasons. We allow for that by distinguishing between level 0, level 1, and level 2 ($L0, L1$ and $L2$) bidders – a fraction λ of each type being behavioral bidders. Level 0 bidders bid the equilibrium bid to a first price auction with N bidders, assuming that none of the other bidders is a behavioral bidder. Yet some Level 0 bidders may be behavioral bidders themselves who round their bid to the nearest multiple of 5. Level 1 bidders place a best response to all other bidders being Level 0, and Level 2 bidders place a best response to all other bidders being Level 1. Hence we end with six types of bidders $\phi(l, h)$: level 0, 1, and 2 bidders ($l = 0, 1, 2$), where bidders of each type can be behavioral ($h = 1$) or not ($h = 0$).

6.2 Simulation set up

The population size is set at $G = 100, 000$. For each population member i, we determine the member's

- valuation $v_i \sim \chi^2(\nu_m)$ for the object;
- bidder type $\phi_i = \phi(l_i, h_i)$, with $h_i = 1$ with probability λ and $l_i = k$ ($k = 0, 1, 2$) with probability l_k.

Aim of the simulation is to find the set of parameters $\theta \equiv (\lambda, l_1, l_2, \nu_m, \mu)$ that minimizes the sum of

[19] We ensure that we do not have auctions with a single bidder by imposing that $n_j \geq 2 \ \forall j$.

the squared differences between the observed and simulated frequency of winning bids per bid value.[20] These optimal values $\overline{\theta}$ are bound by means of a grid search.

We construct a number of $J = 1,000,000$ auctions. First, we draw the number of bidders n_j in auction j from $\chi^2(\mu)$. Then, we populate auction j with n_j bidders that are randomly selected from the population. This implies that each population member on average participates in $J\mu/G = 10\mu$ auctions – the expected total number of bidders divided by the population size. Bidder i in auction j submits a bid that is a function of her own valuation, her type and the number of other bidders in the auction, i.e. $b_i = b(v_i, \phi_i, n_j)$. Hence, each bidder i will adjust her bid to the number of other bidders she faces.

Bids in an auction with n bidders are determined as follows. Non-behavioral Level 0 bidders bid the equilibrium bid associated with a first-price sealed bid auction (without round-number bidders). Using revenue equivalence, this equilibrium bid is equal to the expected second highest valuation conditional on the bidder herself having the highest valuation:[21]

$$b(v_i, \phi(0,0), n) = v_i - \int_{\underline{v}}^{v_i} \left(\frac{F(x)}{F(v)}\right)^{n-1} dx. \tag{5}$$

This bid is calculated for every bidder and for every possible n. Behavioral Level 0 bidders round this bid to the nearest multiple of 5, conditional on that multiple not exceeding their valuation,

$$b(v_i, \phi(0,1), n) = \min\left\{5\left\lfloor\frac{b(v_i, \phi(0,0), n)}{5} + \frac{1}{2}\right\rfloor, 5\left\lfloor\frac{v_i}{5}\right\rfloor\right\}. \tag{6}$$

The expected surplus when bidding x in an auction with n bidders and a valuation of v equals

$$S(x, v|n) = P(x = \text{winning bid}|N = n)(x - v).$$

The probability that x is the winning bid depends on the $n-1$ other bids and equals 1 if x exceeds all other bids. In case of a split, we assume that $P(x = \text{winning bid})$ equals 1 over the number of bidders with the highest bid. We do not have a closed form expression for this probability because of the introduction of behavioral bidders who round their bids to multiples of five. Hence we use a numerical approximation for $P(x = \text{winning bid})$. For a given value of n, we randomly select J times

[20] Note that l_0 follows from $l_0 \equiv 1 - l_1 - l_2$.
[21] This is a standard result in auction theory, see e.g. the derivation and discussion in XXX.

$n-1$ population members who bid according to (5) and (6). For each $j = 1, 2, \dots, J$, we determine the highest bid $\hat{b}^j = \max\{b_{j,1}, \dots b_{j,n-1}\}$ and the number of bidders $\hat{n}^j$ that have submitted this highest bid (i.e. the number of bidders k, with $b_{j,k} = \hat{b}^j$). Then, a bid of x is a winning bid in auction j with probability 1 whenever $x > \hat{b}^j$, with probability $1/(1+\hat{n}^j)$ when $x = \hat{b}^j$, and 0 otherwise. We compute $\hat{P}(x = \text{winning bid}|N = n)$, by taking the average of these probabilities across the J auctions.

Level 1 bidders bid a best response to all other bidders being Level 0. For a sealed bid first price auction with n bidders, we define 'best' as the bid that maximizes bidder i's ($i = 1, \dots G$) simulated expected surplus, so:

$$b(v_i, \phi(1,0), n) = \arg\max_x \; \hat{P}(x = \text{winning bid}|N = n)(x - v_i) \tag{7}$$

for non-behavioral Level 1 bidders. As before, behavioral Level 1 bidders round this bid to the nearest multiple of 5, conditional on that multiple not exceeding their valuation:

$$b(v_i, \phi(1,1), n) = \min\left\{5\left\lfloor \frac{b(v_i, \phi(1,0), n)}{5} + \frac{1}{2} \right\rfloor, 5\left\lfloor \frac{v_i}{5} \right\rfloor\right\}. \tag{8}$$

We use a similar procedure to determine the bids submitted by Level 2 bidders. Level 2 bidders assume that all other bidders are Level 1 bidders.

Having determined the equilibrium bids of all six bidder types in an auction with n bidders, we simulate for each value of n $J = 1,000,000$ auctions and determine for each of these auctions the winning bid and for each population member the expected surplus of bidding x. This gives for each population member i the expected surplus of bidding x conditional on n:

$$S(x, v_i|n) = \hat{P}(x = \text{winning bid}|N = n)(x - v_i).$$

Finally, we aggregate out n and compute the bidder i's overall expected surplus

$$S(x, v_i) = \sum_n \hat{P}(N = n)\hat{P}(x = \text{winning bid}|N = n)(x - v_i),$$

where the estimated probabilities $\hat{P}(N = n)$ are obtained by drawing $J = 1,000,000$ times from a

Table 8: Strucural estimates for a range of items

Item:	Concert	Hotel	High tea
	Empirical data		
# auctions	10815	7188	7952
# bids	110999	64621	61338
avg. winning bid	48.28	27.15	15.00
percentage bids M5	38.18	30.41	23.21
percentage winning bids M5	41.66	39.08	31.05
	Structural estimates		
$\hat{\mu}$	3.5	3.5	1.5
$\hat{\nu}$	47	26	17
$\hat{\lambda}$	0.3	0.25	0.15
$\hat{l}_1$	0.15	0.3	0.05
$\hat{l}_2$	0.05	0.05	0.05
	Expected surplus (€)		
Overall	3.010	2.240	2.696
Non-behavioral bidders	3.080	2.280	2.728
Behavioral bidders	2.849	2.100	2.509
p.p. difference	-7.522	-7.895	-8.056

Notes: TEXT.

$\chi^2(\mu)$ distribution.[22]

A grid search looks for the value $\hat{\theta}$ that minimizes (the square root of) the sum of squared differences between the simulated $\hat{f}(x|\theta)$ and empirical frequencies s_x of winning with a bid of x. That is,

$$\hat{\theta} = \arg\min_{\theta} \sqrt{\sum_{x=1}^{x^{max}} \left(\hat{f}(x|\theta) - s_x\right)^2} \tag{9}$$

The estimates $\hat{\theta}$ that minimize the objective function are found by means of a grid search.[23]

6.3 Structural estimates

Table 8 shows the structural estimates for the top-3 of most auctioned items on the site.

7 Conclusion

TBA

[22]As noted before, we set a lower bound of 2 for n which means that each realization lower than 2 is set equal to 2.

[23]For μ, values between μ_{min} and μ_{max} with steps of 0.5 are evaluated; for ν, values between ν^{min} and ν^{max} with steps of 1; for λ, values between 0 and 1 with steps of 0.05; l_1 and l_2, values between 0 and 1 with steps of 0.05.

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Online Appendix with Supplementary Material

Extended Data for Online Publication

Might as well jump? The role of round jump bids in auctions

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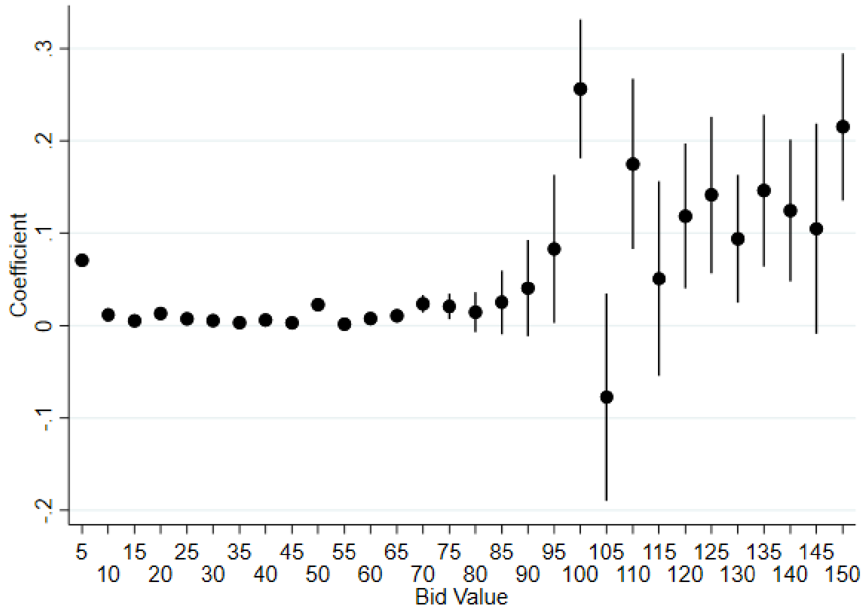
NOTE: generally speaking appendices are not up-to-date with most recent restricted dataset-statistics

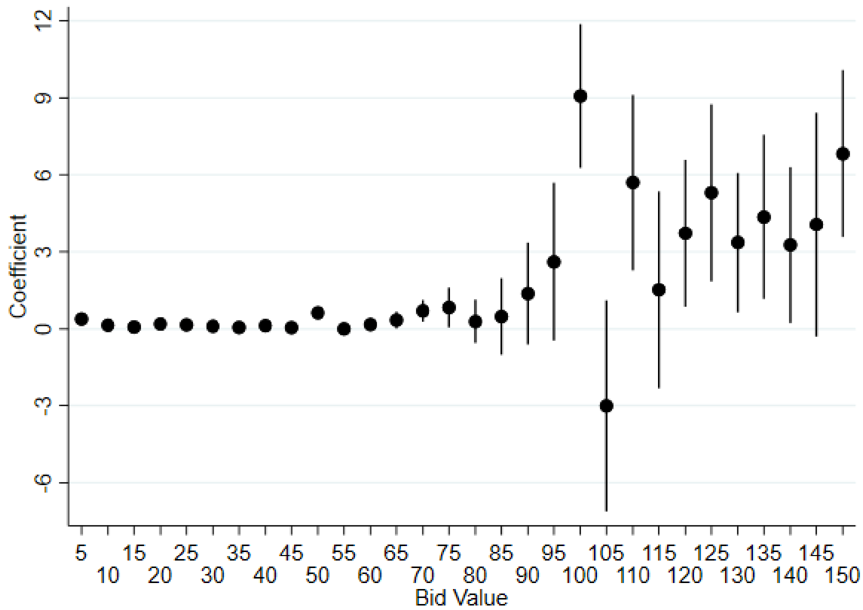
A Data Construction

B Overbidding larger range

Figure B.1: Coefficients on Multiples of 5.



(a) Dep. var: Log(Value Winning Bid)



(b) Dep. var: Value Winning Bid

C Current vs. Next Bid

In Table C.1 and Table C.2, the percentage of bids equal to 'Next Bid' for a given 'Current Bid' is shown for current bids between 45-55 and between 95-105 respectively. These tables show the same pattern of the multiples of 5 clearly standing out as has been shown in Table 4 in the main text.

	Next Bid									
Current Bid	46	47	48	49	50	51	52	53	54	55
45	46.58	9.66	5.60	3.47	21.52	2.69	1.36	0.68	0.24	3.49
46	0.00	40.14	12.24	4.96	27.76	3.88	1.83	0.84	0.41	3.59
47		0.00	42.96	9.22	28.91	5.14	2.66	1.19	0.48	4.57
48			0.00	34.64	39.58	7.84	4.38	1.93	0.87	5.14
49				0.00	61.92	11.12	6.03	2.56	0.83	8.43
50					0.00	45.69	10.16	2.47	1.04	18.29
51						0.00	44.09	6.87	2.00	23.45
52							0.00	44.25	5.32	27.93
53								0.00	36.18	36.00
54									0.00	62.42
55										0.00

Table C.1: Next bid for given current bid (45-55)

	Next Bid									
Current Bid	96	97	98	99	100	101	102	103	104	105
95	35.11	3.42	2.63	5.25	32.32	2.87	0.80	0.64	0.40	2.87
96	0.00	38.91	7.46	6.45	29.23	4.23	0.81	0.60	0.20	2.82
97		0.00	42.39	6.16	30.43	3.99	1.09	0.72	0.72	3.26
98			0.00	34.91	34.91	4.00	2.91	0.73	0.36	3.64
99				0.00	62.40	7.94	1.94	0.81	0.49	3.24
100					0.00	40.31	3.94	0.69	0.39	11.53
101						0.00	39.47	3.16	0.98	15.99
102							0.00	45.00	2.98	17.28
103								0.00	37.99	24.02
104									0.00	60.86
105										0.00

Table C.2: Next bid for given current bid (95-105)

D Two specific items

The histograms showed so far grouped together data from all auctions for all items we observe. In this appendix, we zoom in on the auctions for two specific items to show that the patterns documented in the previous sections are not somehow an artefact of pooling all data together.

We focus here on the two items for which we observe the most auctions. One item is a coupon for a wellnessday/sauna day for 2 persons for which we observe 9795 auctions and 31,440 bids in our subsample. The other item is concert tickets for a Dutch group of artist for which we observe 6425 auctions and 59,990 bids in our subsample. The sauna tickets typically sell for relatively low prices, and the concert tickets sell for much higher prices. For both items the auctions mostly have a short duration (less than 15 minutes), and are of a repeated nature, where the next auction starts once the current one ends.[24]

Figure D.2 shows the histogram of all bids placed for the sauna tickets on the left and the histogram of all winning bids on the right. Most of the bids and winning bids for this item are below 10 euro. We observe a couple of outliers who bid more than 10. The most observed winning bid is 5, and in the histogram of all bids placed, there is a small spike at 5 compared to 4, and a small spike at 10.

Figure D.3 shows these histograms for the concert tickets. The concert ticket sells for higher prices than the concert tickets, and both the histogram with all bids and the histogram with winning bids show a consistent pattern of spikes at multiples of 5. Multiples of 5 are very prominent in the auctions for this item.

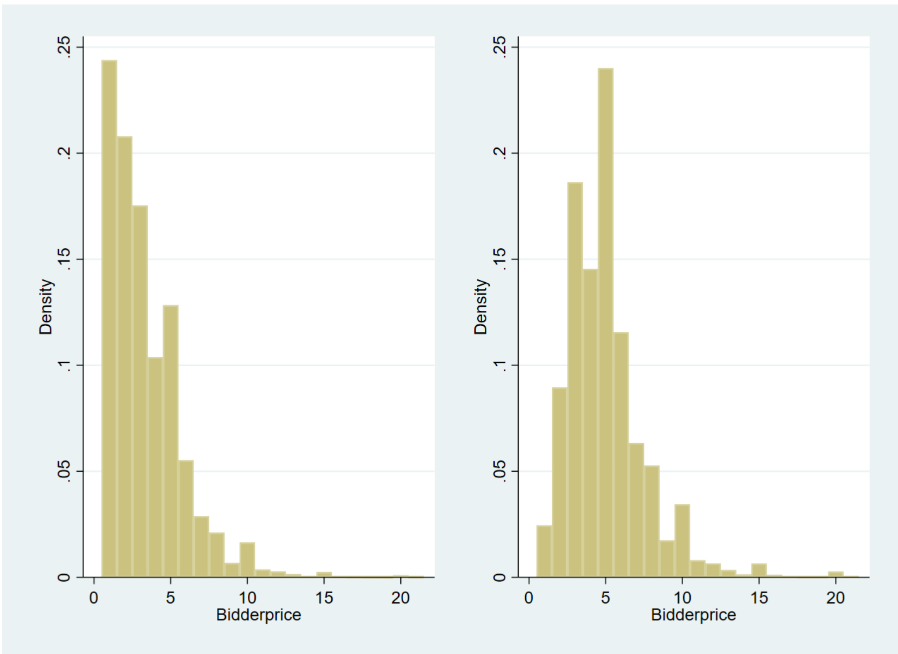


Figure D.2: Histogram all bids (left) and winning bids (right) of auctions for sauna tickets

[24]This item is not the best one to drive the point home, but choosing items for which we observe most auctions does seem to be a sensible/objective selection criterium here.

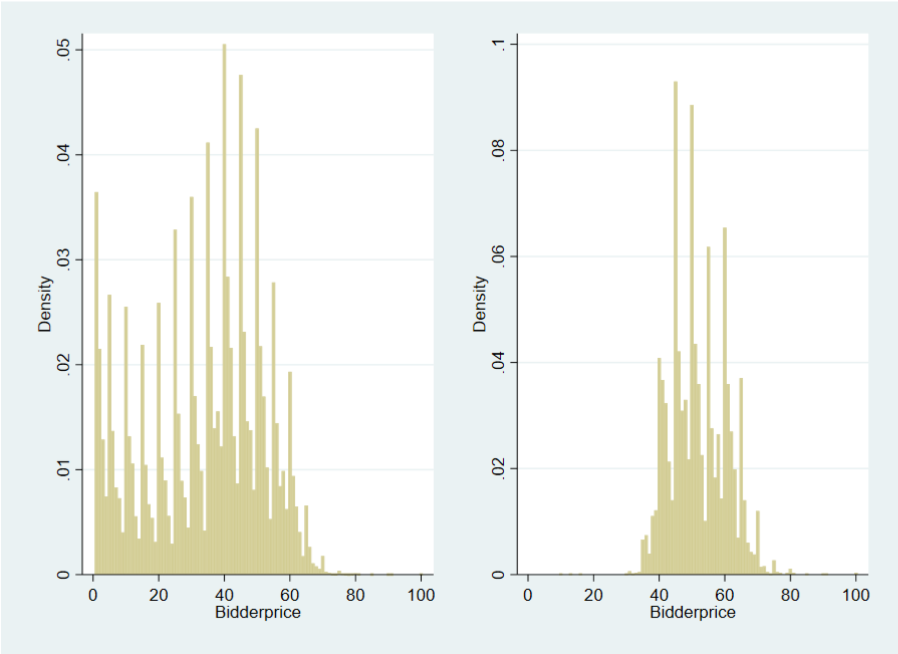


Figure D.3: Histogram all bids (left) and winning bids (right) of auctions for concert tickets