Mass of Bids at Reserve

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We document that partial pooling of bids at the reserve-price is common in a market for digital display advertising that uses a first-price auction mechanism to sell individual impressions. Most bidders we study exhibit the following pattern of bidding: when the reserve randomly shifts to a very low level, the mass point of their bids at the usual reserve level disappears, and the right tail of the their bid distribution above the usual reserve does not change.

The underlying mechanism most consistent with both the above bidding patterns and the actual bidding strategy we directly observe for one of the bidders is that some bidders use a simplified heuristic bidding model. The heuristic model first solves for a univariate bidding strategy as a function of the valuation alone, and then censors the actual bids at exactly the reserve level whenever the valuation of the opportunity exceeds the reserve but the univariate strategy does not.

To understand the economic consequences of this behavior, we use a counterfactual analysis to compare the publisher's revenue and the bidders' surplus under the heuristic bidding strategy apparently employed by bidders, and the Bayes-Nash equilibrium bidding strategy. The counterfactual equilibrium model involves generally higher bids than the heuristic model, increasing the average auction revenue by 7% and decreasing bidders' surplus by 3%- both economically meaningful amounts. Widespread use of simplified bidding heuristics in online advertising can thus lead to suboptimal outcomes for publishers.

1 INTRODUCTION

Equilibrium bidding strategies in simple first-price sealed-bid auctions do not involve any pooling of bids at the reserve price level. Yet, we find that partial pooling at reserve is common in a market for digital display advertising that uses the first-price auction to sell individual impressions. Specifically, we analyze the distributions of bids submitted by twelve large bidders who participated in the Yahoo ad exchange in 2023, and we observe that most of these distributions have a substantial mass of bids at reserve. In this paper, we document this surprising phenomenon, explore potential mechanisms behind it using a unique auction-level dataset, and show that it is economically meaningful in that it can lower the auction revenue by 7 percent relative to counter-factual revenue in a Bayes Nash equilibrium that does not involve any pooling of bids.

To document the partial pooling phenomenon, we rely on a unique way the exchange that provided our data sets reserve prices. Each bidder randomly faces one of only two different levels of the reserve price: the optimized "production" level and a much lower "monitoring" level the exchange uses to learn about bids below the production reserve level. We find that most bidders bid exactly the reserve price with a large positive probability when the reserve is high (i.e. set at the production level), but this mass-point in the bid distribution at the production-reserve level disappears when the reserve shifts to the monitoring level. The partial bid-pooling at the reserve price we find is thus not due to the distribution of valuations having a mass point just where the reserve price happens to be.

For example, Yahoo's own bidder (the Yahoo Demand Side Platform (herafter "Yahoo DSP") faces a production level reserve of $0.71 (CPM) and bids this amount with probability 13 percent when the reserve is $0.71, but conditional on biding at least $0.71, their probability of bidding exactly $0.71

is less than 1 percent when the reserve is set at the monitoring level of $0.05. Moreover, the bidding strategy responding to the lower (monitoring) level of reserve does not exhibit any mass points greater than a few percent of the bids anywhere near the $0.71 level. The partial bid-pooling at the production reserve price we find is thus not due to the Yahoo DSP valuing 13 percent of impressions exactly where the production reserve price happens to be. This pattern of a "disappearing" mass point characterizes the behavior of a vast majority (over 80 percent) of the bidders we observe.

The underlying mechanism most consistent with our data is that some bidders use a simplified heuristic bidding model, which first solves for a "univariate" bidding strategy as a function of the valuation alone, and then censors the actual bids at exactly the reserve level whenever the valuation of the opportunity exceeds the reserve but the univariate strategy does not. This is the first paper documenting such heuristic behavior by real time bidding algorithms in online advertising. We offer both direct evidence for this simplifying heuristic by observing the bidding strategy of one of the bidders, and indirect evidence by comparing right tails of the bidding distributions under the two different levels of reserve introduced above.

For one of the bidders (the Yahoo DSP), we observe the valuation associated with each bid. This allows us to observe the bidder's bidding strategy at the lower level of reserve, showing that 1) it is indeed univariate in that it does not depend on other auction characteristics such as the number of bidders, 2) the censoring mechanism described above can produce the observed mass point at production reserve, and 3) its right tail matches their bidding strategy at the higher level of reserve.

The last piece of evidence introduced in the previous paragraph, namely the comparison of bidding behavior above the production reserve as a function of the actual reserve level can be extended to other bidders for whom the valuations are not observed. We use the two-sample Kolmogorov–Smirnov statistic to compare the two distribution tails within each bidder, and we find that the tails are statistically indistinguishable for half of the analyzed bidders. The bid distributions of these bidders are thus consistent with the heuristic bidding model the Yahoo DSP uses, so the other bidders may be using analogous heuristics.

To measure the economic significance of the partial pooling at reserve arising from the heuristic bidding, we estimate the counterfactual revenue in a Bayes Nash equilibrium that does not involve any mass points at reserve. This exercise is complicated by the fact that the exchange recognizes two types of bidders (Regular DSPs and Rebroadcasters) who face different production reserve prices. We thus need to draw on the recently developed theory of first-price sealed-bid auctions with asymmetric bidders facing different reserve prices by Kotowski (2018) to characterize the counterfactual equilibrium bidding. On the other hand, the exercise is also simplified by the fact we observe the underlying valuations for one of the bidders, so we do not have to separately estimate the valuations of both bidder types. After computing the counterfactual equilibrium, we find that it involves generally higher bids than the heuristic model, increasing the average auction revenue by 7% and decreasing bidders' surplus by 3%- both economically meaningful amounts. The decrease in bidder surplus is not simply shared proportionately between the two bidder types - switching from the heuristic model to the equilibrium one would make regular DSPs better off while making Rebroadcasters worse off. These findings highlight the significant and differential effects that strategic bidding behavior can have on various types of auction participants.

2 RELATED LITERATURE

Previous literature discusses inconsistencies between observational data and predictions from auction theory. For instance, the existence of a mass of bids at the reserve price was documented by Reiley (2006) in his collectible trading cards experiment. Reiley (2006) used a field experiment to verify the predictions of the theoretical model of reserve prices in first-price auctions developed by Riley and Riley and Samuelson (1981). Conditional on having a valuation strictly above the reserve price, standard theory of private-value first-price auctions predicts that increasing reserve prices does not raise bids merely to the level of the reserve, but rather strictly above it. In other words, equilibrium bidding strategies in simple first-price sealed-bid auctions do not involve any pooling of bids at the reserve price level. Reiley (2006) found that, inconsistent with the strategic behavior predicted by the standard theory, some bidders submitted bids equal to the higher reserve price, and concluded that these bidders behaved naively. We extend Reiley's work by finding similar bidding patterns in an economically larger market facilitated by supposedly sophisticated algorithms. In addition, we also directly document the bidding heuristic that leads to the partial pooling, and we estimate its effects on economic outcomes using counterfactual simulations.

Extant auction theory does include equilibrium auction models with partial pooling at reserve, but the assumptions of those models do not hold in the present setting. For example, Haile (2000) finds such partial pooling in markets with resale, but digital advertising impressions cannot be resold. Lauermann and Speit (2023) find that mass-points can occur in bidding for common-value objects, but the detailed targeting of digital display ads based on private information individual bidders have about each opportunity makes the private-value model more relevant here.

Golrezaei et al. (2021) also discuss inconsistencies between observational studies and theoretical predictions. Using data from Google's display advertising exchange in a second-price auction environment, Golrezaei et al. (2021) show that the behavior of some buyers is not consistent with the predictions of classical auction theory. In particular, they found that a significant set of buyers lower their bids in response to higher reserve prices and concluded that this behavior can be explained by buyers' return on investment constraints. This observation contrasts with standard results in second-price auctions, where bidders have no incentive to change their bids as a function of reserve prices. This is not necessarily true in first-price auctions, the mechanism used in our application to allocate and price display advertising. In contrast to Golrezaei et al. (2021), we study a different deviation from theoretical predictions, namely the partial pooling at reserve.

Our counterfactual exercise is based on the theoretical work by Kotowski (2018), who characterizes the equilibrium bidding function in first-price auctions with asymmetric reserve prices and asymmetric bidders. Work based on prior studies of asymmetric first-price auctions, particularly Lebrun (1999, 2006), Lizzeri and Persico (2000), and Maskin and Riley (2003). Methodologically, our empirical approach connects with the structural empirical literature on auctions. We model ad auctions via a first-price auction model with binding reserve prices, and we allow the valuation distributions to differ across different types of bidders to capture the observed differences in their bidding behaviors. We use the approach suggested by Flambard and Perrigne (2006) to recover unobserved valuations.

3 INSTITUTIONAL BACKGROUND: REAL-TIME AUCTIONS FOR DIGITAL DISPLAY ADVERTISING WITH TWO BIDDER TYPES

Our analysis focuses on auctions of digital display advertising. The advertisements are displayed in rectangular boxes between or on the side of the main content of the online publisher which sells the ad space. In addition to location on the webpage, the ads also differ in size (e.g. 300x250 or 600x250 pixels). The "seller" in the auction is the *publisher* whose web page with some ad space for sale is being browsed by a consumer at the moment. In our data, the seller is a popular website in the yahoo.com domain - one of the top ten domains in the U.S. by traffic.

The role of "auctioneer" is fulfilled by an *ad exchange*, which collects the bids and determines the winner of the auction based on pre-announced rules. In our case, the ad exchange is the Yahoo Ad Exchange, which has been using the *first-price sealed-bid* rules with a reserve price since about three years prior to the time of the our data collection (2023).[1]. These auction rules were also the established industry standard at other ad exchanges at the time of our data collection.

The auction is triggered when the user opens the publisher's web page through her browser. The ad exchange sends an ad request with information about the user and the site, among other parameters, to the potential bidders along with a reserve price that may be bidder specific and may depend on factors like user or site characteristics.

We now describe the bidders in this market. Given the large volume of auctions and the complexity and required speed of online bidding, advertisers do not participate in these auctions directly, but instead engage with bidding agents who process the available information about the user and other impression characteristics, determine the bid amount, and act as bidders in the auction. The Yahoo Ad Exchange distinguishes between two types of such bidders: regular Demand-Side Platforms (DSPs) and rebroadcasters. This distinction is relevant because each bidder type faces a different reserve price. Regular DSPs are agents of the advertisers as described above. Rebroadcasters are themselves third-party exchanges that rebroadcast the bid request to their own *DSPs* and bid on their behalf. Importantly for our analysis, rebroadcasters face a higher production reserve price than regular DSPs on Yahoo Ad Exchange. Therefore, rebroadcasters effectively only compete at higher bid-levels, and there is a range of bids between the regular and rebroadcaster reserve prices in which only regular DSPs can win.

During the time of our data collection, the Yahoo ad exchange set reserve prices by type of bidder (regular DSP vs. rebroadcaster) and inventory (i.e. the upper-right banner space in Yahoo Mail vs. the top banner in Yahoo news). However, reserve prices did not generally vary from one impression to another during the day or across bidders within a type other than an occasionally and randomly switching to a much lower level to monitor the bidding landscape. We exploit this randomization in our main analysis.

4 THEORY

What does auction theory predict about the market we just described? In this section, we first establish the central theoretical claim that partial pooling at reserve is incompatible with equilibrium bidding in simple first-price auctions, and then present two theoretical models of the market we

[1]The Yahoo Ad Exchange, along with most other exchanges facilitating real-time bidding on digital advertising impressions switched to the first-price rules in 2019 (Despotakis et al. (2021))

are studying: 1) a fully rational equilibrium model adapted from the literature, and 2) a heuristic model we propose to explain the partial pooling at reserve we observe.

4.1 Mass points at the reserve price are inconsistent with equilibrium

To see why partial pooling at reserve is incompatible with equilibrium bidding, consider a focal bidder with valuation $v > r$ where r is the reserve price in the auction, and assume the bidder's competition involves a mass point of bids at r. The bidder faces an unknown number of competitors in a first-price sealed-bid auction, and his belief about the competition is summarized by a distribution of the highest opposing bid B which can implicitly depend on r and which includes a mass point of size M at r in that $\Pr(B = r) = M$. Assuming a quasi-linear utility function, the bidder's best response to G solves

$$\max_{b \geq r} \Pr(win|b)(v - b) \tag{1}$$

where $Pr(win|b) = Pr(B < r) + Pr(B = r)/2$, breaking ties randomly. It is immediate that there exists an $\epsilon > 0$ such that bidding $r + \epsilon$ does not land at another mass point in the distribution of highest competing bid B, and dominates bidding r. Formally, bidding r yields $[\Pr(B < r) + M/2]\ (v - r)$ while bidding $r+\epsilon$ yields at least $[\Pr(B < r) + M]\ (v-r-\epsilon)$, which exceeds the payoff from bidding exactly r for all $\epsilon < \frac{M(v-r)}{2(M+\Pr(B<r))}$. In words: bidding just over r avoids the possibility of a tie with the highest competitor at r at the cost of an arbitrarily small increase in price paid. The right hand side of the inequality is positive as long as $v > r$, but it becomes zero when $v = r$. So one possible explanation of mass points at the reserve is that the seller happens to set the reserve exactly at a point where the valuation distribution of at least some bidders has a mass point.

Note that the above discussion does not make any assumption about the rationality, number, or symmetry of the competitors the focal bidder is facing. As long as at least some of the competitors bid the reserve price r with positive probability, the above argument, and consistent with previous literature (see Reiley (2006) and Lebrun (1999)), shows that a rational bidder would never respond by bidding r except in the event that his valuation equaled r exactly. In other words, there cannot be an equilibrium that places a positive mass of bids on r.

4.2 Modeling Assumptions

We consider a model with two types of bidders: regular DSPs indexed throughout by $i = 1$ subscript, and rRebroadcasters indexed throughout by $i = 2$ subscript. regular DSP and *Rebroadcaster* types consist of N_1 and N_2 potential bidders, respectively, with $N_1 + N_2 = N$ and $N \geq 2$. Let $v_{i,n}$ for $n = 1, ..., N_i$ denote the valuations of N_i potential bidders of type i. Assume the valuations $v_{i,n}$ are drawn independently from continuous distributions $F_i[\cdot]$ with full support on the interval $[0, \bar{v}]$, and denote the corresponding densities $f_i[\cdot]$.

The auctioneer runs a first-price sealed-bid auction with different public reserve price for each bidder type r_i, where $r_1 \leq r_2 \leq \bar{v}$, and rejects any bid below the corresponding reserve price. The number of actual type i participants in the auction may differ from the number of potential bidders N_i as some bidders may have a valuation below the corresponding reserve price r_i. We assume that bidders know their own valuation as well as their chance of winning at different bid-levels.

Having defined our modeling assumptions, we now introduce the heuristic model that seems to fit the bidding behavior we observe.

4.3 Heuristic Bidding Strategy

Consider a single bidder of type $i \in 1, 2$, who knows its chance of winning at different bid-levels. The following process describes the bidder's bidding strategy:

(1) Given bidder's valuation v, find the univariate bidding strategy $\tilde{b}_i(v)$ that maximizes the expected surplus without a reserve price.
(2) Update the resulting bid from step 1 to the corresponding reserve price value r_i if $\tilde{b}_i(v) < r_i < v$

Mathematically, let the heuristic bidding strategy $\tilde{\beta}_i(v|r_i)$ of type i bidder facing a reserve price r_i be:

$$\tilde{\beta}_i(v|r_i) = \begin{cases} 0 & if \;\; v < r_i \\ r_i & if \;\; v \in [r_i, \tilde{v}_i] \\ \tilde{b}_i(v) & if \;\; v > \tilde{v}_i \end{cases} \tag{2}$$

In words, the bidder does not participate if its valuation of the impression opportunity v is below its reserve r_i. If the valuation is greater than reserve and below some valuation threshold $\tilde{v}_i = \tilde{b}_i^{-1}(r_i)$, then the bidder submits a bid equal to r_i. For valuations above $\tilde{v}_i$, the bidder's response is determined by the univariate bidding function $\tilde{b}_i(v)$.

Note that the heuristic bidding strategy does not involve any notion of equilibrium. Instead, it is a simple response to a challenging environment the bidders find themselves in. In online advertising real-time bidding, bidders face millions of ad requests every second from very heterogeneous publishers. For each request, bidders must decide which ad are going to use in the response and corresponding bid amount. This may entail solving an optimization problem that must be solved in milliseconds. Employing a very complex bidding strategy may add latency in the bid response, increasing the chances that the response takes longer than the time limit imposed by exchanges. The heuristic defined above easily handles variation in the reserve price values enclosed in the bid request.

4.4 Counterfactual: Bayes-Nash Equilibrium Bidding Strategies

We now consider a counterfactual bidding strategy where both regular DSPs and Rebroadcasters bid according to Bayes-Nash equilibrium strategies. Theorem 2a in Kotowski (2018) shows that if $r_1 < r_2$ and the following condition holds

$$\int_{r_1}^{\bar{v}} F_2[r_2]^{N_2} F_1[z]^{N_1 - 1} dz < \int_{r_2}^{\bar{v}} F_2[z]^{N_2 - 1} dz \tag{3}$$

there exists a Bayesian-Nash equilibrium where all bidders of type $i \in \{1, 2\}$ adopt the strategy

$$\beta_i(v|r_i) = \begin{cases} 0 & if \;\; v < r_i \\ b_i(v) & if \;\; v \in [r_i, \hat{v}_i] \\ \hat{b}_i(v) & if \;\; v > \hat{v}_i \end{cases} \tag{4}$$

where:

(a) The function $b_i : [r_i, \hat{v}_i] \rightarrow [r_i, \bar{v}]$ is given by the symmetric Bayes Nash equilibrium characterized by Riley and Samuelson (1981)

$$b_i(v) = v - \int_{r_i}^{v} \left[\frac{F_i[z]}{F_i[v]} \right]^{N_i - 1} dz \tag{5}$$

(b) The function $\hat{b}_i : [\hat{v}_i, \bar{v}] \rightarrow [r_2, \bar{v}]$ is defined as $\hat{b}_i = \phi_i^{-1}$, where (ϕ_1, ϕ_2) is the unique solution to the system of differential equations

$$[\phi_i(b_i) - b_i] \left[\frac{N_j f_j \left[\phi_j(b_i)\right] \phi_j'(b_i)}{F_j[\phi_j(b_i)]} + \frac{(N_i - 1) f_i \left[\phi_i(b_i)\right] \phi_i'(b_i)}{f_i[\phi_i(b_i)]} \right] = 1 \tag{6}$$

for $i \neq j$, satisfying the boundary conditions

- $\phi_1(\eta^*) = \phi_2(\eta^*) = \bar{v}$ for some $\eta^* \in (r_2, \bar{v})$
- $\phi_1(b^*) = \hat{v}_1$ and $\phi_2(b^*) = \hat{v}_2$ where $b^* = b_2(\hat{v}_2)$

To gain intuition for the system of Equations 6, note that each equation is a type-specific first-order condition of the optimization problem of a type i bidder who maximizes:

$$(v - b) F_j[\phi_j(b)]^{N_j} F_i[\phi_i(b)]^{N_i - 1} \tag{7}$$

whenever valuations are above the threshold $\hat{v}_i$[2]. Interestingly, the equilibrium bidding function β_1 of the lower type (in the present context, this is the regular DSP) is discontinuous at $\hat{v}_1$, see Kotowski (2018)'s Figure 2, Case 1. Kotowski (2018) also analyzes the equilibrium when Equation 3 does not hold, but we will see in the estimation results section that the condition holds. So the above Equation 4 characterizes the Bayes-Nash bidding behavior of buyers in our setting.

5 DATA DESCRIPTION

We employ exchange bidding data from auctions selling advertising space on a popular website in the yahoo.com domain. We consider a sample of user impressions from the United States during one day in February 2023. For each auction in the sample, the exchange data contains all bids submitted by all bidders (regular DSPs and rebroadcasters). We then complement the Yahoo exchange bidding data with contemporaneous information coming from Yahoo's own DSP, which incorporates Yahoo DSP's valuations of all the ad opportunities in our sample, including both the valuations behind every bid the Yahoo DSP submitted and valuations of opportunities on which the Yahoo DSP did not bid.

[2]Note that the terms in Equation 6 have been rearranged with respect to the Equation 7 appearing in Theorem 2a in Kotowski (2018) to fit the present definitions

Table 1 presents summary statistics of key variables in the dataset. The column marked as *All* reports aggregate information, while columns *Monitoring Reserve* and *Production Reserve* slice data according to the reserve price value enclosed in the bid request. Recall that the *Monitoring* reserve price value is smaller than the *Production* one and equal to all bidders. On the other hand, the reserve price used in production depends on the bidder type: Regular DSP and rebroadcaster.

Table 1. Summary Statistics

	All	Monitoring Reserve	Production Reserve
Auction - Yahoo Exchange:			
No. Bids	1,553,592	1,197,821	355,771
No. Auctions	225,379	115,791	109,588
Bid (× $1000)	0.75	0.62	1.21
	(0.49)	(0.44)	(0.38
No. Bidders	6.89	10.34	3.25
	(5.95)	(5.78)	(3.37)
Winning_Bid (× $1000)	1.31	1.18	1.48
	(0.56)	(0.59)	(0.46)
%_Bids_at_Reserve	12.54%	8.37%	26.59%
Yahoo DSP:			
No. Auctions	225,379	115,791	109,588
No. Bids	53,773	34,176	19,597
Bid (× $1000)	1.18	0.94	1.43
	(0.78)	(0.76)	(0.71)
Winning_Bid (× $1000)	1.72	1.59	1.89
	(0.86)	(0.91)	(0.77)
Winning_Frequency	8.74%	9.43%	8.02%
%_Bids_at_Reserve	6.17%	2.98%	11.74%
Valuation_with_Valid_Bid (× $1000)	9.16	7.66	11.77
	(79.99)	(74.73)	(88.37)
Shaded_Bid (%)	45.34%	44.61%	46.62%
	(17.65%)	(19.12%)	(14.67%)
Valuation_All (× $1000)	2.35	2.36	2.34
	(39.72)	(41.23)	(38.05)

Notes: The variables *Bid*, *Winning_Bid*, *Valuation_with_Valid_Bid*, and *Valuation_All* are in thousands of dollars.

Our sample of exchange bidding data consists of over 1.55 million bids from 225,379 auctions. The variable *Bid* corresponds to the average submitted bid price in the Yahoo exchange. In every auction, we also observe the *Number of Bidders* who participated in the auction and submitted a valid bid above the corresponding reserve price, as well as the *Winning Bid*. As expected, the number of bidders is larger when the reserve price is set low (10.34 in the *Monitoring* bucket) than when it is high (3.25 participants in the *Production* bucket). The difference between *Production* and *Monitoring* buckets is also significant when looking at the average clearing price: $1.48 and $1.18 respectively. The final reported exchange variable, *%_Bids_at_Reserve*, indicates the percentage of

submitted bids that are equal to the reserve price[3]. This percentage is high for both reserve price levels, 26.59% and 8.37% for the *Production* and *Monitoring* buckets respectively.

Table 1 also contains information about the additional data from the Yahoo DSP. Column *No. Auctions* repeats the size of our sample of auctions. The *No. Bids* variable indicates that the Yahoo DSP responded 53K times with bids above the reserve price (19K responses in the production bucket, and 34K in the monitoring one). The average Yahoo DSP submitted bid equals $1.18, greater than the $0.75 average observed bid from the exchange as a whole. Yahoo DSP's winning bid is also significantly higher than the exchange average winning bid: $1.72 and $1.31 respectively. The winning frequency is similar across buckets - Yahoo DSP wins 8.74% of the times when looking at aggregate data. According to the column *%_bids_at_reserve*, Yahoo DSP submits a bid that is equal to the reserve price in 6.17% of cases. As in the auction exchange data, this percentage is larger in auctions with production reserve prices: 11.74% and 2.98% for production and monitoring buckets respectively.

The key additional information available for the Yahoo DSP summarized at the bottom of table 1 is the data about valuations of all opportunities. We differentiate the Yahoo DSP valuations leading to a bid above the corresponding reserve value (column *Valuation_with_Valid_Bid*) from valuations of advertising opportunities independently if they are above or below the corresponding reserve price (column *Valuation_all*). The average Yahoo DSP valuation with a valid bid in our sample equals $9.16, while the average Yahoo DSP valuation for all ad opportunities equals $2.35. The lower overall valuation is expected because some of Yahoo DSP valuations are below the reserve price threshold. The *Shaded_Bid (%)* variable represents the ratio, on average, of the submitted Yahoo DSP bid relative to the corresponding valuation, and equals 45.34%. As expected in a first price auction environment, the ratio is less than one since DSPs have no incentives to submit a bid equal to their valuation.

Table 2 summarizes our exchange bidding data by bidder type and reserve level. While both bidders' type face the same monitoring reserve price (r_0 = $0.15), rebroadcasters have a higher reserve price in production: r_2 = $1.15 > r_1 = $0.71. Our dataset contains 874K valid bids submitted by Regular DSPs and 678K from Rebroadcasters. As expected, the lower reserve price value explains the larger number of submitted bids in the monitoring bucket independently of the bidder type. The overall average bid submitted by regular DSPs equals 66 cents, significantly lower than the average rebroadcaster bid of 86 cents. This is also true in the monitoring level, where both types face the same reserve price. We take this as preliminary evidence that the rebroadcasters have generally higher valuations than the regular DSPs, and the ad exchange is thus well advised to impose higher reserves on them.

When looking at the percentage of bids that are equal to the reserve price (*%_bids_at_reserve*), overall, the percentage among Rebroadcasters is slightly lower than the one of Regular DSPs (11.95% and 13.00% respectively). However, in the production bucket the difference is significant: 42.42% for Rebroadcasters vs. 14.79% for Regular DSPs. In the monitoring bucket, the percentage of bids at reserve submitted by Rebroadcasters decreases significantly to 3.17%, while Regular DSPs percentage does not drop much (12.45%).

[3]We consider that the bid equals the reserve price if the submitted bid is within the range corresponding reserve price and reserve price plus one cent.

Table 2. Summary Statistics by Bidder Type

	All	Monitoring Reserve	Production Reserve
Regular DSPs		$r_0 = \$0.15$	$r_{dsp} = \$0.71$
No. Bids	874,887	670,944	203,943
No. Auctions	180,325	108,699	71,626
Bid (× \$1,000)	0.66	0.53	1.10
	(0.50)	(0.42)	(0.44)
%_Bids_at_Reserve	13.00%	12.45%	14.79%
No. Bidders	3.89	5.80	1.86
	(3.29)	(3.08)	(2.05)
Winning_Bid (× \$1,000)	1.32	1.20	1.47
	(0.82)	(0.84)	(0.75)
Winning_Frequency %	41.75%	46.24%	37.02%
Rebroadcasters		$r_0 = \$0.15$	$r_{reb} = \$1.15$
No. Bids	678,705	526,877	151,828
No. Auctions	157,059	96,903	60,156
Bid (× \$1,000)	0.86	0.73	1.33
	(0.44)	(0.39)	(0.24)
%_Bids_at_Reserve	11.95%	3.17%	42.42%
No. Bidders	3.01	4.56	1.38
	(3.12)	(3.32)	(1.80)
Winning_Bid (× \$1,000)	1.27	1.13	1.46
	(0.46)	(0.45)	(0.42)
Winning_Frequency %	43.42%	49.28%	37.22%
No_Winners_Frequency	14.82%	4.47%	25.74%

Notes: The variables Bid, and $Winning_Bid$ are in thousands of dollars.

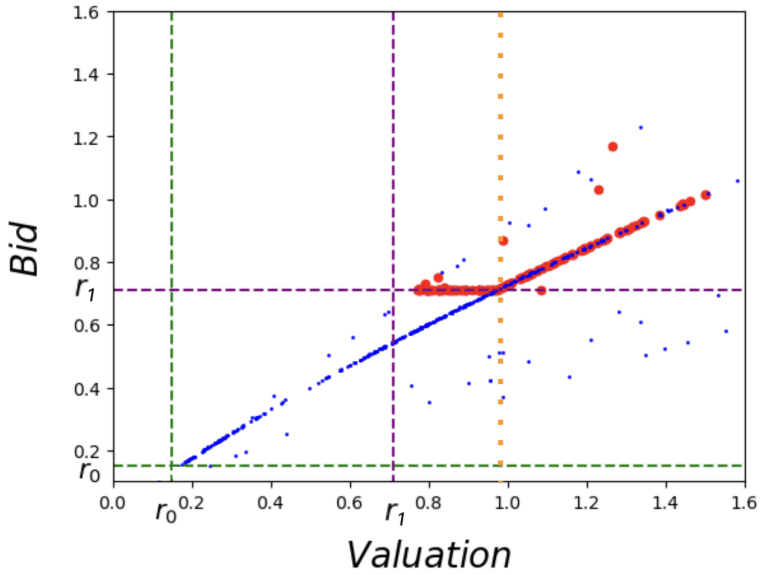
6 EVIDENCE FOR THE HEURISTIC BIDDING MODEL

6.1 Direct evidence: the Yahoo DSP bidding function

Yahoo DSP data provides information about its submitted bids and corresponding valuations for each opportunity and ad campaign, allowing us to infer Yahoo DSP bidding function. As an illustration, Figure 1 displays the observed valuations of a randomly chosen ad campaign with significant valuation support, and corresponding bids for monitoring and production reserve prices (blue and red dots respectively). Consistent with our proposed heuristic mechanism, for bids strictly above the reserve price set in production ($r_1 = \$0.71$), the function mapping Yahoo DSP valuations to bids is the same independently on the reserve price enclosed in the bid request.

Differences arise for valuations between the production reserve level r_1 and the 98 cents (vertical dotted line in orange) valuations for which Yahoo DSP bids equal the reservation value r_1 when the exchange sends the production reserve price in the bid request. On the other hand, for requests with the monitoring reserve price r_0 and valuations within the same interval, Yahoo DSP bidding decision for the ad campaign is strictly increasing. This pattern is a direct evidence

Fig. 1. Observed Yahoo DSP Bid Responses for a Particular Ad-Campaign



Note: Bid responses for *Monitoring* (blue dots) and *Production* (red dots) buckets

of our proposed mechanism whereby the DSP effectively censors the bids at the reserve price whenever the underlying candidate bid based on valuation alone does not clear at the reserve but the valuation of the opportunity does. Our data also shows that, in the production bucket the number of auctions where Yahoo DSP censors bids at the reserve is not negligible: 38% of the total number of responses in the ad campaign illustrated in Figure 1. This bidding behavior is common across most of the Yahoo ad campaigns in which 11.79% of bid responses facing production reserve prices are censored to the reserve price value.

6.2 Indirect Evidence: Disappearing Mass Point at Reserve and Right-Tail Comparisons

Having documented that the heuristic model fits the behavior of the Yahoo DSP well, we now provide evidence that it is also consistent with the behavior of at least half of the other DSPs (based on tail-comparison tests between the two reserve levels), if not a vast majority of them (based on disappearing mass point at the production reserve level). We begin with the partial pooling evidence.

The data summaries in Tables 1 and 2 already include aggregate evidence that both types of bidders engage in partial pooling at the reserve price, especially when the reserve price is set at the production level. In this section, we analyze the bidding behavior more thoroughly at the bidder level by examining the empirical distributions of bids submitted by different bidders, starting with the Yahoo DSP as a representative example.

Figure 2 displays the bidding distribution of the Yahoo-owned DSP for a particular inventory. As discussed earlier, each bidder in our sample faces two reserve prices: a low monitoring level and a higher production level. Figure 2a captures Yahoo DSP bid responses when facing the *Monitoring* reserve (r_0 = \$0.15), while Figure 2b illustrates responses when the reserve is set at the *Production*

level (r_1 = \$0.71). In both figures, we observe a mass of bid responses at the applied reserve price. But in Figure 2a, we do not observe a mass of bids at the *Production* reserve price value (vertical red line at r_1). In the language of the Introduction, this mass point seems to have "disppeared" when the reserve switched to the monitoring level. Note also that Figure 2a does not exhibit any mass points nearly as high (13%) as the r_1 mass-point in Figure 2b, so we can reject the possibility that the disappearing mass point has simply shifted to a different bid level. In summary, Figure 2 shows that Yahoo DSP considers the reserve price value when deciding how much to bid for the advertising opportunity, and it submits bids equal to the reserve price much more frequently than bids just above the reserve when the reserve is set at the production level.

By comparing the right tail of the bid distribution strictly above the highest of the two reserve prices in Figure 2a to the equivalently defined right tail of the bid distribution in Figure 2b (i.e., bid distributions strictly above r_1), we can test whether the bids depend on the reserve price beyond the obvious shift in the mass point. We use Quantile Treatment Effects (QTEs) to compare the two distribution tails. In our application, QTEs are defined as the difference between the quantile bids of both bid outcome distributions (see Firpo (2007) and Callaway (2023)).

In Figure 3, the y-axis corresponds to the difference of the tau-th quantile bid of both distributions, denoted as $QTE(tau)$. When *tau* on the x-axis equals 0.5, we are examining the difference between the median bids of both distributions. The dashed lines correspond to the 95% confidence interval thresholds. Figure 3 shows that the differences are not statistically significant for any quantile level (except for the 75th and 80th quantiles), suggesting that the Yahoo DSP's bidding strategy above the *Production* reserve price does not depend on the applied reserve price value.

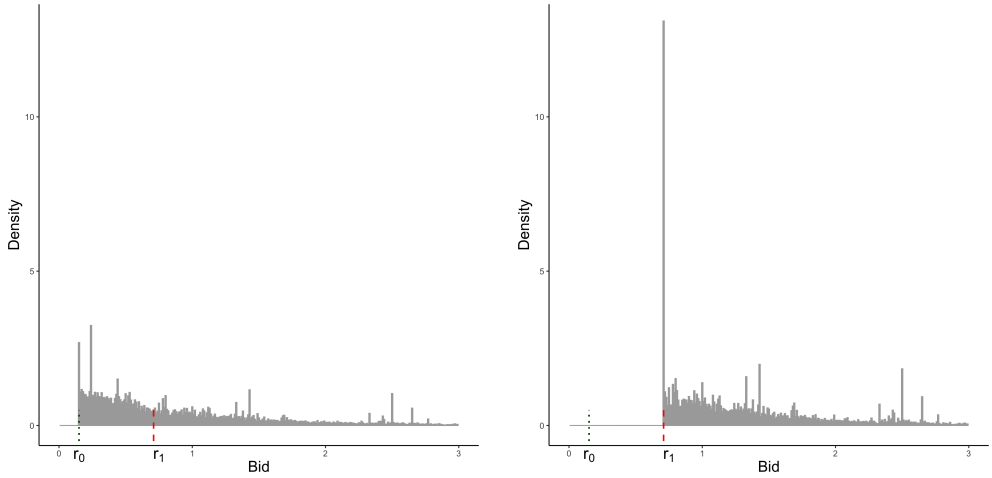
This data pattern is consistent with the heuristic bidding model, which employs the same univariate bidding strategy for high-enough valuations, and merely censors the bids at the reserve price whenever the valuation exceeds the reserve but the univariate candidate bid does not.

In addition to providing evidence for the heuristic model, we also note that having a strategy that does not depend on reserve prices is inconsistent with previous theoretical work on first-price auctions. As Reiley (2006) and Lebrun (1999), among others, point out, the equilibrium bidding response should be strictly increasing with reserve prices. This inconsistency motivates our counterfactual exercise, where we explore differences between the heuristic bidding model that is consistent with the observational data and the expected behavior in the Bayes-Nash equilibrium.

The partial pooling bid pattern evidenced by Figure 2 is not unique to Yahoo DSP. Other bidders participating in the Yahoo exchange show similar behavior. Figures A.1, A.2, and A.3 in the Appendix show the bid distributions for *Monitoring* and *Production* reserve prices of several regular DSPs and rebroadcasters, which, together with Yahoo DSP, account for more than 90% of the total spend on the analyzed display inventory. For each bidder in the figures, we display the bid distributions for *Monitoring* and *Production* reserve prices in a manner analogous to Figure 2, and the corresponding quantile treatment effect for bids strictly above the production reserve price in a manner analogous to Figure 3. The figures show that a mass of bids at the reserve price level is a common phenomenon among bidders, and in several cases, the bid distributions above the production reserve value do not depend on the applied reserve price.

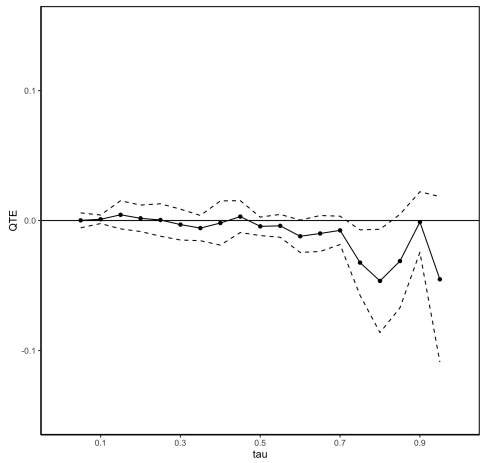
Table 3 provides further evidence of bid pooling and the heuristic mechanism employed by bidders to determine bids. The table compares the *Monitoring* and *Production* buckets of several regular DSPs and rebroadcasters. For each *Bidder_id* and corresponding *Type*, the table shows the percentage of submitted bids between the *Production* reserve price value and the *Production*

Fig. 2. Yahoo DSP Bid Distributions for Monitoring/Production Reserve Prices



(a) *Monitoring* Reserve Price (b) *Production* Reserve Price

Fig. 3. QTE



Notes: difference between the tau-th quantile bid of *Production* and *Monitoring* experiment buckets

reserve price plus one cent for both *Monitoring* and *Production* experiment buckets , defined as follows:

- $P_0 = Pr\left(bid \in [r_{prod}, r_{prod} + \$0.01) | reserve = r_0, bid \geq r_{prod}\right)$
- $P_{prod} = Pr\left(bid \in [r_{prod}, r_{prod} + \$0.01) | reserve = r_{prod}, bid \geq r_{prod}\right)$

where *prod* stands for the production level of reserve, i.e. r_1 for regulard DSPs and r_2 for rebroadcasters. For example, Yahoo DSP's percentage of bids at or just above the *Production* reserve

price ($r_{prod} = r_1 = \$0.71$) is 0.96% in the Monitoring bucket with reserve set to r_0, significantly lower than the 13.04% percentage in the *Production* bucket. The column denoted as $H_0 : P_0 = P_{prod}$ indicates whether we reject the hypothesis that both proportions are equal at a 5% significance level. Results suggest that in all cases, we do reject this hypothesis, and in ten of the twelve cases, P_{prod} is substantially larger than P_0. In summary, about 80 percent of the bidders we analyze exhibit the disappearing mass point at the production reserve level in their bid distributions.

Columns $QTE(5\%)$ and $KS(D)$ provide insights regarding the bid distributions of both buckets for bids above the production reserve price plus one cent. Specifically, column $QTE(5\%)$ shows the difference between the 5th quantile bid of each distribution. The adjacent column $H_0 : QTE(5\%) = 0$ indicates if this difference is significant at the 5% level. Column $KS(D)$ reports the two-sample Kolmogorov–Smirnov statistic, and the adjacent column $H_0 : KS(D) = 0$ indicates if we reject the hypothesis that both distributions are the same at the 5% significance level.

If bidders do not adjust their high-value bids in response to reserve prices, we should not reject the null hypothesis the the right tails of the bidding distribution are the same. For instance, both the QTE and KS statistics for Yahoo DSP cannot reject this hypothesis. Considering all the bidders, we find that these tail-comparison tests cannot reject their null hypotheses for seven bidders when we look at the QTE statistic, and five bidders when we look at the KS test. In summary, the tail-comparison tests summarized on the right side of Table 3 indicate that the bidding distributions of about half the bidders we analyze are consistent with the heuristic model.

7 ESTIMATION OF REBROADCASTER VALUATIONS AND HEURISTIC BIDDING STRATEGY

To perform our counterfactual analysis, we first need to estimate the distribution of valuations for both types of bidders. We assume that regular DSPs all have the same valuation distribution as Yahoo DSP, which is observed in our dataset. For rebroadcasters, we use a structural model to recover their valuations. Specifically, we assume all rebroadcasters follow the heuristic bidding model, and we use bidding data from the *Monitoring* bucket with low reserve price r_0 to infer their valuations. This section first explains the estimation procedure, and then illustrates the estimates.

7.1 Estimation Procedure

We use tools developed in previous literature to recover the distribution of rebroadcaster valuations F_2 . Since both bidder types face the same reserve price r_0 in the *Monitoring* bucket, we can follow the two step nonparametric procedure suggested by Flambard and Perrigne (2006) to recover F_2. In this section, we outline the details of our estimation procedure. Flambard and Perrigne (2006) analyze a lowest-bid procurement auction, so we need to adapt their procedure to our highest-bid auction as follows: Let $\tilde{\phi}_i = \tilde{b}_i^{-1}$ be the inverse of the univariate bidding function of type i in Equation 2. The heuristic bidding model then proposes that rebroadcasters derive their univariate bidding function $\tilde{b}_2(v)$ by maximizing their expected surplus in an auction without a reserve:

$$(v - b)F_1[\tilde{\phi}_1(b)]^{N_1}F_2[\tilde{\phi}_2(b)]^{N_2-1} \tag{8}$$

Recall that in our dataset, we observe the distribution of valuations F_1 of the Yahoo DSP, as well as its univariate bidding strategy $\tilde{b}_1(v)$. In this estimation procedure, we assume all the other

Table 3. Bidding Distributions Comparison between Reserve Price Levels

Bidder_Id	Type	P_0	P_{prod}	H_0:P_0=P_{prod}	QTE(5%)	H_0 : $QTE(5\%)$=0	$KS(D)$	H_0:$KS(D)$=0
YahooDSP	RegularDSP	0.96%	13.04%	Reject	1.40E-04 (2.93E-03)	No Reject	1.12E-02	NoReject
A	Rebroadcaster	2.61%	17.29%	Reject	3.40E-02 (1.37E-03)	Reject	2.44E-01	Reject
B	Rebroadcaster	4.95%	39.26%	Reject	1.02E-02 (8.96E-05)	Reject	1.20E-01	Reject
C	RegularDSP	0.76%	2.02%	Reject	-1.88E-03 (1.87E-03)	No Reject	6.78E-03	No Reject
D	RegularDSP	2.87%	5.44%	Reject	-2.42E-03 (6.31E-04)	Reject	7.52E-02	Reject
E	RegularDSP	1.75%	17.21%	Reject	1.23E-03 (1.09E-03)	No Reject	5.00E-03	No Reject
F	RegularDSP	1.95%	38.51%	Reject	2.90E-03 (1.67E-03)	No Reject	6.34E-02	Reject
G	Rebroadcaster	2.22%	35.78%	Reject	6.50E-02 (5.06E-03)	Reject	1.99E-01	Reject
H	Rebroadcaster	2.13%	79.97%	Reject	3.35E-03 (1.82E-03)	No Reject	3.89E-02	No Reject
I	Rebroadcaster	0.98%	61.93%	Reject	-3.52E-03 (3.96E-03)	No Reject	3.53E-01	No Reject
J	Rebroadcaster	4.58%	30.66%	Reject	-5.03E-03 (2.37E-03)	No Reject	2.58E-02	No Reject
K	Rebroadcaster	1.91%	1.58%	Reject	2.62E-01 (1.92E-03)	Reject	4.25E-01	Reject

Note: Statistical tests are performed at 5% significance level

regular DSPs (bidders of type $i = 1$) have the same distribution of valuations and use the same univariate bidding functions when formulating their heuristic bids. Given the known inverse bid function of regular DSPs $\tilde{\phi}_1$, the function $\tilde{\phi}_2$ is thus the unique solution to the corresponding first-order condition [4]:

$$\left[\tilde{\phi}_2(b_2) - b_2\right]\left[\frac{N_1 f_1\left[\tilde{\phi}_1(b_2)\right]\tilde{\phi}_1'(b_2)}{F_1[\tilde{\phi}_1(b_2)]} + \frac{(N_2-1) f_2\left[\tilde{\phi}_2(b_2)\right]\tilde{\phi}_2'(b_2)}{F_2[\tilde{\phi}_2(b_2)]}\right] = 1 \tag{9}$$

Satisfying the boundary conditions

- $\tilde{\phi}_1(r_1) = \tilde{v}_1$ and $\tilde{\phi}_2(r_2) = \tilde{v}_2$
- $\tilde{\phi}_1(\gamma_1^*) = \tilde{\phi}_2(\gamma_2^*) = \bar{v}$ for some $\gamma_1^* \in (r_1, \bar{v})$ and $\gamma_2^* \in (r_2, \bar{v})$

Flambard and Perrigne (2006) show that the differential Equation 9 can be rewritten in terms of bid distributions. The binding reserve introduces a complication because we do not observe

[4]This first-order condition is the analogue of Equation 3 in Flambard and Perrigne (2006) in our auction setting.

observe rebroadcaster bids below r_0. Therefore, we can only recover the truncated distribution of valuations above this reserve. Let $G_i^*(b) = (F_i[\phi_i(b)] - F_i[r_0])/(1 - F_i[r_0])$ be the distributions for each bidder type $i \in 1, 2$ truncated below at r_0, and let g_i^* be the corresponding densities $g_i^*(b) = (f_i[\phi_i(b)]\phi_i'(b))/(1 - F_i[r_0])$. Then, we can follow Flambard and Perrigne (2006), express all elements in Equation 9 in terms of the truncated bid distributions, and invert the first-order condition as follows:

$$v_2 = b_2 + \frac{1}{\frac{N_1 g_1^*(b_2)(1-F_1[r_0])}{(1-F_1[r_0])G_1^*(b_2)+F_1[r_0]} + \frac{(N_2-1)g_2^*(b_2)(1-F_2[r_0])}{(1-F_2[r_0])G_2^*(b_2)+F_2[r_0]}} \tag{10}$$

Proposition 1 in Flambard and Perrigne (2006) shows that if certain conditions hold, Equation 10 nonparametrically identifies $F_2[\cdot]$ on $[r_0, \bar{v}]$ from the distributions of observed bids G_i^*.

When handle $F_i[r_0]$ and N_i, the remaining parameters in Equation 10, as follows: As mentioned above, $F_1[\cdot]$ is observed in our data on all support $[0, \bar{v}]$, and, consequently, $F_1[r_0]$ is also observed. We simply assume that $F_2[r_0] = F_1[r_0]$, where $F_1[r_0]$ is directly estimated using the observed valuation distribution of Yahoo DSP evaluated at the reserve price value r_0. And for N_i, we use the maximum number of observed participants $N_{i,t}^*$ of each type i across all observed auctions t as an estimate of the number of potential bidders N_i , which are assumed to be constant across all auctions. That is we set $N_i = max_{t=1,\ldots,T} N_{i,t}^*$ in Equation 10 .

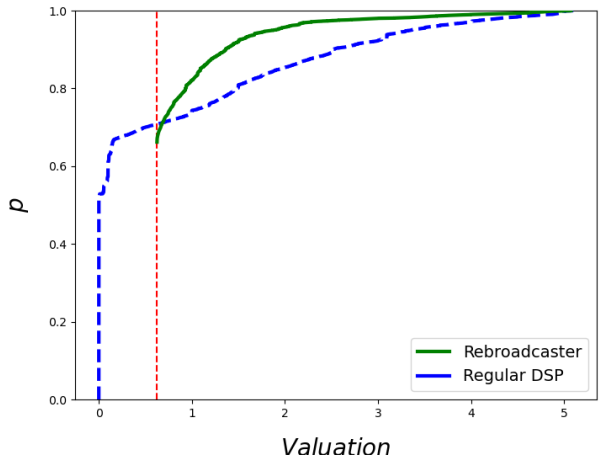
Given the known valuation distribution F_1 of the regular DSPs and the estimated distribution F_2, we can infer the heuristic bidding strategy of the rebroadcasters $\tilde{b}_2(\cdot)$ characterized in Equation 2. To obtain the corresponding regular DSP bid function $\tilde{b}_1(\cdot)$ in Equation 2, we use OLS and regress the Yahoo DSP bids on valuations and the square of valuations, using observations with bids strictly above r_0. Given $\tilde{b}_i$, building $\tilde{\beta}_i(\cdot|r_i)$ is straightforward for any reserve price value r_i. This is specially useful in our counterfactual exercise where we compare the publisher's revenue and bidders' surplus of the heuristic bidding strategy currently used in production with the counterfactual Bayes-Nash equilibrium strategy.

7.2 Estimation Results

To capture changes in impressions opportunities patterns during the day, we perform our analysis hourly. As discussed in the previous section, we assume that the valuation distribution of regular bidders is the same as the observed one from Yahoo DSP. For rebroadcasters, we use Equation 10 to recover the valuations, and use nonparemetric kernel techniques to estimate the corresponding distribution.

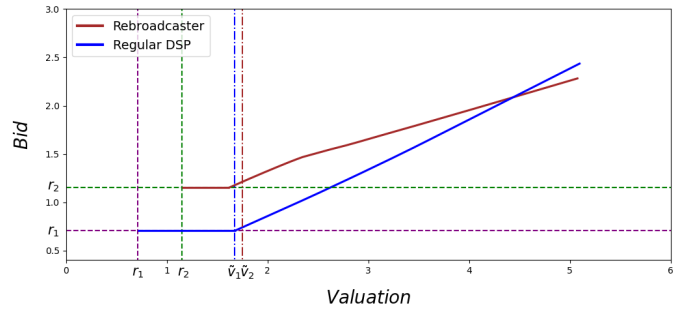
As an illustration, Figure 4 shows the valuation cumulative distribution functions of the regular DSPs (blue dashed line) and rebroadcasters (green line) during the 13th hour of the day (UTC time). For further details, Figures A.4 and A.5 in the Appendix display the distributions of bidders for each hour of the day. The rebroadcasters' cumulative distribution function is truncated for valuations below 56 cents, for which corresponding unobserved bids are below r_0 (dashed red line in Figure 4). This is not the case for regular DSPs for which we do observe Yahoo DSP valuations independently of the submitted bids. Note that not all opportunities are valuable for regular DSPs. In particular, Figure 4 shows that around 60% of opportunities have no value for regular DSPs.

Fig. 4. Valuation CDFs: Regular DSPs and Rebroadcasters (Hour 13th)



Notes: Plots of the valuation CDF of regular DSPs and the truncated valuation CDF of rebroadcasters.

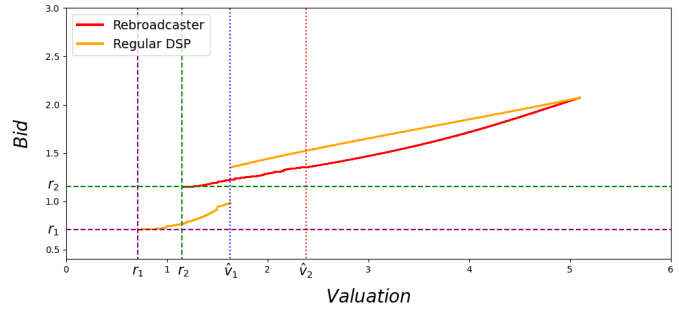
Fig. 5. Current Heuristic Bidding Functions (Hour 13th)



Notes: Plots of the current heuristic bid functions $\tilde{\beta}_1$ and $\tilde{\beta}_2$ of regular DSPs and rebroadcasters respectively during the 13th hour of the day (UTC time)

Figure 5 displays the observed heuristic bidding function $\tilde{\beta}_1$ of the regular DSPs (blue line) and the estimated heuristic bidding function $\tilde{\beta}_2$ of the rebroadcasters (purple line) during the 13th hour of the day when facing the asymmetric reserve prices used in production (r_1 and r_2), as characterized in Equation 2. As previously discussed, each bidder type does not participate in the auction if valuations are below the assigned reservation value. Bidders submit a bid that is equal to the reserve price when valuations are above the reserve price and below the corresponding thresholds $\tilde{v}_1$ and $\tilde{v}_2$, which are equal to \$1.67 and \$1.84 respectively. Finally, bidding functions are strictly increasing for valuations above $\tilde{v}_1$ and $\tilde{v}_2$.

Fig. 6. Bidding Functions: Bayes-Nash Equilibrium (Hour 13th)



Notes: Plots of the Bayes-Nash bid functions β_1 and β_2 of regular DSPs and rebroadcasters respectively

8 COUNTERFACTUAL: BAYES-NASH EQUILIBRIUM MODEL

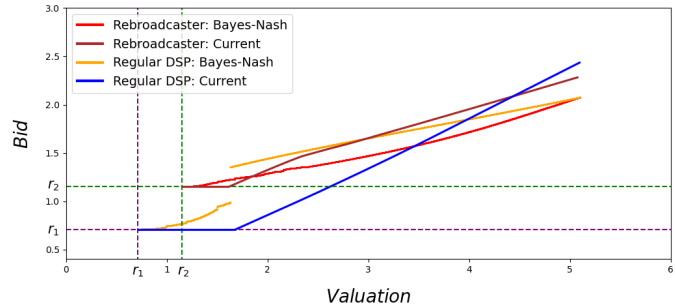
Given valuations and corresponding distribution estimates, we can simulate the impact of bidders adopting a Bayes Nash equilibrium bidding strategy (β_1 and β_2) characterized in Equation 4. The portion of the function captured by the function $b_i(v)$ can be nonparametrically estimated using Equation 5. For $\hat{b}_i(v)$, we follow Bajari (2001) and Hubbard et al. (2013), and use a polynomial approximation of the functions ϕ_1 and ϕ_2 (see Appendix for details). Note that the Bayes-Nash equilibrium characterization in Equation 4 is valid if inequality in Equation 3 holds. We confirmed this condition holds for all hours.

As in the previous section, figures below illustrate the results for the 13th hour of the day. Figure 6 shows the Bayes-Nash equilibrium bidding strategy. The orange lines correspond to the Bayes-Nash bidding function employed by regular DSPs (β_1), and the red line captures rebroadcasters bidding function (β_2), evaluated at the production reserve prices r_1 and r_2 respectively. The functions are the result of the equilibrium conditions characterized in Equation 4. Both bidding functions are strictly increasing starting at the corresponding reserve price: r_1 for regular DSPs , and r_2 for rebroadcasters. As discussed in Kotowski (2018) , there is a discontinuity in the regular DSP bidding function at the valuation $\hat{v}_1$ that is equal to \$2.52. At $\hat{v}_1$, regular DSPs are indifferent between bidding as if rebroadcasters did not participate in the auction (Equation 5), and fully internalizing rebroadcasters' competition (differential Equation 6).

Figure 7 overlaps the current heuristic and the Bayes-Nash bidding strategies. Under the heuristic model, bidders are consistently underbidding when their bid response equals the reserve price. On the other hand, for high valuations, the Bayes-Nash response of regular DSPs falls below their current heuristic. This is a common pattern across all hours of the day (see Figures A.6 and A.7 in the Appendix).

The impact of different bidding strategies on metrics like publisher revenue and bidder surplus depends on the valuation distributions. To estimate the counterfactual, we proceed as follows: First, we recover valuations by sampling auction data from the monitoring bucket with reserve price r_0. Each sample contains information about the number of participants of each type and their corresponding bids, allowing us to recover valuations using the estimated inverse heuristic bidding function. We then compute bid responses for both the heuristic and the Bayes-Nash bidding strategies when reserve prices are set to production (r_1 and r_{prod}), enabling us to determine the

Fig. 7. Bidding Functions: Bayes-Nash vs Current (Hour 13th)



Notes: Plots of the current and Bayes-Nash bid functions of regular DSPs and rebroadcasters

Table 4. Counterfactual simulation of Bayes-Nash Equilibrium

	Current	Bayes-Nash	Lift ($)	Lift (%)
Publisher revenue per request	1.24	1.33	0.08	6.84
	(0.62)	(0.58)	(0.28)	
Bidder surplus per request	1.21	1.18	-0.03	-2.80
	(0.99)	(1.05)	(0.34)	
% Non-Cleared Auctions	7.24%	7.24%		0.00%

Notes: Simulated results are based on 48,000 auctions randomly drawn from the data.

average bid, bidder surplus, and corresponding publisher revenue for each strategy. We simulate 48,000 auctions and report the results in Tables 4 and 5.

Table 4 compares the overall impact of switching from the current heuristic to the Bayes-Nash bidding strategy. The change would benefit publishers, increasing their expected auction revenue by 8 cents (a 6.84% increase). However, this comes at a cost to bidders, who would experience a 3-cent reduction in surplus per auction (a limited 2.8% decrease). Both strategies maintain the same proportion of auctions (7.24%) with no bids above the reserve price, as bidders in both cases submit bids whenever their valuations exceed the reserve prices.

Table 5 breaks down these effects by bidder type, revealing substantial heterogeneity. The impact on publisher revenue differs dramatically between bidder types: regular DSPs would generate a 24-cent increase (a 33.83% rise from 72 to 96 cents), while rebroadcasters would cause a 16-cent decline (a 30% drop from 52 to 37 cents). Differences extend to winning frequencies: regular DSPs would increase their win rate by 11.44%, while rebroadcasters would see a nearly identical but opposite decrease of 11.54%. In terms of surplus, regular DSPs would face a 3-cent increase (3.85% in percentage terms), while rebroadcasters would experience a substantially larger 7-cent decline (20% decrease). The only metric showing no variation is the percentage of auctions with no bids above their respective reserve prices.

Table 5. Counterfactual simulation of Bayes-Nash Equilibrium by Bidder Type

	Current	Bayes-Nash	Lift ($)	Lift (%)
Publisher's Revenue per request				
Regular DSPs	0.72	0.96	0.24	33.83
	(0.81)	(0.80)	(0.52)	
Rebroadcaster	0.52	0.37	-0.16	-30.03
	(0.65)	(0.60)	(0.54)	
Winning Frequency				
Regular DSPs	54.07%	65.53%		11.44%
Rebroadcaster	38.76%	27.22%		-11.54%
Surplus per request				
Regular DSPs	0.88	0.92	0.03	3.85
	(0.80)	(0.79)	(0.06)	
Rebroadcaster	0.33	0.26	-0.07	-20.50
	(0.65)	(0.62)	(0.29)	
% All Bids Below Reserve				
Regular DSPs	20.27%	20.27%		0.00%
Rebroadcaster	47.62%	47.62%		0.00%

Notes: Simulated results are based on 48,000 auctions randomly drawn from the data.

9 DISCUSSION

We document a simplified bidding heuristic that leads to partial pooling at the reserve price in auction markets for digital display advertising. Our evidence is both direct - in the form of the actual bidding strategy observed for one of the bidders - and indirect in the form of two patterns in the distribution of bids: 1) a mass point at reserve that disappears whenever the reserve randomly shifts to a much lower level, and 2) a right tail of the distribution that does not change when the the reserve randomly shifts to a much lower level.

To understand the economic consequences of this non-equilibrium heuristic behavior and its associated partial pooling of bids at reserve, we use a counterfactual analysis to compare the publisher's revenue and the bidders' surplus under the heuristic and the Bayes-Nash Equilibrium bidding strategies. We find that the bidding heuristic with partial pooling can lead to suboptimal outcomes for publishers relative to Bayes-Nash equilibrium strategies. Specifically, we find that switching to a Bayes-Nash equilibrium model could increase publisher revenue by 7%. The counterfactual analysis also reveals that while publishers would benefit from a shift to more strategic bidding, Rebroadcasters would specially experience a 20% decrease in surplus (7 cents per auction) under the Bayes-Nash equilibrium.

Our study also underscores the importance of understanding real-world bidding behavior in online ad auctions. Classical auction theory, while providing a useful framework, does not always accurately predict how bidders act in practice. The prevalence of simpler, heuristic-based strategies, like the one identified in this paper, highlights the need for more empirical research to inform the development of more effective auction mechanisms.

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A APPENDIX

A.1 Details of Polynomial Approximation of $\hat{b}_i(v)$

For $\hat{b}_i(v)$, we follow Bajari (2001) and Hubbard et al. (2013), and use the following polynomial to approximate the functions ϕ_1 and ϕ_2 :

$$\phi_i(b) = \eta^* + \sum_{m=0}^{3} \alpha_{i,m}(b - \eta^*)^m \tag{11}$$

for $i \in \{1, 2\}$. η^* and coefficients $\alpha_{i,m}$ for $m \in \{0, 1, 2, 3\}$ are parameters to be estimated along with the valuation thresholds $\hat{v}_1$ and $\hat{v}_2$. To recover the parameters we derive the function $H_{i,t}(\cdot)$ from Equation 4 as follows

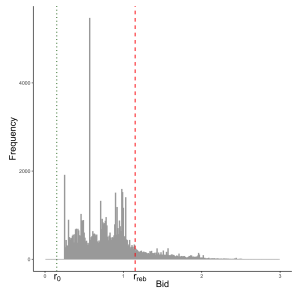
$$H_{i,t}(b, \alpha_i, \alpha_j, \hat{v}_i, \eta^*) = \begin{cases} 0 & if\ \phi_i(b) < r_i \\ b_i(\phi_i(b)) - \phi_i(b) + \int_{r_i}^{\phi_i(b)} \left[\frac{\hat{F}_i(z)}{\hat{F}_i(\phi_i(b))}\right]^{N_i-1} dz & if\ \phi_i(b) \in [r_i, \hat{v}_i] \\ 1 - [\phi_i(b) - b]\left[\frac{N_j \hat{f}_j[\phi_j(b)]\phi_j'(b)}{\hat{F}_j[\phi_j(b)]} + \frac{(N_i-1)\hat{f}_i[\phi_i(b)]\phi_i'(b)}{\hat{F}_i[\phi_i(b)]}\right] & if\ \phi_i(b) > \hat{v}_i \end{cases} \tag{12}$$

for $i \neq j$ and $i, j \in \{1, 2\}$. $\hat{F}_i[\cdot]$, $\hat{F}_j[\cdot]$, $\hat{F}_i[\cdot]$ and $\hat{f}_j[\cdot]$ correspond to the cumulative distribution function and probability distribution function estimates of the valuations. $\alpha_i = (\alpha_{i,0}, \alpha_{i,1}, \alpha_{i,2}, \alpha_{i,3})$ and $\alpha_j = (\alpha_{j,0}, \alpha_{j,1}, \alpha_{j,2}, \alpha_{j,3})$ correspond to the set of parameters defining the inverse bidding functions in Equation 11.

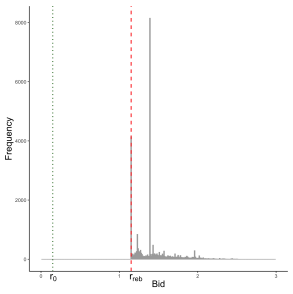
We solve the following constrained optimization problem to obtain α_1, α_2, $\hat{v}_1$, $\hat{v}_2$ and η^*

$$\begin{aligned} \min_{\alpha_1, \alpha_2, \hat{v}_1, \hat{v}_2, \eta^*} & \sum_i \sum_t H_{i,t}(b, \alpha_i, \alpha_j, \hat{v}_i, \eta^*) \\ \text{s.t.} \quad & \phi_1(\eta^*) = \phi_2(\eta^*) = \bar{v} \\ & \phi_1(b_2(\hat{v}_2)) = \hat{v}_1 \\ & \phi_2(b_2(\hat{v}_2)) = \hat{v}_2 \end{aligned} \tag{13}$$

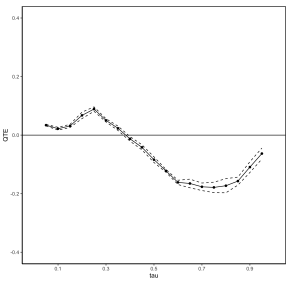
Fig. 1. Bid Distributions for Low/High Reserve Prices Bidders



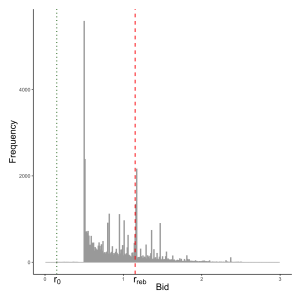
(a) Low Reserve Price Rebroadcaster A



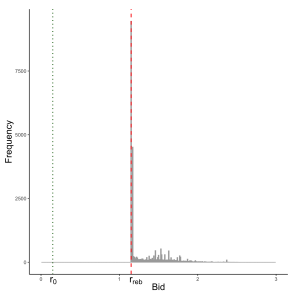
(b) High Reserve Price Rebroadcaster A



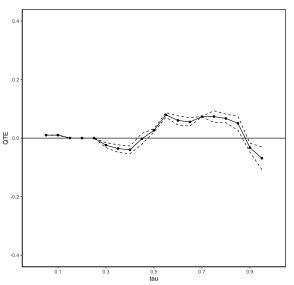
(c) QTE Rebroadcaster A



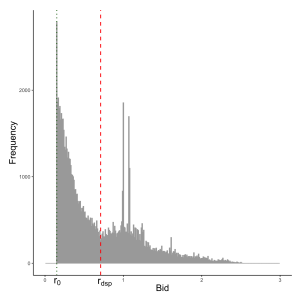
(d) Low Reserve Price Rebroadcaster B



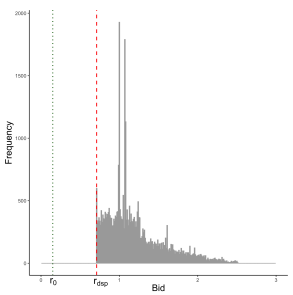
(e) High Reserve Price Rebroadcaster B



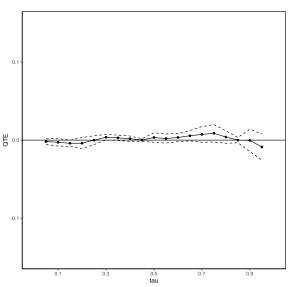
(f) QTE Rebroadcaster B



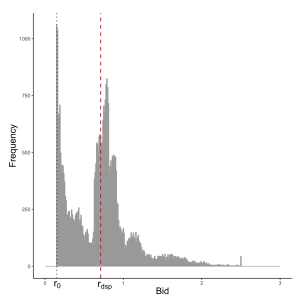
(g) Low Reserve Price Regular DSP C



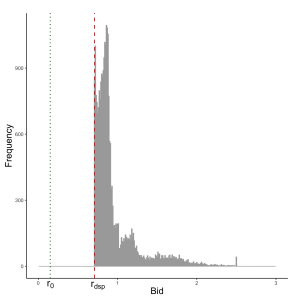
(h) High Reserve Price Regular DSP C



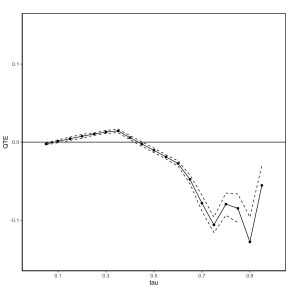
(i) QTE Regular DSP C



(j) Low Reserve Price Regular DSP D

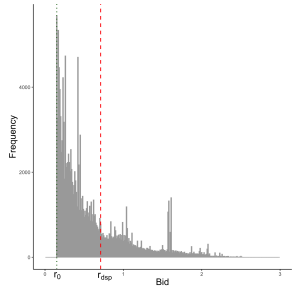


(k) High Reserve Price Regular DSP D

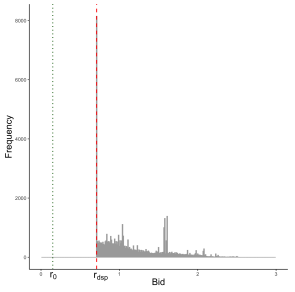


(l) QTE Regular DSP D

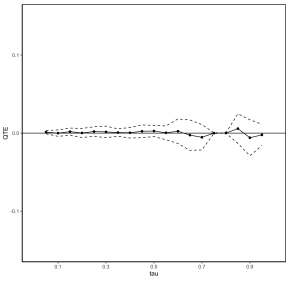
Fig. 2. Bid Distributions for Low/High Reserve Prices Bidders



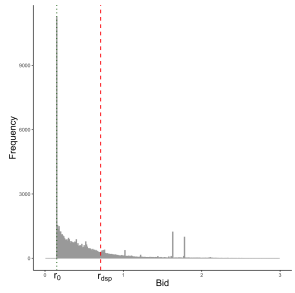
(a) Low Reserve Price Regular DSP E



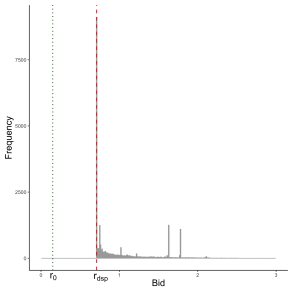
(b) High Reserve Price Regular DSP E



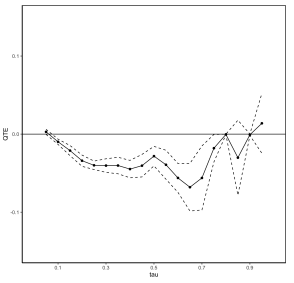
(c) QTE Regular DSP E



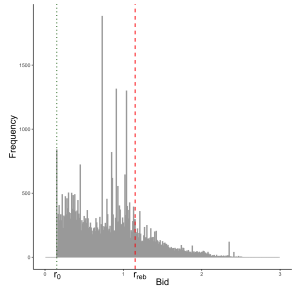
(d) Low Reserve Price Regular DSP F



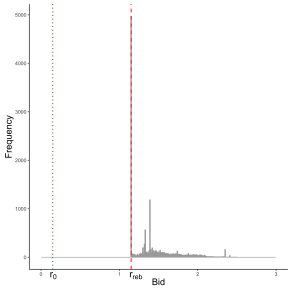
(e) High Reserve Price Regular DSP F



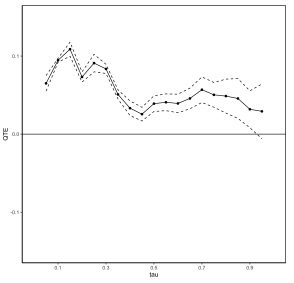
(f) QTE Regular DSP F



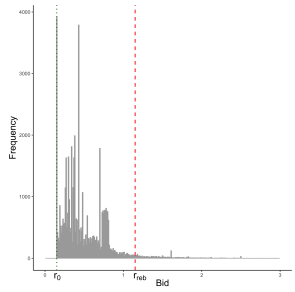
(g) Low Reserve Price Rebroadcaster G



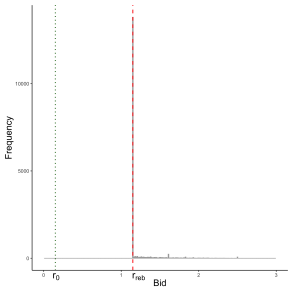
(h) High Reserve Price Rebroadcaster G



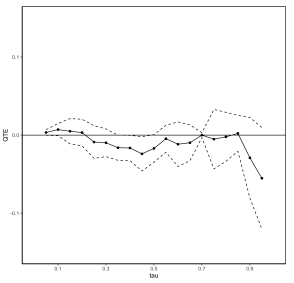
(i) QTE Rebroadcaster G



(j) Low Reserve Price Rebroadcaster H

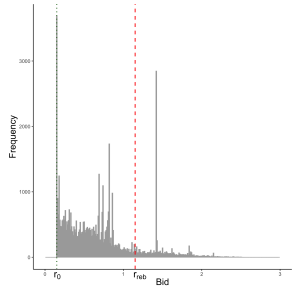


(k) High Reserve Price Rebroadcaster H

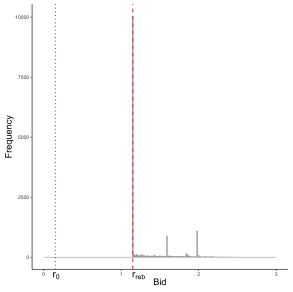


(l) QTE Rebroadcaster H

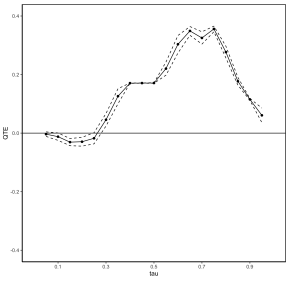
Fig. 3. Bid Distributions for Low/High Reserve Prices Bidders



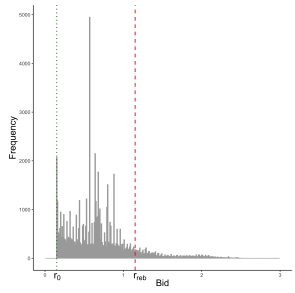
(a) Low Reserve Price Regular DSP I



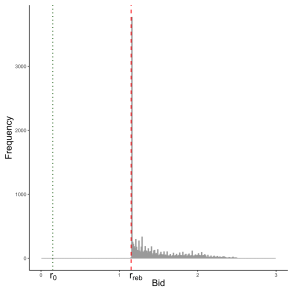
(b) High Reserve Price Regular DSP I



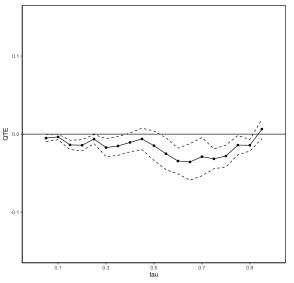
(c) QTE Regular DSP I



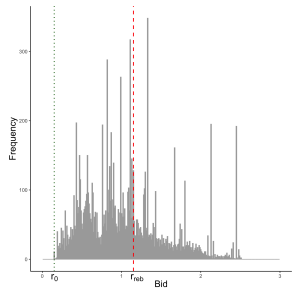
(d) Low Reserve Price Regular DSP J



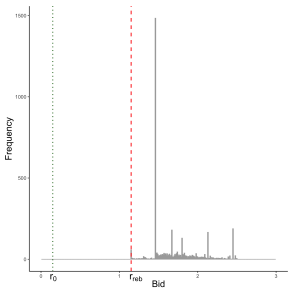
(e) High Reserve Price Regular DSP J



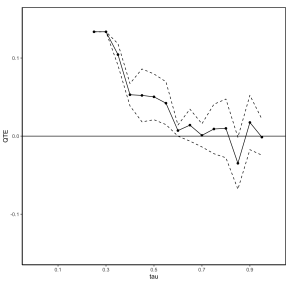
(f) QTE Regular DSP J



(g) Low Reserve Price Rebroadcaster K

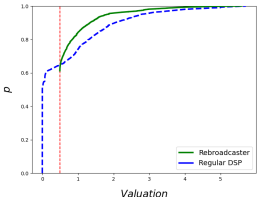


(h) High Reserve Price Rebroadcaster K

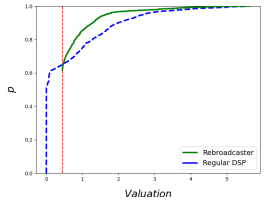


(i) QTE Rebroadcaster K

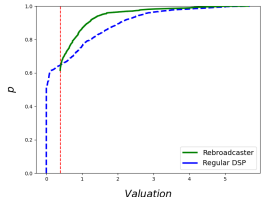
Fig. 4. Valuation CDFs per Hour 0-11: Regular DSPs and Rebroadcasters



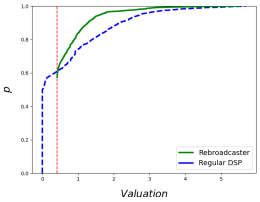
(a) CDFs Hour 0



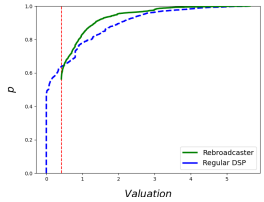
(b) CDFs Hour 1



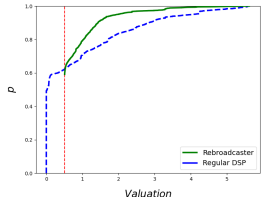
(c) CDFs Hour 2



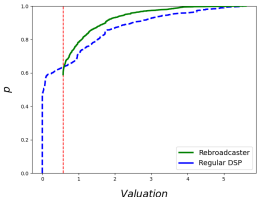
(d) CDFs Hour 3



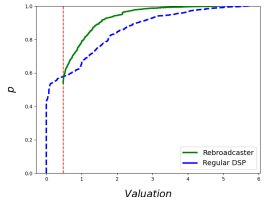
(e) CDFs Hour 4



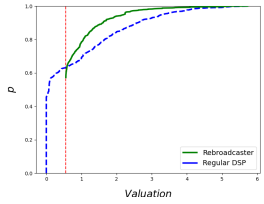
(f) CDFs Hour 5



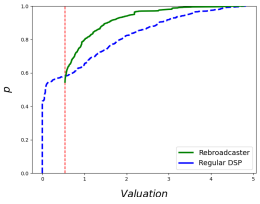
(g) CDFs Hour 6



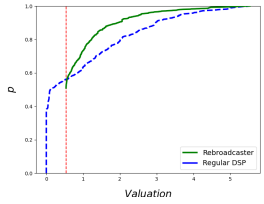
(h) CDFs Hour 7



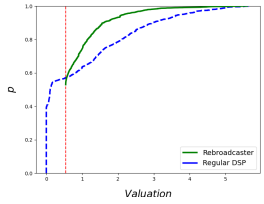
(i) CDFs Hour 8



(j) CDFs Hour 9

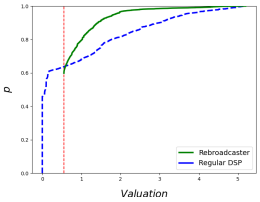


(k) CDFs Hour 10

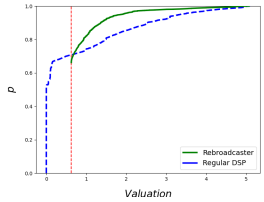


(l) CDFs Hour 11

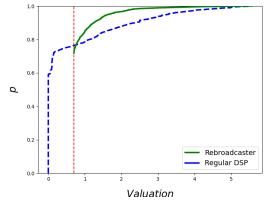
Fig. 5. Valuation CDFs per Hour 12-23: Regular DSPs and Rebroadcasters



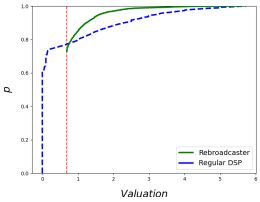
(a) CDFs Hour 12



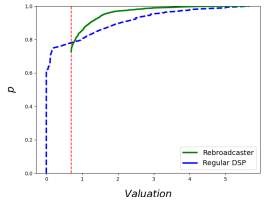
(b) CDFs Hour 13



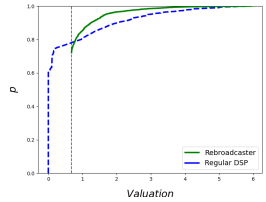
(c) CDFs Hour 14



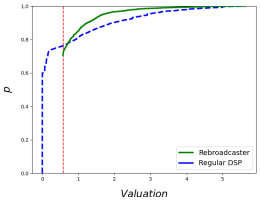
(d) CDFs Hour 15



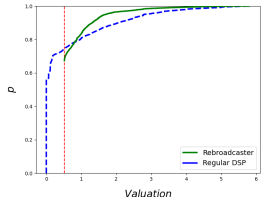
(e) CDFs Hour 16



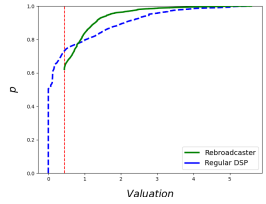
(f) CDFs Hour 17



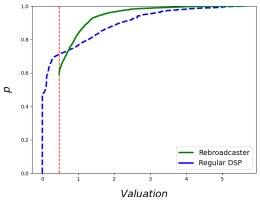
(g) CDFs Hour 18



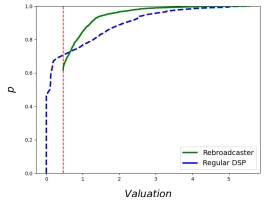
(h) CDFs Hour 19



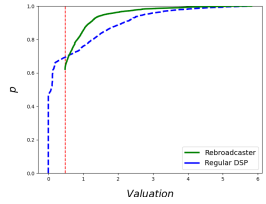
(i) CDFs Hour 20



(j) CDFs Hour 21

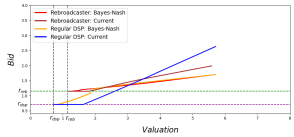


(k) CDFs Hour 22

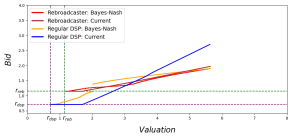


(l) CDFs Hour 23

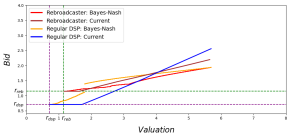
Fig. 6. Bidding Strategies per Hour 0-11: Regular DSPs and Rebroadcasters



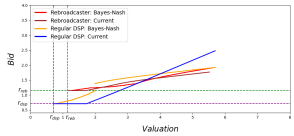
(a) Hour 0



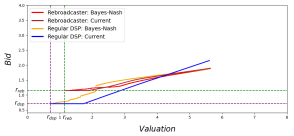
(b) Hour 1



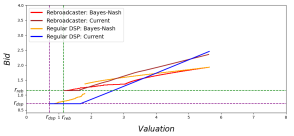
(c) Hour 2



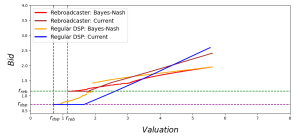
(d) Hour 3



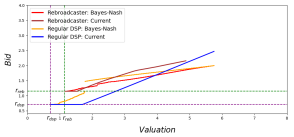
(e) Hour 4



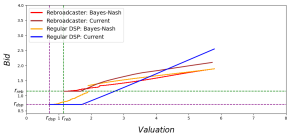
(f) Hour 5



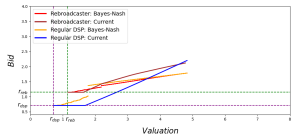
(g) Hour 6



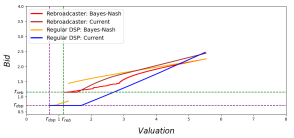
(h) Hour 7



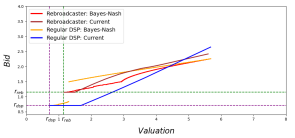
(i) Hour 8



(j) Hour 9

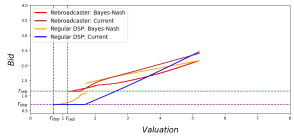


(k) Hour 10

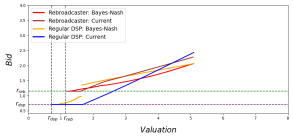


(l) Hour 11

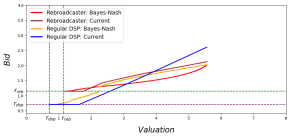
Fig. 7. Bidding Strategies per Hour 12-23: Regular DSPs and Rebroadcasters



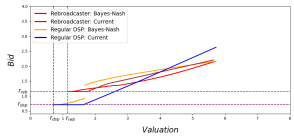
(a) Hour 12



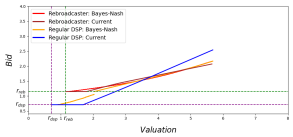
(b) Hour 13



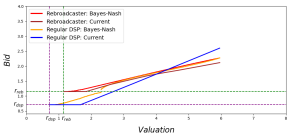
(c) Hour 14



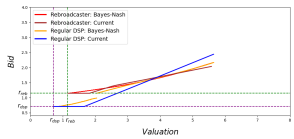
(d) Hour 15



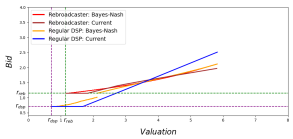
(e) Hour 16



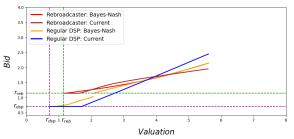
(f) Hour 17



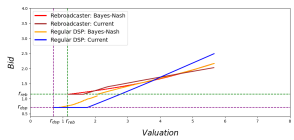
(g) Hour 18



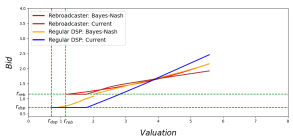
(h) Hour 19



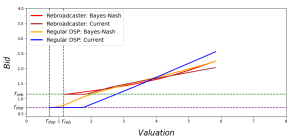
(i) Hour 20



(j) Hour 21



(k) Hour 22



(l) Hour 23