

# Information Disclosure in Markets: An Empirical Analysis of a Search Advertising Market with Heterogeneous Advertisers

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## Abstract

Bidding in search advertising is commonplace today. However, determining a bid can be challenging in light of the complexity of the auction process. By designing the mechanism and aggregating the information of many bidders, the advertiser platform can assist less sophisticated advertisers. We analyze data from a platform that initiated a bid recommendation system and find that some advertisers may simply adopt the platform’s suggestion instead of constructing their own bids. We discover that these less sophisticated advertisers were lower-rated and uncertain about ad effectiveness before the platform began offering information through the recommended bids. We characterize an equilibrium model of bidding in the Generalized Second Price (GSP) auction and show that following the platform’s bid suggestion is theoretically sub-optimal. We then identify sophisticated and less sophisticated advertisers’ private values using observed bids and the disclosed information. Counterfactual results suggest that the ad platform can increase revenue and the total surplus when it shares more information. Furthermore, the hybrid of auto-bidding with manual bidding could be a more efficient mechanism as we substitute less sophisticated bidding behavior for algorithmic bidding. These results shed light on the importance of exploring interactions between sophisticated and less sophisticated players when designing a market.

## 1 Introduction

Search advertising is a significant component of online advertising, with its revenue in the United States being projected to reach US\$67,742 million in 2021.<sup>1</sup> It is also a powerful form of advertising since it reaches the group of consumers who already identify their interests through the use of search engines. Given its significant effect, it attracts advertisers from various industries. In this largely diverse group of advertisers, some are large corporations such as Apple, Amazon, and Nike, which are more experienced in advertising. Other advertisers

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<sup>1</sup><https://www.statista.com/outlook/dmo/digital-advertising/search-advertising/united-states>

are small business owners (such as mom-and-pop shops around the corner) who are less business-savvy, are less familiar with advertising strategies, and have limited budgets. Additionally, large search advertising platforms, such as Google, use a complicated auction format known as the Generalized Second Price (GSP) auction. The auction requires advertisers to form knowledge about quality score distributions, the bid distribution, and the number of clicks at each ad position before they bid (Edelman, Ostrovsky, and Schwarz (EOS 2007)[1], Varian 2007[2]). Obtaining these sets of information is costly since it requires effort and experience, and they are constantly change, increasing the difficulty for advertisers, especially those with limited resources.

In response to the difficulties faced by individual advertisers during the bidding process, ad platforms have developed numerous strategies for sharing information. For example, online advertising exchange marketplaces provide bid landscape forecasting of the probability distribution of market prices in real-time bidding ad auctions. Directly, Google shares its first-page bid estimates with all advertisers as a means to provide an estimate of how much they will need to bid in order for their ads to appear on the first page of search results. Amaldoss, Desai, and Shin's (2015)[3] analytical model indicates that if advertisers adhere to these bid estimates, the ad platform will generate more revenue. To our knowledge, limited empirical evidence is available on the impact of such strategies on market outcomes and advertisers' behaviors, probably due to the lack of quasi-experimental data with variations in information disclosure.

In this paper, we explore the impact of platform's information disclosure on advertisers and equilibrium market outcomes using unique data. In particular, we explore the following questions. How does releasing bid estimates influences market outcomes, e.g., prices and revenue? How does such information impact advertisers differently? Finally, how does the current information-sharing strategy compare with other mechanisms available in the advertising industry? To answer the above questions, we collaborate with a Yelp-like platform in China that releases the top three ad slots' bid estimates to all advertisers within a city while not revealing the information to advertisers in other cities for a month. Using such quasi-experimental variations in information availability, we can examine its impact on market outcomes and advertiser behavior. In addition, because of the unique context and event in this dataset, we can identify bidder behaviors that differ from the theoretically optimal bid in GSP, which are difficult to detect outside of the laboratory since bidder valuations are not observed. Then we measure the extent to which the different bidders' behaviors influence the market efficiency in our sample and explore reasons for observed deviations from profit maximization. Finally, we investigate alternative information sharing schemes in light of heterogeneous bidding behaviors and values.

We first use difference-in-differences methodology to examine the impact of bid estimates on market outcomes, comparing with another similar city according to pre-intervention metrics. We find that on average, advertisers submit higher bids which increase by 35%. Higher bids lead to higher market equilibrium prices: we observe the ad price (cost per click) grows by 19% post information release. To elucidate the reasons for market changes, we investigate the descriptive patterns of advertiser reactions. After the information release, 69 advertisers follow

the bid estimates on 20 percent of the bid-change occasions in order to compete for top ad positions. The pre-intervention data indicates that these advertisers are inferior in terms of their ratings and are uncertain about the advertising effectiveness and the bidding process. This "bidding right at the cutoff behavior" is a probability zero event under theoretically optimal bidding strategies in the GSP auction. We conjecture that these advertisers are displaying some form of availability heuristics (Tversky and Kahneman 1974) when they see the readily available bid estimates for use. As a result, they directly follow the suggestion instead of accessing probabilities and formulating an optimal bid themselves given the information. In response to such behavior, other advertisers, especially 114 high-value advertisers, have to raise their bids to increase their chances of winning the top advertising positions, which are valuable in generating consumer clicks. As a result, the competition for top ad slots becomes more intense due to the entry of less sophisticated advertisers who rely more on the bid estimates, which ultimately leads to an increase in the market equilibrium price.

To evaluate alternative information-sharing mechanisms, we need to understand what advertisers' private values are behind their bids. The complexity of the GSP mechanism makes it difficult to empirically model equilibrium bidding behavior in this auction. In addition, the interaction between strategic and non-strategic behaviors also presents a challenge. To address the issue, we adopt different empirical approaches for two groups of behaviors. For sophisticated advertisers, we characterize an equilibrium model of bidding in the GSP auction. We extend the symmetric independent private value (IPV) model developed by Guerre, Perrigne, and Vuong (GPV 2002)[4] to the GSP auction. We specifically incorporate realistic characteristics of the GSP auction environment in our model, which is different from the existing theoretical models (e.g., Edelman, Ostrovsky, and Schwarz (2007)[1], Ghose and Yang (2009) [5], Mela and Yao (2009) [6], Varian (2007)[2]). In our model, we establish the nonparametric identification of the Symmetric Independent Private Value (SIPV) model from observed bids in a GSP auction. This approach enables us to recover the joint distribution of bidders' private values from observed bids. We then propose a consistent two-step nonparametric approach for investigating the joint distribution of private values, which extends Guerre, Perrigne, and Vuong (GPV 2000)[4] findings to the case in GSP auctions.

In addition, for less sophisticated advertisers who rely on bid estimates, we nonparametrically estimate the upper bound and lower bound of their value distribution based on the observed bids and three bid estimates per bid change event (Haile and Tamer 2003 [7], Aradillas-Lopez et al. 2013). Based on these estimated values, we simulate advertisers' bids under alternative information environments in an envy-free equilibrium proposed by EOS (2007). According to our analysis, the current mechanism of information sharing among the top three bid estimates increases ad revenue by 6-14% and the overall surplus by 6-7%. We also consider three alternative mechanisms of information sharing. First, we propose that the ad platform may redesign the top bid estimates by showing the expected top 3 values instead of the historical three highest rank scores. The redesign of the top 3 bid estimates raise revenue by 17% to 24%. Then we show how revenue and surplus perform when the platform share full information by designing bid estimates for all ad positions. The full information mechanism increases the advertising platform's

revenue by 29-45% and increases its total surplus by 16-18%. Then, we design the personalized bid estimates for the bid estimate takers, which is equivalent to bidding for this group of advertisers given their values. An analogy to this mechanism may be found in the popular automated bidding system currently in use by large ad platforms such as Google, Facebook, Microsoft, etc., as well as by third-party advertising agencies that bid on behalf of their clients. We find that the personalized bid estimates increase total surplus by 19-20% and the platform’s revenue by 44-56%. In addition, the surplus fluctuates with the proportion of less sophisticated bidders in the overall bidder population since their previous inefficient bidding patterns cause a deficit in the surplus. These counterfactual results have potential implications for evaluating alternative information-sharing strategies for advertising platforms.

Our contributions to the growing literature on characterizing strategic and non-strategic behavior in response to information disclosure are empirical, methodological, and policy-oriented. Empirically, we document advertisers’ heterogeneous responses to bid estimates released in the GSP auction. Indeed, this is the first empirical evidence that some advertisers do adhere to the bid estimates provided by advertising platforms, even though we have shown that this is not optimal for them to do. In addition, we leverage our unique setting to identify some sub-optimal bidding behaviors that are well-documented in laboratory studies but are more difficult to detect in the field data due to the absence of data on valuations. This type of documentation is precious because it illustrates the importance of careful market design in that even a small variation in market design will have a significant impact on market outcomes. It also emphasizes the importance of evaluating not only the equilibrium behavior we might expect experienced and sophisticated players to show but also the effects the design may have on less sophisticated players and the interaction between them.

Methodologically, we develop an equilibrium model of bidding in the GSP auction that is both empirically realistic and computationally feasible and convenient for researchers to infer bidder valuations. Moreover, we leverage our unique setting and data to back out valuations from non-strategic players’ bids, which is different from other empirical literature that analyzes asymmetric behaviors in auctions (e.g., Krasnokutskaya (2011), Hortacsu and Puller (2008), Gayle and Richard (2008)). The proposed approach relies less on the equilibrium assumption of all bidders’ behaviors. Instead, we deploy bidders’ responses to the information to infer their underlying values. Since GSP auctions are widely used in search advertising, our proposed equilibrium model and GPV-like approach combined with novel data utilization can be implemented in other empirical research that seeks to understand bidder heterogeneity in GSP auctions.

On a policy level, this paper quantifies the benefits of information disclosure for the ad platform and its heterogeneous group of advertisers. This exercise provides insights for platforms when weighing the designs of information disclosure for their participants. Additionally, given the documented non-strategic responses to the information, we propose alternative mechanisms for sharing information that can achieve higher efficiency in a market with non-strategic advertisers. Our research specifically compares two popular bidding strategies utilized by most search advertising platforms: manual bidding and automated bidding. The counterfactual exercise indicates

that auto-bidding can be a more efficient mechanism, given that some advertisers may lack the knowledge required to bid optimally in a complex auction mechanism like GSP. The result is indeed consistent with the observation that some third-party advertising agencies and the ad platforms themselves are bidding on behalf of advertisers.

The rest of the paper is organized as follows. In the next session, we will review related work. Section 3 describes the empirical background and the information disclosure event. In section 4, we will demonstrate empirical evidence of advertisers' heterogeneous responses and the impact of information on market outcomes. In section 5, we establish an empirical model of bidding in GSP and show estimation results. In section 6, we conduct several counterfactual exercises to show how market outcomes vary with different information disclosure mechanisms. Lastly, section 7 concludes the paper and points out the direction for future research.

## 2 Related Literature

### 2.1 Empirical Analysis of Information Disclosure on Market Outcomes

This study contributes to the growing empirical literature on the effects of information disclosure on market outcomes. Many empirical studies in this area directly test the Linkage Principle, for example, De Silva et al. (2008) [8] and Cho, Paarsch, and Rust (2014) [9]. There are no common value components in the information structure in our particular case. The information contains historical bids as references for advertisers. Further, the GSP setting assumes that advertisers have private value, i.e., bidders know their own value per click. Therefore, even though they are informed about how others are bidding through bid estimates, they do not change their value per click. Thus, the Linkage Principle is unlikely to play a role in our empirical study.

In addition to papers that directly test the Linkage Principle, Tadelis and Zettelmeyer (2015) [10] study the impact of information disclosure in wholesale automobile auctions. The researchers conduct field experiments releasing car quality information for dealers and find such information increases the match between horizontally differentiated buyers and vertically ranked used cars, enhancing competition and increasing the auctioneers' revenue. In our study, we find a similarly significant increase in revenue generated by a different channel. We find that the information of bid estimates encourages previously uncertain and inferior advertisers to compete for the top ad slots, thereby causing the market price to rise.

### 2.2 GSP

In 2002, Google introduced the "generalized second price" auction. Since then, there has been a proliferation of literature that looks at this widely used auction mechanism in search advertising. Edelman, Ostrovsky, and Schwarz (EOS 2007) and Varian (2007) first develop the envy-free equilibrium that produces the lowest revenue but the highest surplus for advertisers under complete information. With incomplete information, EOS 2007 modeled the GSP as an ascending auction for multiple goods (they call it the Generalized English auction). Athey and

Nekipelov (2011) [11] develop a new model that incorporates more realistic features of GSP auctions in sponsored search advertising. Specifically, they consider the fact that queries arrive more quickly than advertisers can change their bids. This uncertainty leads to less efficient allocations than alternative models. This paper defines a model of bidding under incomplete information. Bids are submitted simultaneously, and bidders have private values about each click. We also consider bidders' uncertainty regarding query arrivals. We assume a Bayesian Nash equilibrium which contains the locally envy-free equilibrium as one special case. In our counterfactual simulations, we will adopt this approach of bidding in a Generalized English auction to compute the optimal bids for sophisticated advertisers given their valuations, similar to Ostrovsky and Schwarz (2016) [12].

### 2.3 Empirical Studies of Online Search Advertising

Moreover, our paper contributes to the broader empirical literature in marketing that discusses the position effects in online search advertising. Jerath et al. (2011) [13] point out an interesting phenomenon in the GSP auction under a pay-per-click mechanism: the inferior firm has an even stronger incentive to bid aggressively since it only has to pay for consumers who are unfamiliar with the firms' reputations. Narayanan and Kalyanam (2015) [14] also find that position effects are stronger when the advertiser is smaller and when the consumer has little prior experience with the keyword for the advertiser. This empirical evidence is consistent with our observation that lower-rated advertisers are determined to get to the top and thus tend to follow bid estimates.

In addition to the position effect literature, this paper contributes to a broader discussion about search advertising (e.g. Ghose and Yang (2009), Mela and Yao (2009)). In general, the listed papers focus on the consumer side and examine how consumer behaviors influence advertisers' strategies. We emphasize the supply side of the industry by studying the interaction between advertising platforms and advertisers, which is equally significant to the platform economy but is largely ignored due to a lack of quasi-experimental data.

### 2.4 Empirical Findings of Behavioral Firms in Auctions

The empirical evidence of advertisers' nonstrategic response to bid estimates contributes to the body of literature documenting behaviors that deviated from profit-maximizing strategies. In the absence of information on the bidders' values, it can be difficult to observe the nonstrategic behavior of bidders outside of laboratories. As a result, the studies in this literature may be context-specific. A number of papers have documented that bidders sometimes submit their bids at the last possible moment in eBay auctions, a phenomenon known as "sniping." Even though sniping is theoretically predicted to be costly and ineffective, researchers find an empirical pattern of sniping and attempt to explain it. (See Ockenfels and Roth (2002, 2006) [15] [16], Bajari and Hortacsu (2003) [17], Barbaro and Bracht (2004) [18]) Additionally, in the electricity market, Hortacsu and Puller (2008) [19] find that small-scale firms used excessively steep bid schedules, which significantly deviates from theoretical benchmarks, whereas large companies followed a theoretically static profit maximization pattern. The examples provided above demonstrate

the importance of considering heterogeneity among participants and the interaction between sophisticated and unsophisticated agents when designing a new market. In our research, we document bidders' nonstrategic responses in a GSP auction, which is commonplace in search advertising but seldom studied. In addition, we discuss the economic significance of such behavior in the market, as well as alternative information-sharing schemes for the ad platform to enhance market efficiency, taking into consideration the heterogeneity of advertisers.

## 2.5 Empirical Estimation of Value Distributions in Auctions

The paper contributes to methodological literature on the identification of bidder value distribution based on observed bids. In its early contributions, Paarsch (1992), Donald and Paarsch(1993, 1996) [20] [21], Laffont, Ossard and Vuong (1995) [22] parametrically identify bidders' private values at a first-price auction with symmetric bidders. Guerre, Perrigne and Vuong (2000) first proposes a computationally feasible estimation method for first price auction within the symmetric independent private value paradigm. Moreover, Campo, Perrigne, and Vuong (2003) [23] propose a consistent estimation procedure for first-price auctions with asymmetric bidders and affiliated private values. In this paper, we propose an independent value model of bidding in GSP, which is an understudied auction mechanism in the empirical auction literature, most likely due to the complexity of GSP being a non-truthful auction mechanism and its multiple equilibria. We describe the Bayesian Nash equilibrium of GSP bidding, considering the realistic features of the auction: quality scores. We show that equilibrium bids are "ex-post optimal" and therefore are straightforward to compute, given information on the equilibrium bid distribution and their quality score distributions. We can then infer bidders' value from the observed bid distribution and mark-up terms calculated from observed empirical data, similar to the GPV (2000) approach.

## 3 Data and Background

### 3.1 The Ad Platform

We collaborate with a leading online destination for discovering lifestyle services in China.<sup>2</sup> The advertising platform operates sponsored search advertising for a wide variety of lifestyle services, including restaurants, takeouts, travel, wedding services, etc. We specifically focus on the wedding service category because the platform introduced bid estimates in this category.

Advertisers bid on targeted time slots to have their ad displayed at the top of the page or among the organic search results. The top five slots are reserved for ads on the search result page. After that, ads are placed among every four organic search results. For example, the 6th ad is placed at the 9th position if one counts from the top down. Advertisers submit one bid for all positions, and then the ad platform ranks them based on their bids

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<sup>2</sup>The platform is similar to Yelp+Groupon in North America. As of 2020, it has 510.6 million Annual Transacting Users and 6.8 million Annual Active Merchants. The Company operates in over 2,800 cities and counties in China.

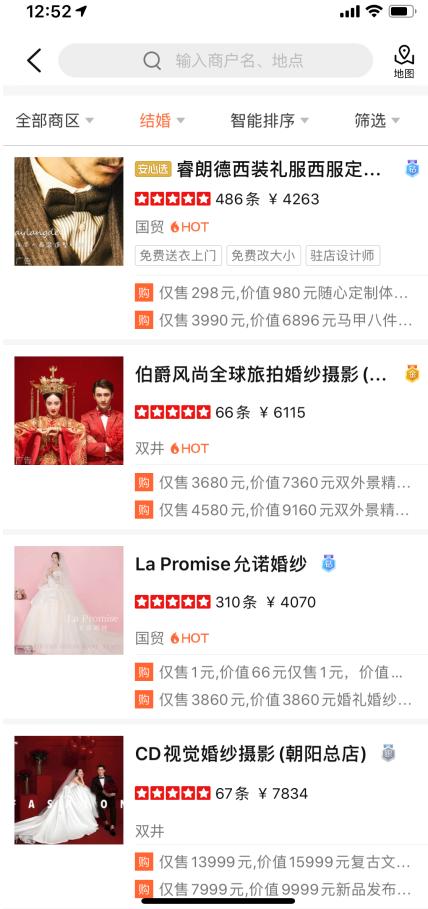


Figure 1: Wedding Service Category Search Result

and their quality scores. These are native ads, which means that the ad remarks are difficult to perceive since the sponsored ad logo is hidden under the merchant picture.

Similar to other sponsored search advertising platforms, this ad platform conducts Generalized Second Price (GSP) auctions.<sup>3</sup> The auction happens at the consumer's query level. Every time a consumer starts a search, the ad platform returns a list of advertisers that matches the query criterion. Then the platform assigns a quality score for each advertiser. The ad platform deploys a list of variables to predict a real-time quality score that can be thought of as a predicted Click Through Rate (CTR). After that, the ad platform ranks advertisers based on a ranking score  $r$ , which is equal to the multiplication of a quality score  $q$  and advertiser's bid  $b$  (i.e.,  $r = q * b$ ). Advertisers pay per click price. The price for ad slot  $k$  is the  $k + 1$ th highest rank score  $r_{k+1}$  divided by  $k$ th highest rank score ad's quality score  $q_k$  (i.e.  $p_k = \frac{r_{k+1}}{q_k}$ ).

<sup>3</sup>See Edelman et al. 2007. Varian 2007

### 3.2 The Introduction of Bid Estimates

The ad platform introduced bid estimates for wedding service advertisers in Xi'an, China, on August 13th, 2019.<sup>4</sup> On October 10th, 2021, the platform released bid estimates across the country. Accordingly, based on pre-intervention bid data, we selected Chengdu as a comparable city for evaluating the impact of information disclosures in Xi'an using the difference-in-differences method.

Following Google's First Page Bid Estimate strategy, the ad platform designed bid estimates as the top three highest rank scores adjusted by quality scores to inform advertisers how much they need to pay per click to get on the first, second, and third ad slot.<sup>5</sup> Formally, bid estimate for the first slot shown to advertiser  $j$ :  $s_{1j}$  is computed as the second-highest rank score  $r_2$  divided by that advertiser  $j$ 's quality score  $q_j$  ( $s_{1j} = r_2/q_{ij}$ ). The platform utilizes the most recent information available to predict the top three ad position bid estimates, and it updates this information on a daily basis. Specifically, the platform simulates a number of consumers  $i$  from various locations in the city who search for this specific advertiser  $j$  and predict their quality scores with this advertiser  $q_{ij}$  using some machine learning algorithms that take into account various features. The platform shows advertisers one bid estimate from the distribution of bid estimates based on multiple simulations of consumers.<sup>6</sup> Considering that bid estimates use all *ex-ante* information, they cannot guarantee 100% success in winning the top three positions since other bidders may change their bids and unexpected consumers may arrive in real-time.<sup>7</sup>

Figure 2 shows the advertiser's bidding page post bid estimates release. The section below the bid is where advertisers observe today's bid estimates for the first, second, and third positions. Below these estimates, there is a button that is labeled "Use This Price." Upon clicking this button, the advertiser's bid will automatically turn into the bid estimate they have selected.

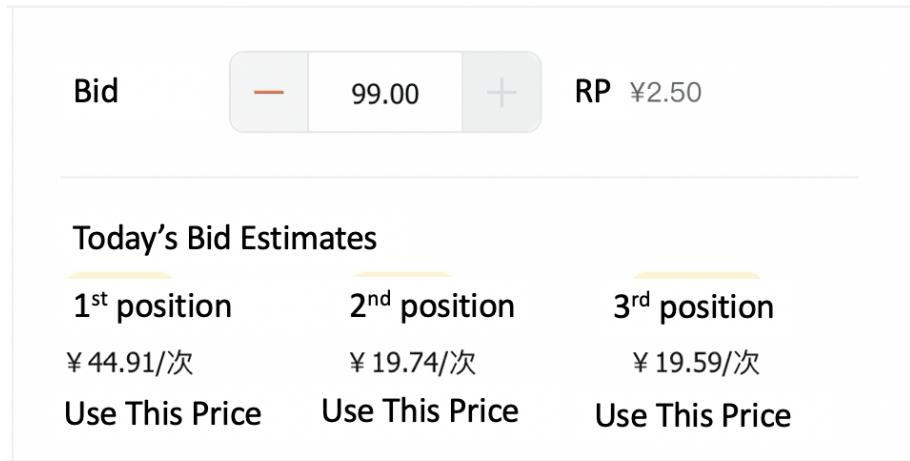


Figure 2: Advertiser's Bidding Page Display

<sup>4</sup>Xi'an is a capital city in Shanxi province.

<sup>5</sup>Prior to the introduction, the advertising platform informed advertisers about the advent of the new information and the method for estimating bids.

<sup>6</sup>The exact criteria for selection are confidential. However, notwithstanding the exact selection rule, this is just one random number from a distribution of estimated bids for the top slot, so this information is not representative of the entire distribution.

<sup>7</sup>This fact is also conveyed to advertisers

### 3.3 Data

The data spans 30 days pre and post-introduction of bid estimates on August 13th, 2019. With respect to bid-change occasion data, we observe when advertisers log onto their personal ad account, whether they change their bid during the log-in activity, their original bid, the new bid, and three daily bid estimates displayed. The advertiser performance dataset includes an advertiser's average daily cost per click (CPC), the total number of clicks and impressions a day, the advertising budget set by the advertiser, the average quality score, and the average position displayed. For the advertiser characteristics data set, we observe the daily review rate, review number, good review ratio, whether the advertiser is a new advertiser who has joined the platform that day, and the number of days the advertiser has been active on the platform for both organic and paid search.

## 4 Descriptive Evidence

### 4.1 Documentation of Theoretically Sub-Optimal Bidding Pattern

On August 13th, 2019, the ad platform initiated bid estimates about the top three ad positions for advertisers in the wedding service category in Xi'an. Figure 3 shows the distribution of bid and three bid estimate differences at each bid change event in this city. The histogram indicates that there is a clear mass at the zero cutoffs, i.e., a proportion of the bids equals one of the three estimate numbers.<sup>8</sup> Given that advertisers' values are continuous, independent of quality scores, and quality scores are also continuous, this "bidding at the cutoff" behavior is a probability zero event and thus cannot be rationalized under Bayesian Nash Equilibrium. (See proof in the Appendix 9.1.).

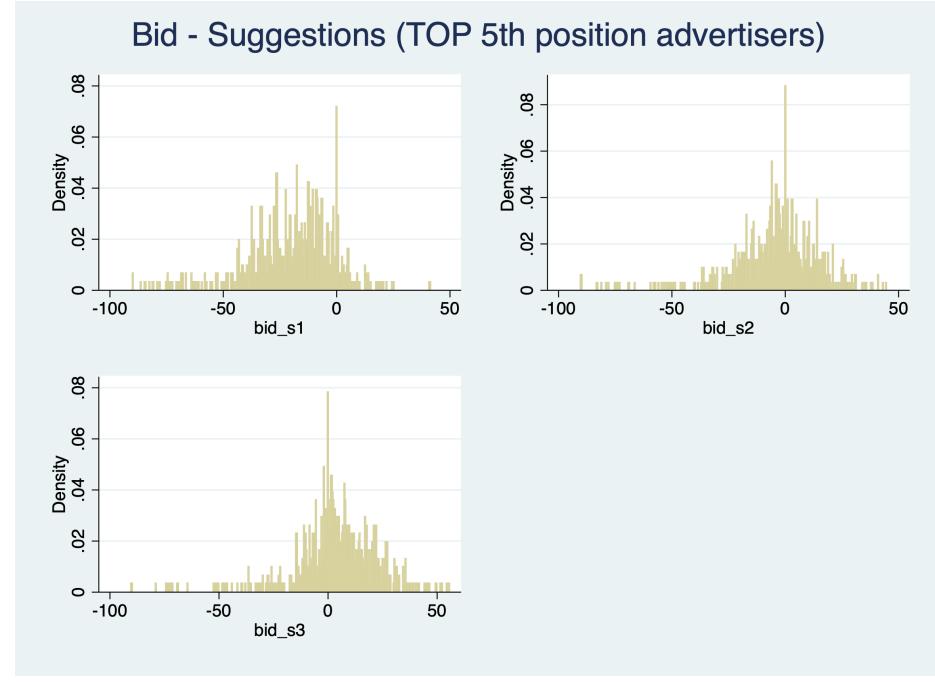
### 4.2 Why Advertisers Follow Bid Estimates

If following bid estimates precisely is not a theoretically optimal bid behavior, then why do advertisers behave that way? In this subsection, we delve into the group of advertisers who behave the "theoretically sub-optimal" way. First of all, we define this group of advertisers as "less sophisticated bidders" and another group of advertisers who had bid higher than the lowest bid estimates at least once but never bid exactly right at one of the bid estimates as "sophisticated bidders." Among less sophisticated bidders, there are 69 ones with 883 total bid change occurrence observations post information release, among which they bid at the cutoffs around 7% of the time. The group of sophisticated bidders includes 114 advertisers, with 2649 total bid change occasion observations post-intervention. Then, we compare how the two groups differed before the arrival of information based on features like review, budget, bid, ad expenditures, and ad performance. Figure 4 displays the discrepancy between two groups in terms of their daily budgets and the average bids they submit. The vertical red line in Figure 4 represents the beginning of the information release. Towards the left of the event's happening date, we observe that less

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<sup>8</sup>As a comparison, we do not find such a pattern in the comparable city, Chengdu, where we constructed the pseudo bid estimates and compare those with advertisers' bids.

Figure 3: Theoretically Sub-Optimal Bidding Pattern



\* Figure 3 shows the distribution of  $b_{it} - s_{ikt}$  where  $i$  indexes advertiser,  $t$  indexes bid change occasion, and  $k$  indexes ad positions. This is a difference between each advertiser's submitted bid  $b_{it}$  and three individual specific (adjusted by quality scores) bid estimates  $s_{ikt}$  at each bid change occasion post information release. The clustering at zero means that advertisers bid right at what the bid estimates suggest. We have shown that this bunching at the cutoff behavior cannot be rationalized under the assumption that value distribution is atom-less and is independent of quality scores.

sophisticated bidders have already submitted lower bids and allocated a lower advertising budget as compared to sophisticated bidders. This pattern suggests that this group of less sophisticated bidders were uncertain about the bid-to-position probabilities and thus were more risk-averse than the other group according to the "Ellsberg Paradox" where Ellsberg (1961) observes people are averse to ambiguity.<sup>9</sup> Their risk aversion results in them investing less in advertising, and this is reflected in their ad budgets.<sup>10</sup>.

Figure 5 informs us about the quality dimension of this group of less sophisticated bidders. They had lower review stars but had more number of reviews. Using review stars as a proxy for merchant quality, the less sophisticated bidders were inferior to the sophisticated bidders before intervention. According to the position paradox observation made in Jerath et al. (2011) [13], inferior advertisers have a stronger incentive to be at the top because they only need to pay for those consumers who are new to their business, whereas experienced consumers are less likely to click on them if they were inferior. However, attaining the top objective proved to be difficult due to the fact that bid-to-position probabilities were difficult to obtain due to their large volatility.<sup>11</sup> Therefore, when the clear information about a mapping from bid-to-position arrives, this group of advertisers decided to directly use

<sup>9</sup>A more general definition of "ambiguity" by Frisch and Baron (1988) states that ambiguity is uncertainty about probability created by missing information that is relevant and could be known. In our specific context, this ambiguity is more likely to relevant to the bid-to-position probabilities that advertisers might care about but are hard to learn on their own.

<sup>10</sup>According to the Expected utility theory dated back to von Neumann and Morgenstern (1947)

<sup>11</sup>Figure 11 and Figure 12 in the Appendix 9.3 presents the volatility of the bid estimates. As you can see, it would be nearly futile for advertisers to learn it through themselves since what they learn one day may be irrelevant the next.

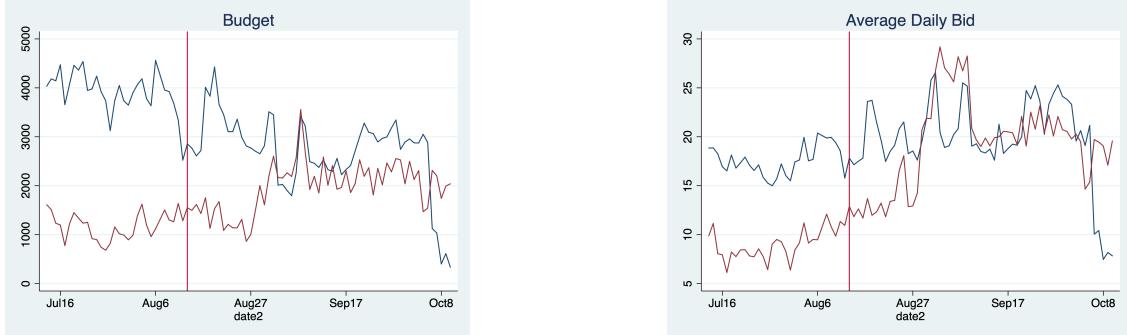


Figure 4: Ad Investment

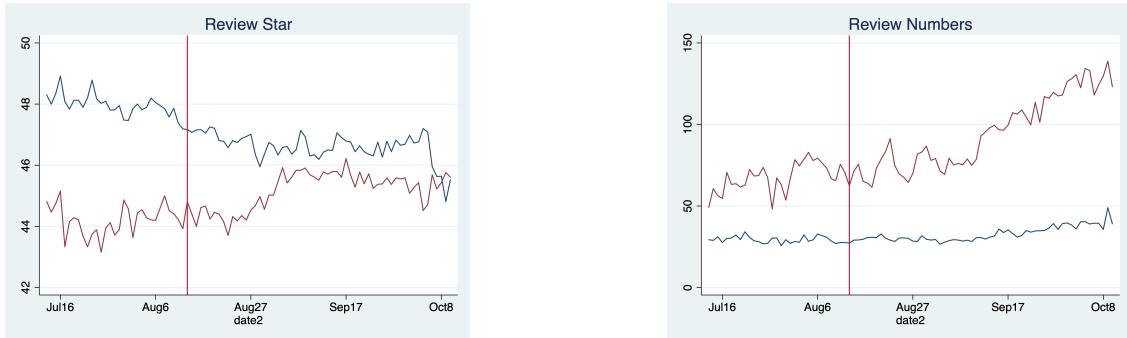


Figure 5: Review Improvement

the information.

As shown in Figure 6, less sophisticated bidders perform differently in advertising both before and after taking bid estimates. As a whole, we see improvements relating to advertising performance and review for less sophisticated bidders after taking the platform’s suggestions. Less sophisticated bidders appear to have occupied lower positions than sophisticated bidders, perhaps because they bid less. They achieved higher positions as a result of taking the suggestions. Furthermore, Figure 5<sup>12</sup> also depicts that their reviews have improved in the sense that they have gained more reviews, most likely from new consumers (Narayanan and Kalyanam (2015) [14]), and have subsequently raised their star ratings. They may, however, improve their quality in the interim. However, without reaching the top positions, the improvement might not be as efficient as shown in Figure 5.

According to Figure 7, we observe that at the end of the wedding season, high-budget bidders in the sophisticated group cease to advertise on the platform. The exit also results in a decrease in the daily budgets and bids, as seen in Figure 4. However, we do not observe such a pattern in the less sophisticated group. This discrepancy suggests that sophisticated bidders are more responsive and aware of demand fluctuations on the platform than the other group.

<sup>12</sup>The drop in the average number of reviews represent that the underlying set of advertisers are changing over time.

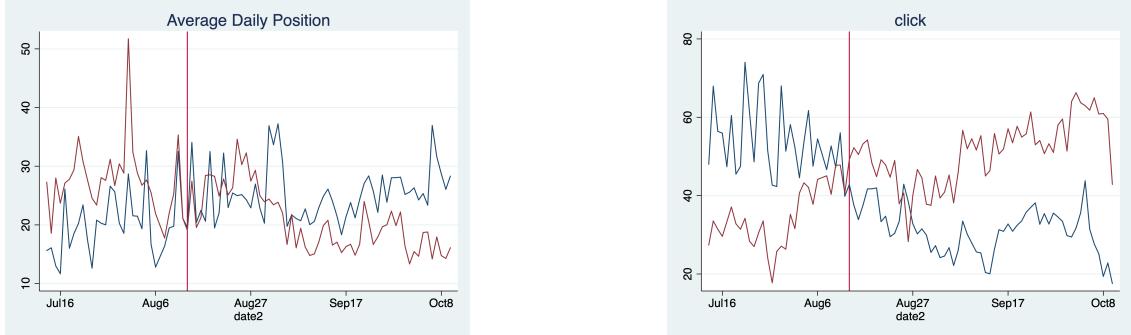


Figure 6: Ad Performances

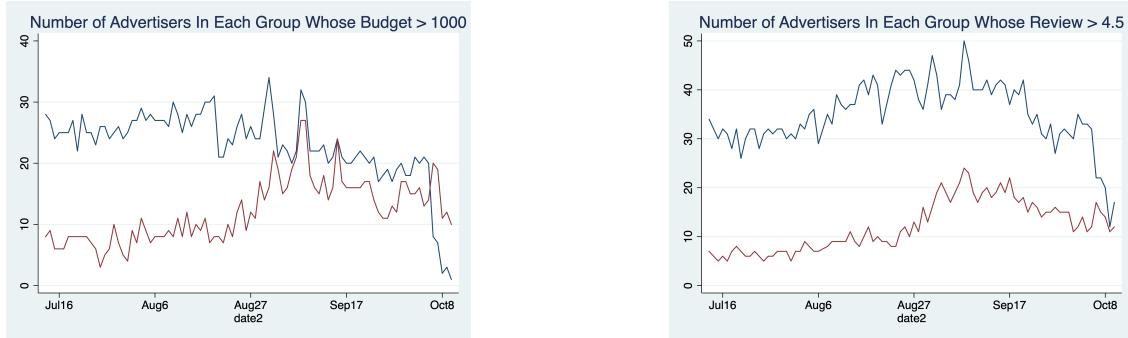
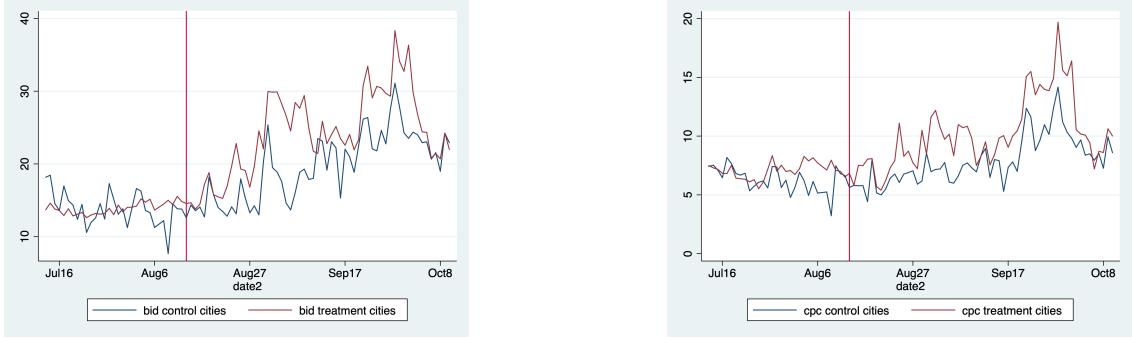


Figure 7: Exit of High Budget Advertisers After Wedding Season Ends

### 4.3 Impact of Information On Market Outcomes

In this section, we investigate the impact of bid estimates release on the equilibrium market outcome. To begin with, we exhibit the effect of the bid estimates on the bids and CPC in Figure 8. The left graph shows the average daily bid of the top five ad positions in Xi'an (red line) and Chengdu (blue line) prior to and after the introduction of bid estimates, and the right graph shows the average CPC of the top five ad positions in two cities. Before the policy change, average bids among top positions were very close in Xi'an and Chengdu. Upon the implementation of the bid estimates on August 13th, 2019, the average bid price in Xian did not increase immediately compared to Chengdu. The difference in bid levels became evident three days later. We suspect that this is due to the design of bid estimates, which are computed based on yesterdays' bids across many advertisers. In the meantime, advertisers may need time to learn about the information before embracing it fully. Among the top five ad positions, we can see that bid levels in Xi'an significantly increase after three days after bid estimates were introduced. The gap between the two cities' bid levels persisted until the end of September when the peak wedding season is about to end.<sup>13</sup> After October 1st, the price competition in the wedding service category decreases with the number of high bid and high budget advertisers exiting the market. With respect to the mid and lower slot ad groups, I have not observed a substantial difference in bid levels following the introduction of bid estimates. In other words, by inspecting the effect of bid estimates on three different groups of ads, one can conclude that it is the effect on the

<sup>13</sup>The first week of October is a peak wedding season in China because it is also a week of national holiday



(a) Average Bid of Top 5 Ad Slots

(b) Average Cost Per Click (CPC) of Top 5 Ad Slots

Figure 8: Pre-and-Post Changes in Bid and CPC of Top 5 Ad Slots

top slot ads that is driving the increase in bid level in Xi'an, which is also supported by the regression results in the subsequent section in the later section.

In terms of effects on market equilibrium prices, Figure 8b shows the trend of daily average CPC among the top five ad positions in two cities before and after the policy change. First, we notice that the movement of CPC levels is closely related to the movement of bid levels, which is logical, as CPC is mainly a market-clearing price determined by advertisers' bids. Among the top five ad positions in Xi'an, we can see that the information arrival is responsible for the increase in per click prices. Meanwhile, Chengdu's CPC level remains relatively unchanged until September, when preparations begin for the wedding week in October and advertising prices begin to rise. Even so, there is a noticeable difference in the level of CPC between the two cities, an effect which may be attributed to the disclosure of information in Xi'an. In the next subsection, we will show regression results that also reflect the effect of information release on the bids and CPC.

#### 4.3.1 Descriptive Analysis: Difference-in-Differences Regressions

To evaluate the effect of introducing bid estimates, we employ a difference-in-differences strategy to compare changes in bids and CPCs in Xian against Chengdu. Chengdu was selected as the control city based on a weighted match of average bid, CPC, number of ads, and advertising revenue a month before the policy change.

Formally, we explore the effect of bid estimates on bids and CPC based on the following regression model:

$$Y_{it} = \alpha_1 * (T_i * Post_t) + \alpha_2 * group1 + \alpha_3 * group2 + \alpha_4 * group3 + \alpha_5 * (T_i * Post_t * I\_group) + fe_i + fe_t + \epsilon_{it}$$

where the unit of observation is ad-per-day,  $i$  denotes an ad.  $t$  means date.  $Y_{it}$  consists of two outcome measures: bid and CPC.  $Post_t$  is an indicator of any date after the information release.  $T_i$  indicates whether or not an ad  $i$  is in the treatment city Xi'an.  $group1$  is an indicator variable that is one if the ad is located at top 5 positions<sup>14</sup>.  $group2$  is an indicator variable that is one if the ad appears between positions 6 and 25. The  $group3$  variable indicates whether the advertisement is located below 25th position if it is 1.  $fe_i$  controls for advertiser specific

<sup>14</sup>The number of positions includes both ads and organic search results

effect that is constant over time.  $fe_t$  controls for day-specific effect but is constant across ads.  $\alpha_1$  captures the difference-in-differences effect of information disclosure, which is the main coefficient of interest. Additionally, we are interested in the heterogeneous effect of treatment as captured by  $\alpha_5$ . Essentially,  $alpha_5$  shows us the marginal effect of information disclosure on three groups of ads located on the top, mid and lower slots.<sup>15</sup>

To measure the effect of information on bids, we use daily bids averaged across multiple bid change occasions within a day, if there are any.<sup>16</sup> The difference-in-differences coefficient represents the bid change due to the arrival of new information. On average, the bid increases by 2.19 RMB post bid estimate releases. This change corresponds to a 35% increase relative to the pre-policy change period average levels. Next, we explore heterogeneity by allowing the information disclosure effect to vary by groups determined by an ad's position on that day. In column (2) of Table 1, we report regression results that include an interaction between post information disclosure dummy times Xi'an dummy with a group id dummy. On any given day, information disclosure has a greater impact on ads that are located in the top five positions. On average, we find that post bid estimate releases, top slot ads increase their bids by 5.37, a 39% increase compared to the pre-period. It is approximately twice as large as the average effect on the whole group, as shown in column (1). The average bid increase for ads positioned between the sixth and twenty-fifth slots is 2.31, which is close to the mean for the entire group. Even though every advertiser sees the same list of three bid estimates for positions 1, 2, and 3, they react differently to it. The strongest effect on the top slot ads may be related to the fact that top slot bid estimates are relevant primarily to this group. The lower slot ads may not be as interested in competing for the top slots as the top group. In this regard, the effect of new information on lower ad slots is not as significant as on the top group.

After examining how information affects individual bidders' behavior, it is time to investigate how information affects the platform's ad price. Column (3) of Table 1 illustrates an average increase of 0.67 RMB on CPCs that advertisers paid when advertising on the platform. This is equivalent to 19% change relative to the pre-period. This effect is not only statistically significant but also economically important in terms of the average level. Column (4) reports the effect on CPC when heterogeneous groups of ads are compared. The top slot ad group has experienced the largest increase in ad price, which is a 28% increase. It appears that the mid-slot group of ads have experienced an increase in ad price of 0.44 RMB (11%), which, however, is not as significant as the high-slot group ads. It is the second-highest bid rather than the one submitted by the advertiser that determines the ad prices in GSP. In this regard, it is not surprising to observe that the effect on ad price is relatively smaller than the effect on bids.

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<sup>15</sup>We employ a clustered standard error at the advertiser level in all regressions, consistent with Bertrand, Duflo, and Mullainathan's (2004) research. Standard errors are clustered at the ad level to avoid artificially understating the size of the standard errors as a result of the use of repeated panel data.

<sup>16</sup>In the case of no-bid change within a day, the average daily bid today is the same as the previous day, so the bid remains the same within an ad.

Table 1: Difference-In-Differences Regression Table

	(1) bid	(2) bid	(3) cpc	(4) cpc
T*Post	2.193*** (0.394)	0.633*** (0.207)	0.669*** (0.152)	0.168* (0.0906)
group1		0.256 (0.601)		-0.0695 (0.243)
group2		0.217* (0.130)		0.129*** (0.0487)
T*Post*group1		5.372*** (1.203)		1.902*** (0.478)
T*Post*group2		1.705*** (0.289)		0.436*** (0.0991)
<i>N</i>	73044	73044	73044	73044
adj. <i>R</i> <sup>2</sup>	0.903	0.908	0.866	0.868

Standard errors in parentheses

ad and day fixed effects, cluster at advertiser level

\*  $p < 0.10$ , \*\*  $p < 0.05$ , \*\*\*  $p < 0.01$

#### 4.3.2 Discussion: Why the Increase in Bids and Ad Prices

We conclude this section by discussing the possible mechanisms underlying the rise of equilibrium market ad prices, particularly at the top of the ad slots. Initially, there is a group of people who directly follow the bid estimates. Those advertisers are high-value advertisers who bid low before the release of information due to uncertainty. Disclosure of the information encourages their participation in the competition for the top ad slots. Therefore, other advertisers, especially those who compete for top slots, were required to increase their bids. Due to such fierce competition for the top advertising slots, the market-clearing price rises.

## 5 Empirical Model

### 5.1 Model of Sophisticated Bidding in GSP

Here, we present a computationally feasible and convenient framework for modeling sophisticated advertisers' bidding in the generalized second-price auction. We assume a SIPV (symmetric independent private valuation) model for the sophisticated bidders. For the sophisticated bidders, besides the distributional information of the quality score distributions, they also observe the realization of their own valuations each day. The sophisticated bidders adopt a Bayesian Nash Equilibrium bidding strategy, which allows us to identify their valuations given the rank score distributions. The model allows for a realistic aspect of the GSP auction, quality scores, which are

widely implemented by most ad platforms.<sup>17</sup> The quality score is calculated each time when a consumer initiates a search query. Each day, there could be hundreds of queries of this nature, and thus hundreds of quality scores could be calculated. At the beginning of the day, neither the platform nor the advertiser could anticipate these queries. We model that a sophisticated advertiser  $i$  forms a belief about his daily quality scores  $q_{it}$  being drawn from a normal distribution  $F_i(\bar{q}_i, \epsilon_t)$  distributed around some advertiser  $i$ 's specific mean  $\bar{q}_i$  and a daily noise  $\epsilon_t$  that reflects the variation in daily consumer demands that is same across bidders within a day.

We decide to model sophisticated advertisers' daily bidding behavior in line with our empirical observation. In this model, a single bid is submitted by a sophisticated advertiser every day for all ad positions.<sup>18</sup>. The platform receives advertisers' bids and calculates a quality score whenever a consumer initiates a relevant query for the advertiser. Then the platform ranks all advertisers by a rank score which is the multiplication of the advertiser  $i$ 's submitted bid  $b_i$  and his quality score  $q_i$ . Each advertiser is assumed to have a private value  $v_i$  per click generated from advertising. Advertisers do not know others' private values but know that all values are drawn from a common distribution  $F_v$  with a continuous density  $f_v$  with support  $[v, \bar{v}]$ . The distribution of value distribution  $F_v$ , the number of clicks at each position  $\alpha_k$  are common knowledge. All advertisers are identical ex-ante, and the game is symmetric. Each bidder is assumed to be risk-neutral.

We assume sophisticated bidders are bidding in a Bayesian Nash Equilibrium given the behavior of the less sophisticated bidders. They submit one bid  $b$  for all auctions happening within the same day to maximize their expected payoff daily. We assume sophisticated ones have a belief about the equilibrium rank score distribution that includes less sophisticated bidders' quality scores and bids  $g_{k-1,k}(r_k, r_{k-1})$ , where  $r_k$  denotes the  $k^{th}$  position's rank score. Meanwhile, they have a belief about their daily quality score distribution  $F_i(\bar{q}_i, \epsilon_t)$ .

Let  $R_k$  be the  $k^{th}$  order statistic of the other advertiser's rank score, which is equal to quality score times bids. Hence,  $R_{k+1} < R_k < R_{k-1}$ . Let  $g_k(\cdot)$  and  $g_{k-1,k}(\cdot, \cdot)$  be the density of  $R_k$  and the joint density of  $R_{k-1}$  and  $R_k$ , respectively.  $\alpha_k$  is the number of clicks generated at  $k^{th}$  position.  $r_k$  is a random number of the rank score at the  $k^{th}$  position. Let  $q_i \sim F_i(\cdot)$  be the realized quality score of the advertiser  $i$  in a particular auction. The profit function will become:

$$\begin{aligned}\pi(b|v, q \sim F_i) &= \int \left[ \sum_{k=1}^K \alpha_k \int \int 1(r_k < qb < r_{k-1}) \left( v - \frac{r_k}{q} \right) g_{k-1,k}(r_{k-1}, r_k) dr_k dr_{k-1} \right] dF_i(q) \\ &= \int \left[ \sum_k \alpha_k \int_{qb}^{\infty} \left( \int_0^{qb} \left( v - \frac{r_k}{q} \right) g_{k-1,k}(r_{k-1}, r_k) dr_k \right) dr_{k-1} \right] dF_i(q)\end{aligned}$$

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<sup>17</sup>Google first introduced "quality score" adjusted auctions in order to maximize ad platform's revenue. It multiplies each advertiser's bid by a "quality score," which is mainly reflecting consumers' click-through rate (CTR) of the advertiser to compute its "rank score." Then, Google ranks advertisers according to their ranking scores and charges each advertiser the least amount necessary to outrank the next advertiser.

<sup>18</sup>We observe that the frequency of changing bids from advertisers is on average 4.3 times a week. And our observation for bidding data is at the daily level

Taking the first derivative with respect to  $b$ :

$$\begin{aligned}
\pi'(b|v, F_i) &= - \int \left[ \sum_k \alpha_k \left( \int_0^{qb} q \left( v - \frac{r_k}{q} \right) g_{k-1,k}(qb, r_k) dr_k - q(v-b) \int_{qb}^{\infty} g_{k-1,k}(r_{k-1}, qb) dr_{k-1} \right) \right] dF_i(q) \\
&= - \int \left[ \sum_k \alpha_k \left( g_{k-1}(qb) \int_0^{qb} q \left( v - \frac{r_k}{q} \right) g_{k-1,k}(r_k|qb) dr_k - q(v-b) \int_{qb}^{\infty} g_{k-1,k}(r_{k-1}, qb) dr_{k-1} \right) \right] dF_i(q) \\
&= - \int \left[ \sum_k \alpha_k \left( g_{k-1}(qb) q \left( v - \frac{1}{q} E(r_k|r_k < qb) \right) - q(v-b) g_k(qb) \right) \right] dF_i(q)
\end{aligned}$$

Setting  $\pi'(b_i|v_i) = 0$  and solving for  $v$

$$\begin{aligned}
v_i &= \frac{\int [\sum_k \alpha_k (g_{k-1}(qb) E(r_k|r_k < qb) - qbg_k(qb))] dF_i(q)}{\int [\sum_k q\alpha_k (g_{k-1}(qb) - g_k(qb))] dF_i(q)} \\
&= b_i + \frac{\int [\sum_k \alpha_k g_{k-1}(qb) E(r_k - qb|r_k < qb)] dF_i(q)}{\int [\sum_k \alpha_k q (g_{k-1}(qb) - g_k(qb))] dF_i(q)} \\
&= b_i + \frac{\int [\sum_k \alpha_k g_{k-1}(qb) E(qb - r_k|r_k < qb)] dF_i(q)}{\int [\sum_k qg_k(qb) (\alpha_k - \alpha_{k+1})] dF_i(q)}
\end{aligned} \tag{1}$$

Equation (1) is a GPV-like expression (GPV 2000). It describes the advertiser's private value  $v_i$  as a function of his equilibrium daily bid  $b_i$ , number of clicks generated at each position  $\alpha_k$ , the distribution of  $(k-1)^{th}$  density  $g_{k-1}(\cdot)$ , the distribution of  $k^{th}$  density  $g_k(\cdot)$ , and the distribution of his daily quality score  $F_i(\cdot)$ . Appendix 9.2 presents the proof of identification of values from observed bids. Note that both the numerator and denominator of the markdown term are positive. Hence, the mark-up term is a positive term, which implies that advertisers are shading their bid below their value in equilibrium.

## 5.2 Incomplete Model of Less Sophisticated Bidding in GSP

We assume an incomplete model for the less sophisticated bidders. This model leads to the partial identification of their valuation as bounds. For the less sophisticated bidders, they adopt a specific bidding model that depends only on their own valuations and is independent of other bidders' strategies. We assume that the less sophisticated bidders would not overbid, i.e. they are not going to bid over their current values. This assumption gives us the lower bound estimation of their valuation. Pre-intervention, the less sophisticated bidders shade their valuations, and how they shade their valuations depends on the modeling choice. In the counterfactual session, we assume one form of this shading behavior model, which is random shade their valuation by submitting  $b_i = \alpha v_i$ , where  $v_i$  is the valuation and  $\alpha$  follows a standard uniform distribution.

After the intervention, the less sophisticated bidders never bid below the lowest bid estimate if their value exceeds that. For example, if at one period, a less sophisticated bidder draws a  $v_t = 3$  and the lowest bid estimate is  $s_3 = 2$ , we assume she will bid within the range of [2,3]. This assumption allows us to identify the upper bound of the valuation for this group.

## 6 Estimation

### 6.1 Estimation of Sophisticated Advertisers' Valuation

The basic concept of value estimation is straightforward. If one knows the density  $g_{k-1}$  and  $g_k$ , then one can estimate values from the equation (1). The density  $g_{k-1}$  and  $g_k$  is unknown but can be approximated nonparametrically from the observed bid data. We assume that the observed data is generated from sophisticated bidders' bidding equilibrium strategy and less sophisticated bidding according to our proposed formula mentioned in the previous section. We employ GPV 2000's two-step estimator approach. First, we construct a sample of pseudo values from (1) using nonparametric estimates of the density functions for the observed bids. We then use the pseudo values generated in the previous step to estimate the density of bidders' values.

To clarify, we first simulate 100 auctions each day (total 30 days) for sophisticated bidders. For each auction, we simulate a quality score  $q_{ita}$  for advertiser  $i$  at day  $t$  in auction  $a$ , which is distributed  $N(\bar{q}_i, \epsilon_t)$  where  $q_{it}$  is advertiser  $i$ 's observed quality score averaged across all queries within a day, and  $\bar{q}_i$  is advertiser  $i$ 's observed mean level of quality scores averaged across  $q_{it}$ .  $\epsilon_t$  is estimated using observed daily quality score residuals ( $q_{it} - \bar{q}_i$ ) among all advertisers in each day. The underlying assumption is that advertisers face the same variance of quality scores that reflect the variation of consumer demand. For example, when the wedding season approaches, we can expect more demand to arrive on the platform to search for wedding services, and the range of customers could be greater than when there is no wedding season. Then we calculate each advertiser  $i$ 's rank score for that auction  $r_{ita} = b_{it} * q_{ita}$ . After obtaining the auction level empirical distribution of rank scores, We estimate the density for 1-24th ad position  $g_k$  using kernel density estimation.

$$\tilde{g}_k(b) = \frac{1}{ILh_g} \sum_l \sum_i K_g\left(\frac{b - B_{il}}{h_g}\right)$$

where  $h_g$  is a bandwidth  $h_g = 1.06\sigma_b(IL)^{-1/5}$  and  $K_g(\cdot)$  is a normal kernel.

Then using equation (1), we estimate pseudo value  $\tilde{V}_{il}$ . After this, we compute private value density:

$$\tilde{f}(v) = \frac{1}{ILh_f} \sum_l \sum_i K_f\left(\frac{v - \tilde{V}_{il}}{h_f}\right) \quad (2)$$

We observe 7458 out of 8117 daily bid observations for 520 sophisticated bidders out of 556 total number of bidders existed before the platform released its bid estimates.<sup>19</sup> To estimate the rank score distribution, we employ all bidders' rank scores as that depicts the equilibrium rank score distribution. We expand it to auction level with 811700 observations. In the first step, we estimate  $g_k$ . Then we compute pseudo  $\tilde{V}_{il}$  using (1) based on only sophisticated bidders' bids that fulfill the condition  $I(r_k < qb < r_{k-1})$  according to the profit function and

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<sup>19</sup>We use pre-information release sample to estimate sophisticated bidders' values because we document that the information change less sophisticated bidders' behavior in some sub-optimal way, which will affect the equilibrium strategies of the other group, while in the pre-sample, we do not have such interference from the information.

the first-order condition. From this pseudo data, we estimate the private values density function using (2).

The estimated value for sophisticated bidders is as follows:

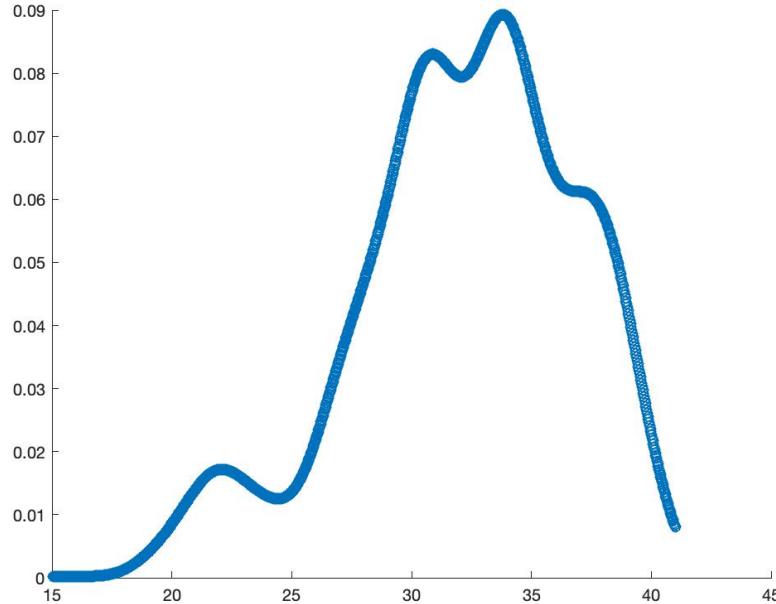


Figure 9: Sophisticated Advertiser's Valuation Density

## 6.2 Estimation of Less Sophisticated Advertisers' Valuation

For less sophisticated bidders, we leverage the incomplete model proposed in section 5.2 to infer their bounded valuation. In particular, we nonparametrically estimate the bounds of their valuation using their bids and the three bid estimates that they observe each time when they change their bids. When less sophisticated bidders submit their own bids, we infer that their values are below the lowest bid estimate that they witness, i.e.  $v_i < \min(s_{i1}, s_{i2}, s_{i3})$ . This assumption gives us the lower bound of the value. If they submit a bid that is within the range of three bid estimates, we assume that the upper bound of the value is the closest higher bid estimate. For instance, if we observe in the data that at one bid change occasion  $t$ , a bidder submit her bid  $b_{it}$  which is  $s_{i3t} < b_{it} < s_{i2t}$ , where  $s_{i2t}$  and  $s_{i3t}$  stand for the bid estimate for position 2 and position 3 respectively, then we infer that her value  $v_i$  is between  $[b_{it}, s_{i2t}]$ . In the case where we observe the bidder submit a bid that is equal to or larger than the highest bid estimate, most likely  $s_{i1t}$ , then we assume her value  $v_i$  is in the range of  $[b_{it}, \infty]$ .

The estimated bounded value for less sophisticated bidders is as follows:

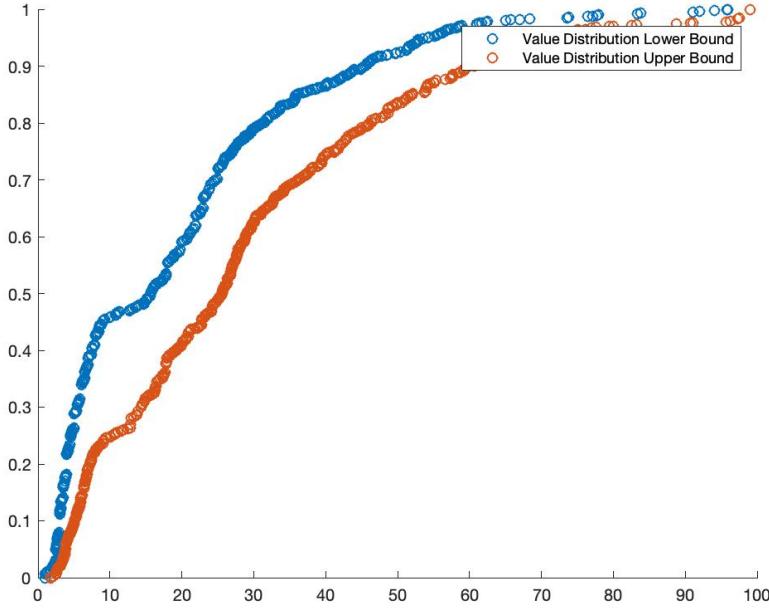


Figure 10: Less Sophisticated Advertiser’s Valuation Bounds in CDF

## 7 Counterfactual

This section simulates alternative information-sharing mechanisms that the platform may employ. The mechanisms include re-designing the top three bid estimates, providing bid estimates for each position, and personalizing bid estimates for less sophisticated bidders with the different level of knowledge in their valuations.

First, we specify two groups: sophisticated and less sophisticated bidders’ bidding patterns in the counterfactual exercise. For sophisticated bidders, we assume they are playing envy-free equilibrium strategy in a generalized English auction following EOS (2007) [1].<sup>20</sup> <sup>21</sup> We also simulate the pre-intervention data and post-intervention with current bid estimates in this specified equilibrium instead of directly using our observed revenue data. Since multiple Bayesian Nash equilibrium may arise in the generalized second-price auction, the bids we observed from data may not coincide with the equilibrium bids resulting from the envy-free equilibrium, which makes it incomparable between data and simulated counterfactual scenarios.

In the counterfactual simulations, we assume that less sophisticated bidders adopt the following bidding pattern – before platform releases bid estimates, a bidder  $i$  with valuation  $v_i$  would submit bid  $b_i = \alpha v_i$ , with  $\alpha$  being a standard uniform random variable,  $\alpha \sim U[0, 1]$ . After information release, after observing bid estimates for the first position to  $k^{th}$ ,  $[s_1, \dots, s_k]$ , bidder  $i$  with valuation  $v_i$  would submit bid  $b_i = \alpha v_i$ , if  $v_i$  is smaller than the smallest bid estimates. If  $v_i \geq s_k$ , he will take the highest possible bid estimate that is below the valuation  $v_i$  to

<sup>20</sup>The equilibrium we imposed on sophisticated bidders is an ex-post equilibrium – given the bid-estimate takers’ exogenous strategy, and given the rest of the sophisticated bidders follow the envy-free equilibrium strategy, it is the best response for bidder  $i$  following the envy-free equilibrium strategy.

<sup>21</sup>Note that envy-free equilibrium belongs to the class of Nash equilibrium [24].

ensure the likelihood of obtaining a higher ad position,  $b_i = \max_{j \in \{1, \dots, k\}} \{s_j, s_j < v_i\}$ . The bidding pattern for less sophisticated bidders is fixed and independent of sophisticated bidders' bidding strategy. To note, it is also known to the sophisticated bidder. We assume that the platform only has distributional information about the bidder's valuation.<sup>22</sup>

We use the estimated valuation from section 5. Based on our sample, the number of less sophisticated bidders is 69, and the number of sophisticated bidders is 114. We take 1000 realizations of valuations for both sophisticated and less sophisticated bidders in our sample. We impose the proposed bidding pattern on less sophisticated bidders for each realization and impose the envy-free equilibrium bidding strategy on the sophisticated bidders. This paper examines a case where quality score interventions are not applied, and all bidders share the same invariant quality score at each auction. However, similar intuition and results hold with quality scores. In order to evaluate alternative mechanisms, we rely on two metrics, the ad platform revenue and the total surplus of the ad platform and bidders. We also introduce another performance metric that evaluates how the mechanisms influence the surplus for less sophisticated bidders – % gap, which is the percentage surplus gap between strategic and non-strategic bidding. Note the % gap might be negative, which implies that bidders actually benefit more by following the platform's suggestions.

$$\% \text{ gap} = \frac{\text{Less sophisticated bidders' surplus under strategic bidding} - \text{their surplus when they follow suggestions}}{\text{Less sophisticated bidders' surplus under strategic bidding}}$$

## 7.1 Counterfactual Scenarios and Results

We first analyze the case with no variation in quality scores (they equal to 1 for everyone). This case helps us understand the intuition behind why adding bid estimates would help increase both revenue and total surplus. Note here the total surplus means the surplus of both the platform and the bidders.

	Revenue	Total Surplus	% gap
1 <b>Pre-intervention</b> scenario: GSP in envy-free equilibrium	5.04 (-)	5.12 (-)	93%
2 <b>Post-intervention</b> scenario: current bid estimates	5.07 (0.7%)	5.15 (0.5%)	13%
3 Redesign <b>top 3</b> bid estimates	5.08 (0.8%)	5.15 (0.5%)	5%
4 Redesign bid estimates for <b>all positions</b>	5.09 (0.9%)	5.15 (0.5%)	4%
5 <b>Customized</b> bid estimates with knowledge of valuations	5.10 (1%)	5.15 (0.5%)	29%

Table 2: Same value distribution of sophisticated bidder and less sophisticated bidders

The pre-intervention is the baseline case. We simulate the bidding strategies for less sophisticated bidders as  $b_i = \alpha v_i$ . Sophisticated bidder  $i$  that receives position  $k$  bids the optimal strategy  $b_i = \frac{\alpha_k}{\alpha_{k-1}} b_{k+1} + (1 - \frac{\alpha_k}{\alpha_{k-1}}) v_i$  under the locally envy-free equilibrium in a generalized English auction following [1], where  $b_{k+1}$  is the bids for receiving position  $k + 1$ . We draw realizations of sophisticated bidders' valuations from the value distribution obtained in section 5.1. We draw less sophisticated bidders' valuations from either the same distribution as the

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<sup>22</sup>Even though this is only one of the models that could describe less sophisticated bidders' bidding behavior, our counterfactual results hold as long as they shade their bids and do not overbid.

	<b>Revenue</b>	<b>Total Surplus</b>	<b>% gap</b>
1 <b>Pre-intervention</b> scenario: GSP in envy-free equilibrium	5.44 (-)	6.77(-)	16%
2 <b>Post-intervention</b> scenario: current bid estimates	5.75 (6%)	7.26 (7%)	6%
3 Redesign <b>top 3</b> bid estimates	6.34 (17%)	7.72 (14%)	15%
4 Redesign bid estimates for <b>all positions</b>	6.96 (29%)	8.16 (21%)	25%
5 <b>Customized</b> bid estimates with knowledge of valuations	7.80 (44%)	8.13 (20%)	44%

Table 3: Use the lower bound valuation

	<b>Revenue</b>	<b>Total Surplus</b>	<b>% gap</b>
1 <b>Pre-intervention</b> scenario: GSP in envy-free equilibrium	6.47 (-)	8.86 (-)	-31%
2 <b>Post-intervention</b> scenario: current bid estimates	7.38 (14%)	9.41 (6%)	-12%
3 Redesign <b>top 3</b> bid estimates	8.05 (24%)	9.88 (11%)	-0.1%
4 Redesign bid estimates for <b>all positions</b>	9.38 (45%)	10.50 (18%)	38%
5 <b>Customized</b> bid estimates with knowledge of valuations	10.08 (56%)	10.52 (19%)	56%

Table 4: Use the upper-bound valuation

sophisticated bidders (results shown in Table 2), or the lower bound of the value distribution (results shown in Table 3), or the upper bound of the value distribution (results shown in Table 4). We simulate 1000 times and take the average of three metrics, including the platform’s revenue, total surplus, and % gap.

For the post-intervention scenario with current bid estimates, we simulate two groups bidding strategies when facing the historical highest three bids. We gather the bids simulated from the pre-intervention scenario and take the average of the top 3 highest bids across 1000 realizations on valuations as the current bid estimates to mimic the real-life bid estimates. In reality, the bid estimates that the platform provides is the previous period’s top 3 highest rank scores adjusted by individual-specific quality scores. We used the average historical top 3 bids from the pre-intervention case as the current bid estimates across all realization of valuations and takes the average of revenue, total surplus, and %gap. In general, we observe an increase in surplus and revenue post information release. The effect is smaller when two groups share the same value distribution. The effect on providing bid estimates is larger when the valuation distribution for the less sophisticated bidder is different from that of the sophisticated bidder. The explanation for the increase in revenue and surplus is as follows. Without any information, the bid-estimate takers heavily shade their bids. They received lower positions because of their lower bids. Post-intervention, they follow the suggestions and thus raise their bids. Consequently, platform’s revenue increases. Total surplus is higher if a higher valued bidder is matched with a higher position. The provision of bid estimates also increases the total surplus, as when less sophisticated bidders raise their bids, they reach higher positions than they should have received with their high valuation. As a result, providing bid estimates makes the current equilibrium more efficient.

In terms of alternative market designs on bid estimates, one way to improve the current design is to provide expected bid estimates based on value distributions because historical data might be unrealistic for future predictions. Therefore, we wish to provide information about an expected fixed point of one equilibrium when two groups of bidders bid according to our pre-specified model. In scenarios 3 and 4, we create a heuristic about this expected fixed point that achieves the highest revenue for the platform. Since bid estimates only affect less sophisticated

bidders and the platform only has distributional information about valuations, we provide the expected highest three values among less sophisticated bidders as the new top 3 positions' bid estimates. We draw 69 independent realizations from the less sophisticated bidder's valuation distributions 1000 times and take the averages of the top 3 highest valuations. We use these simulated expected highest three values among less sophisticated bidders as our bid estimates for the top three bid estimates. This design generates an increase in revenue by 17-24 % and in surplus of 11-14 % based on Table 3 and Table 4. Furthermore, we could redesign the bid estimates for all positions. Similarly, we provide the top 20 highest valuations among less sophisticated bidders as the bid estimates for the top 20 ad positions. Under this information design, the platform's revenue increases by 29-45%, and the total surplus increases by 16-18%.

Lastly, we consider the fifth case where the knowledge of the exact valuations realization is available to the platform. Access to such information is possible, as several leading online advertising platforms including Facebook, Twitter, and Yelp have already adopted the mechanism by asking bidders to report their valuations and bid for them according to their reported values.<sup>23</sup> If all bidders report truthfully, then the information of exact realization on valuations is accessible to the platform. And the platform should generally bid at their exact valuation for them if it knows their valuation since this strategy ensures the likelihood of gaining highest position per value while leaving positive payoffs in this second price auction. Our counterfactual simulation shows that when the platform customizes bid estimates with knowledge of valuations, the platform's revenue rises by 44 – 56 percent, and the total surplus is 19 – 20 percent higher.

## 7.2 Difference between Strategic and Non-strategic Bidding

In this subsection, we discuss the implications of the percentage gap between strategic bidding and non-strategic bidding. Table 2 displays the case where sophisticated bidders and less sophisticated bidders share the same valuation distribution. In this case, following the bid suggestions would result in their payoffs being closer to those obtained under the equilibrium bidding strategy. The reason is that, prior to intervention, less sophisticated bidders have no idea how to bid optimally. They overshade and as a result, they end up in lower positions. After following the bid estimates, they raise their bid and end up in a better position, which is closer to what they should do in equilibrium if they were more sophisticated. The loss in surplus by following the current bid estimates is 13% of the total surplus that one would receive when bidding optimally in the equilibrium. When we design the bid estimates more accurately, we find that the gap is reduced to 5% when we redesign the top three bid estimates and further down to 4% if we can share information about all ad positions. Moreover, when the platform bid less sophisticated bidders' true valuation for them in scenario 5, this group get a much lower (29%) payoff than playing locally envy-free equilibrium strategy. These findings emphasize the importance of carefully designed information mechanisms by platforms to assist players in their decision-making process.

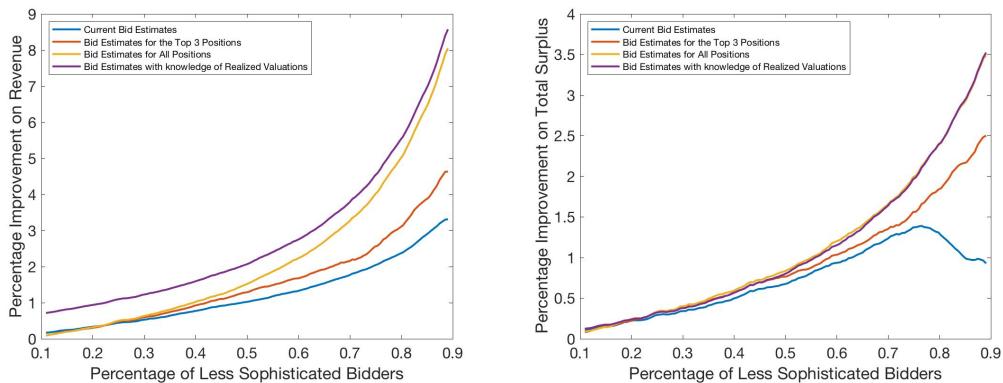
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<sup>23</sup>This mechanism is also noted as auto-bidding mechanism that has been adopted increasingly among online advertising platforms.

In contrast, similar intuition does not hold for Tables 3 and 4, primarily because the estimated valuations for less sophisticated bidders tend to be consistently higher than those for sophisticated bidders. Given the large discrepancy between the two groups' valuations, the top position is likely to be occupied primarily by less sophisticated bidders with high values. These bidders would experience intense competition among themselves if they were all strategic bidders. The optimal equilibrium bids will be much higher than the current suggested bids. By following the bid estimates provided by the platform, these bidders are able to collude by jointly shading their bids at the bid estimates so that they successfully win the top positions with less payment. Moreover, because their valuation is high, the savings from reduced payments greatly outweigh the loss associated with getting a lower position. As a result, in Tables (3) and (4) we observe that the behavioral bidders actually perform better when they follow bid estimates and in turn shade their bids lower than the optimal level of bids that they would submit in an equilibrium. Therefore, it is worth noticing that the surplus gap between bidding in equilibrium and following platform's recommendations is not always negative. It highly depends on the value distribution of these bidders.

### 7.3 Comparative Statistics: Effects on the Percentage of the Less Sophisticated Bidders

Here we examine the effect of a higher percentage of less sophisticated bidders on the platform's revenue and the overall surplus. We assume that the distribution of valuation for both behavioral and sophisticated bidders is the same, so varying the composition of the two groups would keep the total pie of surplus at the same level. In line with our expectation, as the proportion of less sophisticated bidders increases, the platform's profit and total surplus increase as shown in Figure 7.3. The intuition is similar, as we increase the percentage of less sophisticated bidders, we increase the proportion of the bidders who are more likely to adopt the bid estimates that is higher than their previous bids. However, the total surplus under the status-quo bid estimates first increases with the increase in the percentage of less sophisticated bidders, and then decreases as the percentage further grows. This is probably driven by the fact that the current bid estimates are not optimally designed in order to maximize the efficiency of the mechanism.



## 8 Conclusion

In search advertising, some advertisers may find it challenging to submit bids due to the uncertainty regarding advertising effects and complexity of the auction mechanism. In order to assist advertisers with their bidding processes, ad platforms aggregate information from many bidders and provide them with bid recommendations. However, it is unclear whether disclosure of such information to advertisers has any effect on the outcome of the equilibrium market. We analyze data from a Yelp-like platform that initiated a bid recommendation system. By leveraging this unique event, we document that some less sophisticated advertisers simply adopt the platform's suggestions rather than calculating their own bids. We characterize an equilibrium model of bidding in the GSP auction and demonstrate that such "bidding at the suggestions" patterns are theoretically suboptimal. We discover that these less sophisticated advertisers were lower-rated and uncertain about ad effectiveness before the platform began offering information through the recommended bids. The empirical documentation makes the case for more careful information design by ad platforms, since even the slightest design difference could have significant effects on less sophisticated players and the interaction between more sophisticated and less sophisticated players.

To evaluate alternative information sharing mechanisms, we identify sophisticated and less sophisticated advertisers' private values using observed bids and the disclosed information. We then simulate two alternative market designs in GSP auction. According to our counterfactual study, the provision of full information about bid estimates for all ad positions achieves greater efficiency and revenues than the current design of the bid estimates, due to the customization of information for more relevant advertisers. Additionally, we simulate the market efficiency achieved under the increasingly popular auto-bidding scheme for online advertising auctions. When the advertising platform bids for the less sophisticated advertisers by eliciting their valuations *ex ante*, the market gains more efficiency, intuitively as we are able to eliminate suboptimal behaviors in the bidding process. Whether such a hybrid system is superior to the auction itself is dependent upon the percentage of sub-optimal bidding behavior present in the market.

We believe that our findings are not constrained to information sharing in the search advertising industry. Indeed, the paper sheds light on the importance of providing information for heterogeneous participants in online marketplaces, where there is often information asymmetry between platform and individual participants. Airbnb, for example, observes the exact variation in demand that is important to individual hosts at the time of determining their lodging prices. As a result, a typical Airbnb host receives lodging price recommendations from the platform based on consumer demand for housing and the competitive environment. We should keep in mind, when designing such information disclosures, that even small differences in design can have a significant impact on agent behavior. Considering the equilibrium outcome of sophisticated participants is essential, but it is also vital that we consider the actions taken by less experienced and less sophisticated participants. For example, the paper emphasizes the value of customizing information for less sophisticated players in the search advertising auction market. The idea

of sharing information that is tailored to the needs of different market participants is also recommended in other online marketplaces.

In summary, this paper studies individual advertisers' heterogeneous responses to information disclosure in the search advertising market. In a broader sense, it opens up the question as to how individual firms develop marketing strategies in a complex environment. In the future, we hope to collaborate with the company to conduct field experiments to assess the empirical impact of alternative information disclosure mechanisms on firms' behavior.

## 9 Appendix

### 9.1 Proof: Bidding at cut-off is not a best response

In this subsection, we first show the case where there is only one suggestive bid for the first position, and the rest of bidders follows that particular suggestive bid. We prove that bidding at the same cutoff being a best response is a measure-zero event. The proof can be easily extended to the case where there are multiple suggestive bids, and the rest of the bidder follows each suggestive bids with positive probability. We first list the assumptions required.

**Assumption 9.1** *The following assumptions are required on proving proposition 9.2.*

- *The valuation of bidder  $i$  at period  $t$  is drawn from  $v_i^t \sim V_i^t$ , where  $V_i^t$  is an atomless distribution with positive support.*
- *Quality scores at period  $t$  for each bidder are independently drawn across time and bidder from distributions  $Q_i^t$  with continuous positive support on  $[0, \infty)$  (note the distributions are not required to be identical).*
- *Valuation distributions are independent from quality score distributions, and the bidder knows her own realization of valuation at period  $t$ ,  $v_i^t$ , and knows the quality score distributions at period  $t$  and period  $t - 1$ .*
- *Bidder  $i$  is aware of the suggestive bid generation process, which is, for the  $k^{th}$  position, a player  $i$  at period  $t$  receives suggestive bid  $s_i^t(1) = \frac{r^{t-1}(2)}{q_i^t}$ . Where  $r^{t-1}(2)$  is the period  $t - 1$ 's rank score of the second position, and  $q_i^t$  is a sample of bidder  $i$ 's quality score at period  $t$ .*
- *Bidder  $i$  is a rational Bayesian player that maximizes her expected utility.*

With assumption 9.1, we are ready to state the proposition.

**Proposition 9.2** *Under assumption 9.1, given the rest of bidders follow the suggestive bid for position  $k$ , following suggestive bid for position  $k$  being a best response is a probability zero event.*

When observing the quality score adjusted suggested bid at period  $t$  for position  $k$ ,  $s_i^t(1)$ , bidder  $i$  first updates the belief on the distribution on the rank score at period  $t - 1$  for the second position,  $r^{t-1}(2) = s_i^t(1)Q_i^t$ . Given the

other bidders following the suggestive bid,  $b_j = \frac{r^{t-1(2)}}{Q_j^{t-1}}$ , and the rank score associated with  $b_j$  follows distribution  $r_j = s_i^t(k) \frac{Q_i^t Q_j^t}{Q_j^{t-1}}$ . As long as suggestive bid not equals to 0, by independence of quality scores and quality scores has continuous positive support on  $[0, \infty)$ ,  $r_j$  has continuous positive support on  $[0, \infty)$ , and bidder  $i$  knows the joint rank score distribution  $g_{k-1,k}$  for all positions  $k$ .

Observing the realized valuation at period  $t$ ,  $v_i^t$ , Bidder  $i$  thus solves the following optimization problem to maximize her expected profit.

$$\pi(b|v, q \sim Q_i^t) = \int \left[ \sum_k \alpha_k \int_{qb}^{\infty} \left( \int_0^{qb} \left( v - \frac{r_k}{q} \right) g_{k-1,k}(r_{k-1}, r_k) dr_k \right) dr_{k-1} \right] dQ_i^t(q)$$

Taking the first order derivative and sets it to zero, one have

$$v_i^t = b + \frac{\int [\sum_k \alpha_k g_{k-1}(qb) E(qb - r_k | r_k < qb)] dQ_i^t(q)}{\int [\sum_k q g_k(qb) (\alpha_k - \alpha_{k+1})] dQ_i^t(q)} \quad (3)$$

Given the valuation realization  $v_i^t$ , the best response on bid  $b$  of a Bayesian expected utility maximizer should satisfy equation 3. Suppose bidder  $i$  follows suggestive bid  $s_i^t(1)$ ,

$$\hat{v}_i^t = s_i^t(1) + \frac{\int [\sum_k \alpha_k g_{k-1}(qs_i^t(1)) E(qs_i^t(1) - r_k | r_k < qs_i^t(1))] dQ_i^t(q)}{\int [\sum_k q g_k(qs_i^t(1)) (\alpha_k - \alpha_{k+1})] dQ_i^t(q)} \quad (4)$$

Since  $v_i^t$  is drawn from an atomless distribution  $V_i^t$ ,  $P(v_i^t = \hat{v}_i^t) = 0$ . This implies for bidder  $i$  with valuation  $v_i^t$ , following suggestive bid being a best response is a probability zero event.

## 9.2 Identification for Estimation

We first propose the following lemma on showing that the bidding strategy is increasing in valuation – with higher valuation, optimal bid derived in Section 5 is higher.

**Lemma 9.3** *Let  $b(v)$  be the bidding strategy that maximizes the payoff function  $\pi(b|v, q \sim F_i)$ .  $b(v)$  is monotone increasing in  $v$ .*

We prove this by showing that the expected payoff of bidding  $b$  given  $v$   $\pi(b|v, q \sim F_i)$  has increasing difference.

We have

$$\frac{\partial \pi(b|v, q \sim F_i)}{\partial b} = - \int \left[ \sum_k \alpha_k \left( g_{k-1}(qb) q \left( v - \frac{1}{q} E(r_k | r_k < qb) \right) - q(v-b) g_k(qb) \right) \right] dF_i(q)$$

And

$$\begin{aligned} \frac{\partial^2 \pi(b|v, q \sim F_i)}{\partial b \partial v} &= \int \sum_k \alpha_k q(g_k(qb) - g_{k-1}(qb)) dF_i(q) \\ &= \int \sum_k (\alpha_k - \alpha_{k+1}) g_k(qb) dF_i(q) > 0 \end{aligned}$$

Hence  $\pi(b|v, q \sim F_i)$  has increasing difference in  $(b, v)$ , and  $b(v)$  is monotone increasing in  $v$ . Further, since feasible bid  $b \in (0, \infty)$  and  $b = 0$  gives  $\pi(b|v, q \sim F_i) = 0$ , the maximizer is in the interior of the feasible bid set, which implies that if exists, the maximizer  $b$  must satisfies the following first order condition, which is the following condition.

$$v_i - \left( b_i + \frac{\int [\sum_k \alpha_k g_{k-1}(qb) E(r_k | r_k < qb)] dF_i(q)}{\int [\sum_k q g_k(qb) (\alpha_k - \alpha_{k+1})] dF_i(q)} \right) = 0$$

Lastly, we show that all the  $(b_i, v_i)$  pair that satisfies the first order condition indeed implies  $b_i$  is the maximizer of function  $\pi(b|v_i, q \sim F_i)$ . Consider one  $(b_i, v_i)$  pair that satisfies the first order condition in previous equation, let  $\underline{b} < b_i < \bar{b}$ . Further, let  $(\underline{v}, \underline{b})$  be such that  $\underline{b}$  maximizes  $\pi(b|\underline{v}, q \sim F_i)$  and  $(\bar{v}, \bar{b})$  be such that  $\bar{b}$  maximizes  $\pi(b|\bar{v}, q \sim F_i)$ . We know  $(\underline{v}, \underline{b})$  and  $(\bar{v}, \bar{b})$  all satisfies the first order condition and  $\underline{v} < \bar{v}$ . Hence,  $\frac{\partial \pi(b|v_i, q \sim F_i)}{\partial b}|_{b=\underline{b}} = v_i - \underline{v}$  and  $\frac{\partial \pi(b|v_i, q \sim F_i)}{\partial b}|_{b=\bar{b}} = v_i - \bar{v}$ . We have  $\frac{\partial \pi(b|v_i, q \sim F_i)}{\partial b}|_{b=\underline{b}} < \frac{\partial \pi(b|v_i, q \sim F_i)}{\partial b}|_{b=\bar{b}}$  for  $\underline{b} < b_i < \bar{b}$ . Hence all  $b_i$  that satisfies the first order condition satisfies  $\pi'(b) < \pi'(\bar{b})$  for  $\underline{b} < b_i < \bar{b}$  (where  $\pi'(b) = \frac{\partial \pi(b|v_i, q \sim F_i)}{\partial b}$ ). Hence the function  $\pi'(b)$  satisfies single crossing in  $b$ , and for  $b_i$  that satisfies  $\pi'(b) = 0$ , we have  $\pi'(\underline{b}) > 0$ ,  $\pi'(\bar{b}) < 0$  for  $\underline{b} < b_i < \bar{b}$ . Hence the first order condition is sufficient to pin down the maximizer. and all  $(b_i, v_i)$  pair that satisfies the first order condition implies that  $b_i$  is the maximizer of function  $\pi(b|v_i, q \sim F_i)$ .

## 9.3 Advertiser Bidding Pattern Plots

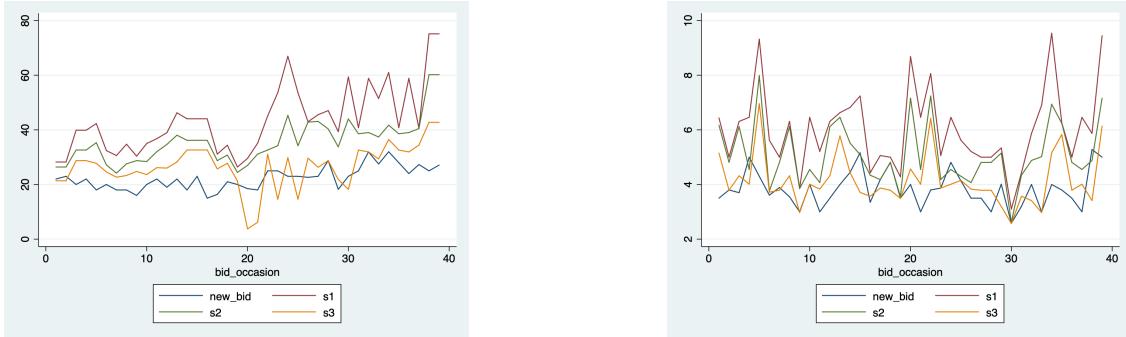


Figure 11: A Bidder’s Witnessed Three Bid Estimates Over Time 1

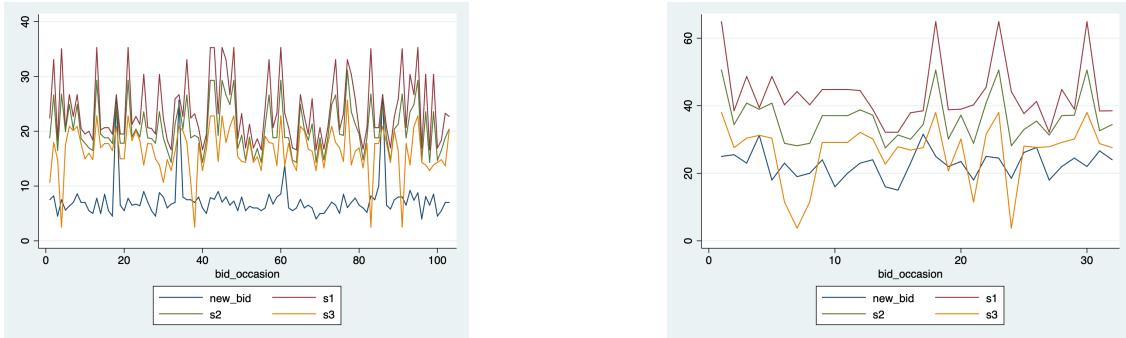


Figure 12: A Bidder’s Witnessed Three Bid Estimates Over Time 2

## References

- [1] Benjamin Edelman, Michael Ostrovsky, and Michael Schwarz. Internet advertising and the generalized second-price auction: Selling billions of dollars worth of keywords. *American economic review*, 97(1):242–259, 2007.
- [2] Hal R Varian. Position auctions. *international Journal of industrial Organization*, 25(6):1163–1178, 2007.
- [3] Wilfred Amaldoss, Preyas S Desai, and Woochoel Shin. Keyword search advertising and first-page bid estimates: A strategic analysis. *Management Science*, 61(3):507–519, 2015.
- [4] Emmanuel Guerre, Isabelle Perrigne, and Quang Vuong. Optimal nonparametric estimation of first-price auctions. *Econometrica*, 68(3):525–574, 2000.
- [5] Anindya Ghose and Sha Yang. An empirical analysis of search engine advertising: Sponsored search in electronic markets. *Management science*, 55(10):1605–1622, 2009.
- [6] Song Yao and Carl F Mela. A dynamic model of sponsored search advertising. *Marketing Science*, 30(3):447–468, 2011.
- [7] Philip A Haile and Elie Tamer. Inference with an incomplete model of english auctions. *Journal of Political Economy*, 111(1):1–51, 2003.

- [8] Dakshina G De Silva, Timothy Dunne, Anuruddha Kankamamge, and Georgia Kosmopoulou. The impact of public information on bidding in highway procurement auctions. *European Economic Review*, 52(1):150–181, 2008.
- [9] Sung-Jin Cho, Harry J Paarsch, and John Rust. Is the ‘linkage principle’ valid? evidence from the field. *The Journal of Industrial Economics*, 62(2):346–375, 2014.
- [10] Steven Tadelis and Florian Zettelmeyer. Information disclosure as a matching mechanism: Theory and evidence from a field experiment. *American Economic Review*, 105(2):886–905, 2015.
- [11] Susan Athey and Denis Nekipelov. A structural model of sponsored search advertising auctions. In *Sixth ad auctions workshop*, volume 15, 2010.
- [12] Michael Ostrovsky and Michael Schwarz. Reserve prices in internet advertising auctions: A field experiment. In *Proceedings of the 12th ACM conference on Electronic commerce*, pages 59–60, 2011.
- [13] Kinshuk Jerath, Liye Ma, Young-Hoon Park, and Kannan Srinivasan. A “position paradox” in sponsored search auctions. *Marketing Science*, 30(4):612–627, 2011.
- [14] Sridhar Narayanan and Kirthi Kalyanam. Position effects in search advertising and their moderators: A regression discontinuity approach. *Marketing Science*, 34(3):388–407, 2015.
- [15] Axel Ockenfels and Alvin E Roth. Late and multiple bidding in second price internet auctions: Theory and evidence concerning different rules for ending an auction. *Games and Economic behavior*, 55(2):297–320, 2006.
- [16] Alvin E Roth and Axel Ockenfels. Last-minute bidding and the rules for ending second-price auctions: Evidence from ebay and amazon auctions on the internet. *American economic review*, 92(4):1093–1103, 2002.
- [17] Patrick Bajari and Ali Hortaçsu. The winner’s curse, reserve prices, and endogenous entry: Empirical insights from ebay auctions. *RAND Journal of Economics*, pages 329–355, 2003.
- [18] Salvatore Barbaro and Bernd Bracht. Shilling, squeezing, sniping: Explaining late bidding in online second-price auctions. *Working article. University of Mainz, Mainz, Germany*, 2004.
- [19] Ali Hortaçsu and Steven L Puller. Understanding strategic bidding in multi-unit auctions: a case study of the texas electricity spot market. *The RAND Journal of Economics*, 39(1):86–114, 2008.
- [20] Stephen G Donald and Harry J Paarsch. Piecewise pseudo-maximum likelihood estimation in empirical models of auctions. *International Economic Review*, pages 121–148, 1993.
- [21] Stephen G Donald and Harry J Paarsch. Identification, estimation, and testing in parametric empirical models of auctions within the independent private values paradigm. *Econometric Theory*, pages 517–567, 1996.

- [22] Jean-Jacques Laffont, Herve Ossard, and Quang Vuong. Econometrics of first-price auctions. *Econometrica: Journal of the Econometric Society*, pages 953–980, 1995.
- [23] Sandra Campo, Isabelle Perrigne, and Quang Vuong. Asymmetry in first-price auctions with affiliated private values. *Journal of Applied Econometrics*, 18(2):179–207, 2003.
- [24] Brendan Lucier, Renato Paes Leme, and Éva Tardos. On revenue in the generalized second price auction. In *Proceedings of the 21st international conference on World Wide Web*, pages 361–370, 2012.