Estimating the Efficiency Improvement of the Resource Allocation in the Yahoo! Keyword Auction

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Abstract

The keyword auction is a successful pricing mechanism which helps search engine companies sell navigation service to advertisers. Correctly understanding the performance differences among different types of keyword auctions will not only affect the multibillion dollar revenue of search engine companies, but it will also help develop more superior keyword auctions in the future. For the two popular keyword auctions— the Generalized First Price (GFP) auction and the Generalized Second Price (GSP) auction—current consensus in both the industry and academia is that the GSP auction is more efficient than the GFP auction. Specifically, a bidder with a higher value will be more likely to win a higher and better slot for her advertisement. However, there is no empirical examination on this claim. I investigate this issue by exploiting a natural experiment of the Yahoo! keyword auction system upgrade in 2002. I construct an efficiency index and show that the GSP auction mechanism is at least 4% more efficient.

Key Words: Online advertising, keyword auction, efficiency comparison

1.Introduction

The keyword auction has played an indispensable role in the success of search engine giants like Yahoo! and Google. For example, Yahoo!'s first half-year revenue in 2008 was $3.62 billion and at least 50% of that revenue came from the keyword auction.[1] For Google, its first half-year revenue in 2008 was $10.55 billion with 97% of this revenue generated by the sponsored search auctions.[2] Actually, the keyword auction is not only crucial to search engine companies, but it is also "vital to the success of many other small business" such as bid management software firms, bidding campaign consulting firms, and key word selecting firms, etc. (SeeJansen and Mullen(2008).)

The keyword auction is a pricing mechanism which helps search engine companies sells navigation services to advertisers. When addressing search requests, search engines display both the search results and advertisers' web links, which are called sponsored links. These sponsored links attempt to navigate potential customers to specific product web sites. Be- cause this targeting of potential costumers has proven effective, advertisers are willing to pay in order to obtain an ideal placement for their web link on a search result page. Search engine companies invented the keyword auction to sell these sponsored link placements.

The keyword auction was first introduced in 1998 by Goto for Yahoo! Since then, search engine designers have upgraded the mechanism several times. The purpose of replacing an old sponsored search auction with a new one is "to bring more stability to the auction bidding, increase profits, and help reduce strategic bidding". (SeeJansen and Mullen(2008).) One of the major transformations the keyword auction has undergone was Yahoo!'s switch from the Generalized First Price (GFP) auction to the Generalized Second Price (GSP) auction.[3]This auction rule change, which took place on June 26, 2002, is generally believed to have been a success by both the industry and academia in the sense that "superior designs" have replaced the "inefficient market institutions". (See Edelman, Ostrovsky and Schwarz (2008)and Jansen and Mullen (2008).)

[1] See Yahoo! Quarterly Report on Form 10-Q to SEC for the quarter ended June 30, 2008 and Borgers, Cox, Pesendorfer and Petricek (2007).
[2] See Google Inc Quarterly Report on Form 10-Q to SEC for the quarter ended June 30, 2008 and Borgers et al.(2007).
[3]During 2002, the Yahoo! keyword auction was managed by a company named Overture, which later was acquired by Yahoo!. Without causing confusion, this paper does not distinguish these two names and will always use Yahoo! keyword auction.

The GSP auction is believed to be more efficient because while using it, bidders will be less likely to "game the system". Edelman et al. (2008) constructs a specific example and illustrates how the GSP auction brings more efficiency when it replaces the GFP auction. That means that an individual bidder with a higher value will be more likely to win a higher and better position with a higher amount of clicks.

Correctly understanding and evaluating how different sponsored search auctions perform is important for both economists and the search engine industry. Having the correct answers will not only affect the multibillion dollar revenue of search engine companies, but it will also help develop more superior sponsored search auctions in the future. However, in the literature, there is no empirical examination on this efficiency issue. This paper investigates the claim that the GSP auction is superior to the GFP auction using bid data collected from Yahoo! keyword auctions in 1000 markets from between June 15, 2002 and June 14, 2003.

To measure efficiency, I first construct an index measure based on the following idea: a more efficient auction system should help the bidder with the higher value obtain the higher slot more often. If the auction is fully efficient, bidders with higher values should always dominate the bidders with lower values, and we should observe that the probability that higher value advertisement rank higher than always be 1. The less efficient the mechanism is, the smaller this probability will be. Therefore, this relative ranking between two bidders can be used as an index to measure the efficiency of the auction mechanism.

The challenge of identifying the efficiency improvement is that bidders' true values were unobservable. However, we can observe the following facts. If the new system can improve the bidding efficiency, on average, if a bidder dominates his competitor most of the time in the old system, he will be more likely to do so in the new auction system; on the other hand, if a bidder is dominated by his competitor most of the time in the old system, he will be more likely to be so in the new system. Based on these observations, I propose estimation strategy and findthat the newauction mechanism is at least 4% more efficient. In other words, the GSP auction system gives the advertiser with a higher value a 4% better chance to obtain a higher slot.

This paper contributes to the keyword auction literature in two aspects. First, in the past there was no empirical analysis to compare and evaluate the performances of different sponsored search auctions. In past literature, the comparison between the two popular auctions—the GFP auction and the GSP auction—was illustrated purely by hypothetical examples, which will be discussed in detail in section 3. This paper, however, provides solid empirical evidence contradicting the current beliefs about the comparison between the GFP auction and GSP auction.

Second, this research constructs an efficiency index and it is also the first to empirically evaluate the efficiency improvement of the GSP auction. Understanding and evaluating how efficiently the auction system allocates link placements is both an important and challenging question, especially when each bidder's true value in the auction is unobservable. This paper turns measuring efficiency into comparing the relative ranking between two bidders and is the first to identify the efficiency improvement brought by the GSP auction.

The paper is organized as follows. Section II introduces the Yahoo! keyword search auction. Section III briefly surveys the keyword auction literature and especially examines the conventional wisdom about the performance of the GFP auction and GSP auction. Section IV constructs an efficiency index and sets up the econometric model. Section V introduces the data and presents the simple statistics. Section VI evaluates efficiency improvement of the GSP auction over the GFP auction. Section VII concludes.

2.Yahoo! Keyword Auction

In the search engine industry, there are three key players: the advertisers, the search engines and the potential customers. Search engines navigate potential customers to advertisers' product web sites by displaying their web links when potential customers conduct keyword search requests. These advertisers' links are called sponsored links. Sponsored links distinguish themselves from the organic (non-sponsored) web search results by whether or not a fee is paid to the search engine company.

Figure 1 shows an example of sponsored links for the key word "refinance". When someone uses Yahoo! to search for information about "refinance", the search engine will display search results along with sponsored links, which are circled in Figure 1. Usually around 10 sponsored links, located on the top and on the right of each page, will be displayed.Advertisers are interested in buying these link slots for their product web sites because they may target the potential customers more efficiently.

In 1998, Goto first introduced the sponsored search auction in the search engine industry to sell these link slots.[4]The keyword auction is a multi-object dynamic auction in which each individual advertiser bids for the ideal slot for his web site. Keyword auctions usually have the following common features. First, all the link slots are auctioned at the same time. As shown in Figure 1, there were at least 12 sponsored link slots being auctioned at that time. Second, the auction is dynamic with an infinite time horizon. Each bidder can change or withdraw his bid at any time, which will be immediately reflected in the slot placement. Third, all search engines share a common payment rule: pay per click (PPC), which means that whenever thereis a click on the sponsored link, the bidder will pay Yahoo! once. And lastly, in Yahoo!'s keyword auction, all the information, including bids and slot placement, is public information, which can be observed by all the bidders directly.

In keeping with the keyword search for Figure 2 "Refinance", shows all bidders' bids and slot allocation information as it was captured by a free public web site.[5] The bid range is from \$16.13 to \$7.49 and each bidder's position is determined solely by his bid. As can been seen, "LendingTree" had the highest bid; therefore, this advertisement was placed at the highest slot as shown in Figure 1.

[4]Goto was later renamed to Overture and acquired by Yahoo! in late 2003.
[5] The free bid check website is http://keyword.secretstohighprofit.com/default.aspx. Figure 1 and Figure 2 were captured at the same time on March 28, 2007.

Figure 1: Sponsored Links for the Keyword "Refinance"

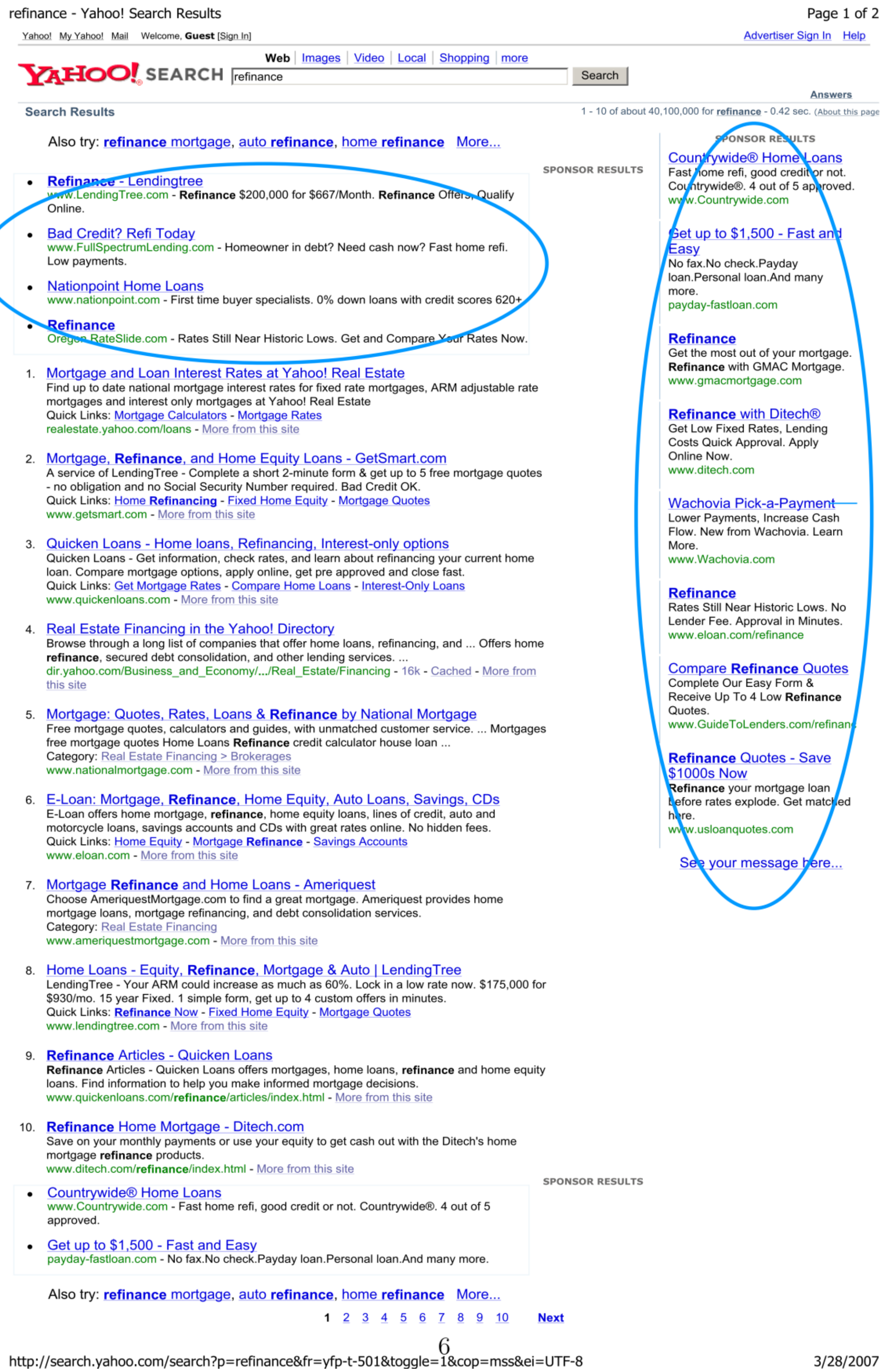
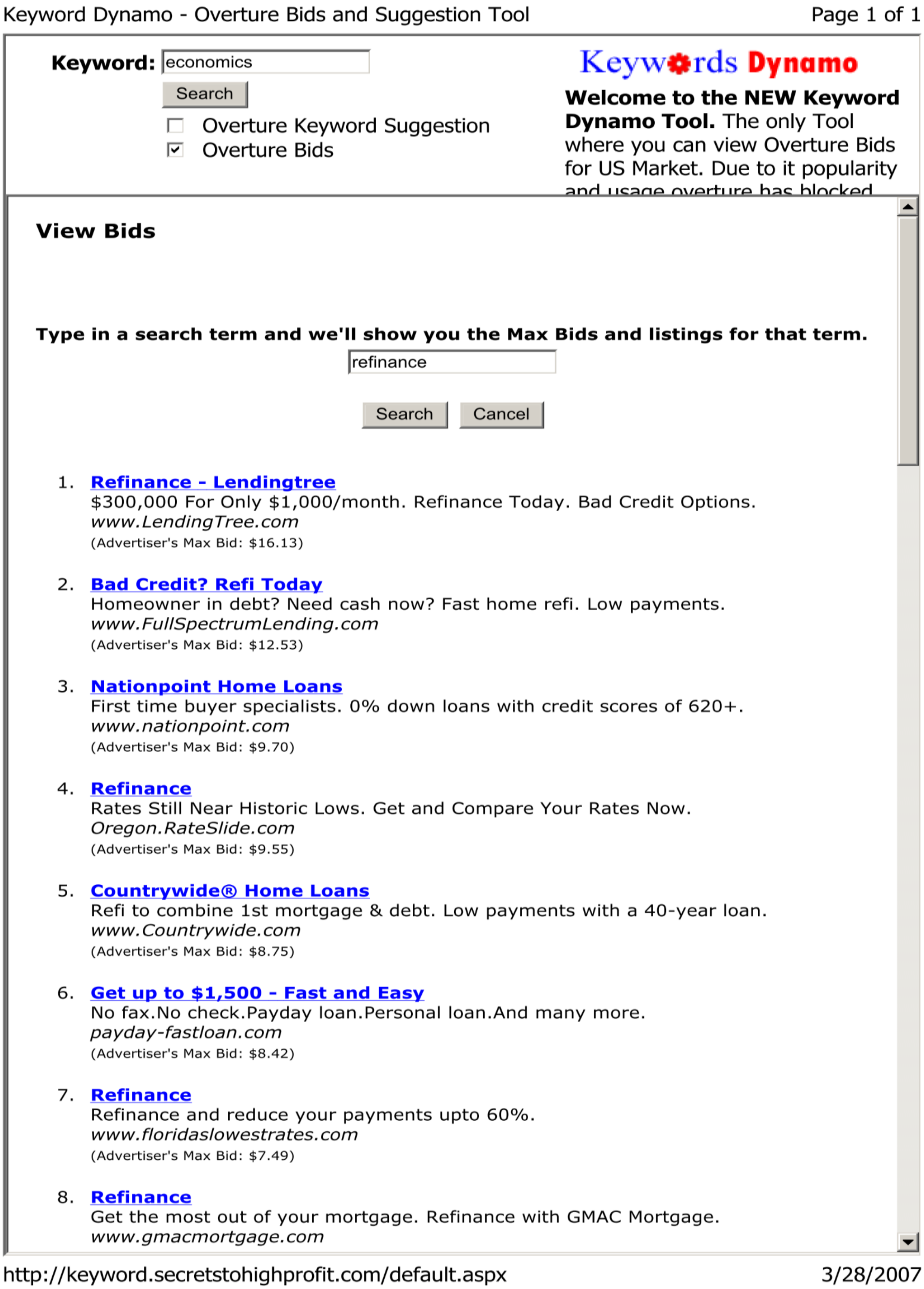


Figure 2: Bids and Rankings



Keyword Dynamo - Overture Bids and Suggestion Tool Page 1 of 1

Keyword: economics

Search

Overture Keyword Suggestion

Overture Bids

Keywords Dynamo

Welcome to the NEW Keyword Dynamo Tool. The only Tool where you can view Overture Bids for US Market. Due to it popularity and usage overture has blocked

View Bids

Type in a search term and we'll show you the Max Bids and listings for that term.

refinance

Search Cancel

1. **Refinance - Lendingtree**
   $300,000 For Only $1,000/month. Refinance Today. Bad Credit Options.
   www.LendingTree.com
   (Advertiser's Max Bid: $16.13)
2. **Bad Credit? Refi Today**
   Homeowner in debt? Need cash now? Fast home refi. Low payments.
   www.FullSpectrumLending.com
   (Advertiser's Max Bid: $12.53)
3. **Nationpoint Home Loans**
   First time buyer specialists. 0% down loans with credit scores of 620+.
   www.nationpoint.com
   (Advertiser's Max Bid: $9.70)
4. **Refinance**
   Rates Still Near Historic Lows. Get and Compare Your Rates Now.
   Oregon.RateSlide.com
   (Advertiser's Max Bid: $9.55)
5. **Countrywide® Home Loans**
   Refi to combine 1st mortgage & debt. Low payments with a 40-year loan.
   www.Countrywide.com
   (Advertiser's Max Bid: $8.75)
6. **Get up to $1,500 - Fast and Easy**
   No fax.No check.Payday loan.Personal loan.And many more.
   payday-fastloan.com
   (Advertiser's Max Bid: $8.42)
7. **Refinance**
   Refinance and reduce your payments upto 60%.
   www.floridaslowestrates.com
   (Advertiser's Max Bid: $7.49)
8. **Refinance**
   Get the most out of your mortgage. Refinance with GMAC Mortgage.
   www.gmacmortgage.com

http://keyword.secretstohighprofit.com/default.aspx 3/28/2007

Designing efficient auction rules regarding how the advertisers pay the search engine and how the search engine allocates the link slots among the advertisers is a key challenge faced by the search engine designers because the decision to adopt different forms of sponsored search auctions has an important impact on the success of search engine companies.

In the past 6 years, Yahoo! upgraded its sponsored search auction several times hoping to find a better auction mechanism to bring more stable bidding behaviors and higher auction revenue.Before June 26, 2002, a bidder in the Yahoo! sponsored search auction paid Yahoo! his bid multiplied by the number of the clicks on his web site. For example, if a bidder bid $3 and his web site received 3000 clicks, the bidder would have to pay Yahoo! $9,000. The literature calls this type of keyword auction "Generalized First Price (GFP) Auction" to distinguish it from the standard first price auction.

On June 26, 2002,Yahoo! upgraded its Generalized First Price (GFP) Auction to a Generalized Second Price (GSP) Auction. In this new auction system, the web site placement was still determined solely by a bidder's bid, but each bidder, instead of paying his own bid per click, only had to pay 0.01 more than the next highest bid below his. For example, if two bidders bid $0.4 and $0.6, respectively, in the old bidding system, the winner would pay $ 0.6 per click received; however, in the GSP auction system, he would be charged at a rate of $0.41.The most recent Yahoo! keyword auction upgrade took place in 2007. Before May 2007, slot allocation was determined only by bidders' bids. The bidder with higher bids got higher link slots as shown in Figure 1 and Figure 2. After May 2007, Yahoo! sponsored search auctions no longer determined slot allocation solely based on bidders' bids, but also by the quality of an advertiser's web site. To do this, Yahoo! created a score system to rank bidders' links.Even though this rule change of Yahoo! keyword auction in 2007 is also very important and interesting.

This paper keeps its focus on the Yahoo! keyword auction upgrade whichhappened in 2002.

3.Literature

Recent research on the keyword auction mainly focus on three perspectives. First, economists are interested in providing a theoretical game foundation for this new auction mechanism.Varian (2006) and Edelman et al. (2008) first introduced equilibrium concepts for the GSP auctions based on the idea of "envy-free", which assumes that in the equilibrium no bidder would like to place a bid that would cause retaliation. All authors suggest that the GSP auction can achieve efficient allocations. In a similar setup, Athey and Ellison (2007) further introduce consumer search behavior into the model and analyze the implications for reserve prices, product variety, etc.

Second, both economists and search engine developers are interested in the bidders' overall advertising campaign performances taking the keyword auction as given. Ghose and Yang (2007) propose a novel empirical model to quantify how different metrics affect bidders' advertising campaign performances. Rutz and Bucklin (2007) use hierarchical Bayes binary choice model to estimate the keyword conversion rate and, based on the model, propose better advertising campaign strategies.

Third, many other topics derived from the keyword auction are also attracting economists' attention. Goldfarb and Tucker (2008) investigate the relationship between matching difficulty and bidding prices. They found evidence showing that the more difficult it is to make a match between the firms and customers, the higher the bids in the keyword auction. Animesh, Ramachandran and Viswanathan (2005) study the relationship between an advertiser's quality and his bidding strategies and find evidence of significant adverse selection associated with product uncertainty.

This research is an empirical work, which is closely related to the second group of the literature. A bidder's advertising campaign mainly consists of two parts. The first part is how to place a bid to obtain a good placement, which is related to costs; the second part is how to increase purchases to generate more revenue. This paper mainly focuses on the cost side and asks the question: How will a specific type of keyword auction affect advertisers' bidding behaviors? Althoughstudying the performance differences amongdifferent keyword auctions is an important question, from the perspectives of both the search engine developers and advertising bidders, all of the current empirical research analyzes economic behavior under one specific keyword auction. None has conducted any empirical comparisons among different keyword auction mechanisms adopted in the industry. This paper, to my knowledge, is the first empirical paper comparing the performances of the GFP auction mechanism and the GSP auction mechanism.

These results also have important implications for the current keyword auction theory literature. The theory papers authored by Edelma et al. (2008), Varian(2006) and Athey and Ellison (2007) are based on a static game theory structure that analyzes the GSP auction. Edelman et al. (2008) and Varian (2006) argue that this game framework "describes the basic propertiesof the prices observed in Google's ad auction reasonably accurately."

Especially, they claim this GSP auction is more efficient than the GFP auction at allocating the keyword search resource. If the evidence shows that the bidding behaviors in the GSP auction are more efficient than the GFP auction, it may add our confidence on the explanation power of the current theory framework, which actually had provided the guidance for the latter keyword auction upgrade. The following subsections willintroduce the current prevailing belief about the GSP auction and the GFP auction, which is the hypothesis this paper will test.

3.1 Conventional Wisdom about the GSP auction

Currently theories mainly focus on the GSP auction in a static setting; in contrast, hardly any formal theoretical analysis has been done on the GFP auction. The conventional wisdom about the comparison of the two auctions was based mainly on concrete examples instead of formal game theory setup. Edelman et al. (2008) proposed a simple example, which the following literature frequently cited. (Edelman and Ostrovsky, 2006; and Jansen and Mullen, 2008) In this subsection I also follow this example to illustrate the current consensus and what it misses.

Example 1(Edelman et al., 2008): There are two slots for the links. The first slot receives400 clicks per hour, and the second slot receives 100 clicks per hour. There are threeadvertisers bidding to place their product. Then values per click for the bidders are $5, $4 and $2. Call these three bidders A, B, C respectively.

Edelman et al. (2008) use this example to illustrate the superiority of the GSP auction. They show that in the GSP auction, the equilibrium bids of A, B, C will be $5, $4 and$2 and that with these bids, efficient allocation is achieved. But in the GFP auction, the equilibrium will not be stable. B will bid $2.01 instead of $4 and A will bid $2.02 instead of $5. B willoutbid A at $2.03 and the bids escalate until $4. B will pull his bid back to $2.01 and the bid escalation goes on again. These bidding behaviors will result in the sawtooth pattern of a bidding war, which is well documented in the literature. Based on this example, they argue that the GSP auction is more efficient at allocating resources and more stable when it comes to bids with the GFP auction.

However, there is no empirical examination on this claim. In the following research, I will construct an efficiency index and estimate how much more efficient the GSP auction is. The idea is the following: Because the GSP auction can more efficiently allocate the resources, the bidder with a higher value will obtain the better slots more often.

4. Model Setup

In this sectionIwanttoanswerthequestion ofhowmuchwastheefficiencyimprovementundertheGSP auction system, asclaimedbythe literature. Tomeasure efficiency, Ifirst constructanindexmeasurebasedonthe ranking.

Suppose there are two bidders, A and B. A's value per click is V_A and B's value per click is V_B with $V_A > V_B$. If the system is efficient and higher ranks receive more clicks, then Pr [A higher than B] = 1. If the auction mechanism is less efficient, this probability will be smaller than 1; the less efficient the mechanism is, the smaller the probability should be.Therefore, this relative ranking between two bidders can be used as an index to measure the efficiency of the auction mechanism. Based on this efficiency index, the idea behind the identification is the following: If the system improves the bidding efficiency, it should make the winner more likely to win and the loser more likely to lose. In other words, theprobability index bigger than 1/2 should be even bigger than 1/2 in the new auction system,and the probability index smaller than 1/2 be even smaller than 1/2 in the new system.

Given a unit of time, define λAB to be the portion of time that A ranks higher than B.[6]If $VA \geq VB$, because of the inefficiency of the GFP auction design or measurement error, λAB should be smaller than 1. This difference will reflect the efficiency loss.

Assumption1: If $V_A \geq V_B$, *then* $\lambda_{AB} = 1 - \alpha + u_{AB}$ *with* $\alpha < 1/2$.

Here α captures the efficiency loss caused by the GFP auction design and u_{AB} can be taken the measurement error, or a random shock. Assumption 1 also implies that in the GFP auction, although the bidder with the low value might take advantage of the auction design and sometimes dominate his competitor, this should not happen over 50% the time. In other words, the bidder with the higher value should get the higher position more often.

[6]The unit of time can be an hour, a day, etc.

Assumption2: *Eu_{AB}= 0 and uAB is iid. Its distribution function is denoted by F(u).*

As the literature claims that the GSP auction improves efficiency. Therefore, α will decrease according to the prediction.

Assumption3: *Under the GSP auction, the observed frequency is*$\lambda_{AB}=(1-\alpha)+\beta+u_{AB}$

Therefore, theestimation function becomes:

$$\lambda_{AB}=(1-\alpha)+\beta * I(GPS)+u_{AB} \quad (1)$$

As I cannot observe V_A or V_B directly, therefore I do not know which is bigger if I just randomly pick any bidders of A and B. The above estimation will be meaningless if I simply regress the equation 1.

Therefore, the empirical question becomes how to estimate β. The following propositions show the estimation strategy, which is discussed at the beginning of the section.

Proposition1: Let*Nbethenumberoftheobservations.* *Define*$\eta_{AB}=max\{\lambda_{AB},1 - \lambda_{AB}\}$. *Regress*$\eta_{AB}=\gamma_\alpha+\gamma_\beta * I(GSP)+u_{AB}$.*ThentheOLSresultprovidesalowerboundfor*β. *Thatis*$\lim_{N\longrightarrow\infty}\gamma_{\beta N}=\beta_\infty<\beta$

Proof: ByOLS,itcanbeshownthat

$$\begin{aligned}
\beta_\infty &= E\{\max\{(1-\alpha)+\beta*I(GSP)+u_{AB}, 1-((1-\alpha)+\beta*I(GSP)+u_{AB})\}\} \\
&\quad -E\{\max\{(1-\alpha)+u_{AB}, 1-((1-\alpha)+u_{AB})\}\} \\
&= (1-\alpha)+\beta+2\int(-u-(\frac{1}{2}-\alpha+\beta))I(u<-(\frac{1}{2}-\alpha+\beta))dF(u) \\
&\quad -((1-\alpha)+2\int(-u-(\frac{1}{2}-\alpha))I(u<-(\frac{1}{2}-\alpha))dF(u)) \\
&= \beta+2\int(-u-(\frac{1}{2}-\alpha+\beta))I(u<-(\frac{1}{2}-\alpha+\beta))dF(u) \\
&\quad -2\int(-u-(\frac{1}{2}-\alpha+\beta))I(u<-(\frac{1}{2}-\alpha))dF(u) \\
&\quad -2\beta\int I(u<-(\frac{1}{2}-\alpha))dF(u) \\
&= \beta-2\beta\int I(u<-(\frac{1}{2}-\alpha))dF(u) \\
&+ \ 2\int(u+(\frac{1}{2}-\alpha+\beta))I(-(\frac{1}{2}-\alpha+\beta)<u<-(\frac{1}{2}-\alpha))dF(u)
\end{aligned}$$

Because $I(-(\frac{1}{2}-\alpha+\beta)<u<-(\frac{1}{2}-\alpha)) \leq I(u<-(\frac{1}{2}-\alpha))$ *and* $u+(\frac{1}{2}-\alpha+\beta)\leq\beta$ *when* $u<-(\frac{1}{2}-\alpha)$

Therefore $2\beta\int I(u<-(\frac{1}{2}-\alpha))dF(u) > 2\int(u+(\frac{1}{2}-\alpha+\beta))I(-(\frac{1}{2}-\alpha+\beta)<u<-(\frac{1}{2}-\alpha))dF(u)$

Therefore $\beta_\infty < \beta$.

Proposition 2 *Let* $N = N_1 * N_2$. *Define* $\eta_{AB,\ N_1} = \max\{\frac{\Sigma\lambda_{AB}}{N_1}, 1-\frac{\Sigma\lambda_{AB}}{N_1}\}$. *Regress* $\eta_{AB,\ N_1} = \gamma_\alpha + \gamma_\beta * I(GSP) + u_{AB}$. *Then the OLS result provides a consistent estimate. That is* $\lim_{N_1,N_2\to\infty}\hat{\gamma}_{\beta_{N_1,N_2}} = \beta_\infty = \beta$

Proof. *: By OLS, it can be shown that*

$$\begin{aligned}
\beta_\infty &= \lim_{N_1\to\infty}\beta+2\int(-\frac{\Sigma u_{AB}}{N_1}-(\frac{1}{2}-\alpha+\beta))I(\frac{\Sigma u_{AB}}{N_1}<-(\frac{1}{2}-\alpha+\beta))\Pi(dF(u)) \\
&- \int(-\frac{\Sigma u_{AB}}{N_1}-(\frac{1}{2}-\alpha))I(\frac{\Sigma u_{AB}}{N_1}<-(\frac{1}{2}-\alpha))dF(u)
\end{aligned}$$

$$As\ Eu_{AB} = 0\ and\ u_{AB}\ is\ iid,\ \frac{\Sigma u_{AB}}{N_1} \to 0.\quad And\ | - \frac{\Sigma u_{AB}}{N_1} - (\frac{1}{2} - \alpha + \beta) < 2,\ therefore$$

$$\begin{aligned} |\int (-\frac{\Sigma u_{AB}}{N_1} - (\frac{1}{2} - \alpha + \beta))I(\frac{\Sigma u_{AB}}{N_1} &< -(\frac{1}{2} - \alpha + \beta))\Pi(dF(u))| \\ &\leq 2\int I(\frac{\Sigma u_{AB}}{N_1} < -(\frac{1}{2} - \alpha + \beta))\Pi(dF(u)) \\ &\to 0 \end{aligned}$$

Therefore $\beta_\infty = \beta$.

5. Data

Yahoo!'s research department provides a data set, which records all of the bids for the top 1000 keyword search by volume and all of the associated accounts for the time period from June 15, 2002 through June 14, 2003.

Each observation in the data has 5 variables: bidder ID, bidder's bid, the time when the bid was submitted, auction market and a dummy variable indicating whether the bid was placed under the GFP auction rule or under the GSP auction rule.

Table 1 shows the market statistics: the max bid, mean bid, minimum bid and the stan- dard deviation for the top 10 most clicked markets. Five cents is the minimum requirement for bidding. One striking observation is the value of the maximum bid. According to this data set, some bidder is paying Yahoo! $9,170 for just one click through the sponsored search.[7] I also present the individual bidding statistics from June 15, 2002 through July 15, 2002 in Table 2. Table 2 provides the maximum value, mean value, minimum value and the standard deviation for the following daily statistics: The Maximum bid, 75 percentile bid, mean bid, median bid, and 25 percentile bid of each bidder on each day.

Table1:BidStatistics oftheTop10MostClickedMarkets

Market	Observations	mean	stddev	min	Max
All1,000Markets	18,634,347	5.70	9.10	0.05	9,170
1	1,455,161	16.73	6.52	0.05	60
2	2,041,397	12.24	5.27	0.05	50
3	58,269	7.07	2.41	0.05	22.01
4	14,467	18.86	9.88	0.05	50
5	294,538	14.86	4.06	0.05	50
6	22,884	4.92	2.95	0.05	50
7	20,659	17.98	6.88	0.05	50
8	21,136	14.34	7.06	0.05	50
9	28,695	5.06	3.82	0.05	50
10	17,850	18.63	8.91	0.05	50

Note: Thereare18,634,347bidscollectedfrom1,000markets inthesample.

Bid frequency and bid range measure the bidding stability of the auction system. maximum bid, 75 percentile bid, median bid, mean bid and the 25 percentile bid measure the impact on the bid distribution of an individual bidder from June 15th to July 5th, 2002Table 2 shows how the mean values of the above

[7] 19 out of 18.6 million bids are negative or less than $0.04, and there are 201,068 bid with value of $0.05. Therefore, I delete the observations with bid smaller than 5 cents.

statistics change after the launch of the new auction. The mean values of both the daily bid frequency and the daily bid range increase, which suggests that the new auction system is more unstable. The mean values of the max bid and 75 percentile bid increase while the mean value of the 25 Percentile bid decreases, which suggests that the bids are more dispersed.

Table2:Summary Statistics fromJune15thtoJuly5th

BeforeJune25th	Mean	Stv	Min	Max
BidFrequency	20.9	108	1	4,934
BidRange	0.617	1.55	0	48.99
MaxBid	2.66	3.69	0.05	100
75percentilebid	2.74	3.89	0.05	100
MedianBid	2.54	3.59	0.05	100
MeanBid	2.52	3.55	0.05	100
25Percentile bid	2.38	3.48	0.05	100
AfterJune25th	**Mean**	**Stv**	**Min**	**Max**
BidFrequency	23.3	143	1	6,011
BidRange	0.983	3.33	0	49.95
MaxBid	3.02	4.64	0.05	100
75percentilebid	2.82	4.10	0.05	50
MedianBid	2.59	3.75	0.05	50
MeanBid	2.56	3.62	0.05	42.8
25Percentile bid	2.30	3.42	0.05	50

Note: Thereare1,099,781 bidscollectedfrom812markets.

6. Estimate

I first randomly pick an auction market and then select two bidders as A and B in this market as a pair. From June 15, 2002 to July 21, 2002, I randomly choose 500 pairs. Second, I calculatefor each day. Next, I define $\eta_A = \max\{\lambda_{AB}, 1-\lambda_{AB}\}$. Then by the above Propositions, the following regression will provide a lower bound for the efficiency improvement:

$$\eta_{AB} = \alpha_{AB} + \beta \times I(GSP) + \sum_{M,Tu,W,Th,F,Sa,Su} \gamma_{day} \times I(weekday) + u_{AB}$$

Here I control for the pair fixed effect α_{AB}, and the weekday effect γ_{day}.

I estimate the efficiency improvement for four cases. The first two cases (1) and (2) include all the bidders, and the regression in (2) also includes the pair dummy variables. The last two cases (3) and (4) only include active bidders who change their bids at least 400 times every day, and the regression in (4) also include the pair dummy variables. Table 3 shows the efficiency improvement brought by the launch of the GSP auction. The value of $\hat{\beta}$ suggests that in the GSP auction, the bidder with the higher value was more likely to dominate the lower-value bidder and that this probability increased at least by around 3.5%. It is consistent with the literature that the GSP auction is more efficient than the GFP auction.

Table3: EstimationResultofRelativeRankingChange

	(1)	(2)	(3)	(3)
β	0.037	0.036	0.037	0.033
	(0.0028)	(0.002)	(0.0027)	(0.0022)
Monday	0.012	0.011	0.012	0.01
	(0.004)	(0.003)	(0.005)	(0.003)
Tuesday	0.012	0.012	0.006	.006
	(0.005)	(0.004)	(0.004)	(0.003)
Thursday	0.014	0.013	0.012	0.012
	(0.005)	(0.004)	(0.005)	(0.004)
Friday	0.019	0.019	0.013	0.013
	(0.005)	(0.004)	(0.005)	(0.004)
Saturday	0.034	0.035	0.031	0.032
	(0.005)	(0.004)	(0.004)	(0.004)
Sunday	0.039	0.040	0.039	0.040
	(0.005)	(0.004)	(0.003)	(0.004)
N of Obs	15,316	15,316	15,343	15,343
R^2	0.1	0.36	0.1	0.37

Note: Wednesday is set to be the base day.

For active bidders, the estimation result is smaller, which means there is not much change in the relative rankings after the launch of the GSP auction. This suggests that the active bidders might still engage in strategic bidding behavior, which is consistent with the results in the RDD section.

7. Conclusion

Understanding and evaluating how efficiently the auction system allocates link placements is both an important and challenging question, especially when each bidder’s true value in the auction is unobservable. This paper proposes an econometric method and applies it to find empirical evidence confirming the current theory prediction. It would be more interesting to explore how efficiency improvements differ across different keywords, if there is richer dataset. This will be left for future research.

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