

Sponsored Search Auctions: Research Opportunities in Marketing

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Abstract

We systematically overview the literature in key word search and propose several promising research directions. The paper is organized by each agent in the search process; searchers, advertisers and the search engine and reviews the key research issues for each. For each group, we outline the decision process involved in key word search. For searchers, this involves what to search, where to search, which results to click, and when to exit search. For advertisers, this involves where to bid and which word or words to bid on, and how searchers and auction mechanisms moderate these behaviors. The search engine faces choices on mechanism design, website design and how much information to share with its advertisers and searchers. These choices have implications for customer lifetime value and the nature of competition between advertisers. Overall, we list a number of potential areas of future research arising from the decision processes of these various agents.

1 Introduction

This paper reviews research on sponsored search auctions. The sponsored search auction is a newly developed auction practice where advertisers bid for premium spots on the search results page of an Internet search engine.¹ Winning advertisers' ads are placed in these premium spots—for example, at the top of the search results list. This new form of advertising can create high levels of brand awareness among Internet users. Moreover, its reach has extended dramatically in recent years. By the end of 2006, over 726M people aged 15 and over were online; and one quarter of these individuals were in the United States (IRI, 2007). In November of 2006 alone, American Internet users conducted 6.7B searches on the 25 leading search engines. By comparison, a top rated TV show such as “Desperate Housewives” only has about 25M viewers (IRI, 2007); and the growing popularity of DVR services offered by TiVo and cable companies has decreased the audience base of traditional TV advertising. Further, sponsored search advertising can boost sales for retailers, especially in online channels. According to a US Census Bureau report in Q1-2007, American e-commerce retail sales achieved a year-over-year increase of 18.4% while retail sales across all channels grew at a much lower rate of 3.2%.² A key driver of sales in online retailing is online promotion (Ansari et al. (2008)). In Qiu et al. (2005), the authors estimate that more than 13.6% of the web traffic is affected by search engines. Hence sponsored search advertising is a powerful tool for generating online traffic. The statistics described above illustrate the importance and efficacy of sponsored search

¹Other than internet search engines, any interactive, addressable media formats (e.g., DVR, satellite digital radio) can be utilized to implement similar auctions for advertising. Another application is to allocate limited shelf space to a variety of products in a retailing store. Due to the limited air time or shelf space, auctions can be used to determine prices and allocate the resources. In such a notion, the research literature on sponsored search auctions can be generalized to a much broader context.

²Resource: US Census Bureau(2007, Q1), Quarterly Retail E-Commerce Sales. (<http://www.census.gov/mrts/www/ecommm.html>)

advertising, and are the reason for the staggering growth of sponsored search advertising. Compared to the slow annual growth of 3.8% in total advertising expenditure (TNS Media Intelligence, 2007), Search Engine Marketing Professional Organization (SEMPO) reports that search engine marketing expenditure reached 9.7B in 2006, a 62% year-over-year growth.³ In addition, over 70% North American advertisers are shifting in whole or in part of their budget from other marketing programs to search engine marketing.

In marketing, auctions have stimulated research interests because of their growing popularity along with the thriving of online marketplace (Chakravarti et al. (2002)). While research on sponsored search auctions remains nascent, there are tremendous potential opportunities in this area. Studies of sponsored search auctions can provide insight into this new practice and guidance for marketing managers.

Since Vickrey's original work (Vickrey (1961)), auctions have generated a rich body of literature. A query on the search engine Google Scholar with the keyword "auction" returns over 300,000 results. Given this extensive literature, we only consider studies that are the most relevant to sponsored search auctions.

The paper is organized according to the different agents involved with sponsored search auctions: Internet users, advertisers and search engines. This organization allows us to focus on issues regarding each agent's behavior and strategies separately. First, we detail the practice of sponsored search auctions in section 2. In section 3, we consider the decision process of Internet users such as their search behavior. Section 4 reviews relevant auction research with an emphasis on advertisers. In section 5 we consider issues from the perspective of search engines with the purpose of maximizing their revenues in the auctions. In each of these sections we also discuss potential research opportunities for the field of marketing. We conclude with section 6.

³Sponsored search auctions account for 86% of the total spending, or 8BB.

2 An Introduction of Sponsored Search Auctions

With the ascendancy of top search engine websites such as Google, Yahoo! and MSN, advertisers have a new media arena in which to implement advertising campaigns—search results pages at these search engines. When an Internet user conducts a keyword search on a search engine, the engine creates a search results webpage displaying websites that are ordered according to their relevance to that keyword. These results are called organic search results. Meanwhile, there are several premium sponsor advertising spots on the webpage, mainly the top or the side of that page (see Figure 1). Advertisers can place their ads in these premium spots. When a customer clicks either an organic result or a sponsored ad, she will be led to the corresponding website to gather further information or make a purchase.

It is widely recognized by practitioners that the appearance of a particular retailer in a top spot in the organic search results or the sponsored ads section can create positive impressions among consumers, increase online traffic and ultimately boost sales. To be placed in a top position in the *organic* search results, advertisers rely on techniques normally termed as “search engine optimization”. Commonly used optimization techniques include changing the website homepage title to more semantically related keywords, rewriting product descriptions on one’s website so they are more visible to search engines and posting website links on popular online bulletin boards and forums.⁴ According to SEMPO, about 10% of North America’s search engine marketing expenditure is used for organic search engine optimizations, a total of over \$600M.

Alternatively, advertisers can compete for premium advertising spots in which to place their ads. The number of these spots is normally much smaller than the number

⁴There are also some illicit methods to increase a website’s ranking such as spam emails and hacker software, which are punished severely by major search engines.

Google [Web](#) [Images](#) [Video](#) [News](#) [Maps](#) [Desktop](#) [more »](#)

sponsored search advertising [Advanced Search](#) [Extensions](#)

Results 1 - 10 of about 41,900,000 for **sponsored search advertising** (0.25 s)

Web New! [View and manage your ads](#)

Google Search Advertising
adwords.google.com in just minutes. Immediate posting. Increase traffic, measure results.

Search Marketing
www.marketing.networksolutions.com "We guarantee top 10 SEO results for your Web site. Learn more now!"

Online Marketing from Yahoo! Search Marketing (formerly Overture)
Search and other partner sites with the **Sponsored Search** program. ... **Local Advertising** Target prospects searching for the businesses in your neighborhood. ...
searchmarketing.yahoo.com/ - 16k - [Cached](#) - [Similar pages](#) - [Note this](#)

Search Engine Marketing: Yahoo! Search Marketing (formerly Overture)
Search engine marketing: Yahoo! **Sponsored Search**, a search engine marketing solution that drives website traffic to new customers.
searchmarketing.yahoo.com/srch/index.php - 12k - [Cached](#) - [Similar pages](#) - [Note this](#)
[[More results from searchmarketing.yahoo.com](#)]

Yahoo Sponsored Search Now on Cell Phones | Marketing Pilgrim
Yahoo has just announced the beta launch of **sponsored search** results on the ... "Yahoo has always been a leader in pay-per-click **search advertising** on the ..."
www.marketingpilgrim.com/2006/10/yahoo-sponsored-search-now-on-cell-phones.html - 40k - [Cached](#) - [Similar pages](#) - [Note this](#)

Pay per Click (PPC) Search Engine Advertising - Sponsored Search ...
Pay per click (ppc) **search engine advertising** programs propel online **advertising** and paid **search** results distribution to a new level. Searchfeed's **sponsored** ...
www.searchfeed.com/ - 27k - [Cached](#) - [Similar pages](#) - [Note this](#)

Pay per click - Wikipedia, the free encyclopedia
Keywords, also referred to as **search terms**, are the very heart of pay per click **advertising**. The terms are guarded as highly valued trade secrets by the ...
en.wikipedia.org/wiki/Pay_per_click - 25k - [Cached](#) - [Similar pages](#) - [Note this](#)

yahoo sponsored search advertising yahoo search marketing ...
The McCord Web Design Yahoo! Sponsored **Search** Easy Start program is a great way to start your Yahoo! **advertising** program off running.
mccordweb.com/internet-marketing/easy-start.php - 42k - [Cached](#) - [Similar pages](#) - [Note this](#)

Google Advertising
Search advertising also enables you to target your ads to the right customers at exactly the right ... Also known as web advertorial or **sponsored** content. ...
www.google.com/ads/glossary.html - 35k - [Cached](#) - [Similar pages](#) - [Note this](#)

Sponsored Links

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Sponsor Link Optimization
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Search advertising
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LookSmart Advertising
Market your Business Online.
Reach your Audience. \$50 in Clicks!
www.LookSmart.com

Yahoo! Search Marketing
Yahoo! Cost Per Click marketing.
Sign-Up & Get a \$50 Credit.
searchmarketing.yahoo.com

Search Engine Marketing
Learn how SendTec can maximize your pay-per-click marketing efforts.
www.SendTec.com

Search Advertising
Do It Yourself **Search Advertising**
Get New Customers in 15 minutes
www.Enhance.com

Interactive Advertising
Find New Prospects by Targeting Qualified North Carolina Customers.
Advertising LocalLaunch.com
North Carolina

Sponsored Search Ads

Organic Search Results

Arrows from the diagram point to the following elements in the screenshot:

- Sponsored Search Ads:** Points to the yellow banner for Google Search Advertising and the 'Sponsored Links' section on the right.
- Organic Search Results:** Points to the main list of search results on the left.

Figure 1: Sponsored Search Advertising Example

of interested advertisers. For most search engines, these premium spots are auctioned off because auctions can simultaneously determine appropriate prices for the spots and efficiently allocate their limited supply. During the auction, an advertiser specifies her bid for one-click of the ad. Following some ranking mechanism, the topmost bidder gets the best spot; the second bidder gets the second best spot and so on. Winning advertisers pay the search engine only when their sponsored ads are clicked by Internet users. The calculation of the payment amount for each click varies across search engines. Some engines use the first-price rule, where the advertiser pays her bid for each click (e.g., www.shopping.com). Others use more complicated payment schemes. For example, Google uses the product of the bid of the very next losing bidder and an internally determined factor to calculate a winner's per-click payment. Each year, these auctions generate billions of dollars revenues for top search engines.

In short, advertisers can use techniques to optimize their positions in the organic search results, or they can attend sponsored search auctions to compete for premium advertising spots. When consumers conduct keyword searches, the advertiser's appearance on the search results page generates positive impressions, increases online traffic and sales. Figure 2 summarizes the relationship among the three agents and serves as the basis for the organization of this paper. We address each agent in turn and summarize extant research and future opportunities for each.

3 Internet Users

Internet users, as the customers addressed by Internet advertising, play a crucial role in sponsored search auctions. For advertisers, Internet users create online traffic to their websites and generate sales. For search engines, Internet users' clicks lead to auction payments from advertisers. Investigations of Internet users behavior can pro-

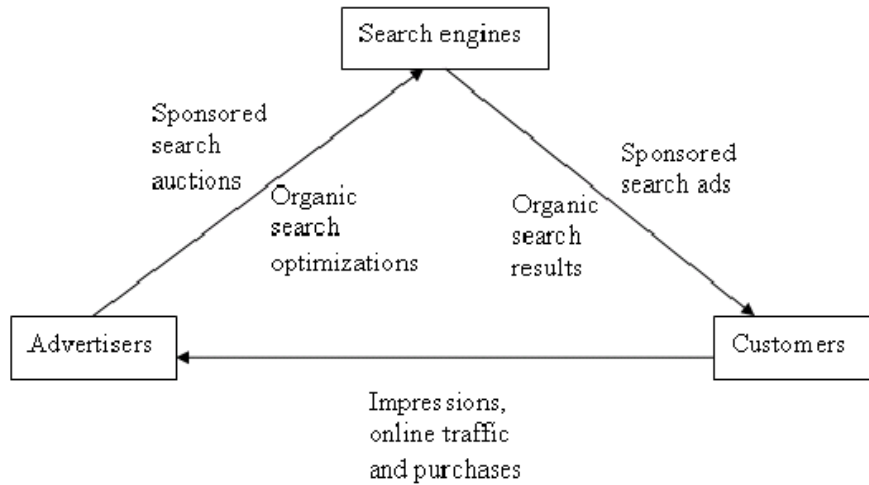


Figure 2: The Relationship among Customers, Advertisers and Search Engines

vide a better understanding of the potential strategies advertisers and search engines could employ. Further, such investigations could shed light on consumer behavior in an online environment.

The search process of an Internet user involves the following decisions. First, the user needs to choose which search engine websites to visit and which keywords to search. Upon viewing the search results, she needs to decide how many linked websites to investigate. After she finishes the investigation, she decides whether to make a purchase and from which advertiser. We will discuss each in turn.

3.1 Choosing Engines and Keywords

Similar to a shopping trip, a user first needs to choose which “stores” and which “categories/aisles” to visit. Which search engine attracts the most consumers? Why? Do consumers choose multiple search engines to visit? What keywords are more

likely to be used by consumers? Answers to these questions have important policy implications for search engines and advertisers; we will discuss these implications in more details in section 4 and section 5. In short, if consumers intend to visit more than one search engine and use various keywords to query, strategic advertisers will attend more auctions across search engines and keywords. Moreover, the keywords that are most likely to be used by consumers determines the intensity of competition for different keywords. For search engines, these issues directly affect competition and revenues from auctions. Most of these questions can be examined empirically or experimentally. Existing discrete choice literature provides a solid ground for future research (cf. Palma et al. (1992)). With the increasing availability of Internet user clickstream data and advanced behavioral research techniques, there are many potential research opportunities for exploration.

3.2 Choosing Search Websites to Investigate

The number of linked websites a consumer clicks will affect the winning advertiser's payment, online traffic and sales, as well as the search engine's revenue. For example, if each consumer clicks more links on average, advertisers may get more online traffic, but will also need to make higher payments to the search engine. In fact, if consumers explore search results more broadly by clicking on multiple links, advertisers could experience a drop in sales because consumers would have more options in their consideration sets. In turn, from the perspective of the search engine, more clicks may not necessarily imply higher revenue. Recall that a search engine's revenue is the product of the volume of clicks and the payment of each click. Thus, although the click volume increases, the per-click-payment may drop since bidders lower their bids due to the possible decrease in sales discussed above. Correspondingly, bidding

strategies, optimal auction mechanism design and even the search results webpage design will adjust. Thus the number of investigated websites is crucial for both search engines and advertisers.

The number of clicks is affected by the search patterns of consumers. Consider two different search patterns that could be used by a consumer when she comes to the search engine website:

1. Searching sequentially: the consumer conducts the search by submitting keyword queries; upon viewing the search results page, she clicks one linked website at a time to investigate. All clicked websites and an outside option (e.g., not purchasing) are in her consideration set. If she is satisfied with one option in her consideration set, she stops the investigation and choose that option; otherwise she will surf back to the search results page and make another click to investigate.
2. Searching nonsequentially: the consumer conducts the search by submitting keyword queries; upon viewing the search results page, she chooses several websites all at once to investigate. All of these investigated websites and an outside option (not purchasing) are in her consideration set. Then she chooses one option out of her consideration set.

Each of these search patterns could describe a consumer's search behavior. One of the factors that determines which model fits better may be the searched product's characteristics.⁵ To be more specific:

⁵Other factors may also affect search patterns. For example, when a consumer is less comfortable with switching windows while surfing, she will probably use the first pattern; if the Internet connection speed is very slow, the user may choose the second style so that all webpages will have been already read into the PC's cache when she is browsing.

- If a product has a very complicated attribute space or is an experience good, the consumer may prefer the second pattern of simultaneous evaluation. For example, hotels have complex attributes such as locations, ratings, prices, facilities and so on. A consumer may choose to open several websites simultaneously to make a comparison. Some search engines even provide a “compare” function which lines up chosen hotels for easier comparison (see Figure 3). Another example where consumers might prefer to evaluate options simultaneously is computer software, an experience good. Customers do not know how well PC software performs until they have used it for some time. In this case, the consumer may prefer to download several trial versions at a time and use them for a few days before making judgment.
- If the attribute space of a product is relatively simple so that the utility of consumption can be easily assessed upfront, for example, a specific textbook, the consumer will mainly focus on prices listed by different book sellers. She will probably use the first pattern to surf through book sellers until she feels satisfied with the price.

Each of the two search patterns above are described by existing search models, which have attracted abundant attention in the theoretical, empirical and experimental literature. The pioneer paper by Stigler (1961) has elicited many studies on search models. In the literature, there are at least two major streams of search models: sequential search and nonsequential search (cf., Stigler (1961); Stigler (1962); Weitzman (1979)). Each matches one of the two aforementioned search patterns. Search is costly in both cases. A sequential search assumes that the user draws only one sample per period to investigate and put it into her consideration set. Based on what is in her consideration set, she makes a decision about whether to continue the

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Comparing Selected Hotels in Durham, NC

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Comparing 3 Hotels

	Remove	Remove	Remove
Hotel name	Quality Inn & Suites	Candlewood Suites Raleigh-cary	Millennium Hotel Durham
Star rating	★★★★	★★★★	★★★★
User reviews	9 user reviews - Write a review	1 user review - Write a review	5 user reviews - Write a review
Average price	\$70 Select	\$70 Select	\$69 Select
Best price found at			 Compare prices from 4 Web sites
Room type	1 King Bed No Pets Allowed Coffee Maker In Room Iron And Ironing Board...Featured More room types	Standard Suite No Preference More room types	Standard 1 King Bed More room types
Hotel address	3710 Hillsborough Rd Durham, NC 27705	1020 Buck Jones Rd Raleigh, NC 27606	2800 Campus Walk Ave Durham, NC 27705
Distance	Durham	from Durham (Raleigh)	Durham
Area/Location			
Pictures			

Done

Figure 3: A Search Engine with the Easy Comparison Tool

search or pick one option out of her consideration set. In contrast, in a nonsequential search model, before making any investigations, a user first chooses the optimal size of her consideration set, i.e., the number of samples for investigation, with the objective of maximizing her expected return. Then she randomly draws samples to fill her consideration set. She finally chooses the best option out of the consideration set. These two models each explain some real life scenarios. The sequential search model can describe the first search pattern mentioned above while the nonsequential model describes the second search pattern better. It is fair to say that in reality the search process may be a mix of both search patterns. In Morgan and Manning (1985), the authors establish that a more generalized optimal search rule should be a combination of both models. Under some conditions, however, the optimal search rule takes one of the two extreme cases of sequential search or nonsequential search.

The newly developed search engine industry provides some promising directions for theoretical, empirical and experimental research that will add to existing search model literature; we discuss these below. A better understanding of consumer search behavior in the online search environment can enrich our knowledge of the strategic behaviors of advertisers and search engines.

1. With the assistance of search engines, should a consumer shopping online search more or less than in a brick-mortar environment? At first glance, since search engines decrease search costs, consumers should search more intensively. However, there are reasons to argue the opposite. First, after investigating several options, the user may have forgotten the exact attribute values of previously observed products. Thus the user cannot easily choose a product that is already in her consideration set. Also, advertiser's website normally open in the same browser window to replace the search results page. To go back to the results page for

another investigation, the user may have to make several backspace clicks. Even worse, some websites that are encrypted for security reason may even block the user from going back to the results page. All of these create barriers to revisiting previously investigated products. In a laboratory setting, Zwick et al. (2003) design a sequential search experiment such that consumers have a probability less than one of fetching previously visited products. They show that consumers stop searching too early compared to the theoretical optimal level of search. Second, Moorthy et al. (1997) argue that consumers stop searching earlier than the optimal if there is little “relative uncertainty” among products, where “relative uncertainty” is defined as the uncertainty about which product is the best. At many search engines especially more specialized ones (e.g., www.shopping.com for merchandise, www.addall.com for books, www.sidestep.com for travel products), consumers can sort and filter products by different criteria such as price and retailer rating. To some extent, such sorting or filtering decreases the “relative uncertainty” and thus may reduce the consumer search behavior to a suboptimal level. Additional research that shows suboptimal consumer search behavior is an experimental study by Gabaix et al. (2006). The authors demonstrate that there may be bounded rationality during a consumer’s search. In particular, during a sequential search, consumers are myopic in the sense that they behave as if every search will be the last search. Because they only consider the expected value of one search ahead rather than integrating out the expected values of all future searches, this myopic behavior results in an underestimation of the value of search. Hence consumers may stop searching too early. Clearly, empirical and experimental research on the welfare implications of search engines would be useful, and could offer theoretical insights to further enrich search models.

2. What are consumers' clicking likelihoods and purchase likelihoods under differently designed search results pages? Design characteristics to consider may include: (1) what advertisers' characteristics can be sorted/filtered by consumers? (2) After sorting/filtering, should a winning sponsor advertiser still appear at the top spot in the sorted/filtered results? (3) How easily can a consumer surf back to the search results page? Answers to these questions will give the search engine insights into how to design the results page to manipulate the number of clicks per consumer.

Why should a search engine consider the number of clicks per consumer under differently designed webpages? As mentioned at the beginning of this section, the number of clicks has important effects on revenues for advertisers and search engines. As discussed, consumers may stop searching online earlier than in traditional brick-mortar environments (Zwick et al. (2003); Moorthy et al. (1997); Gabaix et al. (2006)). On one hand, a shorter search decreases the number of alternatives in the consideration set, increasing the probability of a sale for products already in the consideration set. Since the auctioned advertising spots increase the probability of an advertiser being clicked and hence included in the consideration set, advertisers will value these spots higher. Thus advertisers will bid more aggressively. On the other hand, from the perspective of the search engine, the decreased number of searches has two opposite effects: (1) lowering auction revenue by decreasing the total number of clicks and (2) increasing auction revenue due to the more aggressive bidding. Hence the search engine should be strategic about achieving the optimal number of clicks per consumer.

3. What are the consumer welfare implications of sponsored search advertising? First, sponsored search advertising enriches organic search results with spon-

sored ads for products in which consumers are interested. By aligning relevant product information on the same webpage, the search engine creates a convenient shopping environment. As shown in consumer behavior literature, when consumers can easily make price and quality comparisons across different retailers, their utilities for consuming the chosen products rise (Lal and Sarvary (1999); Lynch and Ariely (2000)). From the point of view of economics, is this increase in utility a simple result of search cost reduction? Or is there something else, such as the pleasant shopping experience itself, which has an impact on the utility of consumption? Further, easy access to product quality information decreases a consumer's disutility of payment by lowering the weight of price in one's utility function (Russo (1977); Häubl and Murray (2003)). Together with the "easy comparison" feature just mentioned, consumers should be more satisfied with their search engine shopping experience than a brick-mortar purchase. Empirically, can we measure this improvement consumer welfare? How does this improvement affect advertisers' revenues? Might the search engine be able to monetize this welfare improvement?

4. Under what conditions, will one of the two search models better describe consumer search behavior? As suggested above, the complexity of product attribute space may be one of the factors that contribute to variance in consumer search patterns. The more (less) complicated the product attribute space, the better nonsequential (sequential) search models should mirror the reality of consumer search. Another factor that may affect a customer's search pattern is the difficulty of fetching searched products from previous periods, or the consumer's intertemporal discount factor. If it is very difficult to fetch previously visited products or the discount factor is fairly small, customers are more likely to use

nonsequential search. For example, a job seeker is likely to search nonsequentially during job-hunting by submitting multiple applications simultaneously. Thirdly, when consumers use sorting at the search results page, they choose an attribute of products that is more important to them to conduct the sorting. After sorting, products are ordered according to levels of that attribute. It is likely that consumers will investigate products sequentially in the order that is produced by the sorting. Fourthly, when a consumer uses filters at a search results page, she faces a much smaller set of products which all satisfy her criteria. She is more likely to consider all products in this set. Thus, a nonsequential model seems to better describe her search behavior. All of these influences on consumer search patterns provide empirical and experimental research opportunities. Hong and Shum (2006) and Hortacsu and Syverson (2004) use observed market price dispersion to infer consumer search behavior. Kim et al. (2009) use market level popularity data to infer consumer search behavior and market structure. These empirical studies establish solid ground for future research using individual level search engine data to explore consumer search behavior. However, little experimental research has been done on this topic. Since experiments provide control over the noise in field data, we believe they can offer great insights onto consumer search behavior in the online search environment.

3.3 Choosing Links to Click

With multiple links presented on the search results page, the user must choose which link(s) to click. For advertisers and search engines, spots that are more likely to be clicked are more valuable; thus, bidding strategies and auction revenues depend on consumers choices about where to click.

3.3.1 The Preference of A Consumer

Intuitively, the user should click the link that present the highest expected utility. But how does a consumer form preferences in the search engine environment? Do online consumers have a different preference construction process than those in a brick-and-mortar environment? Since consumers clicking behavior is directly affect by their expected utilities of search results, answers to these issues will lead to a better understanding about which links are more likely to be clicked and hence have higher value. In the consumer behavior literature, some studies have investigated the influence of the online environment on consumer preference formation. Search engines provide consumers with easier access to price information across different retailers, and consumers put more weight during decision making on attributes that are more convenient to process (cf. Russo (1977); Häubl and Murray (2003)). Alba et al. (1997) hence express the concern faced by many online retailers: since online shopping reduces the search cost for price information, consumers become more price sensitive, which intensifies price competition among retailers and could lead to lower margins. Diehl et al. (2003) provide an additional argument that supports this view on price sensitivity. They show that based on a consumer's keyword query, search engines oversample products that match the consumer's interests; these sampled products are more likely to be close substitutes. Thus, there will be less product differentiation and more intensified price competition. In a theoretical paper by Chen and He (2006), the authors show that such an assortment of close substitutes is in fact an equilibrium of sponsored search auctions. On the contrary, Lynch and Ariely (2000) propose the opposite and argue that search engines may decrease price sensitivity. Search engines not only lead to lower search cost for price information, they also make quality information more salient. Thus, when consumers have easier access to quality

information, the product quality becomes more important to consumers and price sensitivity drops. With more field data, these opposing claims could be tested to see which better reflects reality; such empirical research could also provide insight into theoretical modeling on how search engines affect consumer attitudes towards price and quality.

3.3.2 Possible Empirical Modeling Approaches

For nonsequential search, an empirical modeling issue is that consumers make multiple discrete choice when they are viewing the results page: a consumer needs to pick several links out of the search results. In the marketing literature, Harlam and Lodish (1995) use a discrete choice model to describe multiple brand purchases, while Manchanda et al. (1999) consider the “shopping bracket” problem where consumers make purchases across multiple categories. However, Dubé (2004) may be the most relevant study for this issue. Dubé (2004) uses a “multiple discreteness model,” as outlined in Hendel (1999), to estimate the choice problem where a consumer purchases multiple items across different brands within the same category, soft drinks. These models can be easily extended to the problem of consumer behavior on search engine webpages: a user chooses multiple ads to click; the expected return for investigating these ads is determined by the ads attributes and the user’s characteristics. The user tries to maximize the total return of investigation subject to some constraint such as time.

For sequential search, empirical models following the spirit of Hong and Shum (2006) can be applied. If researchers have detailed individual browsing data, consumer search costs may be inferred by relying on the idea that when a consumer stops searching, this implies that the marginal search cost is higher than the expected return for continuing the search.

In short, the availability of search engine data provides opportunities for marketing

researchers to better understand consumer behavior in the online world.

4 Advertisers

The effectiveness of sponsored search advertising attracts business of all types. Before entering the bidding stage, an advertiser needs to first decide which “products” to choose, i.e., which search engines and which keywords should be used to run her advertising campaign. To do so, she also needs to measure values of the auctioned spots of each keyword at each engine. After making the decision, she needs to decide corresponding bid amounts. During the bidding process, there are also other problems affecting her bidding strategies such as the winner’s curse in auctions. We will discuss these below.

4.1 Which Search Engines and Which Words to Bid

To some extent, sponsored search auctions can be understood as advertisers purchasing products from search engines through auctions. The products are Internet users’ clicks and impressions. There are different search engines and each engine sells multiple keywords. So an advertiser makes discrete choice about engines and keywords before entering an auction. Little research has been done on the advertiser’s choice problem, even though there is abundant discrete choice research that can be applied (cf. Palma et al. (1992)). In order for a choice model about advertisers to be realistic, the following factors should be taken into account:

- (1). The number of Internet users using particular search engines and keywords. The volume of Internet users that visit a search engine and use particular keywords determines the number of impressions and clicks of a sponsored ad. Choosing search engines and keywords with high traffic should be a major consideration for the ad-

vertiser.

(2). The characteristics of Internet users such as likelihoods of clicks and purchases, and the propensity of being influenced by advertising. The likelihoods of clicks and purchases affect online traffic to the advertiser’s website and purchase conversion rate, which will affect sales. Those users with a very specific search purpose will have higher likelihoods of clicking and purchasing. For example, users searching for more specific keywords “hotels los angeles” may be more likely to click and reserve hotels than those searching for “los angeles”. On the other hand, these more specific keywords may be used by fewer Internet users while searching, resulting in fewer impressions. Thus, the advertiser has to make a trade-off between impressions and sales.

(3). The auction mechanism adopted by the search engine and the competitiveness of the auction. Together these factors determine a bidder’s winning probability and payment (cost), where a low probability of winning and a high payment will deter bidders. For example, Edelman and Ostrovsky (2007) show that a flawed auction mechanism used by Yahoo! caused revenues to be 10% lower than they should (optimally) have been.

Supplementing the use of discrete choice models to select search engines and keywords, selection algorithms have been advanced to help advertisers select a cluster of keywords (which may be distributed across multiple search engines). For example, Rusmevichientong and Williamson (2006) propose algorithms for selecting keywords to bid based on the ranking of keywords in a descending order of profit-to-cost ratio. Amer-Yahia et al. (2008) specify a framework of an open source computer language to help advertisers optimize their advertising campaigns. One extension for such algorithms may be how to incorporate competitor response into the algorithms. For example, when the advertiser’s decision to adopt a specific algorithm becomes known

to its competitors, they may predict the focal advertiser's actions. Then it becomes possible for those competing advertisers to strategically beat the focal advertiser, voiding the advantages of using the algorithm at the first place. In short, when designing a general algorithm for the purpose of optimizing keyword advertising campaigns, it is crucial to incorporate the game component into the calculation.

Of further interest is search engine optimization (SEO), or techniques that advertisers use to design their advertisements and websites to command a prominent placement in the organic search results section. While there is extensive research in the field of computer science and engineering about the optimization algorithms (e.g., Joachims (2002); Malaga (2007); Langville and Meyer (2006)), interesting questions remain in the field of marketing. Such questions include how an advertiser should efficiently allocate resources between sponsored search auctions and SEO and whether an SEO substitutes or complements sponsored advertising. A prerequisite question to consider involves how search engine advertising affects advertiser revenue over the long term and we discuss this question next.

4.2 How to Measure the Value of an Advertising Spot

Before bidding, a potential bidder must determine the value of the object in the auction. No matter what auction mechanism is adopted by the search engine, this value will affect the strategy of the bidder.

To assess the value of an advertising spot, there are at least two candidate variables: (1). online traffic (clicks) generated by the spot to the advertiser's website; (2). the number of impressions on the search results page. Both variables can influence the advertiser's sales. Although advertisers normally use only one of them to measure the value of a spot (SEMPO, 2005), we suggest a more accurate measure that takes

both into account should be constructed.

Online traffic (clicks) is used to calculate spot value more often than number of impressions because it is more convenient to obtain: the search engine uses this number to calculate the payment and the number is clearly shown on the advertiser's bill. However, it is still unclear how best to calculate the purchase conversion rate of these clicks. Purchase conversion rate directly affects the advertiser's sales, and refers to "the percentage of web visitors who make a purchase during a visit to an online retailer." (Montgomery et al. (2004)) Using clickstream data from an online retailer, Moe (2003) develops a typology of consumers visits to online stores that includes four groups: browsing, knowledge-building, searching and buying. The author shows that on average purchase conversion rate for "searching" visits is only about 6.64%. Even for "buying" visits, which have the highest conversion rate, only 20% of these visits turn into final purchases.⁶ This low purchase conversion rate may cause the value of spots to be overestimated when value is calculated using number of clicks. However, let us consider the consumer's decision process while visiting an online store. After a click, the consumer may become loyal to the online store due to positive impressions even without a purchase. She may come back to make multiple purchases in the future. With this dynamics ignored, the value of a spot will be underestimated. More intricately, since most online retailers carry a variety of products, even when a click leads to a purchase, it is difficult to predict which product a customer may buy and hence predict the revenue from that transaction. In short, the number of clicks by itself fails to accurately measure the value of a spot.

Other than generating online traffic, sponsored search advertising can also generate impressions similar to banner ads; these impressions increase awareness among consumers. In practice, many firms even bid for "wrong" words so as to create

⁶The other types of visits have much lower purchase rates of less than 0.1%.

awareness by appearing in the results of potentially irrelevant searches. For example, eBay.com has sponsored ads at Google.com across many words related to “eBay” that are typographical errors such as ebbay, ebya, eaby. Since the seminal work by Nerlove and Arrow (1962), a rich literature shows that advertising is a tool to establish “goodwill” among consumers (cf. Naik et al. (1998); Bass et al. (2007)). When an Internet user conducts a search at the engine’s website, even if she does not click the sponsored ad on the results page, the ad still generates an impression and creates “goodwill”. Some empirical work support this argument. In a paper by Manchanda et al. (2006), the authors show that higher impressions of a banner ad has positive effects on an online retailer’s sales. Recently, Rutz and Bucklin (2008) use a dynamic linear model (DLM) to consider the effect of sponsored search ads on clicks (online traffic) and sales. They demonstrate that the effect of “goodwill” on these two variables is significant. As initial attempts, these papers extend our understanding on sponsored search advertising. However, there are still many questions to answer before we can apply impressions as an accurate measure of spot value. For example, because Rutz and Bucklin (2008) only have sponsored search advertising data from *one* advertiser firm on an *aggregate* level, they are not able to consider competition among advertisers, or heterogeneity of surfing behaviors and product preference among Internet users. An even more crucial problem is that with aggregate level data it is difficult to distinguish whether it is “goodwill” that increases clicks and sales or the fact that, even without “goodwill”, the presence of a link on the results page will lead to more clicks and more sales in a probability sense. Further, the value of a spot changes dynamically across time: if the advertiser has run intensive advertising recently, the marginal return of the spot generated from impressions may be lower than otherwise.

In sum, recent studies provide initial steps towards better measures of the profitability of sponsored search advertising. However, many aspects of the problem call

for future research. To name a few potential research questions: First, on the search results page, one retailer’s ad link is adjacent to dozens of competitors’. This assortment may be able to make price and quality information more apparent to consumers as mentioned above; how does competition among ads affect one online retailer’s impressions, online traffic and sales? Second, an advertiser can choose to direct online traffic to the main page of its website or to some specific category that is more related to the searched keyword by consumers;⁷ how does such a choice affect the value of an ad spot? Third, the design of an ad at the search results page affects traffic and impressions; should the retailer disseminate more information in the spot on the search engine’s page or retain information with the hope that consumers will visit the retailer’s site for more information? While the former strategy may create more positive impressions, the latter may increase clicks; how should the retailer make such a trade-off?

4.3 How Much to Bid

In this section, we first summarize studies about bidding strategies in sponsored search auctions in general. Then we extend the discussion by considering additional aspects of this auction game that may affect bidding strategies such as multiple auctions, the winner’s curse, collusion, and so on.

4.3.1 Bidding Strategies: An Overview

The auction formats most pertinent to sponsored search auctions are multi-item first-price auctions and second-price auctions with single demand. That is, there are multiple spots for an auction; each bidder needs only one of the multiple spots.

⁷That is, Bestbuy can direct a consumer who searches for “iPod” to bestbuy.com or directly to the “iPod” section at bestbuy.com.

Payment is calculated based on the bidder's own bid (first-price) or the highest losing competitor's bid (second-price). Below we set forth some established conclusions about these common auction mechanisms.

Take Yahoo! as an example. Before 2004, Yahoo! allowed bidders to submit bids at any time. The highest bidder got the best spot, the second bidder got the second best spot, and so on. A winner pays its bid for each click by Internet users. This auction can be described as a multi-item first price auction that has single demand and no clear ending time. The same mechanism is still being used by many search engines. In existing literature, multi-unit first price auctions have been shown to have a pure strategy Nash equilibrium for independent private value (IPV) under some moderate assumptions (Reny (1999); Athey (2001)). Roughly speaking, a rational bidder's bidding strategy is to submit a bid lower than her true value regarding the object, which is called bid shading. The degree of bid shading decreases when the number of competing bidders increases.

After 2004, Yahoo! followed Google and adopted a more complicated mechanism which is termed as Generalized Second Price Auction by Edelman et al. (2007). Using this new mechanism, bidders can still submit bids over time, but their payments are more similar to those of a second price auction that encourages bidders to bid their true values. The search engine calculates the product of each bidder's bid and her ad's quality factor. The quality factor is mainly determined by the number of past clicks, ad design and relevance to the keyword. Winners are determined based on the ranking of these products. For example, suppose there are two bidders A and B whose bids are b_A and b_B . Their quality factors are Per_A and Per_B . If $b_A Per_A > b_B Per_B$, then A wins the better spot and her payment for one click will be $b_B \frac{Per_B}{Per_A}$. Putting the quality factor aside for a moment, the auction can be considered as a multi-item second price auction, where there is an ex post equilibrium equivalent to the truth-

telling equilibrium, i.e., all bidders submit bids equal to their true values (Edelman et al. (2007); Varian (2007)). However, Katona and Sarvary (2008) extends the analysis by taking the quality factor into account and shows that there are multiple equilibriums which do not have closed form solutions.

Chen and He (2006) try to disentangle the bidding strategies under Google's mechanism from a different perspective. They assume that consumers (Internet users) engage in costly search. An advertiser's valuation for sponsored slots depends on the advertiser's product quality. A click on a high quality advertiser's link leads to a high likelihood of sale and a high value for the slot. Similar to Edelman et al. (2007), Chen and He (2006) show that, in equilibrium, bidders will submit bids equal to their true values. Hence advertisers will be ranked according to their values (qualities). Correspondingly, in equilibrium, consumers will search sequentially according to the ranking of advertisers because this signals their quality.

Athey and Ellison (2008) also consider a model that integrates both consumers and advertisers as in Chen and He (2006) but add several other important features. They assume that advertisers only know the distribution of their competitors' valuations about sponsored slots thus making the auction an incomplete information game. They also assume consumers engage in costly sequential searches that follow an optimal stopping rule (cf. Weitzman (1979)): consumers stop searching when the expected return of further searching is lower than the best choice in their consideration set. Thus, the better slot an advertiser gets, the higher the probability that her product will be purchased by consumers. Intuitively, this is because a better spot will give the product a higher probability to be included in the consumer's consideration set before she stops searching. So a better slot implies higher sales for the advertiser. The equilibrium bidding strategy in Athey and Ellison (2008) is different than those in previous literature. Although bids are still monotonically increasing in values

(qualities), high value (quality) advertisers will bid more aggressively than low value (quality) advertisers.

The rich literature in auctions offers a great start for the investigation of bidding strategies in sponsored search auctions. Still, the existing studies only have limited ability to generalize to this new practice. For future research, the following characteristics of the game need to be considered.

1. The dynamics involved in the auction game. An additional complication of the Google mechanism is the dynamics, i.e., a bidder's current performance will affect her future payoff. A better slot will increase the number of clicks, which will in turn affect the advertiser's future advertisement quality factor. As described above, this quality factor will affect the bidder's winning probability and payment. Hence the bidder may consider dynamics in her bidding strategy. Such dynamics have significant effects on equilibrium bidding strategies. For example, Zeithammer (2006) considers the dynamics of bidding for online auctions such as eBay.com. In his model, by winning in the current period, a bidder gives up the option of purchasing the same or similar items in the future. Hence a rational bidder will bid more conservatively to offset the disadvantage of losing future options. This conservative bidding strategy may lead to inefficiency and welfare loss because it is possible that some low value but myopic bidders bid more aggressively and win the auctions. In an empirical paper by Jofre-Bonet and Pesendorfer (2003), the authors confirm the existence of such conservative bidding behavior in a dynamic setting. Following the same notion but in a reverse direction, in the sponsored search auction, if a bidder is placed at a better spot and hence has a better performance, her future payoff will increase since the current good performance enhances her winning probability

and lower her future payment. If this dynamic effect is prominent, we should see bidders bid more aggressively (Yao and Mela (2008a)). These issues can be studied in future, including the effect of dynamics on the revenue of the search engine and the efficiency of the auction.

2. The competition between sponsored search ads and organic search results (see Figure 1). For example, consumers are more likely to click the organic results when both organic and sponsored results are presented. If an advertiser's link has already appeared in a top position of organic search results, should she still choose to participate in sponsored search auctions? If yes, should she bid more or less aggressively? More essentially, are organic results and sponsored ads complements or substitutes, i.e., do they boost or offset each other's impressions/clicks/purchases? Due to the complexity of this problem, there are currently no closed form characterizations of the equilibrium so far (Katona and Sarvary (2008)). A follow-up managerial question for advertisers is how to allocate resources between sponsored search advertising and organic search optimization. For the latter, advertisers can apply techniques to increase their ranking in the organic search results. Marketing expenditures used for organic search optimizations were over \$600MM in 2005 (SEMPO, 2006). Given the magnitude of the expenditure, this is definitely a significant issue.
3. Dynamic learning of advertisers. Even under the private value setting, the sponsored search auction is still a complicated game. Novice advertisers may not be familiar with the rules or with competitors' characteristics and, more importantly, they may not be certain about the return (value) of sponsored search advertising. We would expect advertisers to update these pieces of information dynamically across time. Dynamic learning models have been used extensively

in marketing to study agents' uncertainty and knowledge building. It would be fruitful to model sponsored search auctions in a dynamic learning framework.

4.3.2 Bidding Strategies: Multi-item Auctions with Multiple Demands

We considered the case of a multi-item auction with single demand above. In practice, each bidder also faces multiple simultaneous auctions held by multiple search engines on multiple semantically similar keywords. This leads to the more complicated auction game of multi-item auctions with multiple demands, i.e., there are multiple items for auction and each bidder may demand multiple units (across search engines and across keywords).

Holding multiple auctions simultaneously is frequently observed in government resource allocation auctions for its quick transaction (e.g., spectrum auctions in the wireless phone industry). In recent years, multiple simultaneous auctions have drawn more attention from researchers due to the booming of B2B commerce, where such auctions are widely used. However, due to the complexity of these auctions, caused by the heterogeneity of auctions/items and bidders' intricate strategies across these multiple auctions/items, the literature on multi-item auctions with multiple demands is much less developed and very few generalizations are available (for a thorough review see Krishna (2002)).

Most studies on sponsored search auctions do not consider this issue for tractability reasons (e.g., Edelman et al. (2007); Varian (2007); Chen and He (2006); Athey and Ellison (2008)). To our best knowledge, Katona and Sarvary (2008) is the first to address this question. The author demonstrates that one equilibrium for such auctions is for bidders to bid on multiple keywords and treat them as independent auctions as long as the generated clicks across keywords are independent. However, the "independence" assumption is hardly satisfied in reality. Normally there will be

complementarity or substitutability among keywords, which will be discussed next. Further, the model only uses the number of clicks (online traffic) as a measure for the value of a spot. While clicks, impressions and sales are all important factors for an advertiser's profits, this assumption limits the generality of the model. Investigation of multiple auctions taking these issues into account would be fruitful.

Another promising aspect for modeling multi-item auctions with multiple demand is the complementarity and substitutability among keywords. Complementarity exists when the sum of each single item's value is smaller than the bundle value of the same set of items. The reverse case implies substitutability among items. When it comes to sponsored search auctions where bidders face multiple keywords, it becomes an empirical question whether these different keywords are complements or substitutes. At first glance, different keywords are substitutes in the sense that generated values across multiple keywords may have diminishing marginal returns. Winning one keyword makes other keywords less valuable to the bidder. However, different keywords may also complement each other semantically (e.g., the words "hotel", "flight" and "car rental"). Further, even for similar keywords, the impressions generated by one keyword may have positive effects on the other keywords (e.g., the impressions from the "wrong" word eaby on eBay). Future research is merited on questions about how to determine complementarity among keywords, how to measure the degree of complementarity and how to allocate bidding resource among complementary keywords. Moreover, complementarity makes winning one item but not the whole bundle less attractive to bidders. Sometimes, bidders will be reluctant to bid since they may win some items but lose the others. This makes the whole bundle's value tainted (Brusco and Lopomo (2009)). This issue also calls for further investigations into how bidding strategies vary and how auction mechanisms should be optimized under different complementarity and substitutability conditions.

4.3.3 Bidding Strategies: Other Aspects of Sponsored Search Auctions

We also list some other promising research directions for sponsored search auctions.

Private Value vs. Common Value It is well established that bidding behaviors and equilibrium results vary dramatically between private value auctions and common value auctions (cf. Milgrom and Weber (1982)). Although it is hard to find a pure private or common value auction in practice, researchers normally have to resort to one of these classifications for model tractability. All the studies about bidding strategies in sponsored search auctions mentioned above rely on the private value assumption. That is, each bidder knows the true value of a spot to her. While this assumption simplifies the analysis, it may be the case that all bidders are not perfectly certain about the impression/traffic/sales generated by a spot and they assign some distribution to the values. This interdependence of values among bidders introduces new complications such as the winner's curse. Bidding behavior under this alternative common value information structure deserves our attention.

The Winner's Curse Related to the puzzle of private value or common value, the winner's curse is another interesting topic in sponsored search auctions. The winner's curse exists in common value auctions. Although theoretically rational bidders will not fall to the prey to the winner's curse since their bidding strategies should have taken the factor into account, both empirical and experimental studies show that some bidders suffer the winner's curse in online auction environment (Jin and Kato (2006); Bajari and Hortacsu (2003); Heyman et al. (2004)). It would be interesting to see whether the effect has been diminished over time as advertisers become more experienced with auctions. Also from the perspective of a search engine, this is an important issue since the winner's curse causes bidders to bid more conservatively

and hence affects the search engine’s revenue. How might search engines attenuate this effect so as to increase profit?

Collusion For sponsored search auctions, major bidders’ identities can easily be observed from the results page. Also, since the auctions repeat over time and across keywords, collusion among bidders can be easily achieved. For example, advertisers may form some type of agreement (which may be implicit) that they win the auction of one keyword alternatively over periods. They may also diverge their bids collusively to different keywords. By doing so, they may be able to find a more profitable trade-off between payments to the search engine and clicks/impressions/sales across auctions/periods. In a theoretical paper by Stryzowska (2005) the author shows an equilibrium where bidders implicitly collude across multiple auctions and multiple periods in the context of online auctions such as eBay.com. In practice, collusive behavior is widely observed for multi-item electronic auctions such as mobile wireless service licenses (Cramton (1995); Wolfram (1998); Grimm et al. (2003)). It is an interesting empirical question to investigate whether collusive bidding behavior exists in sponsored search auctions.

5 Search Engines

A search engine faces multiple intertwined issues throughout the auction process. First, the search engine seeks to design an auction mechanism that maximizes its revenue. Second, in the competitive environment of the online search industry, a search engine needs to consider how to position its “product”, search results, against its competitors. Since sponsored ads are also a part of the product, the positioning decision will affect the auction directly. Third, the existing literature has shown the

benefits of customer targeting and product customization. Search engines need to consider how to incorporate these concepts into their auctions. Related to customer targeting, another issue is sharing of market intelligence between the search engine and advertisers. To allow advertisers to appreciate the value of targeting a segment of customers, the search engine may need to share some market intelligence with them. Fourth, central to the profitability and long-term growth of a firm, the search engine needs an accurate measure of the value of its customers so that it can allocate resources for customer acquisition and retention. In particular, the search engine creates a two-sided market of advertisers and Internet users. The traditional metrics of customer value will be biased in such a two-sided market. Fifth, sustained price dispersion among advertisers still exists given the reduced search cost for consumers under search engines, which contradicts the prediction of existing theoretical search models. How does price dispersion affect the search engine? Sixth, click fraud is a type of deceitful practice of clicking on advertisements to create false impressions of high click-through rates and/or high levels of exposures. It has become a serious issue for the whole industry and may jeopardize the business model of sponsored search advertising. What is the welfare implication of click fraud? This raises the question of which approaches may be adopted to fight click fraud. Seventh, each of these foregoing factors affects both consumer welfare and advertiser revenue. A strategy that enhances a search engine's revenue may be to the detriment of consumers and advertisers. Hence, from a public policy perspective, it is important to ascertain the role of search engine strategy on consumers and advertisers. We discuss these issues next.

5.1 Optimal Auction Design

A search engine faces the revenue maximization problem when it designs its auction mechanism. Auction mechanism design has established a rich literature body since the study by Vickrey (1961). With the purpose of revenue maximization,⁸ the optimal design involves the determination rules of winners, payments and the choice of reserve price.⁹ We discuss each in turn.

5.1.1 Winners and Payments

Central to the design of an auction mechanism is the determination of winners and payments of the auction.

There are common auction formats that are widely used in reality, such as first price auction and second price auction. However, due to the specific nature of sponsored search auctions, these common formats can not be directly applied for the purpose of revenue maximization. To be more specific, consider the following simple example. Suppose there are only 2 bidders, A and B, and one slot for the auction of a focal keyword. Within a given period, A's ad can generate 70 clicks and B's can generate 50. Suppose A bids 4 and B bids 5. With a second-price auction that encourages a truth-telling strategy, B will be the winner and pay \$4 for each click. The engine's revenue is $4 \times 50 = 200$. Suppose the slot was awarded to A instead, even with a lower per-click-payment than 4, say 3, the engine's revenue would be higher: $3 \times 70 = 210$.

In practice, many search engines use more complex mechanisms to determine

⁸Sometimes efficiency of allocation is also an objective of the auction design. An efficient auction mechanism enables the bidder with the highest value to win the best slot, the second value bidder to get the second best slot and so on. While most search engines are profit-seeking firms, we will only focus on the revenue maximization objective.

⁹We will discuss the information release issue in the section on targeted marketing.

winners and payments. For example, Google uses the generalized second price rule mentioned earlier. Continuing with the same example above, under the second price rule, A will be the winner and the payment for each click will be $5 \times 50/70 = 3.57$. The revenue for the engine becomes $3.57 \times 70 = 250 > 200$.

However, even Google's mechanism is far from optimal (Iyengar and Kumar (2006)). The current mechanism fails to consider some important factors in the revenue determination process. For future research, we seek to diagnose the search engine's revenue more carefully. The expected revenue of the search engine from a winning advertiser has two components: the expected number of clicks and per-click-payment. The following factors will affect the values of the two components and need to be considered when designing auction mechanisms:

- Which slot does the advertiser win? A better slot can boost the number of clicks and also implies a higher payment, but the click rate of each slot is not independent of the identity of the winner. That is, different advertisers will have diversified click rates at the same slot.
- The adjacent advertisers matter. For example, if a small online retailer is placed beside a prestigious large retailer, the clicks on the small one may decline since consumers would be attracted to the prestigious retailer.
- What are the organic search results, and how do these impact the click behavior of Internet users? Users probably have different likelihoods of clicking an advertiser's link when the advertiser also appears in the organic results versus otherwise. How should the search engine decide the winning bidders with the organic results taken into account?
- How many auctions should be offered, and how many ad spots should be offered

for each auction? As mentioned in Section 4.3, bidding strategies change dramatically when bidders face multi-item auctions. Auctioning more keywords and more slots may be able to increase the total number of bids. However, it will divert advertisers into multiple auctions and reduce competition within each auction. Multiple auctions may also change bidders' valuations about each spot and affect their bidding behavior.

- Bidders may (implicitly) collude in the online environment. Such collusion reduces the search engine's profits. How might search engines discourage collusion among bidders?

5.1.2 Reservation Price

Search engines can set minimum bids such that any bids lower than the minimum will not be admitted; this minimum bid is termed as a "reserve price" of an auction. Reserve prices are a tool that search engines might use to maximize revenue (cf. Riley and Samuelson (1981)). The basic idea is to set a reserve so that it extracts all surplus from the winner. Although this concept can be applied to the optimization of reserve price in sponsored search auctions, some complications exist, and will require further investigations:

First, a high reserve will deter low value bidders from participation. This reduction in the number of bidders may decrease the intensity of bidding competition and lower revenue for the search engine.

Second, reserve prices create the problem of endogenous entry of bidders. For example, in an auction, the reserve price serves as the minimum payment of a winner. Only if an advertiser's valuation for an ad slot exceeds some threshold that depends on the reserve price, will she attend the auction. This endogeneity causes difficulties,

especially for conducting empirical studies.

Third, which winner's surplus to extract? How much is that winner's surplus? There are multiple winners for a given auction. Intuitively, the search engine should focus on the winner who has the lowest surplus and set the reserve so that the lowest winner is just indifferent between winning or not. However, the identity of that winner is difficult to determine since it is embedded in the winner-payment determination mechanism. With different winner-payment determination mechanisms, the surplus distribution among winners changes dramatically.

5.2 Search Query Results

Search engines compete for both Internet users and advertisers, which are both heterogeneous. The nature of competition across search engines is incumbent upon the advertiser and consumer problems of which search engines to choose. Predicated on those, the search engine will independently choose their policies to maximize their profits. Such policies include both consumer strategies (e.g., web page design and/or search algorithms) and bidder strategies (e.g. auction mechanisms). Here we focus on the former because auction mechanisms are discussed above.

A search engine's product for Internet users is (free) information—search results, including organic results and sponsored ads. For advertisers, a search engine's product is essentially Internet users: the engine is selling users' clicks and impressions to advertisers using auctions. How to effectively deliver the first product, information, to Internet users may be the more crucial service: by attracting more Internet users, the sponsored ads become more valuable to advertisers. The advertisers are more likely to choose a more popular engine over others to run a marketing campaign and bid higher in the auction. Hence, we will focus here on competition for Internet users.

It is impossible for a search engine to perfectly cover all the information on the Internet relevant to the keyword queried. According to some work by Bradlow and Schmittlein (2000) on the efficiency of search engines, even the “best” search engine can only cover about 50% of the information on the Internet. It takes about 6 engines to cover 90% of the information on the Internet.

A strategic decision that search engines must make is whether to exert effort to cover online information as comprehensively as possible, or whether they should differentiate their search results coverage. In the extreme case of the former strategy, all engines would have homogeneous products for heterogeneous customers, i.e., engines have the same set of information and rank results in the same order. Assuming visiting multiple search engines is costly, we may expect rational consumers not to visit several search engines with homogeneous information. This situation will cause (1). intensive competition for Internet users among search engines and (2). less advertisers per search engine and each advertiser has lower valuation regarding the auctioned ad spots. This is because search engines’ products for advertisers are also homogenous per se: if search engines have homogenous information, they will attract customers with the same probability. Thus the composition of the group of users of one engine would be the same as that of other engines. In contrast, when search engines have differentiated information, they attract different segments of Internet users in the market. From the viewpoint of an advertiser, this segmentation makes the sponsored search advertising more valuable: she can customize her ads/products to match some specific segments so that there will be a higher price margin caused by the product differentiation. This differentiation will, in turn, increase the search engine’s revenue from auctions.

Thus we conjecture that a more profitable equilibrium is that search engines differentiate the information presented on their results page. The core of this differen-

tiation is the information provided, which causes segmentation among Internet users and thus leads to another level of differentiation in the auctioned spots. While there are many studies of product differentiation, none has been done in the context of online search. Many research questions can be explored. For example, how should the equilibrium strategies of search engines be characterized? What factors affect the equilibrium level of product differentiation? In reality, we do observe some level of differentiation in the information presented by search engines. Is this difference caused by search engines' strategic actions or is it purely a result of their underlying different search techniques and algorithms? Further, another real-world observation is that some leading search engines such as Google are very comprehensive in terms of their search results, but there are also smaller specialized engines focusing on a few categories. Is this an equilibrium of a sequential entry game, in the sense that Google is among the first few prototypes of web crawler search engines and other smaller ones try to position for niche markets?

5.3 Targeted Marketing—Product Differentiation Across Users

Following the long history of targeted marketing research, Ansari and Mela (2003) demonstrate that targeting customers in the online environment can also be very profitable. In their paper, they show that the expected click rates of promotional emails can increase by 62% after customizing those emails based on customers characteristics.

The same notion can be applied into sponsored search auctions. Based on past clicking and browsing data, a search engine can present more relevant ads to a customer when she makes keyword query. Such customization should increase the advertising ROI due to these ads' high relevance to the user. From the perspective

of advertisers, a bidder may focus on bidding for the most profitable segments of customers.¹⁰ Especially when advertisers' products are differentiated, their profitable segments tend to be different. This will decrease the intensity of competition at the customer purchase stage and hence the value of the auctioned spots should be higher. From the search engine's point of view though, a trade-off needs to be made between the higher value of each bidder and lower bidding competition. While advertisers may increase their values for the auctioned spots due to customization, the search engine essentially turns one auction with all traffic into several auctions where each only has the traffic generated from a single segment of customers. The number of bidders for each auction may decrease and thus bidders may bid less aggressively. How the search engine should make this trade-off is an interesting question to be answered by researchers.

An additional concern about target marketing is the release of information from search engines to advertisers. For advertisers to be clear about the value of each customized segment, the search engine may have to share some information with them. Milgrom and Weber (1982) theoretically prove that the releasing information regarding the value of an item can increase the return of an auctioneer through the existence of the winner's curse in common value auctions. Rational bidders shade their bids to offset the winner's curse. By releasing information, however, bidders' uncertainty about the value of the item is reduced and so the severity of the winner's curse decreases. Thus, bidders bid more aggressively. Goeree and Offerman (2002) and De Silva et al. (2007) confirm this claim in an experimental setting and using field data, respectively. In sponsored search auctions, the problem faced by a search engine is what and how much information to release to advertisers. Most of the information

¹⁰Note that here advertisers are focusing on different segments of internet users within the same search engine while in the last section, advertisers considered different search engines having different segments of users.

may be too sensitive to be released. For example, by releasing the information on the traffic of one spot, bidders can infer the traffic of the retailer who won that spot since the identity is shown on the search results page. Further, clicking and browsing information about consumers is even more sensitive due to privacy concerns. So the information to be released should: (1) be accurate enough to inform advertisers about the value of each segment of customers and (2) not contain any sensitive information. For researchers, the question becomes what aggregate level statistics can provide the best presentation of the value of a customer segment without leaking sensitive information.

5.4 Customer Value in a Two-sided Market

It is central for a firm to understand its customers' value to ensure the firm's long term growth. There has been a recent proliferation of studies focusing on the value of customers. The most commonly used metric is customer lifetime value (CLV): the present value of all future profits generated by the customer (Kamakura et al. (2005)). However, this metric can not be directly applied to the search engine context. The search engine serves as a platform of a two-sided market whose participants are Internet users and advertisers. In this market, there are direct network effect (e.g., competition among advertisers during bidding) and indirect network effect (e.g., Internet users attract advertisers to the search engine and vice versa). Of the two sides, only advertisers generate direct revenues for the search engine. However, without Internet users, the platform loses its functionality. So part of the direct revenue generated by an advertiser should be attributed to Internet users. The traditional CLV metric ignores *indirect* network effects and thus will underestimate the value of an Internet user and overestimate the value of an advertiser. Gupta et al. (2006) attempt

to measure the value of non-paying customers in a two-sided market and estimate a joint system including both sides of the market. Each side contributes to the revenue of the platform and there are interactions between the two sides. These authors find strong direct and indirect network effects and show that a “free” customer is even more valuable than a paying customer. Omitting *direct* network effect can also lead to biased estimation of customer value (Tucker (2005); Yao and Mela (2008b)). In the context of sponsored search auctions, the value of an advertiser is not just her payment to the search engine. An advertiser not only increases the intensity of competition during bidding, but also increases the value of spots to other advertisers since her presence may attract more Internet users to the platform. Ignoring these effects may underestimate the value of an advertiser; however, the opposite may also be true. When a prestigious advertiser is at present, smaller advertisers may be deterred from bidding by the following concerns: (1). the probability of winning a spot is too low (2). upon winning, most traffic will be attracted to the top advertiser’s site; (3). traffic will not convert into purchases since most customers decide to purchase from the prestigious advertiser. As a consequence, the removal of a prestigious advertiser from the market may attract smaller advertisers to the auction and hence increase the search engine’s revenue.

In short, more research should be devoted to accurately measuring customer value in two-sided markets such as the sponsored search advertising market.

5.5 Price Dispersion Among Advertisers’ Goods

Search costs have long been used to explain price dispersion among otherwise homogeneous products. Stahl (1989) suggests that the magnitude of price dispersion should decrease when search cost drops. With the assistance of search engines, researchers

have predicted that search costs drop dramatically. This implies that advertisers should see more intensive price competition. However, the opposite argument may also be true. With the existence of sponsored search auctions, retailers have an additional “product attribute” for differentiation: their ranking in the auctions. Thus, price dispersion may become even more severe. This is because: (1) a winning advertiser is able to charge a higher price given that she is more likely to be included in the consumers consideration set (consider the search model in section 3) and (2) consumers may interpret the ad as a high quality (or relevance) signal of the product (Chen and He (2006); Athey and Ellison (2008)), which justifies a quality (or relevance) premium for the product. Some studies support this conjecture of sustained online price dispersion. For example, Ellison and Ellison (2005) report significant price dispersion in their data, which contain pricing information for small retailers selling homogenous computer parts through an online B2C website,¹¹ where search costs are low.

From the perspective of a search engine, price dispersion among advertisers is beneficial. The fact that a winning advertiser can charge higher price may lead to more aggressive bidding and hence increase the search engine’s revenue. A strategic move by a search engine is thus to stimulate an environment that facilitates price dispersion so some advertisers bid more aggressively. For example, one strategy is to prime consumers so that they become less sensitive to price. It is well established in the experimental literature that priming can influence consumer behavior. For example, Mandel and Johnson (2002) design an experiment to show that consumers’ preferences change when they are shown webpages with the same information but different backgrounds. At a website selling sofas, if the background is blue with

¹¹The study focuses on small retailers so that the branding or prestige has immaterial effects on pricing.

clouds, consumers care more about sofa's comfort and become less price sensitive. Whether this strategy can improve search engine's revenue can be tested empirically or in experiment. More important, it presents interesting strategic choices for search engines in their webpage design.

5.6 Click Fraud

Click fraud refers to the practice of clicking on an advertisement without any intention of product purchase or information exploration. The main purposes of this fraud are (1) creating a false impression of a high click-through rate as well as a high level of exposures and/or (2) exhausting competing firms' advertising budgets. Estimates indicate that about 10-15% of all clicks are fake, representing roughly \$1B annual expenditures in search advertising.¹² Click fraud is especially problematic because it affects advertiser bidding strategy to the detriment of the search engine, advertisers and consumers alike. For example advertisers may be reticent to bid if they reasonably expect that competitors will click excessively on their links because this could prove highly costly and generate little revenue. Means of controlling this problem include mechanism design and information technology (e.g., Anupam et al. (1999); Metwally et al. (2005); Majumdar et al. (2007)). We consider the following topics may be interesting to pursue:

- What is the effect of click fraud on a search engine's revenue? On the one hand, detecting and punishing click fraud is costly for search engines. Indeed, all else equal, click fraud may increase the revenue since winning advertisers are still paying even though those clicks are fake. On the other hand, a high level of click fraud may drive away advertisers to other search engines, placing a downward

¹² "Click fraud—the dark side of online advertising," Business Week, October 2nd, 2006.

pressure on revenue. The equilibrium level of click fraud from the perspective of the engine is probably a result of the trade-off between the two forces as well as the cost of detecting/punishing click fraud. Research on the equilibrium level of click fraud can not only enable us to better regulate click fraud, but also allow a more concrete welfare analysis for consumers and advertisers under click fraud.

- What is the optimal level of information that the search engine should reveal about its click fraud detection? Major search engines such as Google invest great efforts in fighting click fraud to protect advertisers. As discussed in Wilbur and Zhu (2009), search engines who fully disclose click fraud entirely mitigate any negative effects on advertiser welfare. Though fraudulent clicks may lead to high payments for advertisers, informed advertisers lower their bids to offset these effects. However, information disclosure imposes a dilemma for the search engine. On one hand, revealing the detection method/algorithm may help advertisers to adjust their bidding strategy. On the other hand, it may also allow those who commit click fraud to circumvent the detection. A trade-off strategy may be to reveal some noisy information to help advertisers and confuse perpetrators of click fraud. How to design such noisy signals is of interest.

6 Conclusion

Sponsored search advertising is a newly developed but powerful marketing tool. It appeals to marketers due to its efficiency and low cost. In 2005, search engine marketing was a \$5.75 billion industry in North America and the expected volume is \$11.1 billion in 2010.¹³

¹³“The State of Search Engine Marketing 2005”, Search Engine Marketing Professional Organization (http://www.sempo.org/learning_center/research/sempo_research/state_of_sem_2005).

On one hand, the complexity of the sponsored search auction imposes difficulties for researchers. On the other hand, it presents substantial opportunities for research that will result in great insights about consumer and firm behavior. In this paper, we reviewed the current literature on the topic of sponsored search auctions; we summarize the possible research avenues in Table 1. As shown in Table 1, there are plenty of issues left to investigate. We hope this article inspires further work that will enrich our knowledge of this new marketplace.

Table 1. Research Opportunities of Sponsored Search Auctions

	Research Opportunities
Internet Users	<ol style="list-style-type: none"> 1. Discrete choice of search engines and keywords. 2. Sequential search vs. nonsequential search: <ol style="list-style-type: none"> a. how many websites to search? b. the welfare implication of sponsored search ads on consumers. c. under what conditions, one of the two models is more realistic? 3. Discrete choice of links for investigation.
Advertisers	<ol style="list-style-type: none"> 1. Discrete choice of search engines/keywords to bid. <ol style="list-style-type: none"> a. network effect among sponsored ads. b. design of sponsored ads. c. general algorithms for optimizing advertising campaigns d. search engine optimization 2. How to measure the value of an advertising spot? <ol style="list-style-type: none"> a. the number of clicks (online traffic). b. the number of impressions. 3. How much to bid? <ol style="list-style-type: none"> a. modifications to the strategies of first-price and second-price auctions. b. dynamics in bidding strategies. c. competition between sponsored search ads and organic search results. d. dynamic learning about the value of an advertising spot. 4. Bidding strategies in multi-item auctions (across keywords and engines): <ol style="list-style-type: none"> a. bidding strategies across multi-item auctions with multiple demands. b. the complementarity and substitutability among multiple items. 5. Other aspects of bidding strategies. <ol style="list-style-type: none"> a. private value vs. common value. b. the winner's curse. c. collusion among bidders.
Search Engines	<ol style="list-style-type: none"> 1. Optimal mechanism design. 2. Product differentiation across search engines. 3. Targeted marketing-product differentiation across Internet users. 4. Customer value metrics in a two-sided market. 5. Price dispersion among advertisers and its implications on the search engine strategies. 6. Click fraud 7. The effect of search engine strategy on consumer and firm welfare.

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