The Effect of Ad Rank on the Performance of Keyword Advertising Campaigns

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The goal of this research is to evaluate the effect of ad rank on the performance of keyword advertising campaigns. We examined a large-scale data file comprised of nearly 7,000,000 records spanning 33 consecutive months of a major US retailer's search engine marketing campaign. The theoretical foundation is serial position effect to explain searcher behavior when interacting with ranked ad listings. We control for temporal effects and use one-way analysis of variance (ANOVA) with Tamhane's T2 tests to examine the effect of ad rank on critical keyword advertising metrics, including clicks, cost-per-click, sales revenue, orders, items sold, and advertising return on investment. Our findings show significant ad rank effect on most of those metrics, although less effect on conversion rates. A primacy effect was found on both clicks and sales, indicating a general compelling performance of top-ranked ads listed on the first results page. Conversion rates, on the other hand, follow a relatively stable distribution except for the top 2 ads, which had significantly higher conversion rates. However, examining conversion potential (the effect of both clicks and conversion rate), we show that ad rank has a significant effect on the performance of keyword advertising campaigns. Conversion potential is a more accurate measure of the impact of an ad's position. In fact, the first ad position generates about 80% of the total profits, after controlling for advertising costs. In addition to providing theoretical grounding, the research results reported in this paper are beneficial to companies using search engine marketing as they strive to design more effective advertising campaigns.

Introduction

Sponsored search is a form of online advertising where companies promote their products and services on search engine results pages. It is also known as keyword advertising, pay-per-click, and search engine advertising. Since its inception in 1998 (Fain & Pedersen, 2006), sponsored search has become the central business model of the major search engines (Jansen & Mullen, 2008). It is now one of the most rapidly growing segments of the online marketing area (SEMPO Research, 2009), generating billions of dollars for the major search engines (cf., Google, 2011). As such, keyword advertising has helped shape the nature of the web (Jansen, 2011) and is, therefore, of critical research importance to online commerce on the web (Weis, 2010).

By selling advertising keywords to merchants, sponsored search requires advertisers to bid directly on potential query phrases in order to have their ads served on the search engine results page (SERP). Affected by sponsored search's unique auction mechanism, advertisers generally believe that higher bids win them better ad positions that generate more traffic, sales-leads, and revenue for their business. Given the dynamic nature of keyword advertising auctions and lack of control for determining ad position, it can be difficult for advertisers to select their target ad positions and adjust their bids accordingly to target specific user groups (Kathuria, Jansen, Hafernik, & Spink, 2010). Due to this uncertainty, advertisers can spend enormous sums of money competing for higher ad placements. Unfortunately, there has been limited published research concerning the effect of ad position on keyword advertising performance because companies generally have not published their data and statistics. Consequently, other than anecdotal evidence, there is inadequate insight into how users interact with sponsored results in these situations or how profitable the various ad positions might be.

In this research, we use a large-scale data set of a major retailer to examine performance differences in each distinct ad position of an advertiser keyword advertising processes. With the results of our study, advertisers can reassess the

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worthiness of top-ranked positions when creating their advertising strategies and also better understand searcher behavior when interacting with ad listings on search engines. We also believe that our study illustrates the role ad rank plays in the online advertising market and assisting advertisers in avoiding the possibility of intensive bidding wars solely to get the top position without realizing the expected return on investment.

We begin with a literature review, outlining the current state of sponsored search research. We then present our research questions and associated hypotheses, followed by a description of our data and methods utilized. Next, we discuss results and implications for advertisers, online advertising platforms, and consumers. We end with directions for future research.

Literature Review

Serial position effect is the theoretical foundation for this research on ad position's impact on human interaction behaviors during web searching. As proposed by Ebbinghaus (1885), serial position effect has been well studied across many areas of human cognitive behaviors, including recall formation, impression, and preference development. Although web searching may not be identical to making free recalls or preferences, we hypothesize that a similar situation is occurring with the ordered lists presented on SERP, most notably with impression formulation. Therefore, it seems reasonable that the serial presentation of SERP can directly affect the cognitive attention of the searcher and influence their subsequent clicking and purchasing behaviors. A review of prior work indicates that both subcomponents of serial position effect, the primacy and recency effects, are at play in sponsored search, with the primacy effect being the most prevalent due to the ordered ranking of results expected by users of the search engines.

Ebbinghaus (1885) first reported the relationship between recall and serial position, subsequently becoming a major benchmark for future studies. In his work of word list learning, Ebbinghaus proposed a U-shaped curve of recall, with the first and last items in a list being best remembered, referred to as primacy effect and recency effect, respectively. The primacy effect occurs due to the greater rehearsal or mnemonic activities devoted to the first few items in a list (Waugh & Norman, 1965; Atkinson & Shiffrin, 1968; Bjork & Whitten, 1974). In contrast, recency effect is a short-term memory phenomenon with most recently acquired information being quickly recalled (Atkinson & Shiffrin, 1968; Craik & Lockhart, 1972; Capitani, della Sala, Logie, & Spinnler, 1992).

Both primacy and recency effects on free recall have been well documented in a number of studies. In addition to the initial investigation of its impact on word-list memory (Ebbinghaus, 1885; Deese & Kaufman, 1957; Atkinson & Shiffrin, 1968), many researchers have investigated serial position's influence on human's recall of television commercials. Research on traditional advertising media suggested that on a long time scale, ad rank's primacy effect had much greater impact upon brand advertising campaigns than recency effect, since the latter can be more easily masked by time (Pieters & Bijmolt, 1997; Newell & Wu, 2003; Terry, 2005). Instead, ads placed in the earlier positions of a television show were more likely to be remembered by viewers than those ads shown in the middle or at the end (Newell & Wu, 2003). This would suggest a similar effect on the ordering of results listing. Searchers might give preference toward those first results at the top of the listing, especially if they scan the results further down.

Beyond its implication for recall, serial position also has a strong influence on people's impression formation and preference development. Asch's (1946) experiment on personality impression formation reported a strong primacy effect when subjects were asked to describe a person with a list of serially presented traits. Luchins (1957) also found the same primacy effect on impression formation in his later study. He indicated that with prior warnings and continued practice, the primacy effect could decrease, while recency effect would increase. Anderson (1971) validated such primacy effect using attention decrement theory, which suggested that subjects paid little attention to new information due to their attention decrement. He claimed that earlier information would wield more influence than later information, given the more distinctive traces in memory it leaves. In recognition of the influence on personality impression formation, later studies extended the effect of serial position to preferences and choices development. In their studies, Dean (1980) and Coney (1977) both found significant primacy effect in subjects' choices, with their biases toward the first option presented in the list. Li and Epley (2009) showed that primacy and recency effects occurred under different conditions. They found that recency effect can be obtained when options were all equally desirable, whereas primacy effect was observed when options were undesirable. While examining subjects' choices when presented with an online directory, Hoque and Lohse (1999) indicated that humans are more willing to choose from the first few links of the returned result list while ignoring links located at the lower end. It would seem reasonable to transfer the results obtained in organic search to sponsored search.

According to Mantonakis, Lesschaeve, and Hastie (2009), primacy bias in human preference development is due to the repeated pairwise comparison of sequential candidates. During this evaluation process, more attention is placed on early items, causing them to be viewed more favorably. Another explanation of the primacy effect of item favorability is Zipf's (1949) principle of least effort, since searchers would be expected to click on an expected and encountered relevant result rather than cognitively process results further down the listing in some cases. We see this often in all types of searching, where the results at the top of the list account for most user interaction (Wang & Yang, 2003; Beitzel, Chowdhury, Grossman, & Frieder, 2004).

However, unlike its interpretation in free recall, the recency bias in human choice making can be seen as the reflection of their intentions and knowledge levels. For example, more interested and knowledgeable people might be prone to be more persistent and devoted in the pairwise comparison process than those less sophisticated and serious users (Borgman, 1989). As searchers scan the results listing, the last result looked at, which is sometimes at the end of the list, is the one more likely to be retained in short-term memory. We see this behavior sometimes in web searching, where the organic links near the fold (i.e., an imaginary link separating the portion of the page that the searcher can see without scrolling from the portion of the page that the searcher cannot see) gets an increase in clicks relative to the result just above it in the list (Jansen, Spink, & Pedersen, 2005). Regardless, information encountered either first or last exhibited higher recall than information presented in the middle, as in line with the curve in Figure 1.

Although the serial position effect has been studied extensively in a number of areas, its implication in the area of web search has received limited investigation. This may be because applying serial positional effect to searching requires the linkage between memory recall (the focus of serial positional effect) and human behavior (actual clicking on a search results). However, it seems rather obvious that, before a searcher clicks on a result the searcher must be *aware* of the result among other options encountered. Teevan (2008) detected the presence of the primacy effect on users' recall of the search engine-returned results in her study. The probability of both users' recalls and clicks decayed with rank. Similar results were also found in other studies indicating the reliable primacy effect on the click-through-rate of links placed on a web page (Ansari & Mela, 2003; Drèze & Zufryden, 2004), although Ansari and Mela (2003) noticed a recency effect given more clicks on the last item of the page, as did Jansen, Spink, and Pedersen (2005). Noticing such rank bias, researchers have proposed several models aiming to better explain and eliminate such serial position effect (Craswell, Zoeter, Taylor, & Ramsey, 2008; Chapelle & Zhang, 2009). These studies primarily focused on the organic results, not the sponsored results. However, this line of research established the linkage between recall and click behaviors in searchers. One would expect similar user behaviors with sponsored results, given that both organic and sponsored results are ordered lists. However, this would need to be investigated. In addition to the locational differences on the SERP for the two types of listings, searchers tend to view the two types of results differently (Jansen & Resnick, 2006; Jansen, Brown, & Resnick, 2007).

In studies of sponsored results, Brooks (2004a,b) showed how the ad rank affected clicks and conversions, following a curve linear function of the ad's rank; however, he did not focus on why this occurred nor did he provide the data analysis or methodology behind his study. A similar finding was reported for click-through rates by rank in organic search results (Jansen & Spink, 2004). Ghose and Yang (2009) also detected a possible primacy effect on user's clicks and conversion behaviors in sponsored ad positions. However, again, they did not hypothesize why this occurred.

From our review of the literature, sponsored search, as a relatively newly emerged form of Internet marketing, has attracted limited research focusing on serial position effect within the online sponsored search environment. Among the existing studies concerning such position effect in the online advertising environment of the SERP, most studies were conducted under laboratory environments, with the work of Brooks (2004a,b) and Ghose and Yang (2009) as noticeable exceptions. Thus, it is difficult to apply findings from these previous experimental studies to real-world situations. Additionally, even within the studies that have assessed the effect of ad position, few of them covered all the performance matrices of online ad campaigns, including clicks, sales, conversion, and profits. Considering all these limitations, the research reported in this paper examines the effect of an ad's rank using a wide range of keyword advertising metrics.

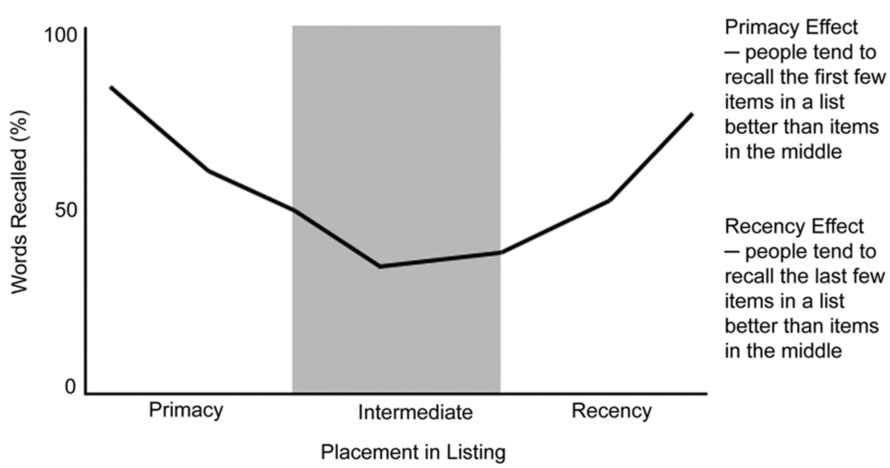

FIG. 1. U-shaped curve showing the primacy, intermediate, and recency effect.

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Research Questions

With this background and motivation, our research question is: *What is the effect of ad rank on the performance of keyword advertising campaigns?*

In the field of real estate, one hears the adage: *location, location, location*. One might say the same of an ad's position. Certainly, given the theoretical underpinnings from prior work, it would seem that the serial position effect would be the theoretical underpinnings linking ad position and user click behavior. There is ample evidence hinting that there is a linkage between recall (the focus of the serial position effect) and search behavior (the act of clicking on a result). This linkage seems reasonable, as a searcher can only click on a result if that result is recalled (from memory) from the set of already observed results on the SEPR. Like physical location in the real world, the rank of the sponsored ads on SERP is also treated as an important locational element regarding the overall keyword campaign performance. In order to obtain better sales revenues, many businesses have engaged in competition for the top-most positions. However, few studies have tested the actual effect of ad rank on the performance of keyword advertising campaigns using a significant amount of real-world data. Given such an unexamined rationale that top-ranked positions lead to more profit, we find it necessary to study whether a premium position is worth it from a business perspective. With a better understanding of the ad's position effect on the consumer's behavior, such as clicks and purchasing, our study provides both a theoretical foundation and empirical results for future research on ranking of ads.

In our research, we extend the serial position effect into downstream actions (i.e., actions beyond the initial click of a result). The findings could help real-world businesses to predict the efficacy of their ranking strategies and to optimize their budget expenditure on the most effective ad positions. Based on the serial position effect, our assumption is that there is a positive correlation between the ad's position and performance (i.e., the ad at or nearest the top position does better than ads in the positions below). We would expect the primacy effect to be paramount relative to recency effect, given the ordered ranking of the results to which searchers are accustomed.

Based on this research question and rationale, our hypotheses are:

> **H1:** An ad in a higher position of the results listing will receive significantly more clicks than an ad in a lower position.

Keyword marketing campaigns typically aim to first guarantee relatively high click volumes. With a higher number of clicks, an ad can bring more traffic to a company's websites for potential profit generation, other conversions, or brand awareness building. Thus, click numbers quite naturally become a very important means to measure the success of an online advertising campaign. Even though clicks alone cannot predict the monetary value that advertisers may gain, clicks do provide advertisers with a sense of the number of viewers who are interested in their ads. As such, the varied traffic volumes would explain the consumer's instantaneous reaction distinctions while being exposed to ads listed in different positions and provide an indication of potential consumer interest.

> **H2:** An ad in a higher position of the results listing will cost significantly more per click than an ad in a lower position.

Keyword advertising usually works on a pay-per-click (PPC) basis. Advertisers are required to bid the amount of money they are willing to spend on their desired keywords per click. Every time a certain keyword is submitted to the search engine by a searcher, a PPC auction returns ads in a descending manner according to their bidding prices and related quality attributes. Given such unique characteristics of the PPC pricing model, traditional wisdom assumes that higher-ranked ads are more likely to be accompanied by higher click volumes. This expected higher click volume results in higher average cost-per-click (CPC) values for the top-ranked positions. Therefore, as an important indicator of online advertising costs, differences in CPC across various ad ranks could help the advertisers better estimate their advertising budget.

> **H3:** An ad in a higher position of the results listing will have a significantly higher conversion rate than an ad in a lower position.

Although the number of clicks can be adopted as a simple measure of the ad performance, it alone cannot guarantee post click-through performance. In other words, click volumes cannot indicate who will end up making a purchase or becoming a sales lead after clicking on an ad. Taking the analysis a step further by the conversion rate (i.e., number of converts divided by the number of clicks) provides advertisers a more accurate measure of the effectiveness of the ad campaigns. As such, a higher conversion rate for ads with certain ranks would indicate the ad position's impact.

> **H4:** An ad in a higher position of the results listing will have significantly higher sales revenue than an ad in a lower position.

The ultimate goal of most online advertising campaigns is to generate a sale or lead (i.e., identifying a potential customer). Naturally, as a primary business activity, it is self-evident that sales or sales leads produce the major income of most organizations. Ad position impact regarding sales revenues would therefore provide valuable insight into the purchasing power of online searchers and the profitability of those online ads relative to a given ad position.

> **H5:** An ad in a higher position of the results listing will have significantly more orders than an ad in a lower position.

Related to sales revenue, companies also examine the performance at an order-level perspective by tracking the number of orders placed for a given keyword. Order-level analysis provides the retailers a channel to further examine their marketing strategy. Any difference in the average number of orders among ads with distinct ranks would indicate a position's impact on the consumer's online shopping behavior.

> **H6:** An ad in a higher position of the results listing will have significantly more items purchased per order than an ad in a lower position.

Associated with orders, the number of items purchased per order is also a key metrics of online sales. Cross-selling (i.e., the process of getting consumers who come to an online store for potentially only one product to purchase related products) is a common retail practice (Berry & Linoff, 2004). Consumers who purchase multiple items may be considered more valuable than consumers who purchase only a single item. Selling products to a new customer takes much more time and effort than selling it to an existing one who has already made a purchase. Therefore, distinct cross-selling performances would indicate online searchers' preferences regarding ads in different ranks. Based on the Mantonakis et al. (2009) claims, we conjecture that casual shoppers are more likely to click on results early in the list with the flexibility in their choice-making process, making them the perfect consumers for potential cross-selling.

> **H7:** An ad in a higher position of the results listing will have a significantly higher return on advertising than an ad in a lower position.

Considering the dynamic online searching environment and the PPC model of sponsored search advertising, and with the huge number of user clicks varied from time to time, considering only the average sales revenue is obviously not enough. In order to run profitable online keyword advertising campaigns, one needs to consider the overall profitability of the keywords. We define profit as return on advertising, which is the money retained after all advertising costs have been counted. The advertising cost equals the CPC multiplied by the number of clicks. Conventional wisdom would often expect more profits for higher ranked ads. Therefore, differences in ad ranks would be expected to shed light on the differentiation of the overall profitability of the online keyword advertising campaigns.

Methods

Overview of Sponsored Search

In sponsored search campaigns on the major search engines, advertisers bid on key phrases that relate to a product or service that they are providing and that they believe searchers will submit to the search engine. These key phrases provide the linkage between the results provided from the advertiser and the queries submitted by potential customers, who are the searchers on the web search engines. When searchers submit queries to the search engines that match a key phase, the corresponding set of results is displayed on the SERP. Although published data are sparse, reports are that about 15% of search engine clicks occur on these keyword advertisements (Jansen & Spink, 2009).

The cost of the keyword for the advertiser is determined via online auctions. The exact cost can be in continual flux, as the amount that an advertiser *must* bid to get an ad to display depends on the overall demand for that key phrase at a given time. The amount that an advertiser is *willing* to bid depends generally on the perceived value of the customer converting (i.e., take some desired action, such as purchasing a product). Multiple advertisers are typically bidding on the same key phrases simultaneously, so the online auction and bid price can be quite dynamic. Search engines provide advertisers an assortment of tools to effectively manage their bids, control risk, and maximize opportunity.

The sponsored results on the SERP are usually shown above the organic results listing (i.e., the north position), to the right of the organic results listing (i.e., the east position), and below the organic results listing (i.e., the south position). The exact display method depends on the search engine, as some engines may not use all three positions. The sponsored result's rank within each listing depends on the bid price, the other bids in the auction, and a quality score (i.e., determined by several factors including bid amount, click-through history, and landing page relevance to the ad, although this formula varies somewhat by search engine). Given these factors, the sponsored search process is an interesting and complex integration of business processes, information technology, and information processing, making it an exciting area for multidisciplinary study.

The sponsored search results are usually textual in nature and normally consist of a short headline, two diminutive lines of text describing the product or service, and a hyperlink that points to the advertiser's landing page (i.e., an advertiser designated webpage). The predominant keyword advertising model is PPC, where an advertiser only pays the search engine if a searcher actually clicks on the displayed ad hyperlink. Thus, the impression of an ad does not cost the advertiser monetarily.

The entire sponsored search process can be extremely complex, and this brief overview cannot do it justice. The interested reader is referred to review articles (Fain & Pedersen, 2006; Jansen & Mullen, 2008) of the sponsored search process.

Data

Our data contain daily information on keyword advertising campaigns from a large nationwide retail chain, with both brick-and-mortar and online sales presences. The data are keyword advertisements by the company during a 33-month period, spanning 4 calendar years, from 30 September 2005 to 9 June 2008. The data set is quite rich, in that we have captured the key phrase that triggered the ad, the ad position, consumer responses, and sales information for each of those keywords.

The data set contains almost 7 million records from nearly 40,000 key phrases, with almost 55,000 advertisements. There is a record for every day in which one of the

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TABLE 1. Fields and descriptors from SEM data log used to investigate the research hypotheses.

Field	Description
Ad number	Unique identifier for the advertisement
Ad position	The positions of the advertisement on that search engine for the day for a given key phrase
Key phrase	The key phrase that triggered the advertisement
Day	Date of data collection
Impressions	The total number of impression for that day for the given advertisement with the given key phrase
Clicks	The number of clicks on the advertisement for that day for a given key phrase
Cost	The total cost for the day for a given key phrase for a given advertisement
Sales	The revenue generated from that advertisement on that day for a given key phrase
Orders	The number of orders from the advertisement for that day for a given key phrase
Items	Number of items purchased from that advertisement on that day for a given key phrase from all orders. One order could have one or more items.

key phrases triggered an ad. Each key phrase for a given day is a unique record. Each record in our data log has a variety of information by key phrase for a given day. The record includes the key phrase that triggered the ad, number of impressions, number of clicks, the average CPC, the number of conversions (or orders), the total sales revenues, and the total number of items ordered. A query may lead to an impression but no click. If there is a click there may not be a conversion (i.e., purchase or order). If there is an order, the order may be for one to several items.

Applicable fields used for the research reported here are shown in Table 1. We believe our data set to be a rich source with which to investigate our research question and hypotheses. There are limited empirical studies of keyword advertising campaigns, and there are no studies from a data set this large, that covers such an extension temporal span, or that contains such a rich range of keyword attributes.

Ad Rank Analysis

Keyword advertising can be all about location, with the most desirable positions usually considered to be at the top of the result listings. That being the case, advertisers strive to obtain a good position on the SERP for their ad in order to attract the eyeballs of online searchers. However, due to the limited space of SERP and searcher's resistance against sponsored results (Jansen & Resnick, 2006), search engine companies usually limit the amount of paid advertising placement on their returned pages, generally around eight or so ads per SERP.

Among all the available positions, the sponsored ads placed on the first SERP are usually the most desirable ones because on average they attract about 70% of the overall traffic (Brooks, 2004a). Even so, it does not mean ads listed on the following SERP are completely worthless, since having ads placed on the following pages are much less expensive and can also generate sales. About 25% of the consumer traffic will visit the second or later SERPs (Jansen, Spink, Bateman, & Saracevic, 1998). However, traffic drops off noticeably further into the SERP listings. Given that traffic volumes are known to differ significantly across various ranks, with the first two pages getting most of the traffic (Richardson, Dominowska, & Ragno, 2007), in this study we only focused on ad positions listed on the first two SERPs, trying to understand how people interact with the list of 16 returned ads for specific keywords. We did this considering the low rate of clicks for individual ads on the subsequent SERPs relative to the high rate of clicks on the first two SERPs, which we will discuss here.

In order to get more valid output, before we conduct the ANOVA we first preprocess the raw data to remove the effect of outliers and confounding variables. Given that any sales leads are closely related to the click volumes, by graphing box plots based on the amount of ad clicks, a total number of 190 ads with extreme click volume were removed from the data set, which correspond to 0.007% of the ad records from the top 16 positions. We removed these outliers, since their inclusion would skew statistical analysis. However, a separate analysis on these outliers would be an area of future research. After eliminating those outliers, the next step was to normalize the data for the day-of-the-week effect.

Past research has demonstrated significant day-of-the-week effect on users' engagement in online searching activities, with relatively fewer queries submitted on Fridays and Saturdays and relatively more searches over the weekdays (Beitzel et al., 2007). To test for the existence of such day-of-the-week seasonality in our data set, we first grouped the data by their releasing day of the week into seven clusters. Then we performed one-way ANOVA tests for comparing ad performance differences on those seven ad groups, which represent the 7 days of the week. Consistent with previous studies, the "weekend" effect is also significant in our data set.

This prompted us to proceed with the adjustment process to standardize the day-of-the-week effect on ad performance. In order to do so, we first divided our data set into seven groups based on their ad release days, with each group representing a day of the week. After calculating the seven group means on click volumes, we then performed the standardization process by dividing those mean values by the overall average clicks. This step enabled us to find the day-of-the-week-specific clicks ratios and then assign them to each individual ad group. Finally, the day-of-week adjusted click for each specific ad was calculated by dividing its observed click numbers by the click weight as calculated in the precious steps. After we finished the adjustment for the day-of-week click numbers, the day-of-week adjusted CPC, orders, items, sales, costs, and profits were then calculated by repeating this process on each different performance metric.

Prior to testing our hypotheses, we used a log transformation to improve the normality for all of the variables. Our data are not multivariate normal; instead, they follow a power law distribution. We transformed the data via the Box-Cox power transformation (Box & Cox, 1964) using ln(variable + 1). After employing the Box-Cox power transformation, we plotted our data to check for normality. The data were successfully normalized, although the distributions were skewed to the left (i.e., weighted toward lower cost click, lower sales, lower number of items ordered, etc.), which would be reasonable given the type of advertising data. Although skewed, several prior works have noted that the ANOVA method is remarkably robust to these deviations from normality (cf., Box & Anderson, 1955; Lindman, 1974; Hull, 1993). The use of the power transformation ensured our statistical approach was valid. By considering the validity of one-way ANOVA in our study, we then were able to conduct it to compare means and variances among ad ranks. Taking into account the relatively large data size, a more conservative threshold of 0.01 was adopted in this study. Tamhane's T2 test was then carried out for the post-hoc evaluation of specific group differences, with significance set at 0.01. Tamhane's T2 test does not assume equal variances among the groups.

Results

Aggregated Analysis

We first present overall statistics for the data set of 6,871,461 records from 30 September 2005 to 9 June 2008, as shown in Table 2. From Table 2, we see that this was a substantial marketing effort generating more than $56 million in sales and moving nearly 700,000 items. Table 2 also presents the average figures per day and the standard deviations. The standard deviations are high due to the nature of retailing, when there are substantial sales on days during the holiday buying season, typically October through early January.

We also display (Table 3) aggregate statistics for the top 16 ads ranks listed on the first two SERPs. From Table 3, we can see that without day-of-the-week adjustment, ads on the first two SERPs lead to about 99% of the total sales shown in Table 2. Consistent with the prior studies of users' click behaviors while interacting with search engines, our study also demonstrated that the top 16 ads cover about 99% of the entire total click volumes. Therefore, payment for ads listed on the first two SERP also covers most of the total spend of a keyword advertising campaign.

Hypothesis Testing

For each of our 16 ad position groups, descriptive statistics were calculated and are presented in this section in their natural form. However, all seven hypotheses testing were carried out using one-way ANOVA and post-hoc Tamhane's T2 test on the log transformation data.

> **H1:** An ad in a higher position of the results listing will receive significantly more clicks than an ad in a lower position.

The results of the one-way ANOVA test on the adjusted click volumes indicated significant differences across ad ranks (F(15) = 635.12, $p < .01$). As indicated by the Tamhane's T2 test, click volume differs significantly among all the 16 ad positions. Therefore, Hypothesis 1 is fully supported.

From Table 4, we can see that the average day-of-the-week adjusted clicks of all 16 ad potions is 3.5543 per day, which is highly affected by the top four ad placements. All pairwise comparisons are significantly different from each other ($p < .01$), with the higher ranked ad positions generally

TABLE 2. Aggregate statistics from the SEM data set.

	Total	Average (per ad per day)	Standard deviation
Impressions	423,129,400	61.8063	811.1091
Clicks	13,284,574	1.9405	44.0299
Advertising cost	$8,484,855	$1.2394	$19.6750
Sales	$5,6,223,924	$8.2126	$37.7716
Orders	372,406	0.0544	2.6224
Items	690,964	0.1009	5.1850

TABLE 3. Aggregate statistics from the top 16 ads ranks.

	Total	Percentage of total data set	Average (per ad by day)	Standard deviation
Impressions	403,868,723	95.4480%	70.6129	884.0084
Clicks	13,227,492	99.5703%	2.3127	48.1625
Advertising cost	$847,397,224	99.8717%	$1.4816	$21.5173
Sales	$5,596,664,315	99.5424%	$9.7853	$413.2000
Orders	370,480	99.4828%	0.0648	2.8689
Items	687,237	99.4606%	0.1202	5.6723

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TABLE 4. Mean click per day by ad rank with change in clicks by position.

Rank	Mean	Change in mean click from the 1st ad rank	Conditional rank	CTR	Change in CTR from the 1st ad rank	Mean impressions
1_a	6.9444	—	1_a	.0928	—	61.1202
2_b	4.6130	−33.5719%	2_b	.0539	−41.9181%	119.9303
3_c	5.4379	−21.6946%	3_c	.0417	−55.0647%	181.8403
4_d	3.8862	−44.0389%	4_d	.0323	−65.1940%	156.2295
5_e	2.8599	−58.8173%	5_e	.0257	−72.3060%	135.9430
6_f	2.0922	−69.8720%	6_f	.0215	−76.8319%	115.5875
7_g	1.4776	−78.7226%	7_g	.0182	−80.3879%	93.0717
8_h	0.9841	−85.8291%	8_h	.0160	−82.7586%	70.3922
9_i	0.7665	−88.9622%	9_i	.0151	−83.7284%	56.9634
10_j	0.5865	−91.5550%	10_j	.0149	−83.9440%	43.7833
11_k	0.5487	−92.0989%	11_k	.0142	−84.6983%	42.6729
12_l	0.4599	−93.3771%	12_l	.0142	−84.6983%	36.8290
13_m	0.4009	−94.2273%	13_m	.0134	−85.5603%	33.6999
14_n	0.3042	−95.6201%	14_n	.0127	−86.3147%	26.4894
15_o	0.2734	−96.0632%	15_{no}	.0124	−86.6379%	25.5058
16_p	0.2295	−96.6952%	16_o	.0125	−86.5302%	21.5285
All ranks	3.5543	—		.0257	—	—

Note. Ad positions containing similar letters are nonsignificantly statistically different in average click numbers by Tamhane's T2 post hoc test results at $p < .01$. In this case, all ad positions were statistically difference.

generating more clicks than the lower ranked ones. Similar to the click distribution among various ad positions, the standard deviation of click numbers among ad groups also drop in a roughly decreasing order, with the top-ranked ads having more variance than ads ranked further down the listing. In other words, the average click numbers of ads near the top of the listings would be more unpredictable than that of ads further down the listings. There is more stability at the lower ranked ads and, therefore, more predictability. However, to our surprise, we also found that the ad ranked in position number three attracts more clicks than the ad in position two.

We also conducted the analysis using click-through rate (CTR, which is defined as the ratio of click-throughs to impressions), rather than absolute number of clicks. As shown in Table 4, the rank and analysis between the two analyses are nearly identical. However, there was no noted increase in CTR at position number three, relative to the top two positions. This indicates that there is an increase in the mean number of impressions for this ad position.

> **H2:** An ad in a higher position of the results listing will cost significantly more per click than an ad in a lower position.

Significant aggregate differences among ad ranks are again apparent in our one-way ANOVA analysis of the average CPC ($F(15) = 12883.06$, $p < .01$). Tamhane's T2 test further indicated that except for the last four ad ranks (i.e., positions 13 to 16), the mean CPC values for all the other 12 ad positions are significantly different from each other. Therefore, hypothesis 2 is partially supported.

As shown in Table 5, the average CPC among all 16 rank categories is $0.7162 per ad per day, which is highly skewed by the top three ads on the first SERP. As indicated by the post-hoc analysis, the top 12 positions (i.e., all eight ads on the first page, as well as the first four ads on the second page) get significantly different CPC ($p < .01$) for each pairwise comparison. In contrast, we failed to find such significant differences among ad ranks 13 through 16, with ad position 14 and 15 with about the same CPC value as both position 13 and position 16. This would indicate that advertisers do not view a ranking advantage this far down in the results listing.

TABLE 5. Mean CPC (in dollars) per day by ad rank with change in CPC by position.

Rank	Mean ($)	Change in mean CPC from the 1st ad rank
1_a	0.9980	—
2_b	1.2129	21.5414%
3_c	0.7495	−24.8970%
4_d	0.4974	−50.1608%
5_e	0.3764	−62.2803%
6_f	0.3198	−67.9573%
7_g	0.2902	−70.9249%
8_h	0.2703	−72.9180%
9_i	0.2556	−74.3918%
10_j	0.2391	−76.0373%
11_k	0.2279	−77.1642%
12_l	0.2161	−78.3435%
13_m	0.2065	−79.3060%
14_{mn}	0.1996	−79.9998%
15_{mn}	0.1951	−80.4508%
16_n	0.1880	−81.1576%
All Ranks	0.7162	—

Note. Ad positions containing similar letters are nonsignificantly statistically different in average CPC (in dollars) by Tamhane's T2 post hoc test results at $p < 0.01$.

As compared to the previous analysis, one interesting aspect that we found is that the second ranked ad has a higher average CPC than an ad in the topmost position, even though the overall clicks by ad ranks still follow a

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decreasing order from the top to bottom positions. We believe that this might be due to the higher quality scores of those topmost ranked ads as compared to those ranked one slot lower.

> **H3:** An ad in a higher position of the results listing will have a significantly higher conversion rate than an ad in a lower position.

The result of conversion comparisons using the one-way ANOVA shows significant differences among ad positions ($F(15) = 485.173$, $p < .01$). However, the follow-up pairwise comparisons of conversion rates among all 16 ad ranks indicated that only the topmost ad position gained significantly higher conversion rates than the other 15. The second and third ad positions only showed significant differences as compared to the top 15 and top 8 ad positions, respectively. There were no such significant differences among all the other ad ranks ($p > .01$, for each pairwise comparison). Therefore, hypothesis 3 is partially supported. Generally, we can say that the top three ad positions have statistically significant higher conversion rates, while there is no difference in conversion rates for ads in positions 4 through 16.

From Table 6, we can see that the average conversion rate for the top 16 ads listed on the first two result pages is 0.0137 per ad per day, which is strongly skewed by the topmost ad position. Different from what we have observed in the previous analysis of average CPC and click numbers, this time the results of Tamhane's T2 test demonstrated that conversion rates remained relatively stable among ad positions, with only the top three ad positions showing statistically significant differences between all pairwise comparisons.

TABLE 6. Mean conversion rate by ad rank with changes in conversion rate by position.

Rank	Mean	Change in mean conversion rate from the 1st ad rank
1_a	0.0266	—
2_b	0.0129	−51.5759%
3_c	0.0094	−64.5739%
4_d	0.0081	−69.6121%
5_d	0.0082	−69.1254%
6_d	0.0076	−71.4806%
7_d	0.0071	−73.4404%
8_d	0.0075	−71.7752%
9_d	0.0081	−69.5386%
10_d	0.0081	−69.5421%
11_d	0.0074	−72.0402%
12_{cd}	0.0080	−69.7969%
13_{cd}	0.0081	−69.4486%
14_{cd}	0.0071	−73.5318%
15_{cd}	0.0077	−70.9358%
16_{cd}	0.0080	−70.0267%
All ranks	0.0137	—

Note. Ad positions containing similar letters are nonsignificantly statistically different in average conversion rate by Tamhane's T2 post hoc test results at $p < .01$.

Like the first ad slot that leads to relatively higher conversions, the second and third ad positions show nonsignificant differences as compared to some of the lower ranked ad placements on the second page. To be more specific, no significant difference was observed in the conversion rate between the second and the 16th ad position. There was also no significant difference between the third ad slot and all eight ad placements on the second SERP. Starting from ad position number four, all the following 13 ad positions revealed nonsignificant between-pair differences for conversion rate measurements. Generally, from Table 6, one can say that, other than position one, there is little difference in conversion rates among ad positions.

> **H4:** An ad in a higher position of the results listing will have significantly higher sales revenue than an ad in a lower position.

The one-way ANOVA test again shows a significant effect of ad positions on the average sales amount ($F(15) = 655.28$, $p < .01$). The follow-up post-hoc analysis also revealed greater sales revenue for the higher ranked positions as compared to those lower ranked ones ($p < .01$). However, ads ranked 9 to 12 and 10 to 16 share approximately equal volume of sales. Therefore, hypothesis 4 is partially supported.

As can be inferred from Table 7, the overall mean sales revenue for all the ads listed on the first two result pages is \$11.9578 per ad per day. Unlike the distribution of the previously mentioned performance metrics, the mean sales revenue across all 16 groups is highly skewed by almost all ads listed on the first SERP, rather than the few topmost ads. All ads on the first SERP generate much higher revenue than ads on the second SERP. In addition to the aggregated position effect on the sales volume, we also identify significantly different level of sales revenues among all eight ads listed on the first SERP. In contrast, ads listed on the second SERP revealed the following patterns for each slot. Individually, among ads on the second SERP the topmost ad slot on the second SERP (ad with rank nine) generate roughly the same sales as ad position number eight. Likewise, the following three slots (i.e., position 10 to 12) have similar sales revenue volumes, and so do the last five ad positions (i.e., ad number 10 through 16).

We also conducted this analysis conditionally by examining the mean sales for only those clicks that resulted in a sale (Conditional rank), rather than by all clicks on at the ad position (Rank). The results are also shown in Table 7. Comparison between the two analyses shows similar trends, with topmost ad position and ad positions on the first SERP generating significantly higher sales revenue than the other ad positions.

> **H5:** An ad in a higher position of the results listing will have significantly more orders than an ad in a lower position.

Similar to the previous analyses, the results of the one-way ANOVA test for the comparison among all 16 groups demonstrate statistically significant rank effects on the average number of orders ($F(15) = 682.69$, $p < .01$). Tamhane's T2 test again showed distinct order amounts among all pairwise

TABLE 7. Mean sales (in dollars) by ad rank with change in sales by position.

Rank	Mean ($)	Change in mean sales from the 1st ad position	Conditional rank	Conditional mean ($)	Change in conditional mean sales from the 1st ad rank
1_{a}	42.0784	—	1_{a}	86.1562	—
2_{b}	10.3920	−75.3032%	2_{b}	20.4708	−76.2399%
3_{c}	9.1312	−78.2996%	3_{c}	18.0628	−79.0349%
4_{d}	4.7856	−88.6270%	4_{d}	10.3292	−88.0111%
5_{e}	3.3083	−92.1378%	5_{e}	8.0862	−90.6145%
6_{f}	2.2307	−94.6987%	6_{f}	6.1724	−92.8358%
7_{g}	1.4852	−96.4705%	7_{g}	4.5154	−94.7590%
8_{h}	0.9963	−97.6323%	8_{h}	3.5162	−95.9188%
9_{hi}	0.8676	−97.9382%	9_{hi}	3.1591	−96.3333%
10_{j}	0.6782	−98.3883%	10_{ij}	2.6834	−96.8854%
11_{ijk}	0.6614	−98.4281%	11_{jk}	2.0585	−97.6107%
12_{jl}	0.5359	−98.7264%	12_{jk}	1.9014	−97.7931%
13_{kl}	0.4229	−98.9949%	13_{jk}	1.6394	−98.0971%
14_{l}	0.3878	−99.0785%	14_{k}	1.6462	−98.0893%
15_{l}	0.3731	−99.1133%	15_{k}	1.3857	−98.3917%
16_{l}	0.3418	−99.1877%	16_{k}	1.0798	−98.7467%
All ranks	11.9578	—	All ranks	30.1517	—

Note. Ad positions containing similar letters are nonsignificantly statistically different in average sales (in dollars) by Tamhane's T2 post hoc test results at $p < .01$.

TABLE 8. Mean number of orders by ad rank with change in orders by position.

Rank	Mean	Change in mean order numbers from the 1st ad rank	Conditional rank	Conditional mean	Change in conditional mean order numbers from the 1st ad rank
1_{a}	0.2782	—	1_{a}	0.5694	—
2_{b}	0.0675	−75.7373%	2_{b}	0.1330	−76.6409%
3_{c}	0.0574	−79.3573%	3_{c}	0.1135	−80.0617%
4_{d}	0.0360	−87.0566%	4_{d}	0.0778	−86.3419%
5_{e}	0.0249	−91.0374%	5_{e}	0.0608	−89.3241%
6_{f}	0.0178	−93.5933%	6_{f}	0.0493	−91.3498%
7_{g}	0.0126	−95.4721%	7_{g}	0.0384	−93.2476%
8_{h}	0.0087	−96.8616%	8_{h}	0.0305	−94.6392%
9_{hi}	0.0073	−97.3927%	9_{hi}	0.0264	−95.3594%
10_{j}	0.0056	−97.9831%	10_{ij}	0.0220	−96.1408%
11_{ij}	0.0055	−98.0132%	11_{jk}	0.0189	−96.6743%
12_{jk}	0.0043	−98.4490%	12_{jk}	0.0156	−97.2527%
13_{jk}	0.0040	−98.5795%	13_{jk}	0.0153	−97.3132%
14_{k}	0.0035	−98.7438%	14_{k}	0.0144	−97.4682%
15_{k}	0.0033	−98.7975%	15_{k}	0.0127	−97.7752%
16_{k}	0.0029	−98.9646%	16_{k}	0.0117	−97.9479%
All ranks	0.0800	—	All ranks	0.2016	—

Note. Ad positions containing similar letters are nonsignificantly statistically different in average order numbers sold by Tamhane's T2 post hoc test results at $p < .01$.

comparisons between the top eight ad placements and all other ad positions. It failed to show such significant differences among ad positions 9 through 11 and positions 12 through 16. Therefore, hypothesis 5 is partially supported.

As can be seen from Table 8, the average order amount of all 16 ad positions listed on the first two SERPs is 0.0800 per ad per day. This average number of orders is again strongly affected by the topmost ad position, which has about three times the order volume compared to the following ad position. Due to their high order volumes, the distribution of the average order numbers is once again highly skewed. For a more fine-grained analysis of the effects of ad positions, our post-hoc analyses revealed highly significant differences in the average order numbers between all pairwise comparisons from position one to position eight. In contrast to those topmost eight positions, the last five ads listed on the second SERPs show nonsignificantly different average order volumes ($p > .01$). We also observed nonsignificant decreases in order numbers from ads in positions 9 to 11 and positions 10 through 13 ($p > .01$). The trend was that the ad positions of the first SERP generate more orders than ads in positions on the second SERP.

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We again conducted this analysis conditionally by looking at the mean orders for only those clicks that resulted in an order (Conditional rank), rather than by all clicks on at the ad position (Rank). These results are also shown in Table 8. As shown, the results between the two analyses show a similar trend. The topmost ad position generates significantly higher orders than the other ad positions.

H6: An ad in a higher position of the results listing will have significantly more items purchased per order than an ad in a lower position.

Again, significant position differences are displayed by the one-way ANOVA test for the mean number of items purchased per order ($F(15) = 665.69$, $p < .01$). Similar to the results reported in the previous hypothesis testing number of orders, Tamhane's T2 is significant only for all the pairwise comparisons for the top eight ad positions, whereas we failed to detect such significant differences between every pair of ads on the second SERP (rank number 9 through 16) on their average item numbers ($p > .01$). Therefore, hypothesis 6 is partially supported.

From Table 9, we see that the average number of items purchased per order is 0.1431, which is greatly affected by the topmost ad position. It is also evident that ad ranks on the first SERP have considerable influence on the mean number of items purchased, with higher ranked ads leading to more items purchased than lower ranked ads. Consistent with our results found in the hypothesis testing of sales volumes and order numbers, we find that ad positions 9 to 11 have nonsignificantly different amounts of items sold, as do the bottom five ads on the second SERP (i.e., ad position 12 through 16).

We also conducted this analysis conditionally for the mean items ordered for only those clicks that resulted in an item being ordered (Conditional rank), rather than by all clicks on at the ad position (Conditional rank). These results are also shown in Table 9. As can be seen, the results between the two analyses again show a similar trend. The topmost ad position generates a significantly higher number of items ordered than the other ad positions.

H7: An ad in a higher position of the results listing will have a significantly higher return on advertising than an ad in a lower position.

The one-way ANOVA test was again significant for average profits generated among the ad positions ($F(15) = 609.92$, $p < .05$). However, Tamhane's T2 test used for between-group comparisons only demonstrate distinct profit margins among all pairwise comparisons generally for the top eight ad positions (except positions four and five, and seven and eight). Thus, in general, ads in higher positions in the first SERP will generate a better return on advertising dollars. However, it failed to elicit such significant differences on comparisons of the last eight ad groups and ad position number 8 to 12. Thus, generally, there was no difference in average return on advertising dollars for ad positions on the second SERP. Therefore, hypothesis 7 is partially supported.

From Table 10, we see that the average return on advertising dollars for all top 16 ads listed on the first two returned pages per day is $9.5634 per ad per day. This average profit is once again strongly affected by the topmost ad position on the first SERP, which yielded about 80% of the total profits for all 16 ad positions. As indicated in Table 10, the profits generated by the second-ranked ad dropped severely as compared to the number one ad position, receiving only 1/6 of the average profits of position number one. From the results of Tamhane's T2 test, we find that ads listed on the first SERP demonstrate significant differences in all their post-hoc pairwise comparisons except ad positions two and three, positions four and five, and positions seven and eight. Our

TABLE 9. Mean number of items sold by ad rank with change in items by position.

Rank	Mean	Change in mean item number from the 1st ad rank	Conditional rank	Conditional mean	Change in conditional mean item number from the 1st ad rank
1_a	0.5009	—	1_a	1.0253	—
2_b	0.1176	−76.5249%	2_b	0.2314	−77.4277%
3_c	0.1020	−79.6458%	3_c	0.2012	−80.3722%
4_d	0.0619	−87.6397%	4_d	0.1338	−86.9513%
5_e	0.0442	−91.1852%	5_e	0.1065	−89.6100%
6_f	0.0317	−93.6746%	6_f	0.0876	−91.4554%
7_g	0.0223	−95.5434%	7_g	0.0679	−93.3807%
8_h	0.0155	−96.9089%	8_h	0.0536	−94.7772%
9_{hi}	0.0135	−97.2969%	9_{hi}	0.0487	−95.2502%
10_{ij}	0.0108	−97.8383%	10_{ij}	0.0422	−95.8794%
11_{ik}	0.0100	−98.0077%	11_{jk}	0.0338	−96.7062%
12_{jkl}	0.0080	−98.3955%	12_{jk}	0.0286	−97.2111%
13_{jkl}	0.0070	−98.6036%	13_{jk}	0.0265	−97.4167%
14_{kl}	0.0078	−98.4399%	14_{jk}	0.0296	−97.1099%
15_l	0.0054	−98.9232%	15_k	0.0215	−97.8999%
16_l	0.0051	−98.9736%	16_k	0.0197	−98.0820%
All ranks	0.1431	—	All ranks	0.3602	—

Note. Ad positions contain similar letters are nonsignificantly statistically different in average item numbers sold by Tamhane's T2 post hoc test results at $p < .01$.

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TABLE 10. Mean return on advertising (in dollars) by ad rank with change in advertising return by position.

Rank	Mean ($)	Change in mean return on advertising from the 1st ad rank
1_a	38.5062	—
2_b	5.0956	−86.7667%
3_b	4.0138	−21.2303%
4_c	2.5445	−36.6062%
5_c	2.0473	−19.5419%
6_d	1.4220	−30.5412%
7_e	0.9670	−31.9968%
8_{ef}	0.6780	−29.8869%
9_{eg}	0.6349	−6.3549%
10_{fgh}	0.5160	−18.7317%
11_{fgh}	0.5191	0.6038%
12_{fgh}	0.4254	−18.0408%
13_{gh}	0.3333	−21.6582%
14_h	0.3215	−3.5513%
15_{gh}	0.3145	−2.1587%
16_h	0.2947	−6.3066%
All ranks	9.5634	—

Note. Ad positions containing similar letters are nonsignificantly statistically different in average return on advertising (in dollars) by Tamhane's T2 post hoc test results at $p < .01$.

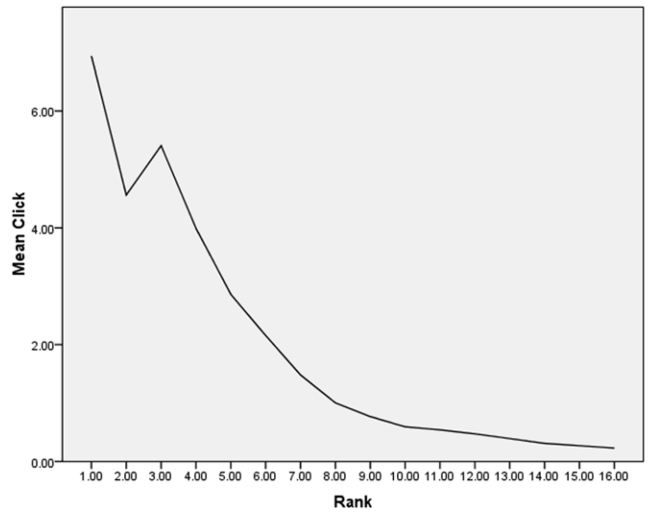

FIG. 2. Mean clicks numbers per day by ad rank.

further comparisons of ads across the two pages revealed that the last ad listed on the first SERP generates about the same amount of mean profits per day as ads ranked number 9 to 12. This may be due to some aspect of the recency effect. With significantly less profits received as compared to most of the higher ranked positions on SERP one, ads listed on the second SERP all together receive about 1% of the total profits generated by all 16 ad positions.

Discussion and Implications

Discussion of Results

Driven by the special bidding mechanism of sponsored search advertising, traditional wisdom believes that ads listed at the top of the SERP should get more clicks and thus yield greater profits than ads with lower ranks. In order to validate this assumption, our research investigated the value of those top ranked ads regarding their impact on number of clicks, CPC, conversion rate, sales revenue, orders, items sold, and return on advertising. Our research shows the influence of ad ranks on the average number of user clicks. As one might expect, all ad rankings exhibited significant differences in their average click volumes per day. According to our findings, the mean number of clicks drops drastically as the ad ranks goes down, with the top four ad positions containing about 80% of the total user clicks. Among those 80% of user clicks, the topmost slot itself covers about half of the click volumes, which is about 21 times more clicks than the ads showing in the last position of the same page and 496 times more than the last ad positioned on the second SERP, as shown in Figure 2.

One interesting finding, shown in Figure 2, is that there is a dramatic rise in click volumes between ad positions two and three, in contrast to the overall decreasing pattern as indicated by the other positions. Some of the increased click volume is due to the ad at position 3 being shown more. Another possible interpretation for this sudden rise is related to the unique design of the search results user interface. As shown in Figure 3, the search engine return page of Google can be divided into three sections: organic search results, paid ads on the top (a.k.a., north) and paid ads on the right-hand column (a.k.a., east, right rail).

On Google, by default, there can be a maximum of three paid ads displayed above the free organic search results and eight slots on its right. However, many times there are only two ads appearing in the premium positions above the non-sponsored search result. Starting from the upper right, the first two ads on the right fall into the intersection regions of the top frame and the right column. This overlapping sometimes leads to the third ad position on the right parallel with the first organic search result. As indicated by Jansen and Resnick (2006), users showed strong preferences for non-sponsored links—82% of the time viewing those free organic results first. According to Fitts' Law (1954) and the principle of least effort (Zipf, 1949), we assume that a larger proportion of those 82% of users would click on the third listed ad on the right rather than the one placed on the second or the first positions, since given the same ad spaces, more effort is needed for the users to move their mouse to the upper right corner as compared to the parallel position. From private conversations with individual search engine marketers, they have noticed that ad position number three is often a high performer. Fitt's Law may be the theoretical underpinning for this observed behavior. Such a discernible shift between the second and the third positions was not detected on the second page (between rank 10 and rank 11). We

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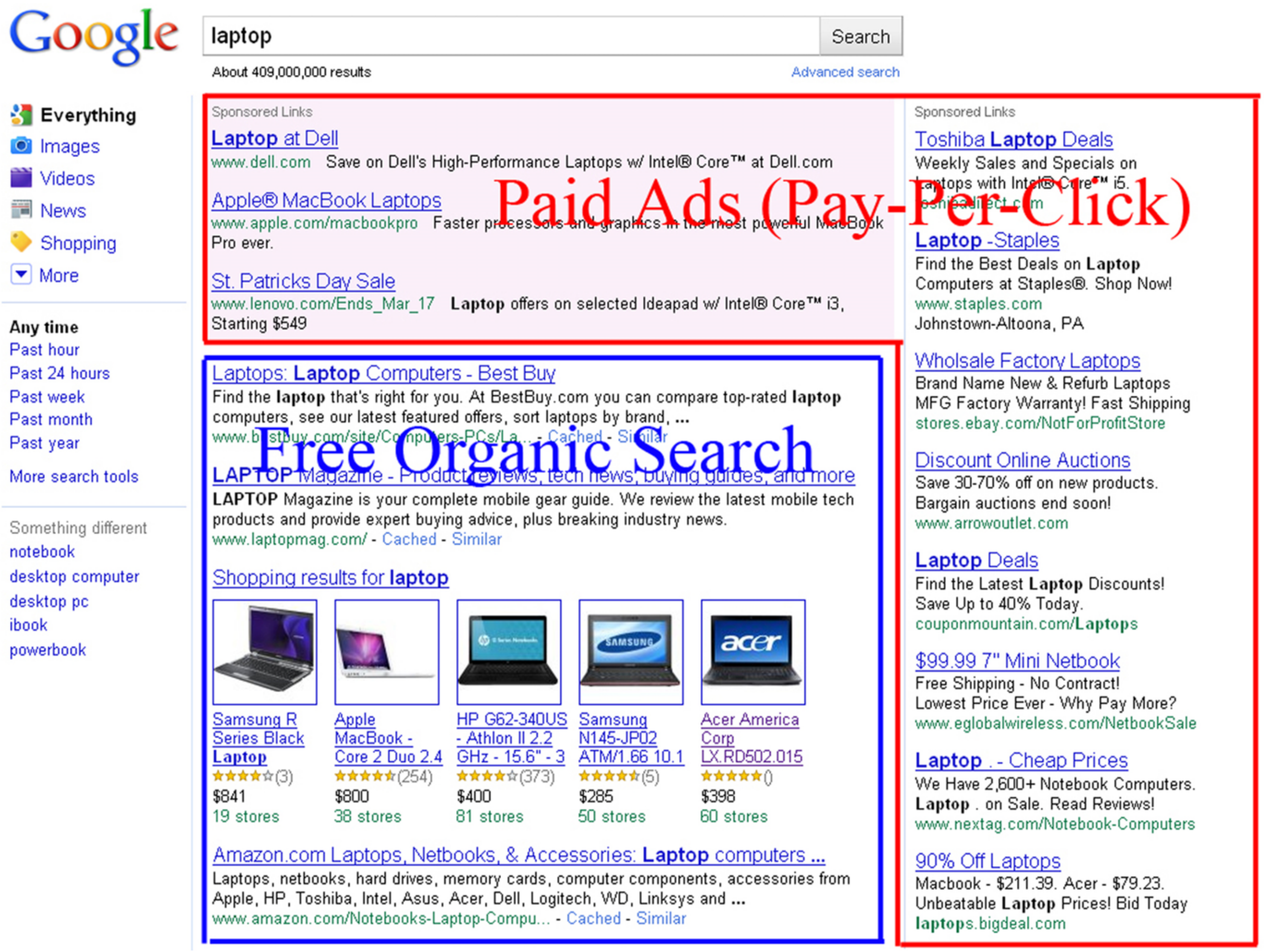

FIG. 3. Sample search engine results page with result sections highlights. [Color figure can be viewed in the online issue, which is available at wileyonlinelibrary.com.]

conjecture this to be a consequence of the rational choices of those serious buyers. Different from the majority of sponsored search users who only click on top ranks, serious buyers are often more involved in their purchasing decision-making process and thus are more willing to visit lower positions (i.e., ads on the second SERP) to satisfy their information needs. Due to their higher perception of risks in making a purchase, serious buyers tend not to follow the "satisficing" or "least effort" path as represented by people who only view the first few positions.

Given that consumers are more likely to be attracted by those top-ranked ads, to ensure better click-through rates for their online keyword advertising campaigns, advertisers strive to bid higher to secure a top position on the SERP. Therefore, it then leads to our findings on the highly positive associations between ad ranks and their corresponding average CPCs. We observed that the mean CPC values suffered a sharp drop after the first four ad positions, with a decrease of about half of the price of the fourth positioned ads on the first SERP. This sudden decline would indicate that even though price differentials did exist for all 16 groups of ads, for ads with their positions out of the top four, such price distinctions tend to be smaller than that of those top four ads. In addition to the overall decreasing trend of average CPCs, we also found that, although the topmost position requires the highest bidding price, the mean CPC value for it is slightly lower than that of position number two. This suggests that for those highly competitive key phrases (the one with relatively higher bids), ad position number two attracts even more clicks than the topmost position, whereas for general terms ad position number one on average performs better than its following positions.

Given the monotonic increasing click volumes and the nonsignificant conversion rates among almost all 14 ad positions, it would be beneficial for advertisers to raise their ad positions to increase profits. However, as indicated by the increasing CPCs as shown in our previous results, usually it costs advertisers more money to secure higher positions. In order to calculate the real cost behind those extra click volumes between adjacent ad positions, incremental CPC was introduced by Google, as the cost of incremental clicks divided by the number of incremental clicks. Table 11

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TABLE 11. Incremental CPCs by ad ranks defined as cost of incremental clicks divided by the number of incremental clicks.

Rank	Mean cost ($)	Mean clicks	Mean CPC ($)	Incremental mean CPC($) from subsequent ad rank
1	3.5722	6.9444	0.9980	–0.2149
2	5.2964	4.6130	1.2129	0.4634
3	5.1174	5.4379	0.7495	0.2521
4	2.2411	3.8862	0.4974	0.121
5	1.2610	2.8599	0.3764	0.0566
6	0.8087	2.0922	0.3198	0.0296
7	0.5182	1.4776	0.2902	0.0199
8	0.3183	0.9841	0.2703	0.0147
9	0.2326	0.7665	0.2556	0.0165
10	0.1622	0.5865	0.2391	0.0112
11	0.1423	0.5487	0.2279	0.0118
12	0.1105	0.4599	0.2161	0.0096
13	0.0896	0.4009	0.2065	0.0069
14	0.0663	0.3042	0.1996	0.0045
15	0.0586	0.2734	0.1951	0.0071
16	0.0471	0.2295	0.1880	—

demonstrates the incremental CPCs among all 16 ad positions as included in our analysis results. The incremental CPC in Table 11 indicates the extra money advertisers need to pay for the incremental click volumes generated by one position promotion. While given that higher incremental CPCs are usually corresponding to higher ranked ad positions, advertisers need to balance their bids strategically to avoid wasting cost in those high incremental CPCs. Conducting position improvement blindly without consideration of the incremental CPC would result in higher cost but nonsignificant sales increase.

Unlike these test results on the average click volumes and CPC rates, our finding regarding the conversion rate differences is contradictory to beliefs held by some. We found that among all 16 ads tested spanning the first two SERPs, only the top two ranked ad positions exhibited profound differences in their conversion rate performance among all the pairwise comparisons. Our observations indicated that unlike the monotonic decreasing clicks and CPC distributions, the conversion rates for ads placed after the second slot remained relatively stable, with all 14 positions sharing roughly the same average conversion rates. Thus, we can conclude that ad rank has only limited effect on final conversion rate after the first three positions, given that the actual conversion rates varied nonsignificantly across all ad positions ranging from 4 to 16, as shown in Figure 4. There is conversion benefit of being in the top three ad positions.

As we introduced earlier, we define conversion rate as the percentage of users who convert their click-throughs into purchases. Given the distinct distributions of average click volumes and conversion rates of all 16 ad positions, we adopted the conversion potential measurement as defined by Brooks (2004b) in order to quantify the ad rank effect on the average conversions. The click rate and conversion rate potentials in our study are the expected percentage changes in the average click and conversion rates as compared to that of position one, whereas the conversion potential is the product of the click potential and the conversion potential compared to that of position one. Table 12 displays the click potentials, conversion rate potentials, and conversion potentials across all 16 ad positions.

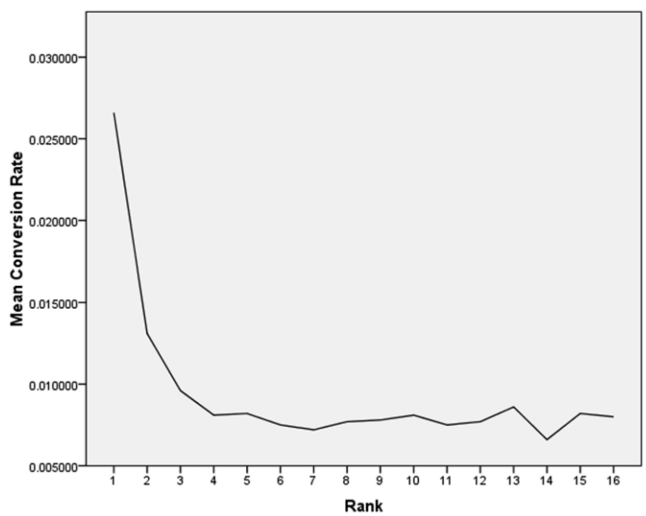

FIG. 4. Conversion rate by ad rank. [Color figure can be viewed in the online issue, which is available at wileyonlinelibrary.com.]

As seen in Table 12, even though conversion rates decreased about only 6% from ad position 3 to 16, the conversion potential dropped about 27%, due to the drastic reduction in the ad position's click potential. Therefore, conversion rate alone cannot be used as a measure of the success of online advertising campaigns. Conversion potential is a more accurate measure of the impact of an ad's position.

As verifications of the conversion potential, our research found that the average sales revenues generated by ads on the first SERP accounted for about 99% of the total

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TABLE 12. Conversion potential by ad rank defined as click potential multiplied by conversion rate.

Rank	Click potential	Conversion rate	Conversion potential	Change in conversion potential
1	100.0000%	100.0000%	100.0000%	—
2	66.4281%	48.4962%	32.2151%	−67.7849%
3	78.3054%	35.3383%	27.6718%	−72.3282%
4	55.9611%	30.4511%	17.0408%	−82.9592%
5	41.1827%	30.8271%	12.6954%	−87.3046%
6	30.1280%	28.5714%	8.6080%	−91.3920%
7	21.2774%	26.6917%	5.6793%	−94.3207%
8	14.1709%	28.1955%	3.9955%	−96.0045%
9	11.0378%	30.4511%	3.3611%	−96.6389%
10	8.4450%	30.4511%	2.5716%	−97.4284%
11	7.9011%	27.8195%	2.1980%	−97.8020%
12	6.6229%	30.0752%	1.9918%	−98.0082%
13	5.7727%	30.4511%	1.7579%	−98.2421%
14	4.3799%	26.6917%	1.1691%	−98.8309%
15	3.9368%	28.9474%	1.1396%	−98.8604%
16	3.3048%	30.0752%	0.9939%	−99.0061%

purchases. Among those eight ad positions listed on the first SERP, the topmost ad placement generated about seven times the overall revenues (more than 70%), as compared to the second slot, which only covers about 12% of total sales. Consistent with the implication of ad rank effect on sales revenues, our analysis of the number of orders and items purchased per order has also demonstrated a strong "top ads effect," with identified drastic declines in both performance matrices. Among those effective top positions, the topmost ad composed more than 70% of both the total orders and items sold.

Additionally, through our final test on the average advertising margins, we also noticed reliable distinctions influenced by ad positions. On a macro scale of between-page analysis, the eight ads listed in positions on the first SERP generated about 99% of the total average advertising margins. This finding is consistent with the previous inference from the tests on the average sales revenues (Figure 5).

This can be further indicated by the nearly overlapping part at the end of the two distributions as shown in Figure 5. On a micro level of within-page analysis, the last ad position on the first SERP generated nonsignificantly higher profits as compared to its former position, as well as ad positions 9 to 12.

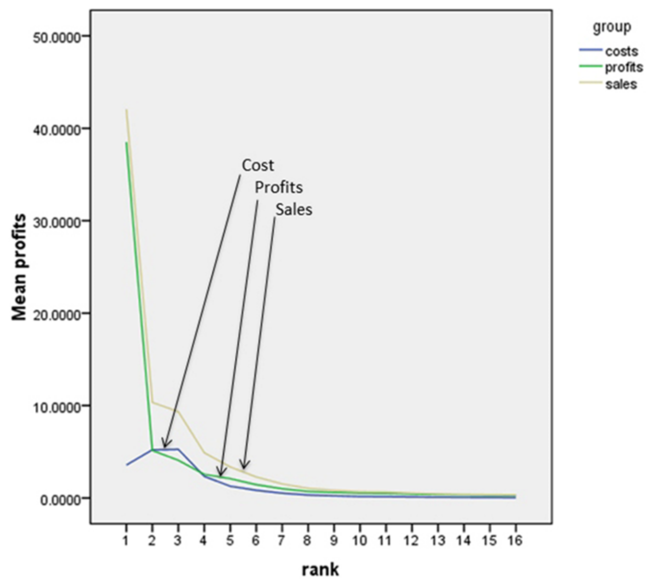

FIG. 5. Comparison of costs, sales, and profits by ad rank. [Color figure can be viewed in the online issue, which is available at wileyonlinelibrary.com.]

Theoretical Implications

In terms of human information-seeking behavior, our findings extend prior studies indicating that the serial position effect, especially the primary effect, occurs in the online advertising environments. Consistent with prior studies indicating position bias in users' clicking behaviors (Ansari & Mela, 2003; Drèze & Zufryden, 2004), our results also show that consumers appear more willing to click on the ads listed in the top positions, thus leading to higher CPC for those top ranked ads. Besides consumer's clicking performance, cognitive bias regarding earlier ad exposures was also found on all performance matrices tested in our studies, including sales, number of orders, and profit margins. With such primacy effect on micro and macro aspects, ads on the first SERP trigger significantly more purchasing related actions than ads placed on the second page. Meanwhile, those top ranked ads in the first SERP often skew the average upwards, with significantly more sales than those intermediate positions and ads listed in the lower positions.

Even though not as obvious as its effect on click volumes and sales generations, the primacy effect is detected in conversion rates. As shown in Figure 3, the conversion rate distribution over all 16 ad positions follows a power-law-like distribution, with the top three ad ranks having extremely high conversion rates and near flat conversion rate distributions for the rest of the ranks. This is different from

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the monotonic case as shown in the tests on click volumes. In other words, an equal proportion of consumers made their purchase leads on ads ranging from 4 to 16, even though the absolute numbers varied significantly. We interpret this relatively stable distribution of conversion rates ranging from position 4 to 16 using models of consumer searching (Johnson, Moe, Fader, Bellman, & Lohse, 2004). Consumers may conduct detailed pre-purchasing research before they actually buy an item. However, given the extra workload that it takes to view or click on more ads, many casual shoppers would stop their browsing within a very limited number of clicks. On the other hand, serious or more knowledgeable buyers are more willing to click and compare more ads during their research due to their stronger purchasing intention, which is consistent with the model proposed in the previous work (Mantonakis et al., 2009). We assume that limited by their short-term memory capacity, as indicated by the recency effect, people choosing from a longer list may make their purchase among the last few items they viewed. Although we did not see the recency effect much in CTRs, we relate this to the principle of least effort (Zipf, 1949), where searchers are finding what they want in the first few items they click on. Thus, there is no need for these consumers to explore further. This leads to the relatively higher conversion rates (although not significantly higher) at the tail part of the whole distribution. The same model can also be used as an interpretation of the recency effect on ad profits, with the eighth position generating about the same amount of mean profits as ads ranked numbers 9 to 12.

Practical Implications

Based on these findings, the ad rank does have an effect on consumer's clicking behavior. The average click numbers of an ad increases monotonously as its placement goes up on the SERP, and the CPC also increases monotonously with the ad position. For advertisers aiming to build or enhance strong brand awareness, it is important to bid at higher positions so as to attract consumers to visit their websites by clicking on their ads. Compared to lower ranked ad positions, the top four ad slots on the first SERP are extremely valuable for brand-building advertisers, since those four positions could bring them about 80% of the total potential customers.

Even though brand building is more important to large companies, there are still a number of small or midsized organizations interested in generating tangible sales through their online advertising campaigns (SEMPO Research, 2009). Performance matrices including average sales, number of orders, and number of items purchased per order can instead be applied in such nonbranding cases. Of all three sales-generating matrices that we have examined, higher ranked ads superiority is limited to those on the first SERP. For those ads listed on the second SERP, if not paying to improve their chances for the first page placement, there is no need for advertisers to be engaged in intense bidding to win the relatively same sales revenue or conversion potential.

More sales do not necessarily translate into more profits. Based on average return on advertising margins, the results indicate the same positional effect on the first SERP. Thus, advertisers need to bid for higher positions on the first SERP. However, advertisers with ads currently located on the second page need to increase their bidding prices higher to get on the first SERP. Otherwise, with the extra money invested in their campaigns to just raise their ranking on the second SERP, the increase in profit margins would still not be significant. The rationale of incremental CPCs can to some extent explain this nonsignificant profit improvement considering the ineffective investment in the incremental CPCs. In general, it is suggested that advertisers benefit if the incremental CPC is lower than the value per click, and lose money if otherwise.

One more implication from this study is that advertisers should not depend on the conversion rate alone to determine their bidding strategies. As shown in Table 11, conversion rates do not change much across different ad positions. However, considering the large click volume and the drastic decreases in clicks, the conversion potential varied significantly even for adjacent ad positions. It is this conversion potential that can be eventually used as a measurement of the successfulness of an ad campaign, rather than the conversion rates. In such cases, lower ranked positions do have significantly less benefit than those higher ranked ads despite discussions of similar conversion rates among ad positions (Friedman, 2009; Michie, 2010).

As our findings show, ad rank does influence the online keyword advertising campaigns. However, contrary to the belief that higher ranked positions lead by the PPC pricing model, our study also points out the limitations of the current pricing mechanism of sponsored search since more clicks on the second SERP cannot guarantee significantly more profits for the advertisers. Similarly, more money invested in higher ad placement does not always result in better sales and profits.

Limitations and Strengths

As with any research, there are limitations to this study. First, the data set comes from one company in the retail sector. Although the data set used is quite large both in terms of number of records and temporal span, further research with other companies and in other industry sectors is needed to ensure that the results are transferable. However, we believe that the research reported here is an important step in this direction and will assist in directing avenues for future research. Second, the data set we used in this study does not contain fields recording users' searching behavior off the SERP. With the current data set, we lack the ability to analyze user's interaction behavior with the associated websites. We can also only get indications on users' purchasing intent within a single query session by analyzing the data from the advertiser's perspective. It would be useful for future studies to focus on the ad rank effect on the user's total search experience. Finally, the method that Google uses for ad placement for positions one, two, and three can vary. Sometimes they (or some subset of these three) may be above the organic listings. Other times, there may be no ads above the organic listing. In this case, all ads are in the right-hand rail. This placement is done by keyword and not ad, so there is no way to identify in which position a particular ad appeared.

The research also has several strengths, including the large data set, the lengthy period of data collection, the analysis of major keyword advertising attributes, and the application of a theoretical construct to address customer behavior. We believe that the research presented here is a valuable contribution to the growing area of study in the sponsored search and keyword advertising area. As well as its academic value, our study is also of practical worth for advertisers currently engaged in online advertising campaigns by providing them a number of ad placement strategies. Given the considerable impact that this technology and business process have had on the development of the web and online commerce, keyword advertising is an area that deserves substantial investigation. Therefore, this research provides valuable insight into consumer behavior in the real-world, e-commerce domain.

Conclusion

This research concludes that serial positional effect does exist in the sponsored search area, with higher ranked ads generating better overall performance than ads in lower positions. Our study shows the position effect of ad ranks on user clicking behaviors interacting with the SERP. However, different from its monotonic influence on click volumes, primacy impact is limited the top ads in their sales and revenue generation performance. Other than the topmost ad slots, there was no evidence of primacy effect in conversion rates. Based on our findings, generally it is beneficial for advertisers to bid for higher positions, especially the top four positions, as their brand building strategy, even if they are now listed in poorly ranked positions. However, for profit generation, advertisers should devote their resources to targeting those top ranked positions within the first SERP. We believe that our study offers advertisers insights into the bidding strategies of online advertising campaigns. For future work, investigating the rank effect on consumer's purchasing intent, with the consideration of the four-stage buying funnel, perhaps could lead to better position bidding strategies in the online advertising environment. We are also interested in investigating other factors besides ad rank that could affect online advertising campaigns, such as user intent of web queries (Kathuria et al., 2010) and user trust in online shopping (Lee, Park, & Han, 2011). Also, experiments on users' clicking behavior while they interact with different designs of the SERP would further benefit us with users' clicking patterns and thus lead to better advertising creations.

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References

Anderson, N.H. (1971). Integration theory and attitude change. Psychological Review, 78, 171–206.

Ansari, A., & Mela, C.F. (2003). E-customization. Journal of Marketing Research, 40(2), 131–145.

Asch, S.E. (1946). Forming impressions of personality. The Journal of Abnormal and Social Psychology, 41(3).

Atkinson, R.C., & Shiffrin, R.M. (1968). Human memory: A proposed system and its control processes. The psychology of learning and motivation. Advances in Research and Theory, 2, 89–195.

Beitzel, S.M., Jensen, E.C., Chowdhury, A., Grossman, D., & Frieder, O. (2004). Hourly analysis of a very large topically categorized web query log. 27th annual international conference on Research and development in information retrieval, Sheffield, U.K.

Beitzel, S.M., Jensen, E.C., Lewis, D. D., Chowdhury, A., & Frieder, O. (2007). Automatic classification of Web queries using very large unlabeled query logs. ACM Transactions on Information Systems, 25(2), Article No. 9.

Berry, M.J.A., & Linoff, G.S. (2004). Data mining techniques: For marketing, sales, and customer relationship management. New York: John Wiley & Sons.

Bjork, R.A., & Whitten, W.B. (1974). Recency-sensitive retrieval processes in long-term free recall. Cognitive Psychology, 6(2), 173–189.

Borgman, C.L. (1989). All users of information retrieval systems are not created equal: An exploration into individual differences. Information Processing & Management, 25(3), 237–251.

Box, G.E.P., & Anderson, S.L. (1955). Permutation theory in the derivation of robust criteria and the study of departures from assumptions. Journal of the Royal Statistical Society, 17(1), 1–34.

Box, G.E.P., & Cox, D.R. (1964). An analysis of transformations. Journal of the Royal Statistical Society, 26(2), 211–252.

Brooks, N. (2004a, July). The Atlas Rank Report I: How Search Engine Rank Impacts Traffic. Retrieved from: http://www.atlassiteoptimization.com/uploadedFiles/Atlas/Atlas_Institute/Published_Content/Rank Report.pdf

Brooks, N. (2004b, October). The Atlas Rank Report II: How Search Engine Rank Impacts Conversions. Retrieved from: http://surf2your.pages.com.au/resources/RankReportPart2.pdf

Capitani, E., della Sala, S., Logie, R. H., & Spinnler, H. (1992). Recency, primacy, and memory: Reappraising and standardising the serial position curve. Cortex: A Journal Devoted to the Study of the Nervous System and Behavior.

Chapelle, O., & Zhang, Y. (2009). A dynamic Bayesian network click model for web search ranking. 18th International Conference on World Wide Web (WWW '09), Madrid, Spain.

Coney, K.A. (1977). Order bias: The special case of letter preference. Public Opinion Quarterly, 41, 385–388.

Craik, F.I.M., & Lockhart, R.S. (1972). Levels of processing: A framework for memory research. Journal of Verbal Learning and Verbal Behavior, 11(6), 671–684.

Craswell, N., Zoeter, O., Taylor, M., & Ramsey, B. (2008). An experimental comparison of click position-bias models. International Conference on Web Search and Web Data Mining (WSDM '08), Stanford, CA.

Dean, M.L. (1980). Presentation order effects in product taste tests. Journal of Psychology, 105, 107–110.

Deese, J., & Kaufman, R.A. (1957). Serial effects in recall of unorganized and sequentially organized verbal material. Journal of Experimental Psychology, 54(3), 180.

Drèze, X., & Zufryden, F. (2004). The measurement of online visibility and its impact on Internet traffic. Journal of Interactive Marketing, 18(1), 20–37.

Ebbinghaus, H. (1885). Memory: A contribution to experimental psychology. New York: Dover.

Fain, D.C., & Pedersen, J.O. (2006). Sponsored search: A brief history. Bulletin of the American Society for Information Science and Technology, 32(2), 12–13.

Fitts, P.M. (1954). The information capacity of the human motor system in controlling the amplitude of movement, 3. Journal of Experimental Psychology, 47(6), 381–391.

Friedman, D. (2009, 18 August, 2009). Conversion rates don't vary much with ad position. Retrieved from: http://adwords.blogspot.com/2009/08/conversion-rates-dont-vary-much-with-ad.html

Ghose, A., & Yang, S. (2009). An empirical analysis of search engine advertising: Sponsored search in electronic markets. Management Science, 55(10), 1605–1622.

Google. (2011, 30 March 2011). Financial tables. Retrieved from: http://investor.google.com/financial/tables.html

Hoque, A.Y., & Lohse, G.L. (1999). An information search cost perspective for designing interfaces for electronic commerce. Journal of Marketing Research, 36(3), 387–394.

Hull, D. (1993). Using statistical testing in the evaluation of retrieval experiments. 16th Annual International ACM SIGIR Conference on Research and Development in Information Retrieval, Pittsburgh, PA.

Jansen, B.J. (2011). Understanding sponsored search: Core elements of keyword advertising. London: Cambridge.

Jansen, B.J., Brown, A., & Resnick, M. (2007). Factors relating to the decision to click-on a sponsored link. Decision Support Systems, 44(1), 46–59.

Jansen, B.J., & Mullen, T. (2008). Sponsored search: An overview of the concept, history, and technology. International Journal of Electronic Business, 6(2), 114–131.

Jansen, B.J., & Resnick, M. (2006). An examination of searchers' perceptions of non-sponsored and sponsored links during ecommerce Web searching. Journal of the American Society for Information Science and Technology, 57(14), 1949–1961.

Jansen, B.J., & Spink, A. (2004). An analysis of documents viewing patterns of web search engine users. Web Mining: Applications and Techniques. A. S. p. Hershey, PA: Idea. pp. 339–354.

Jansen, B.J., & Spink, A. (2009). Investigating customer click through behaviour with integrated sponsored and nonsponsored results. International Journal of Internet Marketing and Advertising, 5(1/2), 74–94.

Jansen, B.J., Spink, A., Bateman, J., & Saracevic, T. (1998). Real life information retrieval: A study of user queries on the web. SIGIR Forum, 32(1), 5–17.

Jansen, B.J., Spink, A., & Pedersen, J. (2005). A temporal comparison of AltaVista Web searching. Journal of the American Society for Information Science and Technology, 56(6), 559–570.

Johnson, E. J., Moe, W. W., Fader, P. S., Bellman, S., & Lohse, G. L. (2004). On the depth and dynamics of online search behavior. Management Science, 50(3), 299–308.

Kathuria, A., Jansen, B.J., Hafernik, & Spink, A. (2010). Classifying the user intent of web queries using k-means clustering. Internet Research, 20(5), 563–581.

Lee, J., Park, D.-H., & Han, I. (2011). The different effects of online consumer reviews on consumers' purchase intentions depending on trust in online shopping malls: An advertising perspective. Internet Research, 21(2), 187–206.

Li, Y.E., & Epley, N. (2009). When the best appears to be saved for last: Serial position effects on choice. Journal of Behavioral Decision Making, 22, 378–389.

Lindman, H.R. (1974). Analysis of variance in complex experimental designs. San Francisco: W.H. Freeman & Co.

Luchins, A.S. (1957). The order of presentation in persuasion. In C.I. Hovland (Ed.), Primacy-recency in impression formation. New Haven, CT: Yale University Press. pp. 33–61.

Mantonakis A., Lesschaeve I, & Hastie R. (2009). Order in choice: Effects of serial position on preferences. Psychological Science, 20, 1309–1312.

Michie, G. (2010). Misinformation and disinformation. Retrieved from: http://www.rimmkaufman.com/rkgblog/author/george/

Newell, S.J., & Wu, B. (2003). Evaluating the significance of placement on recall of advertisements during the Super Bowl. Journal of Current Issues and Research in Advertising, 25(2), 57–68.

Pieters, R., & Bijmolt, T. (1997). Consumer memory for television advertising: A field study of duration, serial position, and competition effects. Journal of Consumer Research, 23(4), 263–277.

Richardson, M., Dominowska, E., & Ragno, R. (2007). Predicting clicks: estimating the click-through rate for new ads. 16th International Conference on World Wide Web (WWW '07), Banff, Alberta, Canada.

SEMPO Research. (2009). The state of search engine marketing 2008. Survey of Advertisers and Agencies Search Engine Marketing Professional Organization (SEMPO) February, 2009, Search Engine Marketing Professional Organization.

Teevan, J. (2008). How people recall, recognize, and reuse search results. ACM Transactions on Information Systems (TOIS), 26(4), Article No. 19.

Terry, W.S. (2005). Serial position effects in recall of television commercials. The Journal of General Psychology, 132(2), 151–164.

Wang, P., Berry, M., & Yang, Y. (2003). Mining longitudinal web queries: Trends and patterns. Journal of the American Society for Information Science and Technology, 54(8), 743–758.

Waugh, N.C., & Norman, D.A. (1965). Primary memory. Psychological Review, 72(2), 89.

Weis, A.H. (2010). Commercialization of the internet. Internet Research, 20(4), 420–435.

Zipf, G.K. (1949). Human behavior and the principle of least effort. Cambridge, MA: Addison-Wesley Press.

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