Investigating the Effect of Results Ranking in Sponsored Search

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ABSTRACT

The objective of this research was to evaluate the effect of ad rank on the performance of sponsored search advertising campaigns. In this study, we analyzed a large log file comprised of almost 7,000,000 records spanning 33 consecutive months of a search engine marketing campaign of a major US retailer. The theoretical foundation of this research is serial position effect, including both primacy and recency effects. One way ANOVA and Tamhane's T2 tests are used in this study as our analytical methods. We examined the effect of ad rank on the critical keyword advertising metrics of clicks and conversions, which translate well to the aspect of relevance in information processing theory. Findings from our research indicate that ad rank does have significant effect on both of these online advertising metrics, although it has less direct effect on conversion rates. Primacy effect was found on clicks, indicating a general compelling performance of ads listed on top positions of the first search engine results page. Meanwhile, conversion rates across all sixteen ad positions we investigated follow a relatively stable distribution, with the exception of the first two ads. Ads in these two positions generated extremely high conversion values. However, examining both clicks and conversion rates combined into a single metric of conversion potential, it is apparent that ad rank has a significant effect on the performance of keyword advertising campaigns. Ad appears at the top of the results listing have a much greater conversion potential. The research results reported in this paper are beneficial to companies using search engine marketing as they strive to design more effective advertising campaigns. Implications from this study could lead to more targeted bidding strategies and thus reduce ineffective bidding in keyword auctions.

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Keywords

Keyword advertising, pay-per-click, PPC, paid search advertising, search engine marketing.

INTRODUCTION

Search engine marketing (a.k.a., sponsored search, keyword advertising, pay-per-click, and search engine advertising.) is a form of online advertising, which allows companies to promote their products and services on the search engine results page (SERP). Since its inception in 1998 (Fain & Pedersen, 2006), search engine marketing (SEM) rapidly 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) and generates billions of dollars for the major search engines (c.f., Google, 2011). As such, sponsored search has helped shaped the nature of the Web today (Jansen, 2011) and is, therefore, an area of critical research importance to online commerce on the web (Weis, 2010). It also represents a unique form of online searching.

By selling advertising keywords to merchants, SEM requires advertisers to bid directly on potential search terms in order to have their ads served on the SERP. Affected by SEM's unique auction mechanism, advertisers generally believe that higher bids could win them better ad positions, and consequently generate more traffic, sales-leads, and revenue for their business. Given the dynamic nature of the keyword advertising auctions and lack of control for determining the optimal ad positions, it can be difficult for advertisers to select their best ad placements and adjust their bids accordingly on targeted specific user groups (Kathuria, Jansen, Hafernik, & Spink, 2010). Due to this uncertainty, advertisers can spend enormous amount of money competing for higher ad placements. Unfortunately there has been limited published research concerning the effect of ad position on keyword advertising performance. Consequently, there is currently limited insight into how users interact with sponsored results in these situations or how profitable the various ad positions might be, other than anecdotal evidence.

In this research, we use a large scale data set of a major retailer to examine the differences in online user behavior and advertiser achievement among varied ad placements. We believe that with the results of our study, advertisers can assess the worthiness of the top-ranked positions before creating their sponsored search advertising strategies. The ultimate goal of this research is to indicate the role ad rank plays in the online advertising market and assist advertisers to avoid intensive bidding wars for top positions while ignoring 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 with justifications, followed by a description of our data and methods utilized to analyze the ad rank effect. 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 adapted as the theoretical foundation of this study to interpret the impact of ad rank on consumer behaviors. Proposed by Ebbinghaus (1885), serial position effect refers to the human propensity of making a recall given the distinct placement of items. There are two sub-types of serial position effects as presented in Ebbinghaus's findings, specifically the primacy effect and the recency effect. The primacy effect happens as the first few items are more likely to be transferred into long-term memory (Waugh & Norman, 1965). Waugh and Norman (1965) stated that the initial items in a list tend to attract human attention more easily than items positioned at the end, since at the beginning there is far less competitions for the limited memory capacity relative to the later stages.

The recency effect happens due to the limited capacity of human's short-term memory. Capitani, Della Sala, Logie, and Spinner (1992) referred to the recency effect in their work as human's recall of items at the bottom of a list given their freshest memory of the most recently acquired information. With recency effect, humans tend to remember the last few items as compared to those intermediate ranked items. Recency effect helps explain the U-shaped serial position curve proposed in Ebbinghaus's (1885) study. No matter primacy effect or recency effects, information presented at the two ends of list demonstrated obvious higher recalls than the ones presented in the middle.

Since its introduction, the theory of serial position effect has been applied in various research fields. Previous studies in the marketing field have also provided evidence for serial position effect on user's purchasing behaviors. Researches on the traditional advertising mediums suggested that on a long time scale, ad rank's primacy effect generated much greater impact upon brand advertising campaigns as compared to the recency effect, since the latter can be more easily masked by time (Newell & Wu, 2003; Pieters & Bijmolt, 1997; Terry, 2005). For example, studies found that ads placed in an earlier position of a television show were easier to be remembered by viewers than those ads showed in the middle or at the end (Newell & Wu, 2003).

Although serial position effect in web search has recently received some research attention, its implication is still limited. Teevan (2008) detected the presence of the primacy effect on user's recall of the search engine returned results in her study in an online environment.. The probability of both user's recalls and clicks decayed with rank. Noticing such rank bias, researchers proposed several models aiming to better explain and eliminate such serial position effect (Chapelle & Zhang, 2009; Craswell, Zoeter, Taylor, & Ramsey, 2008). However, these studies primarily focused on the organic results, not the paid results of sponsored search.

On the basis of the review of literature, we find that SEM, as a newly emerged form of internet marketing, has attracted limited research focusing on the serial position effect within the sponsored search environment. Among the existing studies investigating the effect of ad rank in the online advertising environment of the SERP, most of these studies were conducted under laboratory environments, with the work of Brooks (2004a; 2004b) and Ghose and Yang (2009) noticeable exceptions. So, it is difficult to apply findings from these previous experimental studies to real world situations. Additionally, even within the small number of studies that have assessed the effect of ad position, very few of them covered all the performance matrices of online ad campaigns, including clicks, sales, conversion, and profits. Most of the those studies examined the serial position effect with their focus on the user's eye movements or clicking behavior, which only tells partial story of a keyword advertising campaign's success. Considering all the above limitations, the research reported in this paper examines the effect of an ad's rank using a wide range of keyword advertising metrics.

RESEARCH QUESTIONS

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

As an analogy in the field of real estate, "location, location, and location" are known as the three most important factors when purchasing a piece of property. We can apply a similar axiom to the online business world. Like the physical locations in reality, ad's rank on SERP is also treated as a significant element regarding the overall campaign performance. Location on the SERP can help companies attract potential customers to their site and to patronize their online stores. In order to obtain better sales revenues, a great many businesses have engaged in the competition for the top most positions. Every year, a lot of money is poured into these intensive bidding wars (SEMPO, 2009). However, few studies have tested the actual effect of ad rank on the performance of keyword advertising campaigns. Given that such unexamined rationale is constantly used in nowadays online advertising practices, we find it necessary to first study whether a premium position is worth biding for before delve into the further modeling process. With a better understanding of ad's position effect on consumer's behavior, such as clicks and conversions, we believe our study could provide a theoretical foundation for future ranking-based research in the SEM field. Also, the results could potentially benefit those real world businesses to predict the efficacy of their ranking strategies and to optimize their budget expenditure on most effective ad positions. Based on this research question and rational, our hypotheses are:

Hypothesis 01: *There will be a significant difference in the average number of clicks based on ad ranks.*

Sponsored search marketing campaigns usually have their intention to first guarantee relatively high click volumes. With a higher number of clicks, an ad can bring more traffic to company's web sites for either potential profit generation (or other conversions) or brand awareness building. So, 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, it does provide advertisers a sense of the amount of viewers who actually click on their ad. As such, the varied traffic volumes would explain consumer's instantaneous reaction distinctions while being exposed to ads listed on different positions and provide an indication of potential consumer interest.

Hypothesis 02: *There will be a significant difference in the average conversion rate based on ad ranks.*

The number of clicks can be adopted as a simple measurement of the ad performance. However, it alone can not guarantee the post-click through performance. In other words, click volumes can not 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 analyzing the final purchasing behaviors, the conversion rate (i.e., number of orders divided by the number of click) provides advertisers a more accurate measurement of the effectiveness of the ad campaigns. As such, higher conversion rate for ads with certain ranks would indicate the ad position's impact.

METHODS

Data

The data for our research is daily information on keyword advertising campaigns from a large nationwide retail chain, with both brick and mortar and online sales presence. The data is of keyword advertisements by the company during a 33-month period, spanning 4 calendar years, from 30 September 2005 to 09 June 2008. The dataset is quite rich in that we have the key phrase that trigger the ad, the ad position, and consumer responses and sales information for each of those keywords.

The data log contains just fewer than 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 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, the position of 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.

The applicable fields used for the research reported here are shown in Table 1.

Field	Description
Ad Number	Unique identifier for the advertisement
Key Phrase	The key phrase that triggered the advertisement
Day	Date of data collection
Position	the positions of the advertisement on that search engine for the day for a given key phrase
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.

Table 1. Fields and Descriptors from Sponsored Search Log Used To Investigate the Research Hypotheses

Given the size and the range of fields, we believe our dataset to be a rich source in which to investigate our research question and hypotheses. Moreover, there have been limited empirical studies of SEM campaigns, and there are no studies from a dataset this large, that covers such an extension temporal span, or that contains such rich range of keyword attributes.

Ad Rank Analysis

Similar to traditional advertising methods, sponsored search can be all about location, with the most desirable positions usually considered to be at the top of the result pages. Affected by such expectations, advertisers have been strived to obtain a good position on the SERP for their ad in order to attract the eyeballs of the online searchers. However, as illustrated in Figure 1, due to the inadequate space of SERP and searcher's resistance against sponsored results (Jansen & Resnick, 2006), search engine companies usually limit the number of paid advertising placement on their returned pages, generally around eight or so ads per SERP.

Figure 1. Sample Search Engine Return Page with Result Sections Highlights

Usually, sponsored ads placed on the first SERP are 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 SERPs are completely worthless. Having ads placed on the following pages are much less expensive than putting them on the first SERP. Since there are still about 25% of the consumer traffic who would visit the second or later SERPs (Jansen, Spink, Bateman, & Saracevic, 1998), those lower-ranked ads also have the ability to generate sales offers to the advertisers. However, it is noticeable that traffic drops off severely further into the SERP listings as there are extremely fewer visits beyond the second result page. 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 the top sixteen ad positions listed on the first two SERPs. 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, which we discuss later. In addition, to better control the confounded effect of different sponsored search providers, for our data analysis, we only selected campaign records obtained through one major search engine. In that way, the impact of different search engine brands and result page layouts can be eliminated from our analysis results. Before evaluating our hypotheses, we used a log transformation to improve the normality for all of the variables. Our data is not multivariate normal; instead, it has a power law distribution. We transformed the data via the Box-Cox power transformation (Box & Cox, 1964) using lg(variable+1). After employing the Box-Cox power transformation, we plotted our data to check for normalize. 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 (c.f., Box & Anderson, 1955; Hull, 1993; Lindman, 1974). The use of the power transformation ensured our statistical approach was valid. In addition, day-of-the-week adjustments were also conducted to standardize the temporal effect on ad performance considering the establishment of the seasonality existence in our dataset. The day-of-week adjusted metrics enabled us to better analyze the non-seasonal trend of ad rank effect on online advertising campaigns. 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 of 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

First, we present overall statistics for the data set of 6,871,461 records from the time span of 30 September 2005 through 09 June 2008.As shown in Table 2, all the descriptive statistics are presented in their natural form, without the Box-Cox power transformation.

	Total	Average (by day)	St Dev
Impressions	268,324,418	76.21	650.98
Clicks	10,270,340	2.92	58.04
Advertising Cost	$6,339,019	$1.80	$22.92
Sales	$40,890,733	$11.61	$487.78
Orders	276,332	0.08	3.43
Items	506,700	0.14	6.75

Table 2. Aggregate Statistics from the Sponsored Search

In Table 2, we see that this was a substantial marketing effort generating more than $40 million in sales and moving five hundred thousand items. Table 2 also presents the average figure per day and the standard deviations. The standard deviations are high due to the nature of retailing, when there are substantial sales during the holiday buying season, typically October through early January.

Also, we display (Table 3) an aggregate statistics for the top sixteen ads ranks listed on the first two SERPs.

	Total	Percentage of Total Dataset	Average (by day)	St Dev
Impressions	255,104,761	95.07%	99.84	762.31
Clicks	10,224,411	99.55%	4.00	68.10
Advertising Cost	$6,330,982	99.87%	$2.48	$26.87
Sales	$39,621,138	96.90%	$15.51	$572,08
Orders	268,308	97.10%	0.11	4.02
Items	491,080	96.92%	0.19	7.92

Table 3. Aggregate Statistics from the Top Sixteen Ads Positions

In Table 3, we can see without day-of-the-week adjustment, ads on the first two SERPs lead to about 97% of the total sales as shown in Table 2. Consistent with the prior studies of user's click behaviors while interact with search engines, our study also demonstrated that the top sixteen 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

Given each of our sixteen ad position groups, descriptive statistics as shown in Table 4 and Table 5 were also presented in their natural form, although both hypotheses testing were carried out using one way ANOVA and post hoc Tamhane's T2 tests on the log transformation data.

Hypothesis 01: There will be a significant difference in average number of clicks based on ad ranks.

The one way ANOVA test results on the adjusted click volumes indicated significant differences across ad ranks ($F(15) = 635.12$, $p < 0.01$). Also, as indicated by the Tamhane's T2 test, click volume differs significantly among all the sixteen ad positions. Therefore, hypothesis 01 is fully supported. Ad rank directly affects the volume of clicks that an ad receives.

Rank Classification	Mean	St Dev	Change in Mean Click From the 1st Ad Position
1a	6.94	75.65	—
2b	4.56	28.50	-34.28%
3c	5.41	35.70	-22.12%
4d	3.99	21.02	-42.48%
5e	2.86	15.06	-58.80%
6f	2.16	10.33	-68.96%
7g	1.48	7.35	-78.68%
8h	1.00	4.70	-85.56%
9i	0.77	3.22	-88.93%
10j	0.59	2.32	-91.46%
11k	0.54	1.83	-92.21%
12l	0.47	1.62	-93.20%
13m	0.39	1.42	-94.35%
14n	0.31	1.13	-95.54%
15o	0.27	0.94	-96.11%
16p	0.23	0.82	-96.70%
All Categories	3.55	38.28	—

Note: Ad positions containing similar letters are of no significant difference in average click numbers by Tamhane's T2 post hoc test results at $p < 0.01$. In this case, all ad positions were statistically difference.

Table 4. Mean Click Per Day by Ad Rank with Change in Clicks by Ad Position

In Table 4, we can see that the average day-of-the-week adjusted clicks of all sixteen ad categories is 3.55 per day, which is highly affected by the top four ad placement. All pairwise comparisons are significantly different from each other ($p < 0.01$ for each pairwise comparison), generally with the higher ranked ad positions generates more clicks than the lower ranked ones. However, to our surprise, we also found that the ad ranked in position number three attracts relatively more traffic than the ad in position two.

Along with the generally decreased click volumes, the standard deviation of ads among different rank categories also offers advertisers valuable insights. 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.

Hypothesis 02: There will be a significant difference in the average conversion rate based on ad ranks.

The one way ANOVA test on average conversion rates shows significant differences among ad in each position ($F(15) = 485.173$, $p < 0.01$). However, perhaps surprisingly, the follow-up pairwise comparisons of conversion rates among all sixteen ad ranks indicated that only the topmost ad position gained significantly higher conversion rates than all the other fifteen ad ranks. The second and third ad positions only showed significant differences as compared to the top fifteen and top eight ad positions respectively. There were no such significant differences among all the other ad ranks ($p > 0.01$, for each pairwise comparison). Therefore, hypothesis 02 is partially supported. So, generally, we can say that the top three ad positions have statistically significant higher conversion rates, while there are no such differences in conversion rates for ad positions four through sixteen.

Rank Classification	Mean	St Dev	Change in Mean Conversion Rate From the 1st Ad Position
1a	0.03	0.13	—
2b	0.01	0.09	-50.75%
3c	0.01	0.08	-63.91%
4d	0.01	0.07	-69.55%
5d	0.01	0.07	-69.17%
6d	0.01	0.07	-71.80%
7d	0.01	0.07	-72.93%
8d	0.01	0.07	-71.05%
9cd	0.01	0.08	-70.68%
10cd	0.01	0.08	-69.55%
11cd	0.01	0.08	-71.80%
12cd	0.01	0.08	-71.05%
13cd	0.01	0.09	-67.67%
14cd	0.01	0.07	-75.19%
15cd	0.01	0.09	-69.17%
16bcd	0.01	0.09	-50.75%
All Categories	0.01	0.09	—

Note: Ad positions containing similar letters are of no significant difference in average conversion rate by Tamhane's T2 post hoc test results at $p < 0.01$.

Table 5. Mean Conversion Rate by Ad Rank with Changes in Conversion Rate by Ad Position

In Table 5, we can see that the average conversion rate for the top sixteen ads listed on the first two result pages is 0.01 per day, which is strongly skewed by the topmost ad position. Different from what we have observed in the previous analysis of average click numbers, this time the results of the Tamhane' T2 test demonstrated that conversion rates remained relatively stable among ad positions, with only the topmost ad position showed statistically significant differences between all pairwise comparisons. Although very like the first ad slot, which leads to relatively higher conversions, the second and third ad positions show non-significant 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 rates of the second ranked ads and the sixteenth ranked ones. There was also no such significant difference between the third ad slot and all eight ad placements on the second SERP. Starting from ad position number four, all following thirteen ad positions reveal non-significant between-pair differences for conversion rate measurements. Generally, from Table5, one can say that, other than position one, there is little different in conversion rates among ad positions.

DISCUSSION AND IMPLICATIONS

Given the special bidding mechanism of the 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, our research investigated the value of those top ranked ads regarding their impact on the average number of clicks, and conversion rates. The results of our research indicated a reliable 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 4 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 returned page, as shown in Figure 2.

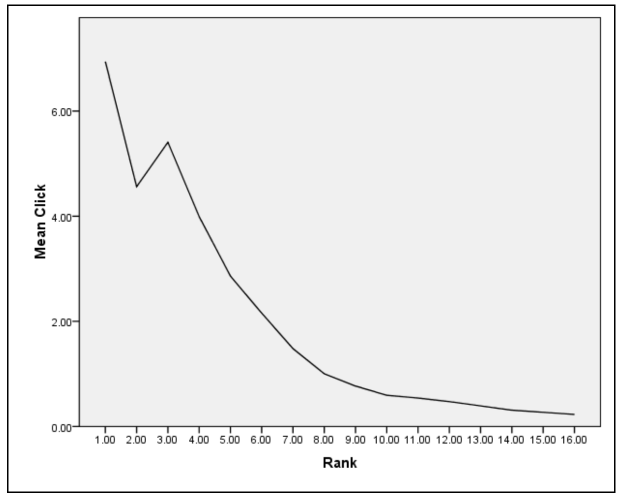

Figure 2. Mean Clicks Numbers per Day by Ad Position

An interesting finding, as shown in Figure 2, is that there is a dramatic rise in click volumes between ad position number two and three, which is against the overall decreasing pattern as indicated by the other positions. One possible interpretation for this sudden rise is related to the unique design of the search results user interface as shown in Figure 1. 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 maximum 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 their strong preferences for non-sponsored links with 82% of the time viewing those free organic results first. According to Fitts' Law (1954), 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 notice that ad position number three is often a high performer. Fitt's Law may be the theoretical underpinning for this observed behavior.

However, unlike the above test results on the average click volumes, our finding regarding the ranking effect on conversion rate surprisingly contradict the widely held beliefs. We find that among all sixteen ads tested spanning the first two SERPs, only the topmost ad exhibits profound differences among its pairwise comparisons on conversion rates. More interestingly, our observations further indicate that unlike the monotonic decreasing clicks and CPC distributions, the conversion rates for ads placed after the second slot remained relatively stable, with all fourteen positions sharing about the same average conversion ratios. So, inspired by those findings, we conclude that ad rank has only limited effect on consumer's conversion actions, given the actual conversion rates varied non-significantly across all ad positions ranging from four to sixteen, as shown in Figure 3, although, there appears to be some conversion benefit of being in the top three ad positions.

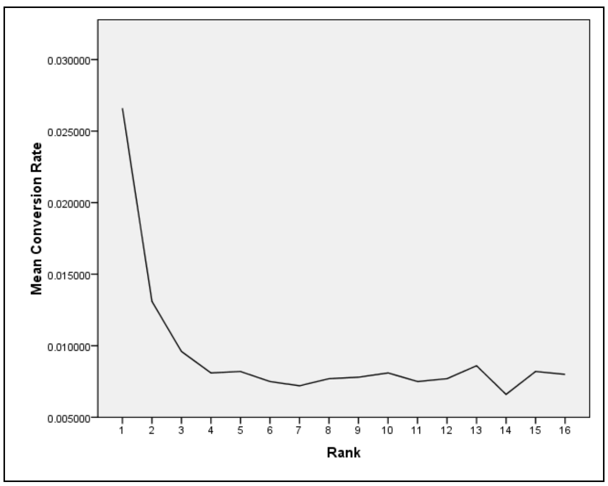

Figure 3. Conversion Rate by Ad Position

Earlier, we defined conversion rate as the percentage of users who convert their click-through into final purchases. Given the distinct distributions of average click volumes and conversion rates of all sixteen ad groups, in order to quantify the ad rank effect on the average conversions, we have adopted the conversion potential measurement as defined by Brooks (2004b). 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 the topmost position, whereas the conversion potential is the product of the click potential and the conversion potential. Table 6 displays all the click potentials, conversion rate potentials, and conversion potentials across all sixteen ad groups. As can be seem from this table, even though conversion rates decrease about only 6% from ad position three to sixteen, the conversion potentials dropped about 27%, due to the drastic reduction in ad position's click potential. Therefore, conversion rate alone can not be used as a measurement of the successfulness of online advertising campaigns.

Rank	Click Potential	Conversion Rate Potential	Conversion Potential	Change in Conversion Potential
1	100.00%	100.00%	100.00%	—
2	65.72%	49.25%	32.36%	-67.64%
3	77.88%	36.09%	28.11%	-71.89%
4	57.52%	30.45%	17.52%	-82.48%
5	41.20%	30.83%	12.70%	-87.30%
6	31.04%	28.20%	8.75%	-91.25%
7	21.32%	27.07%	5.77%	-94.23%
8	14.44%	28.95%	4.18%	-95.82%
9	11.07%	29.32%	3.25%	-96.75%
10	8.54%	30.45%	2.60%	-97.40%
11	7.79%	28.20%	2.20%	-97.80%
12	6.80%	28.95%	1.97%	-98.03%
13	5.65%	32.33%	1.83%	-98.17%
14	4.46%	24.81%	1.11%	-98.89%
15	3.89%	30.83%	1.20%	-98.80%
16	3.30%	30.08%	0.99%	-99.01%

Table 6. Conversion Potential by Ad Rank

Given that our results seem to be compelling on a statistical perspective, one might still suspect its practical implications versus its experimental and theoretical indications. So, here we carry out practical implications of our findings to help provide some guidance on advertiser's biding strategies on ad placement. Based on the findings from our research results, the ad rank does have a full primacy effect on consumer's clicking behavior. The average click numbers of an ad increases monotonously with its placement goes up on the SERP, and these results in the monotonously increasing CPC due to the PPC pricing model of sponsored search. In that sense, 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 those brand building advertisers, since those four positions could bring them about 80% of the total potential customers.

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 6, although conversion rates don't change much across different ad positions, considering the large click volume and the drastic decreases in click potential, 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 significant less benefit than those higher ranked ads despite discussions of similar conversion rates among ad positions (Friedman, 2009; Michie, 2010).

CONCLUSION

Result of this research concludes that serial positional effect does exist in the sponsored search area, with higher ranked ads generate better overall performance than the others. Our study shows the position effect of ad rank on user clicking behaviors while they interact with the SERP. However, different from its monotonic influence on click volumes, the primacy impact is only effective on the first ads on their performance of sales and revenue generation. No such primacy effect was found on the performance of conversion rates across both two SERP except the topmost slots. Based on our findings, generally it is beneficial for advertisers to bid for higher positions, especially the top 4 positions, as their brand building strategies, even if they are now on listed on poorly ranked positions. We believe that our study offers advertisers valuable insights into their 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 us to better position bidding strategies in online advertising environment. Besides, we are also interested in investigating other factors besides ad rank that could also affect online advertising campaigns, such as user intent of web queries (Kathuria, Jansen, Hafernik, & Spink, 2010) and user trust in online shopping (Lee, Park, & Han, 2011). Also, as noticed in our study, experiments on user’s clicking behavior while they interact with different designs of the SERP would further benefit us with user’s clicking patterns and thus lead to better advertising creations.

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