The Power of Search Engine Ranking for Tourist Destinations

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August, 2014

Acknowledgements: The School of Business in the College of Charleston, USA financially supported this research with a summer grant. Part of this research was completed at the School of Hotel and Tourism Management at Hong Kong Polytechnic University while the author spent his sabbatical. Sincerely thanks go to Kathleen Janech and Melinda Patience in the College of Charleston for thorough copyediting.

Preprint, to Cite:
Abstract

Most online travelers in the United States use search engines to seek out travel information. Thus, Destination Marketing Organizations (DMOs) need to attract clicks through returned results on search engines. We model clickthrough rates (CTRs) of several published search engine reports and investigate the CTRs of a Destination Marketing Organization's webpage on different ranks of different properties of a search engine (web, image, and mobile searches). The results validate the power-law distribution of CTRs on different ranks on web search: the top results attract high CTRs but the rates decrease precipitously when the ranks go down. However, top ranks are a necessary condition but not a sufficient one: many top ranked results have low CTRs. Image search and mobile search have different CTR curves based on ranks, providing different opportunities for tourism destinations and businesses.
Introduction

In recent years, around 86% of Americans have used search engines for travel planning purposes (Fesenmaier, Xiang, Pan, & Law, 2011). As a result, search engines have become one of the most important ways that travelers search for and filter information, as well as a vital channel through which hospitality and tourism businesses can reach their potential guests (Xiang, Wöber, and Fesenmaier 2008). Marketing on search engines has become an emerging industry in the developed world (Pan, Xiang, Law, & Fesenmaier, 2011), and was estimated to reach $23 billion in North America in 2012 (SEMPO, 2012).

Although there is no official report on destinations’ spending on Search Engine Marketing (SEM), informal communications in 2008 showed that at least 10-20% of marketing budgets were spent on SEM through some states’ Destination Marketing Organizations (DMOs) in the United States (U.S.) (State Provincial Research Network LISTSERV, 2008). A similar communication in 2014 resulted in an estimate of 10-25% just for paid search advertising for one state’s DMO (State Provincial Research Network LISTSERV, 2014). In 2013, a commercial report on 200,000 websites reported that more than 40% of online traffic came from organic searches. However, the percentage had dropped slightly from December, 2012 (Wong, 2013). Nonetheless, this data shows the importance of SEM to the traffics and revenue of DMOs and websites in general.

However, increasing pressure on accountability for marketing campaigns requires marketers to justify their spending on SEM by the calculation of Return-on-Investment (ROI). For example, how much should one spend on SEM for the destination website? If a $10,000 USD
investment on Search Engine Optimization (SEO) can help one DMO website increase its rank on Google from number five to number two for the destination name as the query, is it worthwhile?

SEM can be roughly categorized into two parts: SEO, which improves a website’s ranking in the organic results section on a Search Engine Result Page (SERP), and paid search, which involves bidding on certain queries in the advertisement section of a SERP. The ROI for the latter is much easier to measure since most of the time an advertiser only pays when web visitors click on their advertisement. Marketers can also track visitors’ follow-up behavior on the websites through web log tools such as Google Analytics. Thus, it is possible to calculate the conversion rates from searches and further the ROI of those paid clicks. For SEO, making the connection is much more complicated, since marketers need to directly connect their SEO spending with increased web traffic and converted visitors which may result from increased ranking on search engines. Previous studies have validated that users will pay more attention to the top results on search engines, and recent studies validated this through experiments (Pan, Hembrooke, Joachims, Lorigo, Gay and Granka, 2007), but a remaining question that we have tried to address is, by what degree does one website’s ranking influence its web traffic and future revenue? In addition, today’s fast developing technology has created widespread information overloading problems (Simon, 1996). A ranking system, as an implicit filtering and recommender mechanism, has become increasingly prevalent everywhere, from general searches, most eCommerce websites, to Online Travel Agencies (OTAs) (Resnick and Varian, 1997). Thus, an understanding of how different ranks perform will be beneficial in understanding the power of ranking in general in the online marketplace.
In this research, we investigated different CTRs on different search engine ranks based on web log data. CTRs are defined as the percentage of search engine users who clicked on a specific result on a SERP, among all the users who searched that query and were possibly exposed to the result. For a business or DMO, this is the first step in converting information searchers to website visitors, and ultimately to their paying customers. The CTRs for different ranks could provide important information and help businesses to calculate the ROI of their SEO effort. In addition, every search engine provides results in different formats through different platforms, such as web (in the format of text), image, and mobile searches. This has given us another question on which to focus our research, namely, are they all following the same type of clickthrough rate distributions, or are they fundamentally different from each other? A meta-analysis on published log reports, as well as a case study on three websites of a DMO, were used to explore the conversion rates from different ranks and different properties of search engine results. The findings provide an understanding of the conversion rates and distributions of search engine rankings on different properties of search engines. The results offer a starting point for measuring ROI for SEM efforts.

**Literature Review**

Researchers in various fields have studied search engines and search engine marketing through many approaches, from design, evaluation, user behavior, marketing, to their social and political implications. This section reviews relevant studies on search engine ranking and reveals the gap in our understanding of this dynamic field.

The studies within the area of computer science focus specifically on the algorithms for ranking returned web documents when users type in a query. The quality of the ranking algorithm
is always the most important criteria in judging the quality of search engines. The underlying assumption is that users will most likely view and click on the results at the top of the SERP. Thus, providing most relevant results at the top helps search engine users saves cognitive effort, provides a smoother search experience, and increases search engine brand loyalty. The ranking algorithm relies on keyword density and frequency, hyperlink structure, and clickthrough rate data as implicit feedback for better ranking algorithms (Brin & Page, 1998; Gandal, 2001; Joachims, 2002). Recently, search engines have started to incorporate social media content into search engine ranking and returned results (Ghose, Ipeirotis, & Li, 2012). Search engines have also continuously updated their ranking algorithms based on current research results in order to wrestle with rogue websites which try to take over the top positions with illegitimate strategies (McCullagh, 2011).

In general, computer scientists focus on tweaking the ranking algorithms and improving system performance in order to provide better results. The maximum match between the most relevant results and users' information needs is the goal for designing better search engine systems.

On the other hand, information scientists focus mostly on user behavior with search engines and, as a result, hopefully understand user intentions and increase the quality of ranking algorithms. This includes studies on user intent and user behavior through web log analysis, users' decisions on clicks, and comparison of search engine use behavior (Jansen, 2007; Jansen & Pooch, 2001; Jansen & Spink, 2009; Jansen, Booth, & Spink, 2008; Jansen, Brown, & Resnick, 2007; Jansen & Spink, 2005 and 2006). These studies highlight the differences and changes in user behavior due to culture, demographics, and the sophistication of users. The dependant variables include search query types, query length, lengths of search time, depth and breadth of searches, the use of Boolean operators, etc. Specifically, researchers studied the characteristics of search
engine queries and information needs (Jansen & Spink, 2009). The ranking effect, e.g. how users view and click on the results in different ranks, was seldom investigated, but its importance was stated in that search engine users only view and click the first one or two search engine result pages and are more likely to click the top ranked results.

In the field of marketing and management information systems (MIS), a few researchers have investigated sponsored search results and related users' click and conversions, and the best ways to achieve maximum revenue for search engines (Agarwal, Hosanagar, & Smith, 2008; Feng, Bhargava, & Pennock, 2007; Ghose, Ipeirotis, & Li, 2014). Feng, Bhargava, and Pennock (2007) tested different mechanisms for ranking sponsored results and their impact on search engine revenue. They found that rank-revision strategy, which gives more weight to clicks on lower ranked advertisements, resulted in better performance for search engine revenues. Agarwal, Hosanagar, and Smith (2011) used hierarchical Bayesian modelling to test the effect of sponsored ad ranks on the clickthrough and conversion rates for an online retailer. Their results showed that the top positions usually had higher clickthrough rates, but not necessarily higher conversion rates. Ghose, Ipeirotis and Li (2014) studied the interaction effect between search engine ranking and product ratings for hotels. Their results demonstrated that hotel rankings based on users' personal characteristics, when compared to non-personalized rankings, were not beneficial to the hotel businesses since fewer tourists made a purchase. Specifically, they found that the top ranked hotels attracted more clicks than the lower ranked ones.

In the tourism and hospitality field, several researchers have investigated search engine use from a variety of perspectives, mainly from search engine query analysis and SERP analysis (Pan, Litvin, & Goldman, 2006). Accommodation searches are always the first ones in the users' search
sequence when planning a trip. Search queries are always associated with cities, and secondly attractions, transportation options, etc. (Pan, Litvin, & O’Donnell, 2007). Researchers have also studied the content and categories of search queries and the tourists' information needs as reflected from those queries (Pan et al., 2006). In addition, social media content is always embedded in search engine results (Xiang & Gretzel, 2010). Studies in this area have not focused on the ranking effect of search results.

Researchers have also studied the changing nature of search engine marketing and the changing behavior of travellers when searching information online. Search engine marketing is a dynamically evolving field. The dynamic relationships exist between search engines, users, and business websites. The three parties always have different goals and objectives, and they are in a continuous gaming process (Pan et al., 2011). Businesses and search engines try to second-guess each other in order to gain an advantage, and as a result, search engines have to continuously revamp their interfaces and algorithms. For example, one of the major players, Google, has tweaked the ranking algorithms to battle against rogue websites which try to take advantage of the ranking system. In February, 2011, Google significantly updated its ranking algorithm with Google Panda (McCullagh, 2011). The change significantly decreased some over-optimized websites with low-quality content and has affected 12% of all search queries. Google further released another major update in April, 2012 termed Google Penguin (Fillmore, 2012). This update penalizes those websites which violated Google Webmaster guidelines, especially on link spamming. Starting on August 30, 2013, Google Hummingbird was released, which was another major overhaul of the ranking system, and this algorithm processes the queries more like questions and answers in order to provide a better user experience (Sullivan, 2013). All these changes affected the rankings of
numerous websites, and they highlight the dynamic nature of the relationship. This shows the tremendous power and influence search engines have as the connection channels between tourists and the destinations and businesses they are trying to research. Thus, search engine ranking is of utmost importance in generating business revenues and the rankings on SERPs have become a battleground for destinations and competitive tourism and hospitality businesses.

A few researchers have investigated the ranking effect - users' decreased attention paid to search engine results close to the bottom of the page (Bae & Ahn, 2013; Pan et al., 2007). Pan and his colleagues (2007) used an eye-tracking experiment to measure the amount of attention and clicks on search engine results when undergraduate students conducted searches for popular topics. They found that users paid most of their attention to results on the first page, especially to the top two or three results. The amount of trust placed in the top results even exceeded users' judgement on the relevancy of the returned results based on the text snippets. Similarly, Bae and Ahn’s (2013) eye-tracking experiment revealed that users only go through a few options when given a large amount of choices to choose from. They term this as “attention decay” - when users' attention drops rapidly on one page - and “attention renewal” - when their attention picks up at the top of the next page. The cause of this phenomenon is the poverty of attention (Simon, 1996), a phenomenon which happens when the amount of information surrounding human beings vastly exceeds their information processing ability. Other researchers have studied the exponential relationship between ranks and clickthroughs with simulations on paid/sponsored results (Agarwal et al., 2008; Ghose et al., 2014). However, these studies did not specifically test the exponential relationships; they mainly focused on paid advertising rather than organic results with empirical data (Agarwal et al., 2008; Ghose et al., 2014).
In conclusion, past academic studies have investigated the design, user behavior, and the dynamic nature of search engines and search engine users. However, one key question still needs an answer: how will the ranks on search engines influence business websites’ performance? Studies in diverse areas have documented the dramatic decrease of clicks as the search engine ranks go down. Some studies investigated the users' attention for search engine results; others have focused on sponsored results on search engines. However, the importance of ranking is taken for granted, and the CTR distributions were never explicitly modelled or statistically tested. In addition, no study has been conducted on different search properties, such as web (text), image, and mobile searches. This study analyzed five industrial reports and conducted a case study on several websites of a DMO. The goal is to answer these questions: How do different rankings in search engines influence CTRs? How do different properties on search engines influence their CTRs?

**Methodology**

Two types of methods were used to investigate the relationships between search engine ranking and CTRs: a meta-analysis and a case study.

In the meta-analysis, five different models of CTR distributions were constructed from five publicly available industrial reports produced by four consulting companies (Hearne, 2006; Optify, 2011; Chitika, 2010; SlingshotSEO, 2012). The five reports were based on the search engines AOL, Google, and Bing; the dates ranged from 2006 to 2011. The sizes of the sample span from 10 thousand to 36 million. They were based on generally available published search engine log data (Hearne, 2006), or proprietary data from their own clients (Optify, 2011; Chitika, 2010;
SlingshotSEO, 2012). The data contained the top 10, 20 or 41 positions for the clickthrough rates of query searches (Table 1). We plotted the CTR curves based on the five reports. CTR curves were the plots of search engine ranks and CTRs on a graph for a web search based on thousands and millions of search queries (text search).

Table 1. Log Linear Regression of Power Law of Five Published Ranking Models

<table>
<thead>
<tr>
<th>Model</th>
<th>Search Engine</th>
<th>Year</th>
<th>User Domain</th>
<th>Sample Size</th>
<th>Number of Positions</th>
<th>Source</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>AOL</td>
<td>2006</td>
<td>Worldwide</td>
<td>36 million searches</td>
<td>41</td>
<td>Hearne, 2006</td>
</tr>
<tr>
<td>2</td>
<td>Google</td>
<td>2010</td>
<td>Unknown</td>
<td>10 million impressions</td>
<td>20</td>
<td>Optify, 2010</td>
</tr>
<tr>
<td>3</td>
<td>Google</td>
<td>2010</td>
<td>U.S. users</td>
<td>10K keywords</td>
<td>20</td>
<td>Chitika, 2010</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td></td>
<td>10K non-branded</td>
<td></td>
<td></td>
</tr>
<tr>
<td>5</td>
<td>Bing</td>
<td>2011</td>
<td>Worldwide</td>
<td>keywords</td>
<td>10</td>
<td>SlingshotSEO, 2012</td>
</tr>
</tbody>
</table>

In the case study, web site traffic data from three different websites from an anonymous Convention and Visitors Bureau (CVB) in the U.S. were analyzed and modelled to determine the relationships between CTRs and search engine ranking. One website was the main CVB site (Site A); the other two were special-themed promotions: one focused on the wedding market (Site B) and the other focused on family-oriented activities (Site C). The data were reported through Google Analytics, a free tool provided by Google Inc. (Plaza, 2011). The tool reports a web visitors’ location, time of access, length of visit, and the referral sites and search engine queries a user typed in to reach the site. If the websites had installed Google’s Webmaster tool, it could also report the ranking of those websites on those queries (Google, 2012). Thus, one could view the corresponding clickthrough rates with the website's rank on that specific query (Table 2 shows some sample data). In addition, Google Analytics reports four different CTRs on different Google properties: web search (text search), image search, mobile search, and video search. Since video search is based
on searches on Google Video, which has a very limited volume, we focused our analysis on web, image, and mobile searches.

<table>
<thead>
<tr>
<th>Query</th>
<th>Impressions</th>
<th>Clicks</th>
<th>CTR</th>
<th>Average Position</th>
</tr>
</thead>
<tbody>
<tr>
<td>atlanta, ga</td>
<td>300,000</td>
<td>22,000</td>
<td>7.33%</td>
<td>3.0</td>
</tr>
<tr>
<td>atlanta</td>
<td>110,000</td>
<td>2,500</td>
<td>2.27%</td>
<td>2.9</td>
</tr>
<tr>
<td>Coca cola center</td>
<td>110,000</td>
<td>400</td>
<td>0.36%</td>
<td>2.8</td>
</tr>
<tr>
<td>atlanta hotels</td>
<td>40,000</td>
<td>1,600</td>
<td>4.00%</td>
<td>1.5</td>
</tr>
<tr>
<td>hotels in atlanta</td>
<td>40,000</td>
<td>1,000</td>
<td>2.50%</td>
<td>2.0</td>
</tr>
</tbody>
</table>

**Table 2. Sample Data from Google Analytics**

**Results**

*Meta-Analysis of Four CTR Curves*

For the meta-analysis, we plotted the CTRs versus ranks for five reports with the open source statistical software R (Team R Development Core, 2005). With the same software, we also ran the power-law modelling on the two variables (ranks and clickthroughs) with logarithmic transformation. The possible exponential relationship required logarithmic transformation for modelling.

The results for the meta-analysis showed that the CTR curves were different (Figure 1): for example, the CTRs for the number one position showed a rate ranging from 10% to 42%. However, the trends were the same: a dramatic decrease in CTRs from the top to the bottom of ranks, which indicated an exponential relationship and a power-law distribution. Thus, log-log plots were created for all five models. If the log-log plots follow a straight line, it validates a power-law distribution. Figure 1 shows five near-straight lines, except for the break-off points at the 10th to
11th positions. That indicates the page break effect of SERP - by default, the first SERP will automatically show 10 results. The 11th to 20th results seem to follow a straight line too, but with sharper slopes. This shows the change of the parameters of the power-law curves on different pages and CTRs dropped more sharply at the second SERP. The log-linear models on the first 10 positions of all models showed the R-square values ranging from 0.918 to 0.997 (Table 3), indicating a high level of fit for power-law distribution. However, the estimated slopes were different. This may have been due to different search engines, query types, products, or the methodologies different reports adopted.
Figure 1. Plots and Log-Log Scatterplot of Five Models of Search Engine Rank and CTR
Table 3. Log Linear Regression of Power Law of Five Published Ranking Models*

<table>
<thead>
<tr>
<th>Model</th>
<th>R Square</th>
<th>Estimated B</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>.969</td>
<td>-1.140</td>
</tr>
<tr>
<td>2</td>
<td>.997</td>
<td>-1.128</td>
</tr>
<tr>
<td>3</td>
<td>.982</td>
<td>-1.122</td>
</tr>
<tr>
<td>4</td>
<td>.972</td>
<td>-1.243</td>
</tr>
<tr>
<td>5</td>
<td>.918</td>
<td>-1.290</td>
</tr>
</tbody>
</table>

*All models are significant at 0.0001 level.

Case Study of CTR Curves of DMO Websites

The results from meta-analysis confirmed the power-law distribution for web search queries. However, the question remains, are the differences in CTRs really statistically significant? In addition, the ranking curves were specifically related to web search, but how were they similar or different for searches on different properties, such as image and mobile search?

In the case study, we first tabulated the total number of visitors, total clicks, and clickthroughs of the three websites of a DMO. The search engine was Google and the time frame was from June 26 to October 1, 2012 (Table 3). The time frame represented all the dates with available data at the time of the study. The rationale for focusing on Google was that only Google seamlessly connects the ranking of the web pages and CTRs for the specific queries, and Google is the largest search engine in the U.S. and the world and has more than 2/3 of market share (Goodwin, 2013).

Table 1 shows the general statistics of the three websites. The traffic for the main CVB website had almost 30 times that of the two specific promotion websites. For the main and wedding websites, traffic from organic searches dominated the total visitors and visits (around 60%); for the family fun website, a large proportion of paid traffic pushed the organic traffic to around 30%,
still a significant amount. This indicated that without paid traffic, organic search dominated the channels of information access for the CVB. Since the ranks were averaged over all possible instances of the website on one specific query and they could contain decimal places, we rounded the ranks in integers. Due to the large quantity of queries, we picked the top 1,000 queries to investigate. The top 1,000 queries represented a large proportion of all clicks from Google (Table 3). We also deleted the queries with less than 100 clicks in order to reduce the amount of outliers. However, when we modeled CTRs on certain properties and the data volumes were limited, we retained all 1,000 queries.

<table>
<thead>
<tr>
<th>Site</th>
<th>Total Visits</th>
<th>Total Visitors</th>
<th>Google Organic Visits</th>
<th>Percent of Organic Traffic</th>
<th>Percent of Traffic of Top 1,000 Keywords</th>
</tr>
</thead>
<tbody>
<tr>
<td>A: Main Site</td>
<td>631,111</td>
<td>466,363</td>
<td>378,329</td>
<td>59.9%</td>
<td>67.9%</td>
</tr>
<tr>
<td>B: Wedding Site</td>
<td>28,005</td>
<td>20,391</td>
<td>18,173</td>
<td>64.9%</td>
<td>64.9%</td>
</tr>
<tr>
<td>C: Family Site</td>
<td>21,308</td>
<td>17,826</td>
<td>6,244</td>
<td>29.3%</td>
<td>35.0%</td>
</tr>
</tbody>
</table>

The three DMO sites showed different average CTRs (Table 4). For web search, the main site had an average of 23.2%, while the wedding and family fun sites were much lower at less than 10% each. Similar patterns emerged for image search: 1.6% of CTR for the main CVB site, but around 0.6-0.7% for the two themed websites. However for mobile sites, the three CTRs were similar, around 11-12%. This indicated that the general CVB sites attracted higher CTRs. However, the users of mobile devices were not very discriminating in that its CTRs are higher than web search for Site B and C. This might have been due to the context in which the mobile devices were used: the users might have been in a hurry, and have had limited time to process the displayed results. Thus, they were relatively more likely to click on the results from limited searches.
With the same software, we also plotted the CTRs versus ranks for the three websites and across different properties with averages and standard errors with boxplots (Figure 2). The boxplots show the averages (the bars in the middle), the 50% of middle quantiles (the boxes), and the smallest and largest values (the bars at the end of dotted lines). In general, the plots show that CTRs decreased when ranks went down. However, different from the meta-analysis, the plots show that different Google properties resulted in different curves. Web searches for three sites show apparent power-law distribution. However, the image searches had a more flat curve: the CTR did not drop that significantly as ranks go down. For mobile searches, Site A showed a power-law distribution with the CTRs that dropped even more sharply; but the small amount of data on Site B and Site C was not sufficient to show any clear patterns. In addition, the large standard errors of CTRs on the top results of web searches show that appearing on top positions was not a guarantee for higher conversion rates. Thus, we produced scatterplots for Site A's ranks with CTRs on different search properties (Figure 3). Figure 3 shows that the higher positioned results may have a lower CTR, indicated by the amount of data points under the boundary curve. Thus, higher ranks on SERP were a necessary condition but not a sufficient one.
The bars in the middle represent the means; the boxes represent 50% of quantiles; the bars on the ends of the dotted lines represent extreme values.

Figure 2. Boxplots of CTRs and Google Ranks of Three CVB websites on Three Properties

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Figure 3. Google Ranks and CTRs on Three Google Properties of CVB Main Site

The power-law models also confirmed a good fit for all three web search curves (Table 5). The R-Squared values range from around 0.3 to 0.5. They were not as large as the values in the
Clickthrough Rates of Search Engine Ranking

meta-analysis since we modelled them beyond the first few SERPs as used in the data of the five industrial reports. However, they were all highly significant.

Table 6. Power Law Model of Log Linear Web Search Model of Site A, B, and C

<table>
<thead>
<tr>
<th>Statistics</th>
<th>Site A</th>
<th>Site B</th>
<th>Site C</th>
</tr>
</thead>
<tbody>
<tr>
<td>R-Squared</td>
<td>0.4650</td>
<td>0.2982</td>
<td>0.5273</td>
</tr>
<tr>
<td>(Intercept)</td>
<td>-1.5189</td>
<td>-2.0435</td>
<td>-1.3714</td>
</tr>
<tr>
<td>B</td>
<td>-0.9898</td>
<td>-0.8067</td>
<td>-0.9218</td>
</tr>
<tr>
<td>Regression Model</td>
<td>CTR = 0.218953 X Rank^{-0.9898}</td>
<td>CTR = 0.446329 X Rank^{-0.8067}</td>
<td>CTR = 0.2537515 X Rank^{-0.9218}</td>
</tr>
</tbody>
</table>

In addition, we also tested the significant relationship between ranks and CTRs with the post-hoc Tukey test for all the queries. The question we wanted to address was, were the differences among CTRs of different ranks really statistically significant? Due to the large sample size, the main CVB website was used for the testing. Figure 4 shows the pairwise results of three properties of the main CVB website. The confidence level was set at 0.95 for testing the significance between different ranks among the top 20 results returned. It clearly indicated that for web search, the first result significantly attracted higher CTR than second result; the top two had a significantly higher CTR than the rest of the results. For image search, all the CTRs among the top 20 were not significantly different. For mobile search, only the top result was higher than the rest. These results validate previous discussions on the effects of different search properties on CTRs: for web search, The number one and the number two results have great advantages over the others; CTRs for image search are very low and not significantly different from each other; the top results on image search do not have as much advantage as in web search; the top one result in mobile search has tremendous advantages over other results.
Figure 4. Groups of CTRs by Google Ranks from Post-Hoc Tests
Conclusions and Discussions

This study shows that on average, the top results on SERPs had higher clickthrough rates, and the CTRs go down sharply with decreasing ranks. This general rule applies to two search properties: web and mobile searches. Power-law model fits well with CTRs of ranking on web searches. Image searches usually have very low CTRs and follow a haphazard pattern: the top positioned ones do not have much advantages. For mobile search, the top one position has tremendous advantage and the slope of the curve of mobile searches drops much more quickly than that of web searches.

The different results are due to the differences in interfaces. Google Images can display many items across one screen, and users process images rather quickly so they may have gone further down the results page; for mobile searches, the interface is small and the users of mobile devices are likely on the move, and thus the mobile users are less likely to go down any further. The interfaces also play a major role in web searches: there are always breaks in the slopes of the CTR curves between results on the first page and the second one. As the results go down further, the decreasing rate becomes even higher. Thus, the study validates not only attention poverty but also the effect of interface and context on attention distribution (Simon, 1996; Bae & Ahn, 2013): different layouts for image and mobile searches lead to different curves; mobile context on searches also decreases the CTRs in general and the poverty of attention is even more severe.

The detailed graphs show that higher ranks in SERPs were a necessary condition for higher CTRs, but not an entirely sufficient one. Many higher ranked web pages have low CTRs. This indicates that other factors were at play - for example, the text snippets or URL displayed, and the actual content of the web pages may have affected CTRs.
Implications

This study confirms that being on the top of a search engine results page has tremendous advantages. Especially for web searches, using the power-law distribution instead of a linear one gives the top results tremendous advantage. The CTRs decrease very sharply with lower ranks. Thus, a business or DMO needs to be at the top of web search in order to be visible. However, it is a necessary condition but not a sufficient one. If the results are less relevant and the text snippets are less attractive, the users still will not click. Tourism businesses and organisations need not only to be on the top of SERPs for their targeted search queries, but they also need to have relevant and meaningful snippets, URLs, and actual web content, for the purpose of attracting more clicks and ultimately more customers.

This study shows that for a specific website, one can build a power-law model to predict increased clickthrough rates on web searches. Based on existing data from Google Analytics and Google’s Webmaster Tool, a specific power-law model could be tested. Through the model, a marketer can justify their investment in search engine marketing practices. For example, moving the position for the CVB main site from the number three to the number one position tripled the amount of traffic to the website in our study.

Moreover, on different properties, the clickthrough rates change at a different slope: the images in lower ranks are not less likely to be clicked than those on top ranks. The image search can give lower ranked websites on web searches an advantage. These give businesses more opportunities: for highly competitive queries on web searches, businesses lower in rank could focus on image searches by making sure their images populate the SERPs on image searches. Those searches can lead to increased web traffic. On the other hand, the visitors are less likely to visit
results in lower positions on mobile searches. For mobile searches, a business has to be the top one of SERPs to attract attention. Thus, the ROIs will be lower for mobile searches. However, with the increasing adoption of smartphones, mobile searches will become a more important and competitive battleground (Wang & Fesenmaier, 2012).

In addition, the results of this study may provide evidence for the power of ranking and the shape of attention distribution curves for different ranks for other information systems, such as eCommerce sites and OTA sites, when they rely on a ranking mechanism to provide product listings. The users’ attention will always focus on the top results, especially in a mobile context. It is hard to gain the top positions for general queries; therefore, businesses should pay more attention to their niche market. For example, if a search on “atlanta hotels” is very competitive, it will be a lot easier to focus on “pet-friendly atlanta hotels”. Finding and focusing on promoting the businesses in their niche market is the key to success in the search world. However, one can also take advantage of opportunities for different properties, for example image search.

**Limitations**

Different from traditional survey research, this study adopted a meta-analysis and a case study method. The results, especially on the CTRs on different search properties, are based on three different websites of one DMO. Though the analysis on three websites helps with the increased validity, the generalization might be limited. The parameters of the power-law models in this study will be different for other websites and search properties. One needs to use specific data to fit the models for different contexts.

The study investigated clickthrough rates on different search engine ranks. However, in order to calculate an accurate ROI, it is still one step less than the actual conversion rates, that is,
the rate of buyers among all the visitors searching for certain queries. More specific tracking needs to be put in place, such as using Google Analytics, to further capture the rate of conversions among all the searchers and website visitors.

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