Click-Through Behavior across Devices In Paid Search Advertising

Why Users Favor Top Paid Search Ads And Are Sensitive to Ad Position Change

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This study investigated differences in consumer click-through behavior with paid search advertisement across devices—smartphone versus desktop versus tablet. The authors examined how different device users behave in terms of their tendency to click on the top paid search advertisement and their sensitivity to advertisement position change, and whether tablet users are more similar to smartphone or desktop users when clicking through paid search advertisements. By leveraging Google AdWords data from 13 paid search advertisers, the authors developed empirical findings that provide insights into paid search advertising strategies across devices.

INTRODUCTION

Paid search advertising accounts for 46 percent of digital-marketing expenditure and is expected to reach $142.5 billion in 2021 (Ironpaper, 2017). One way for advertisers to improve the performance of paid search advertising is to consider segmenting their paid search advertising campaigns by devices. Discussion of the benefits of doing so is inconclusive, however. Although some advertisers suggest that device segmentation is an effective strategy, others believe that it is not worth the trouble of setting up separate campaigns for different devices (Lolk, 2017).

The debate intensifies as mobile usage becomes increasingly prevalent. There has been a dramatic change in search-engine usage over the past few years, as the majority of search activities have shifted from desktop to mobile devices, such as smartphones and tablets. The volume of mobile searches has exceeded that of desktop searches since 2015 (Sterling, 2015).

A recent study (iProspect, 2017) reported that mobile devices accounted for 69.4 percent of Google's paid search clicks in 2017. This share is expected to grow as mobile devices become increasingly affordable and the speed of mobile networks increases. Given the growing predominance of mobile searches, it is imperative for paid search advertisers to understand potential cross-device differences in consumer behavior and thus assess whether and how best to segment paid search advertising campaigns by devices.

Management Slant

- Compared with desktop users, smartphone users, on average, more likely will click on the top paid search advertisement and are more sensitive to advertisement position change for unbranded searches (*i.e.*, queries without the focal advertiser's brand name). Such differences, however, do not exist for branded searches—queries with the focal advertiser's brand name.
- Tablet users are similar to smartphone users regarding both the tendency to click on the top paid search advertisement and the sensitivity to advertisement position change.
- Advertisers should avoid a one-size-fits-all strategy and should make device-specific adjustments to their paid search advertisement campaigns.

Submitted February 4, 2018;
revised April 20, 2019;
accepted May 1, 2019.

DOI: 10.2501/JAR-2020-004

A large body of research has addressed the effectiveness of paid search advertising (Agarwal, Hosanagar, and Smith, 2011; Ghose and Yang, 2009; Jeziorski and Moorthy, 2017; Narayanan and Kalyanam, 2015; Rutz, Bucklin, and Sonnier, 2012). Few studies, however, have differentiated between desktop and mobile (*i.e.*, smartphone and tablet) users. This study aimed to fill the gap in the literature by investigating consumer click-through behavior across devices. Clicks are important to the effectiveness of paid search advertising because advertisers incur explicit expenses for each click (Fulgoni, 2018). Understanding consumer click-through behavior across devices therefore can provide insights into optimizing the effectiveness of paid search advertising.

"Devices" in this study refers to desktops, smartphones, and tablets. The tablet is a controversial device in paid search advertising. Some advertisers group tablets with smartphones, whereas others claim that a tablet is a computer rather than a smartphone (Hein, 2014). These opposing views result from tablet features, which are both similar and dissimilar to those of smartphones and desktops.

On the one hand, tablets are similar to smartphones because both are portable and have smaller screen sizes compared with desktops. On the other hand, tablets are similar to desktops in terms of usage location. Searchers tend to use tablets and desktops at homes or offices, where the devices are connected to a fixed or Wi-Fi network.

This debate also has attracted the attention of researchers, prompting calls for research on whether consumers' behavior on tablet devices is similar to their behavior on desktops or on smartphones (Ghose, Goldfard, and Han, 2012). In the current study, the authors separated tablets from smartphones and desktops and examined the similarity of tablets to each of these devices.

The authors leveraged Google AdWords data that break down daily advertisement impressions, advertisement clicks, and advertisement positions by device. When users conduct searches on Google, they will see paid search listings differently, depending on whether they are using a desktop, tablet, and smartphone, and the positions of the advertisement listings will vary (See Figure 1). The position of each paid search advertisement is recorded in each advertiser's AdWords data.

On the basis of Google AdWords data for 13 advertisers from a wide range of industries (more than 20 million advertisement impressions in total), the authors focused on three research questions:

RQ1: Do different device users—smartphone, tablet, and desktop—behave differently in their tendency to click on the top paid search advertisements?

RQ2: Do different device users—smartphone, tablet, and desktop—behave differently in regard to their sensitivity to advertisement position change?

RQ3: Are tablet users similar to smartphone or desktop users in click-through behavior?

LITERATURE REVIEW

Many studies have examined the determinants of click-through rates in paid search advertising (*e.g.*, Jeziorski and Segal, 2015; Kim, Qin, Liu, and Yu, 2014; Richardson, Dominowska, and Ragno, 2007; Wang, Bian, Liu, Zhang, *et al.*, 2013), with a main focus on how the click-through rate varies as a function of advertisement position. Using different approaches and datasets, these studies consistently have found that click-through rates decline as advertisement positions fall from the top to the bottom of the paid listing (Agarwal *et al.*, 2011; Ghose and Yang, 2009; Rutz *et al.*, 2012; Rutz and Trusov, 2011). None of the existing studies, however, has investigated systematically whether and how the advertisement position effect may vary depending on the devices that consumers use when they conduct online searches.

In contrast, a body of research has examined the effects of mobile devices on various aspects of consumer behavior in different nonpaid search advertising contexts. One study showed that consumers value items more when shopping on a mobile device because the touch interface on a mobile device enhances users' perception that they already own the product (Brasel and Gips, 2014). Another study found that desktop usage elicits instrumental goals, which can lead to a preference for utilitarian products, while tablet usage elicits experiential goals, which can lead to a preference for hedonic products (Liu and Wang, 2016).

Even more interesting is the reported relationship between food orders and device usage. Consumers tend to order less-healthy food on smartphones because orders made through smartphones less likely will be seen by others; users therefore are concerned less about what other people may think of their order (Benartzi, 2017). A more recent study showed that tablet usage can lead to more casual browsing, which in turn can lead to more impulse purchasing and a broader purchase variety (Xu, Chan, Ghose, and Han, 2016). Additional studies found that mobile users more likely will undertake simpler decision-making tasks and shop for habitual products for which they have a purchase history (Maity and Dass, 2014; Wang, Malthouse, and Krishnamurthi, 2015).

These prior studies all suggest that device usage can affect various aspects of consumer behavior. The authors therefore believed that the type of device used in online search also would affect consumers' tendency to click on the top paid search advertisement,

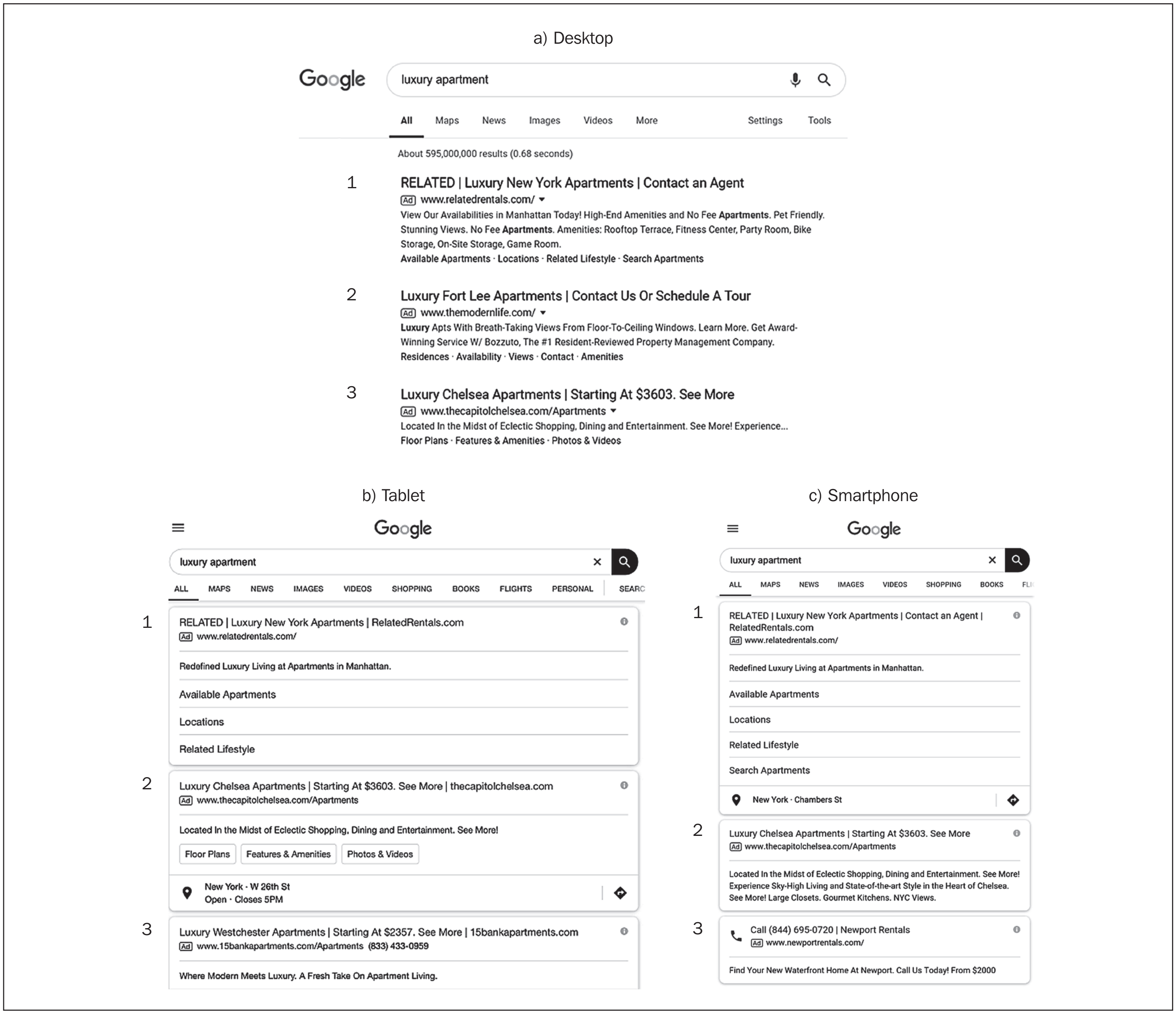

Figure 1 Paid Listings on Different Devices

Note: The numbers (1, 2, 3) stand for advertisement positions, with Position 1 referring to the topmost rank in the paid search listing, Position 2 is one rank below Position 1, and Position 3 is one rank below Position 2.

as well as their sensitivity to advertisement position change in the context of paid search advertising.

Tendency to Click on the Top Paid Search Advertisement

Search costs play a large role in explaining consumer behavior (Seiler, 2013). Economic theory identifies two types of search costs that influence search behavior: external and cognitive. External search costs indicate the costs of resources that consumers invest in searches, such as the monetary costs to acquire information or the opportunity costs of time during information acquisitions. The cognitive search costs are the mental effort expended by consumers to direct the search. The online search environment provides a search channel that significantly reduces external search costs (Chiang, 2006). In the context of online searching, therefore, the search cost mainly refers to cognitive costs.

Previous studies have found that screen size is a key determinant of cognitive costs in online searching. A small screen does not have enough space to display information and can cause information chunking (Chae and Kim, 2004; Ghose *et al.*, 2012). A small screen requires users to scroll more often to obtain the same amount of

The authors examined between-devices differences in sensitivity of click-through rates to advertisement position in paid search advertising.

information compared with a large screen (Sweeney and Crestani, 2006), which imposes a higher cognitive cost on consumers. Users with a smaller screen also need to remember the content and context of the search engine results page that they already have viewed because of information chunking (Ghose *et al*., 2012), which also leads to higher cognitive costs.

These higher search costs associated with smaller screens render consumers less likely to browse on mobile devices (Chen, Ma, and Pan, 2016). Statistics indicate that smartphone searchers spend, on average, 20 fewer seconds examining the search engine result page than desktop searchers (Song, Ma, Wang, and Wang, 2013). Because different devices have different screen sizes, the authors believed that consumers' tendency to click on the top paid search advertisement would differ across devices.

Besides search cost, context—including situational factors such as location (*i.e.*, home or store) and time—also affects users' search behavior (Song *et al*., 2013; Thomadsen, Roodekerk, Amir, Arora, *et al*., 2017). Desktop devices impose stricter limitations on geographical mobility and access, typically constraining it to the office or home or to locations with Internet access, whereas smartphones are free of geographical and temporal constraints and can access the Internet anytime and anywhere (Ghose and Han, 2011; Jung, Umyarov, Bapna, and Ramaprasad, 2014; Muzellec and O'Raghallaigh, 2018; Shankar, Venkatesh, Hofacker, and Naik, 2010). Such ubiquitous Internet access by smartphones supports time-critical activities and facilitates immediate searching (Bang, Lee, Han, Hwang, *et al*., 2013; Venkatesh, Ramesh, and Massey, 2003; Xu *et al*., 2016). When facing time pressures, smartphone searchers may be reluctant to invest in search costs and therefore more likely may click on the top search results.

Similarly, the tablet as a portable device potentially can allow the user to access the Internet anytime and anywhere. Unlike smartphones, however, most tablets are not equipped with cellular plans. It is unclear, therefore, whether tablet users more likely may click on the top advertisement compared with desktop and smartphone users.

Sensitivity to Advertisement Position Change

Because smaller screens lead to higher search costs, devices with smaller screens tend to have a higher advertisement position effect than devices with bigger screens; searchers are more sensitive to advertisement position change. This hypothesis has been borne out by a study that used data from a Twitter-like microblogging service to examine between-devices differences in the sensitivity of click-through rates to content rank (Ghose *et al*., 2012). The findings of this study showed that click-through rates on smartphones are more sensitive to content rank compared with click-through rates on desktops.

Another group of researchers, however, used data from the largest price comparison website in the Netherlands and found a weaker position effect among smartphone and tablet users compared with desktop users (Zheng, Li, and Pavlou, 2016). They suggested that this could have occurred because of mobile-savvy consumers' adaptation over time to navigate more efficiently on smartphones and tablets, despite their smaller screens.

The current study differs from the prior two studies in two ways. First, the authors examined between-devices differences in sensitivity of click-through rates to advertisement position in paid search advertising. Second, the analyses were replicated across multiple advertisers' field data, which should lead to empirical findings with greater generalizability.

METHOD

Data

The authors had access to daily Google AdWords data from 13 different advertisers, which covered all of their paid search advertising campaigns from January 1, 2015, to December 31, 2016. These advertisers belonged to a wide range of industries (*e.g.*, health care, technology services, construction, manufacturing) and included both national and regional companies.

For each advertiser–keyword combination, the authors observed daily advertisement impressions, clicks, average advertisement position, maximum cost per click, and quality score. Advertisement impressions are the number of times the focal company's advertisement appears among the paid search results on a particular day. Maximum cost per click is the highest amount the focal company is willing to pay for a click on an advertisement that is triggered by the focal keyword. The quality score ranges from 1 to 10 and is a key determinant of a company's advertisement position in Google's paid listing.

With respect to direction, quality scores are correlated positively with factors such as keyword–advertisement relevance, landing page relevance and quality, and historical click-through rates. All else being equal, the higher the quality score is, the higher is the position in which an advertisement will be listed (Wordstream, n.d.). Google does not reveal the exact algorithm behind the determination of the quality score or the advertisement position. In

Table 1 Summary Statistics

Company ID	No. Days	No. Keywords	Advertisement Impressions	Advertisement Clicks	CTR	Advertisement Position	Max. CPC	Quality Score
1	727	351	8,308,158	291,964	0.10	1.74	1.13	6.59
2	730	125	6,415,470	400,282	0.13	1.78	0.63	7.97
3	649	51	897,799	4,877	0.02	1.94	2.97	6.75
4	725	212	710,274	15,216	0.05	1.82	2.89	6.45
5	194	136	704,788	33,262	0.10	1.98	2.27	6.65
6	727	86	597,669	33,580	0.09	1.42	6.41	6.70
7	686	42	543,511	23,246	0.08	1.26	3.13	6.32
8	725	190	515,701	39,634	0.13	1.40	5.57	7.16
9	641	125	477,766	12,528	0.05	1.76	6.92	4.89
10	575	160	417,706	4,877	0.03	1.75	6.87	4.69
11	726	14	403,255	26,006	0.15	1.07	3.42	8.34
12	723	156	357,484	18,119	0.09	1.57	3.80	6.89
13	551	22	87,702	1,817	0.07	1.66	8.45	6.26

Note: CTR = click-through rate; Max = maximum; CPC = cost per click.

contrast to prior research on click-through rates in paid search advertising, the data of the current study are reported by device: smartphone versus desktop versus tablet.

The authors applied the following three criteria in screening the raw data.

- First, they focused on exact-match keywords, where the keywords are identical to the search queries that have triggered the focal company's advertisement. Focusing on exact-match keywords instead of broad or phrase-match keywords removes the threat of aggregation bias in Google AdWords data (Yang and Ghose, 2010).
- Second, they focused on observations with a daily average advertisement position in the range of [1, 3], which represents the vast majority of the authors' observations.
- Third, they focused on keywords whose total impressions, summed across all days, were no fewer than 100.

Descriptive statistics of the resulting sample are summarized by company (See Table 1). Because of privacy concerns, however, the authors could identify each company only by an ID number, sorted descendingly by total advertisement impressions, the sum of which exceeded 20 million.

Regarding the average click-through rates by device and advertisement position, the data show that across all advertisers and keywords, smartphone users, compared with desktop users, had higher average click-through rates for Advertisement Positions 2 and 3 but lower click-through rates for Advertisement Position 1. Tablet users had the highest click-through rates across all advertisement positions (See Figure 2). The authors also examined the average cost per click by position and device. Position 1, on average, cost more than Position 2, which cost more than Position 3. The cost was the highest on desktop and the lowest on tablet (See Figure 3).

The authors next calculated the average trade-offs between advertisement cost and click-throughs across advertisement positions for each device. For every 100 impressions, the average cost would be 100 × average click-through rate × average cost per click, and the average clicks would be 100 × average click-through rate. On the basis of such calculations, the authors found the following:

- For every 100 advertisement impressions on desktops, advertisers can, on average, reduce cost by $26.02 when the position changes from 1 to 2 (but receive 7.6 fewer clicks), or save $3.75 and lose 1.1 clicks when the position changes from 2 to 3.
- For every 100 advertisement impressions on smartphones, advertisers can, on average, reduce cost by $17.6 when the position changes from 1 to 2 (but receive 5.8 fewer clicks), or save $3.85 and lose 1.4 clicks when the position changes from 2 to 3; and
- For every 100 advertisement impressions on tablets, advertisers can, on average, save $16.91 when the position changes from 1 to 2 (but receive 8.1 fewer clicks), or save $3.35 and lose 1.6 clicks when the position changes from 2 to 3.

These model-free descriptive statistics suggest that the cross-position trade-offs between advertisement cost and click-throughs

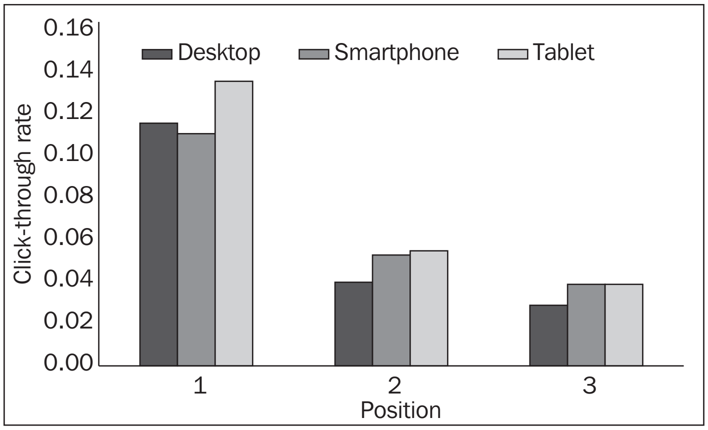

Figure 2 Click-Through Rate by Device and Advertisement Position

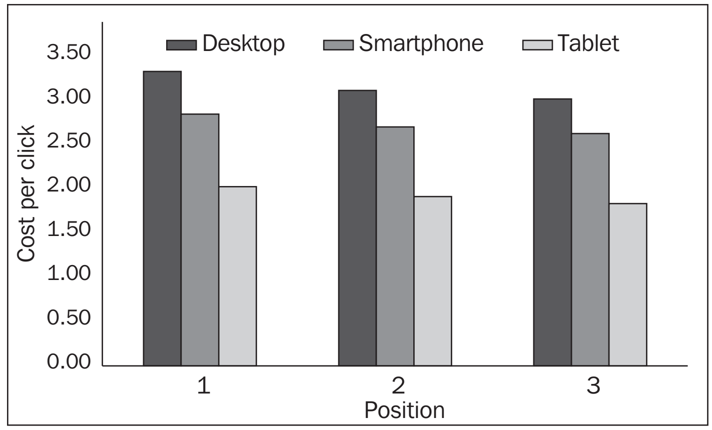

Figure 3 Cost per Click by Device and Advertisement Position

clearly can vary by device. Advertisers should take this into account and thus devise device-specific strategies.

In their empirical analysis, the authors separated keywords into branded versus unbranded, depending on whether they included the focal company's brand name. Prior research on paid search advertising has found that branded searches are associated with higher click-through rates (Ghose and Yang, 2009; Rutz and Bucklin, 2011; Rutz *et al*., 2012). The authors of the current study were interested in determining whether device effects, if any, are different between branded and unbranded searches. The percentages of impressions for branded and unbranded keywords by advertisement position are summarized (See Table 2): Note that in the authors' data sample, advertisement position was always 1 for branded keywords.

In the data, 11.76 percent of searches were branded, and 88.24 percent were unbranded; 44.39 percent were conducted on desktops, 36.77 percent on smartphones, and 18.84 percent on tablets (See Table 3).

Model

From a focal advertiser point of view, searchers can either click or not click on its advertisement when it is shown on the paid search listing. The authors therefore used a binary choice model to examine how the click-through rate varies as a function of advertisement position and, more important, how that relationship is moderated by device. The model was applied separately to branded and unbranded keywords, and separately to each company.

For a focal advertiser, let $Impressions_{itd}$ denote the number of advertisement impressions triggered by keyword search query i on day t and device d, where the focal company's link appeared among the paid search results. The authors assumed that the number of clicks on the focal company's advertisement follows a binomial process:

$$Clicks_{itd} \sim \text{binomial}\left(CTR_{itd}, Impressions_{itd}\right), \tag{1}$$

where "CTR" denotes click-through rate. The authors assumed that CTR_{itd} can be expressed as a logistic function of U_{itd}, the latent utility of clicking on the focal company's advertisement—that is,

$$CTR_{itd} = \frac{e^{U_{itd}}}{1+e^{U_{itd}}}. \tag{2}$$

The authors further assumed that U_{itd} is determined as

$$U_{itd} = \alpha_d^0 + \alpha_d^1 \times \left(Position_{itd} - 1\right) + V_{itd} + \varepsilon_{itd}, \tag{3}$$

where α_d^0 and α_d^1 vary as a function of device,

$$\alpha_d^0 = \beta_0 + \beta_1 \times \left(d = smartphone\right) + \beta_2 \times \left(d = tablet\right) \tag{4}$$

$$\alpha_d^1 = \gamma_0 + \gamma_1 \times \left(d = smartphone\right) + \gamma_2 \times \left(d = tablet\right). \tag{5}$$

V_{itd} is a placeholder for factors that can be correlated with both U_{itd} and $Position_{itd}$. The authors specify in detail later when they address the endogeneity issue; ε_{itd} follows identically and independently distributed Weibull distribution.

The authors calibrated the above model company by company, because a large number of data were available for each company and there was little to be gained by pulling the data across companies. The parameters of key interest were β_1 and β_2, which capture the between-devices differences in click-through rate when advertisement position is equal to 1, and γ_1 and γ_2, which capture the between-devices differences in click-through rate sensitivity to advertisement-position change.

After obtaining the estimates of β_1, β_2, γ_1, and γ_2 by company, the authors pooled the estimates across companies and calculated the overall mean effect by following the basic idea behind meta-analysis in synthesizing effect estimates from multiple studies. The way to pool effect estimates across studies is to multiply each study's estimate, ES_j, by a weight W_j; sum them; and divide the

Table 2 Impression Share by Advertisement Position and Query Type

Position	Branded	Unbranded
1	100%	36.30%
2	0%	38.87%
3	0%	24.83%

Table 3 Impression Share by Device and Query Type

Query Type	Desktop	Smartphone	Tablet	Total
Branded	4.74%	4.57%	2.47%	11.76%
Unbranded	39.66%	32.20%	16.37%	88.24%
Total	44.39%	36.77%	18.84%	100,00%

total by the sum of the weights (See Equation 6). The weight W_j is based on the precision of the individual study's effect estimate, which is equal to the inverse of the estimate variance $Var(ES_j)$ (See Equation 7). The standard error of the overall mean effect is equal to the square root of the inverse of sum of the weights (See Equation 8).

$$\overline{ES} = \frac{\sum W_j \times ES_j}{\sum W_j} \,. \tag{6}$$

$$W_j = \frac{1}{Var(ES_j)} \,. \tag{7}$$

$$SE_{\overline{ES}} = \sqrt{\frac{1}{\sum W_j}} \,. \tag{8}$$

The variance of effect estimate $Var(ES_j)$ in Equation 7 was obtained through the following equations after homogeneity test:

$$Var(ES_j) = v_\theta + v_j \,, \tag{9}$$

$$v_\theta = \frac{Q-(k-1)}{\sum \mathrm{W_j} - \left(\frac{\sum \mathrm{W_j}^2}{\sum \mathrm{W_j}}\right)} \,, \tag{10}$$

$$Q = \left(\sum W_j ES_j^2\right) - \frac{\left(\sum W_j ES_j^2\right)}{\sum W_j} \,, \tag{11}$$

where v_θ is the estimate of the between-studies variance, v_j is the estimate of the variance associated with sampling error, Q is the value of the homogeneity test, and k is the number of effect estimates. Homogeneity test in meta-analysis is conducted to examine whether differences among effect estimates come from sources other than subject-level sampling error, such as differences associated with different study characteristics (Lipsey and Wilson, 2001).

The authors applied Equations (6)–(11) to each estimate of β_1, β_2, γ_1, and γ_2, respectively, and obtained the overall mean effect for each estimate and the corresponding standard error.

Endogeneity Controls

Endogeneity is a major challenge in modeling the click-through rate as a function of advertisement position on the basis of observational data, because many factors can be correlated simultaneously with an advertisement's position and its click-through rate (Rutz and Trusov, 2011). In Equation (3), the authors used V_{itd} as a placeholder for those factors, which can fall into three mutually exclusive and collectively exhaustive categories:

- those that vary across search queries but stay the same over time,
- those that vary over time but are the same across search queries, and
- those that vary across both search queries and time.

In the rest of this subsection, the authors delineate the empirical strategy for dealing with these factors as far as possible, but within reason.

Query-Variant and Time-Invariant Factors

Search queries differ in many ways that can lead to different click-through rates and advertisement positions. Longer queries may have higher click-through rates, because they may be searched by consumers who have a stronger interest. With this knowledge, a company may spend more on longer queries to obtain higher advertisement positions. When this happens and one fails to account for the simultaneous correlation of query length with both the click-through rate and the advertisement position, one has a biased estimate of an advertisement position's impact on the click-through rate. Because the length of query i (n_words_i) is directly observable, the authors included it as a covariate in their model.

Besides length, many other query-specific factors may be correlated with the click-through rate. Although the authors of the current study are not privy to these factors, companies may know about them and might have acted on them strategically, which would lead to different advertisement positions for different search queries. To account for such unobserved query-specific factors, a query-specific random effect, $e_i \sim N(0,\sigma^2)$, was specified.

Time-Variant and Query-Invariant Factors

Different days may have different baseline click-through rates. Click-through rates on weekdays may be higher than

Search queries differ in many ways that can lead to different click-through rates and advertisement positions.

click-through rates on weekends. On the basis of this information, a company may bid more on paid search advertisements to obtain higher positions on weekdays. When this happens and one fails to account for the simultaneous correlation of weekdays with the click-through rate and the advertisement position, one has a biased estimate of the advertisement position's impact on the click-through rate. Because day t was observed as either a weekday or a weekend, a weekday dummy ($weekday_t$) was included as a covariate in the model.

Besides weekdays versus weekends, many other day-specific factors can be correlated with the click-through rate. Consumers more likely might click on paid search advertisements during holidays. With this knowledge, a company could spend more on paid search advertisements during holidays, which would result in a spurious correlation between the click-through rate and the advertisement position. Alternatively, a company might become better known among consumers over time, and the increased awareness could result in higher click-through rates and better advertisement positions—hence another source for spurious correlation between the click-through rate and the advertisement position. Rather than including additional covariates to capture seasonality or long-term trends in the click-through rate, the authors included a daily random effect, $u_t \sim N(0,\varphi^2)$.

Query-Variant and Time-Variant Factors

Besides query-specific and day-specific factors, there could be factors that vary by query and day and that are correlated with both the focal company's advertisement positions and click-through rates. Certain search queries may become less popular than others and receive increasingly lower click-through rates. In response, the company may adjust its paid search advertising spend across queries, creating a spurious correlation between click-through rates and advertising positions.

To address concerns such as these, the authors included the following covariates in the model:

- the number of advertising impressions generated by query i on day t and device d, $Impressions_{itd}$;
- the maximum cost per click, Max_CPC_{itd};
- the quality score, QS_{itd};
- the number of impressions generated by query i on device d and day $t-1$, $Impressions_{it-1d}$;
- the focal company's advertising position for query i on day $t-1$ and device d, $Position_{it-1d}$; and
- the number of clicks on the focal company's advertisement for query i on day $t-1$ and device d, $Clicks_{it-1d}$.

In addition, the authors specified a query by day random effect, $v_{it} \sim N(0,\omega^2)$.

In summary, to account for confounding factors that could influence both the focal company's paid search advertisement click-through rates and its advertising positions, the model includes three types of controls,

- query variant and time invariant,
- time variant and query invariant, and
- query variant and time variant,

which enter the model through V_{itd} as

$$\begin{aligned} V_{itd} = {} & \alpha^2 \times \ln\left(Impressions_{itd}\right) + \alpha^3 \times weekday_t \\ & + \alpha^4 \times n\_words_i + \alpha^5 \times Max\_CPC_{itd} + \alpha^6 \times \left(Max\_CPC_{itd} = 0\right) \\ & + \alpha^7 \times QS_{itd} + \alpha^8 \times \left(QS_{itd} = 0\right) + \alpha^9 \times \ln\left(Impressions_{it-1,d}\right) \\ & + \alpha^{10} \times \ln\left(Clicks_{it-1,d}\right) + \alpha^{11} \times Position_{it-1,d} + e_i + u_t + v_{it}. \end{aligned} \tag{12}$$

RESULTS

Between-Devices Differences in Top Paid Advertisement Click-Through Rates

The estimates of β_1 and β_2 in Equation (4) capture the between-devices differences in the click-through rate when the advertising position is equal to 1: β_1 captures the differences between smartphone and desktop users, whereas β_2 captures the differences between tablet and desktop users. Therefore, $\beta_1 - \beta_2$ captures the differences between smartphone and tablet users. The authors obtained these estimates by company and then examined the overall mean effect separately for unbranded queries and branded queries.

Among the results for unbranded queries (See Figure 4), the differences between smartphone and desktop users for most companies, as well as the overall mean effect, were positive and significant (See Figure 4a). This indicates that, with all else being equal, smartphone users, compared with desktop users, on average more likely would click on the top paid search advertisement when they conducted unbranded searches.

In the comparison of tablet users and desktop users, all individual effects and the overall mean effect were positive and significant (See Figure 4b). This indicates that, with all else being equal, tablet users, compared with desktop users, on average more likely

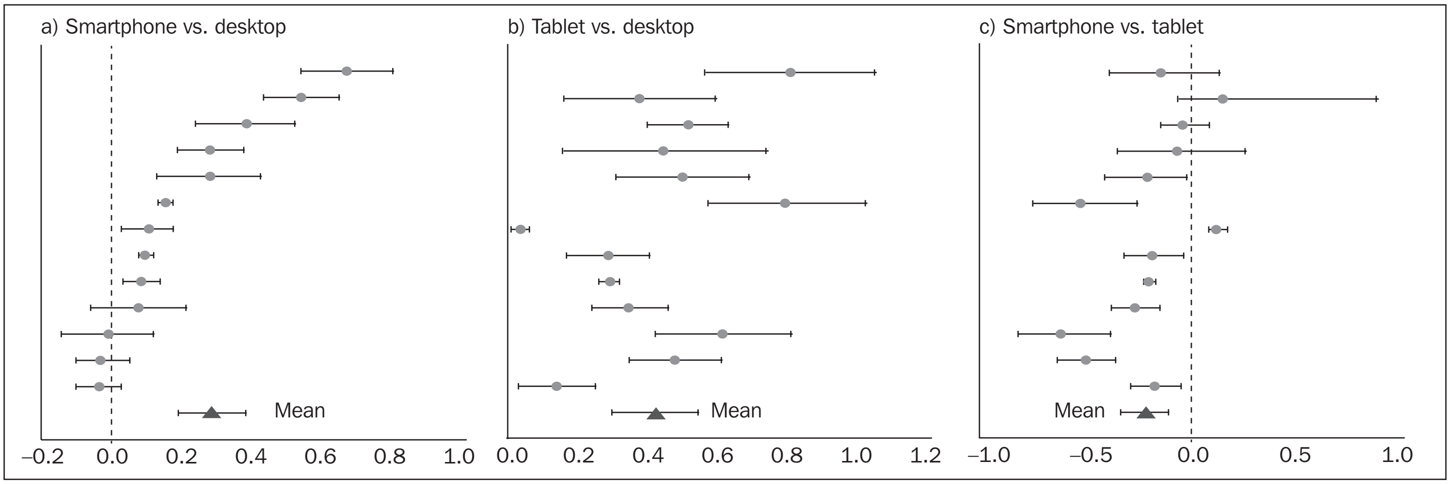

Figure 4 Top Paid Search Advertisement Click-Through Rate for Unbranded Queries
Note: Each circle represents the effect estimate of a particular company; each triangle at the bottom represents the overall mean effect.

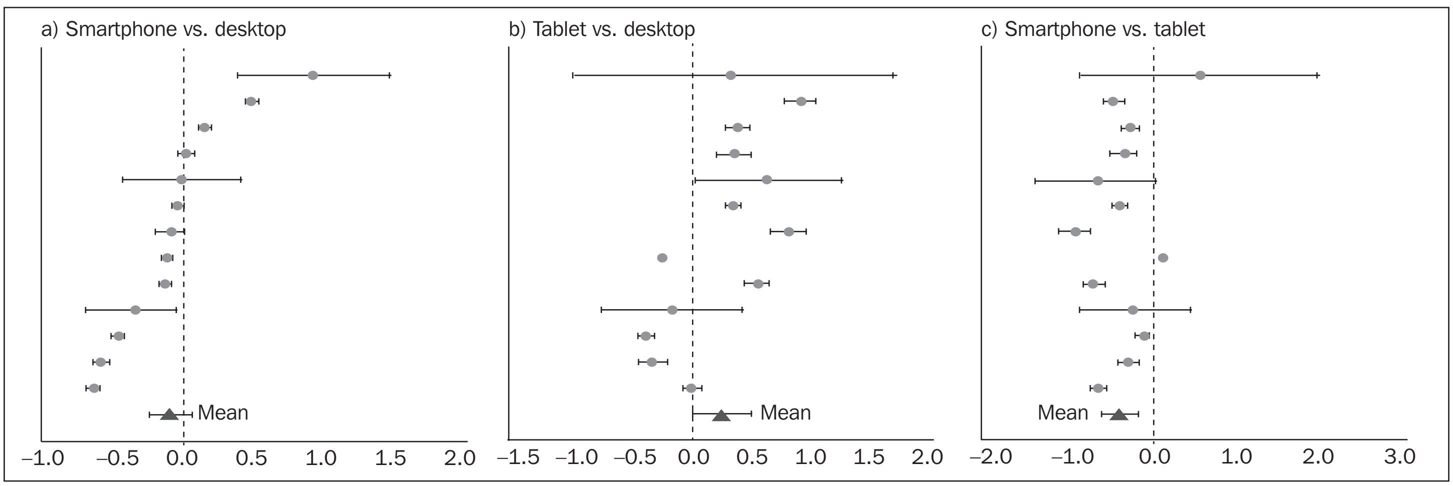

Figure 5 Top Paid Search Advertisement Click-Through Rate for Branded Queries
Note: Each circle represents the effect estimate of a particular company; each triangle at the bottom represents the overall mean effect.

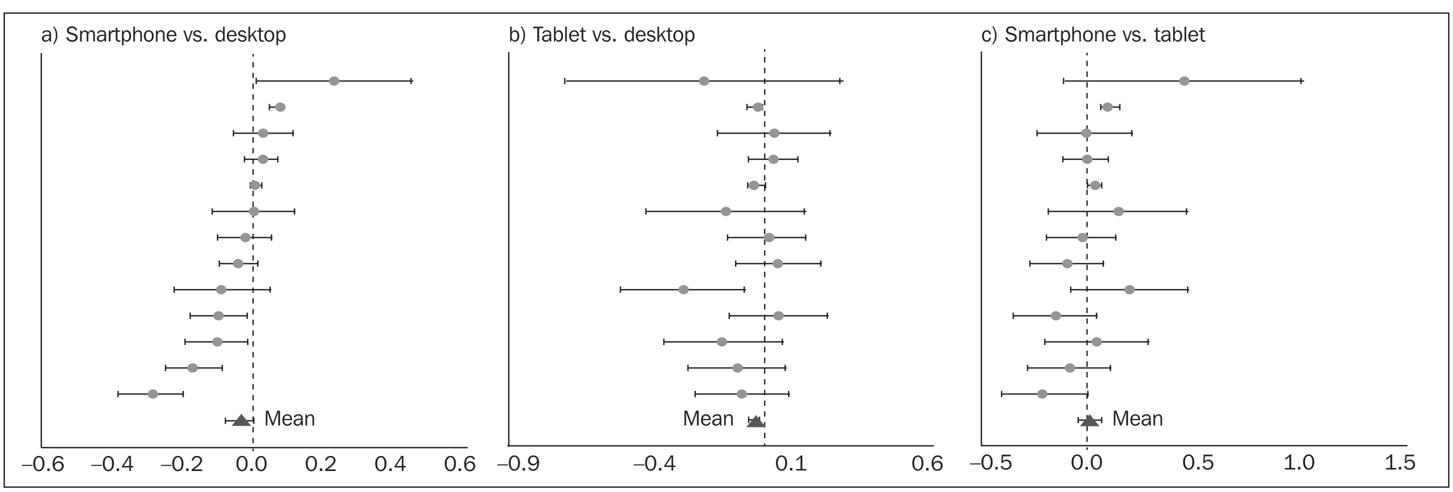

Figure 6 Sensitivity of Click-Through Rate to Advertisement Position Change for Unbranded Searches
Note: Each circle represents the effect estimate of a particular company; each triangle at the bottom represents the overall mean effect.

Smartphone users, compared with desktop users, on average more likely would click on the top paid search advertisement when they conducted unbranded searches.

would click on the top paid search advertisement when they conduct unbranded searches. Regarding the differences between smartphone and tablet users, the overall mean effect was significantly negative (See Figure 4c). This indicates that, with all else being equal, smartphone users, compared with tablet users, on average less likely would click on the top paid search advertisement when they conducted unbranded searches.

Among the results for branded queries (See Figure 5), in terms of the differences between smartphone and desktop users, the overall mean effect was insignificant (See Figure 5a). This indicates that, with all else being equal, there was, on average, no significant difference between smartphone and desktop users in their tendency to click on the top paid search advertisement when they conducted branded searches. Compared with desktop users, however, tablet users, on average, significantly more likely would click on the top paid search advertisement when they conducted branded searches (See Figure 5b). The difference between smartphone and tablet users was significantly negative, indicating that smartphone users, on average, significantly less likely than tablet users would click on the top paid search advertisement when they conducted branded searches (See Figure 5c).

Between-Devices Differences in Sensitivity of Click-Through Rate to Advertisement Position Change

The estimates of γ_1 and γ_2 in Equation 5 capture the between-devices differences in click-through rate sensitivity to advertisement position change. γ_1 captures the differences between smartphone and desktop users, and γ_2 captures the differences between tablet and desktop users; therefore, $\gamma_1 - \gamma_2$ captures the differences between smartphone and tablet users. These estimates were obtained by company, and the overall mean effect was examined. As mentioned before, the advertisement position is always 1 for branded queries. The sensitivity to advertisement position change, therefore, was examined for unbranded queries only.

The overall mean effect across companies was negative and significant (See the similar pattern in Figures 6a and 6b). This indicates that, compared with desktop users (for whom γ_0 in Equation 5 was negative and significant), the average decline in the click-through rate when advertisement position changed from 1 to 2 (or 2 to 3) was greater for smartphone (γ_1) and tablet (γ_2) users. With all else being equal, click-through rate sensitivity to advertisement position change was higher on mobiles than on desktops. Finally, there was no significant difference between smartphone and tablet users in click-through rate sensitivity to advertisement position change (see the overall mean effect on the chart in Figure 6c).

The empirical findings are summarized below (See Table 4). For the first research question—whether different device users (smartphone, tablet, and desktop) behave differently in their tendency to click on the top paid search advertisements—the results suggest that, for unbranded searches, the click-through rate for the top paid search advertisement was, on average, the highest on tablets, followed by smartphones, and the lowest on desktops. For branded searches, the click-through rate for the top paid search advertisement was, on average, higher on tablets than on smartphones or desktops.

For the second research question—whether different device users behave differently in regard to their sensitivity to advertisement position change—the results suggest that tablet and smartphone users were more sensitive than desktop users to advertisement position change. As advertisement position moved down from the top, the click-through rate, on average, declined more on tablets and smartphones than it did on desktops.

Finally, for the third research question—whether tablet users are similar to smartphone or desktop users in click-through behavior—the results suggest that, for both unbranded and branded searches, tablet users were more similar to smartphone users than they were to desktop users when the authors considered click-through behavior toward paid search advertisements.

DISCUSSION

Managerial Implications

Using daily Google AdWords data for 13 advertisers from a wide range of industries (covering more than 20 million advertising impressions in total), this study is the first one to document how click-through rates differ across desktops, tablets, and smartphones in paid search advertising. The managerial implications of the findings are multifold.

First, paid search advertisers should bear in mind that there can be significant device effects on the click-through rate; instead of a one-size-fits-all strategy, they should make device-specific adjustments to their paid search campaigns. In setting bidding

Table 4 Summary of Findings

Click-Through Rate for Top Ad	Click-Through Rate Sensitivity to Ad Position Change
Unbranded	
Tablet > smartphone > desktop	Tablet = smartphone > desktop
Branded	
Tablet > smartphone = desktop	

prices, paid search advertisers should account for significant differences in the click-through rate for the top advertisement from one device to another, or for a significant variation across devices in the decline in the click-through rate from the top to lower advertisement positions.

Second, paid search advertisers should be mindful that these device effects can differ between branded and unbranded queries. For unbranded queries, the authors found that the click-through rate for the top advertisement typically was higher on smartphones than on desktops and that the decline in the click-through rate from top to lower advertisement positions typically was greater on smartphones than on desktops. These findings suggest that paid search advertisers may consider paying a higher top-position premium on smartphones than on desktops for unbranded queries. They may not want to do so for branded queries, however, because the authors found that there was, on average, no significant difference between smartphones and desktops with respect to the click-through rate for the top advertisement for branded queries.

Third, the authors found that consumer click-through behavior on tablets was more similar to smartphones than it was to desktops. This finding suggests that paid search advertisers probably are better off grouping tablets with smartphones and treating them differently from desktops. Because the results indicate that the click-through rate for the top advertisement typically was higher on tablets than on smartphones, and because tablets still accounted for a substantial share of online searches (more than 18 percent in the current sample), the authors recommend that paid search advertisers should resist the temptation of expediency to group tablets with either smartphones or desktops. Rather, they should consider optimizing their paid search advertising campaigns for each device type (*i.e.*, smartphones versus desktops versus tablets); this has become readily doable, because Google AdWords and other paid search advertising platforms have made it increasingly easy to make device-specific adjustments in running paid search campaigns.

Finally, aside from the overall mean effects, the authors observed large heterogeneity in device effects across the 13 advertisers examined in this study. This suggests that paid search advertisers should collect their own data and conduct their own analyses to establish how consumer click-through behavior varies across devices in their specific context, and then make device-specific adjustments accordingly.

Limitations and Future Research

This study has several limitations, which the authors hope can be addressed in future research. First, the device effects that were found in the data could have been caused by

- different search advertisements on different devices,
- different users with different click-through behavior on different devices, or
- the same users with different click-through behavior on different devices.

Given the limitations of the data, these causes could not be differentiated. The device effects found in the data reflect the confluence of different underlying causes. Richer data are needed to identify the specific underlying causes for the device effects.

Second, this study showed that advertisers can predict click-through rates as a function of not only the advertisement position but also the device—a factor that to date has been neglected in the literature. The findings, however, cannot inform an approach that can maximize the return on investment (ROI) of paid search advertising. To do so, one would need information about the conversions that follow after consumers click on paid search advertisements. Because the study only had access to click-through data and not to conversion data, it could not assess the ROI or make ROI-maximizing policy recommendations. Future research can build on this study and examine how conversion behavior differs across devices, which might lead to an approach to maximize the ROI of paid search advertising. JAR

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