CLICK BEHAVIOR IN SEARCH ENGINE MARKETING

A Dissertation

Presented to

the Faculty of the C.T. Bauer College of Business

University of Houston

In Partial Fulfillment

of the Requirement for the Degree

Doctor of Philosophy

By

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July, 2017

ACKNOWLEGEMENT

I would like to give my sincere gratitude to my advisor Rex Du, for his excellent guidance on both research and life. He taught me how to become an independent researcher in all regards, from forming the research question to writing a good research paper. He also taught me a lot of life lessons and helped me plan my future career like an older brother. I would never have been able to finish my doctoral degree without his guidance.

I also would like to express my sincere appreciation to my committee members: Ye Hu, Seshadri Tirunillai and David Peng, for giving me valuable suggestions and being supportive all the time. Without their assistance, this dissertation would not have been accomplished. I also want to thank Ed Blair for his valuable comments on my dissertation and unconditional support through my graduate career.

My sincere gratitude also goes to Christopher Pappas, who provides me with unconditional support in all regards: from offering me the opportunity to work as an intern at Forthea to giving me lots of good suggestions about my research. My thanks also extend to all team members at Forthea.

Last but not least, I would like to thank my family: my dad and my mom, for everything they taught me; my husband, for his unconditional support and patience.

ABSTRACT

When a consumer uses a keyword to search for information on search engine, the page returned is search engine results page (SERP). An SERP is composed of organic section and paid section, where the paid section is on either the top or the bottom of the page and the organic section is below the top of paid section. Over the past decade, search engine has become one of the dominant advertising channels for marketers. The popularity of search engine marketing has motivated a significant amount of research on various aspects of search engine marketing (Feng, Bhargava and Pennock 2007; Edelman, Ostrovsky and Schowarz 2007; Hosanagar and Cherapanov 2008; Skiera and Nabout 2013; Animesh, Viswanathan and Agarwal 2011, Klapdor et al. 2014; Narayanan and Halyanam 2015; Jeziorski and Moorthy 2015; Haans et al. 2013; Jerath, Ma and Park 2015; Yang and Ghose 2010; Agarwak et al. 2011; Chan et al. 2011, Blake et al. 2015).

This dissertation consists of two essays, both seeking to advance our understanding of consumer click behavior on search engine results pages. The first essay aims at resolving a critical controversy about the interaction between paid and organic search results, which our empirical results show depends on the nature of the underlining search query. Specifically, a firm's paid search ad increases the searcher's tendency to click on the firm's link in the organic section for unbranded searches (the 'spillover effect'); while a firm's paid search ad decreases the searcher's tendency to click on the firm's link in the organic section for branded searches (the 'substitution effect'). The second essay examines how consumer click behavior on paid search ads differs across devices by examining their tendency to click on the top ad and sensitivity to ad position.

We find that, as compared to desktop users, a) tablet users are more likely to click on the top ad for both branded and unbranded searches; b) smartphone users are more likely to click on the top ad for unbranded searches but not for branded searches; and c) both smartphone and tablet users are more sensitive to ad position for unbranded searches.

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Essay 1

TO CLICK OR NOT TO CLICK: THE INTERACTION BETWEEN ORGANIC AND PAID SEARCH RESULTS

Introduction

Promoting products and services on search engine results pages (SERPs) has become an integral part of many firms' marketing mix. Understanding consumer click behavior on SERPs has therefore attracted a large amount of research interest in recent years (e.g., Berman and Katona 2013; Ghose and Yang 2009; Jeziorski and Segal 2015; Rutz, Bucklin, and Sonnier 2012; Narayanan and Kalyanam 2015; Yang and Ghose 2010). This study attempts to contribute to this literature by focusing on modeling consumer click behavior when a focal firm's link is shown in both the organic and the paid listings. We differ from previous studies in this area by leveraging a Google AdWords data field that has heretofore been little known to both practitioners and academics, which breaks down daily impressions, clicks and positions for each query into three distinct scenarios: (a) only paid results from the focal firm are shown ("Ad Shown Only"), (b) only organic results from the focal firm are shown ("Organic Shown Only"), (c) both organic and paid results from the focal firm are shown ("Both Shown").

Figure 1 provides an illustration of the above three scenarios. For example, in Intel's Google AdWords account, the SERP in Figure 1 would be recorded as an "Ad Shown Only" impression. For Amazon, it would be recorded as an "Organic Shown Only" impression, and for BestBuy, it would be recorded as a "Both Shown" impression. By comparing consumer click behavior under different scenarios across millions of SERPs, we attempt to quantify: (1) how a focal firm's mere presence in the paid listing affects its organic clicks; (2) how the focal firm's paid position affects its organic clicks; (3) how the focal firm's organic position affects its paid clicks.

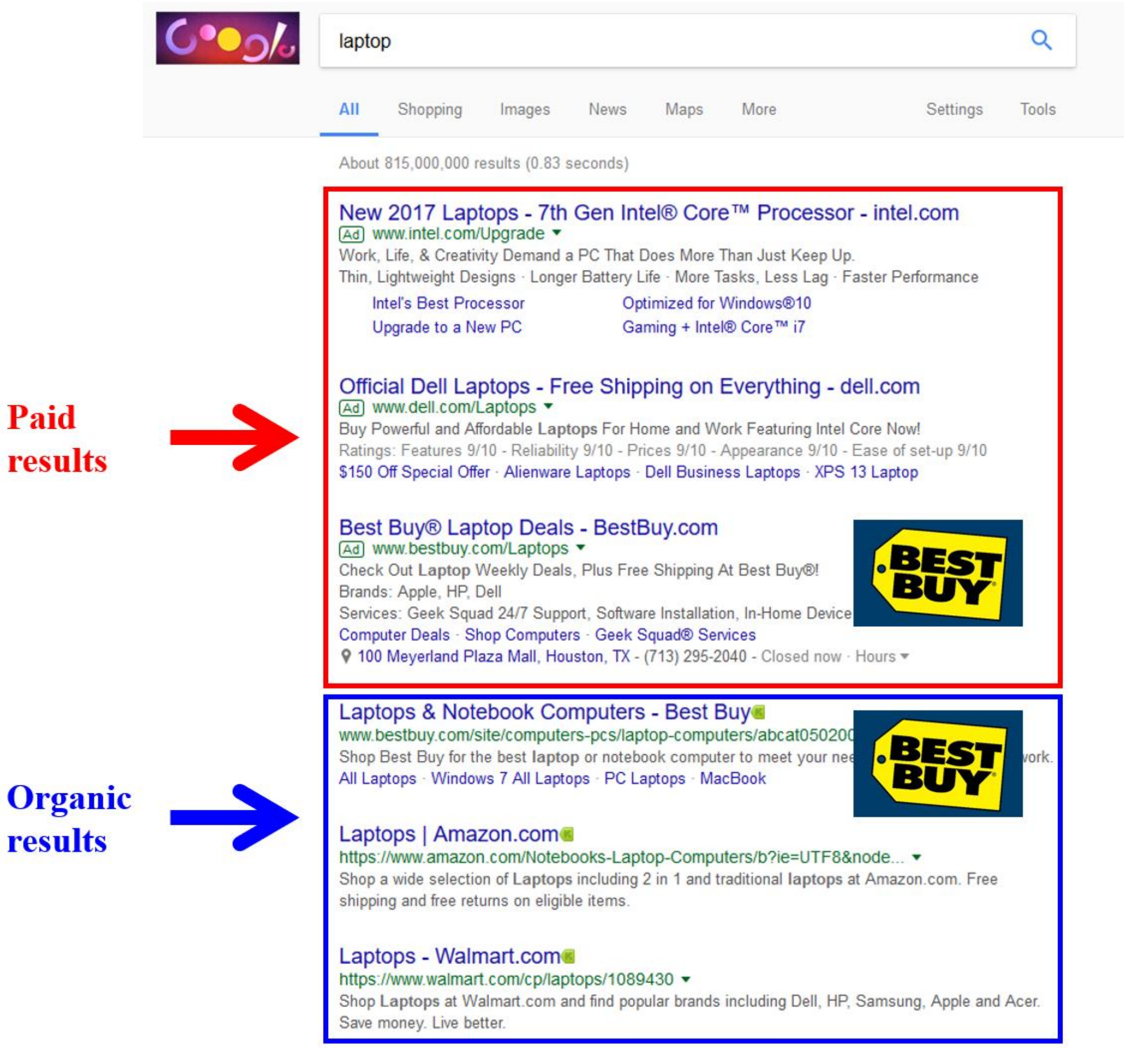

Figure 1 Search Engine Results Page (SERP)

Addressing these questions helps firms better understand the interaction between organic and paid search results, which in turn can help them better coordinate efforts in search engine optimization (SEO), which aims to improve a firm's organic positions, versus pay per click (PPC) campaigns, which aims to optimize a firm's paid positions. For example, many firms are reluctant to run PPC campaigns on queries for which their link is already well positioned in the organic listing (Chan et al. 2012), with the underlying assumption being that having another link in the paid listing would only serve as a costly substitute to the cost-free organic link, siphoning click-through traffic that would have occurred via the organic link anyway.[1]

Yang and Ghose (2010) were among the first academic researchers to examine the interaction between organic and paid search results. For the focal firm included in their study, they found that, instead of substitution, there is actually a complementary effect; that is, all else being equal, the focal firm's paid link increases a searcher's tendency to click on its organic link, and vice versa.

Following Yang and Ghose (2010), there are a few other studies that have examined the interaction between organic and paid search results and have come to a different conclusion. For example, Chan et al. (2011, 2012) and Blake, Nosko, and Tadelis (2015) found that, for the firms included in their studies, there is predominantly a substitution effect; that is, all else being equal, the focal firm's presence in the paid listing decreases a searcher's tendency to click on its organic link.

Our study is partially motivated by a desire to reconcile the seemingly contradictory findings in the literature. Could there be a contingency factor that moderates the effect of the presence of paid link on organic clicks? Our empirical results show that it depends on the nature of the search query. When the query is unbranded, the presence of paid link increases organic clicks, serving as a complement. However, when the query is branded, the presence of paid link decreases organic clicks, serving as a substitute.

Besides the effect of the presence of paid link on organic clicks, we also examine whether different positions in the paid listing can lead to different organic clicks, and

[1] http://searchengineland.com/different-types-ads-influence-organic-ctr-google-204676

whether different positions in the organic listing can lead to different paid clicks. Our empirical results show that, conditional on being present on the first SERP, the cross effects of paid and organic positions are insignificant.

In the remainder of the paper, we proceed as follows. We develop a set of empirically testable hypotheses regarding how organic and paid search results may interact with each another in influencing consumer click behavior on SERPs. We then present our statistical model, data and results. We conclude with a discussion of the managerial implications.

Hypotheses

Broadly speaking, consumer information search can fall into two basic categories: goal-directed versus exploratory (Janiszewski 1998). With goal-directed searches, consumers are focused on achieving a pre-determined, well-defined objective. When conducting such searches, consumers prioritize expediency when they navigate through the different pieces of information presented to them because they know what they are looking for and it is just a matter of locating the desired information. In contrast, with exploratory searches, consumers are more deliberate in processing the different pieces of information vying for their attention because they are still trying to determine what exactly they are looking for by examining the information they have encountered.

In the context of information search via search engines, researchers have posited that branded searches (i.e., queries that include specific brand names) are more likely to be goal-directed, while unbranded searches are more likely to be exploratory (Agarwal, Hosanagar, and Smith 2011; Ghose and Yang 2009; Jerath, Ma, and Park 2014; Rutz and Bucklin 2011). In other words, when a query contains a specific brand name, the searcher is more likely to have a clear destination in mind and the goal is to find a link to the desired webpage. As a result, we argue that with branded searches the searcher tends to focus on finding a link with the focal brand name and is likely to click on the first such link they encounter. Thus, if the focal brand's link is present in the organic listing and the searcher starts processing search results from the organic listing, it stands to reason that the presence or absence of the focal brand's link in the paid listing would have little impact on the searcher's click behavior because the searcher would click on the focal brand's link in the organic listing anyway.

However, for searchers who start processing search results from the paid listing, the presence or absence of the focal brand's link in the paid listing would make a difference. When the focal brand's link is present in the paid listing, such a searcher would be more likely to click on the paid link. Only when the focal brand's link is absent from the paid listing, such a searcher is likely to move on to the organic listing and click on the focal brand's link there. In other words, for searchers who start processing search results from the paid listing, the presence of the focal brand's link in the paid listing would serve as a more convenient alternative, siphoning click traffic that would have otherwise gone through the focal brand's link in the organic listing. Therefore, to the extent there are searchers who start processing search results in the paid listing, we hypothesize that:

H1 -- All else being equal, for branded searches, a firm's presence in the paid listing would decrease its organic click through rate.

Relative to branded searches, unbranded searches are more likely to be exploratory and involve more information-processing in order to produce a more desirable outcome (Moe 2003). Unlike branded searches, information quality, instead of expediency, plays a more important role in unbranded searches (Jansen and Resnick 2006). As a form of advertising, presence in the paid listing can send a signal of quality to the searcher (Basuroy, Desai, and Talukdar 2006; Kirmani and Rao 2000; Kirmani and Wright 1989) because higher quality advertisers can generate larger returns over time, which in turn allows them to spend more on advertising over time (Nelson 1974; Song, Jang, and Cai 2015). Thus, we argue, relative to branded searches, with unbranded searches, where searchers care more about information quality, presence in the paid listing can increase the searcher's tendency to click on the focal firm's organic link due to an enhanced quality perception of the focal firm.

Furthermore, when the searcher sees the focal firm's link twice on the same search engine results page -- once in the organic listing and the other in the paid listing -- there can be a reduction in perceived uncertainty and an increase in persuasiveness caused by message repetition (Cox and Cox 1988).

In summary, the existence of potential signaling and repetition effects and the possibility that information quality plays a more important role in unbranded searches lead us to hypothesize that:

H2 -- All else being equal, for unbranded searches, a firm's presence in the paid listing would increase its organic click through rate.

H1 and H2 deal with the effects of mere presence in the paid listing on organic clicks. A natural extension is to determine whether different positions in the paid listing can lead to different organic clicks, and whether different positions in the organic listing can lead to different paid clicks. According to the Google AdWords data we have access to, for the vast majority of branded searches, it is the rule rather than the exception that the focal brand's link takes the topmost position in the paid listing as well as the organic listing. Hence in this study we limit our attention to unbranded searches when investigating the cross effects of paid/organic positions on organic/paid clicks.

According to eye tracking studies, searchers tend to scan vertically from top to bottom on an SERP and most attention is paid to the topmost positions, for both organic and paid listings.[2] One explanation is that searchers have learned over time that results on SERPs are positioned in such a way that the higher the rank, the higher the relevance (Narayanan and Kalyanam 2015). Consequently, searchers process results from top to bottom with diminishing attention. Another explanation for such a pattern lies in that searchers have limited cognitive capacity, which gets depleted after processing each additional search result (Xu and Kim 2008). Both explanations suggest that, for unbranded searches, when a focal firm's paid position declines, the signaling and the repetition effects that a paid link may have on organic clicks would be attenuated as the paid link receives less attention from searchers. This leads us to hypothesize that:

H2a -- All else being equal, for unbranded searches, a decline in a firm's position in the paid listing would decrease its organic click through rate.

Similarly, for unbranded searches, when the focal firm's organic position declines, both the signaling and the repetition effects are likely to weaken because less attention would be paid to the focal firm's organic link as it moves down towards the bottom of the SERP, which leads us to hypothesize that:

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[2] https://moz.com/blog/eye-tracking-in-2014-how-users-view-and-interact-with-todays-google-serps

H2b -- All else being equal, for unbranded searches, a decline in a firm's position in the organic listing would decrease its paid click through rate.

In summary, we have developed testable hypotheses about the interaction between organic and paid search results. We posit that the nature of this interaction is contingent on the nature of the search. For branded searches, we hypothesized that the focal firm's paid result would serve as a substitute for its organic result. In contrast, for unbranded searches, we hypothesized a positive interaction between the focal firm's organic and paid results, and furthermore we predicted that the degree to which they serve as complements to each other would decrease when either the organic or the paid position declines. In the next section we present the statistical model and empirical strategy we shall employ to test our hypotheses.

Model

Starting August 2013 (but seemingly unbeknownst to most practitioners and academics), advertisers can request Google AdWords to track daily impressions, clicks and positions for a set of queries (e.g., those included in past PPC campaigns) and have those numbers broken down by three distinct scenarios: (a) only paid results from the focal firm are shown ("Ad Shown Only"), (b) only organic results from the focal firm are shown ("Organic Shown Only"), (c) both organic and paid results from the focal firm are shown ("Both Shown").

Let $\mathrm{NO}_{\mathrm{it}}$ denote the total number of impressions generated by searches of query i on day t where the focal firm's link is shown only in the organic listing. For $\mathrm{CO}_{\mathrm{it}}^{\mathrm{or}}$ of those "Organic Shown Only" impressions searchers clicked on the focal firm's organic link. For the remaining $\mathrm{CO}_{\mathrm{it}}^{\mathrm{none}}$ ($\stackrel{\text{def}}{=}$ $\mathrm{NO}_{\mathrm{it}} - \mathrm{CO}_{\mathrm{it}}^{\mathrm{or}}$) impressions, searchers did not click on the focal firm's link.

We assume that, under the "Organic Shown Only" scenario, the data generating process is binomial logit where,

(1) $$\mathrm{CO}_{\mathrm{it}}^{\mathrm{or}}, \mathrm{CO}_{\mathrm{it}}^{\mathrm{none}} \sim \mathrm{binomial}(\mathrm{pO}_{\mathrm{it}}^{\mathrm{or}}, \mathrm{pO}_{\mathrm{it}}^{\mathrm{none}} \,|\mathrm{NO}_{\mathrm{it}}),$$

(2) $$\mathrm{pO}_{\mathrm{it}}^{\mathrm{or}} = \frac{e^{\mathrm{uO}_{\mathrm{it}}^{\mathrm{or}}}}{1+e^{\mathrm{uO}_{\mathrm{it}}^{\mathrm{or}}}},$$

(3) $$\mathrm{pO}_{\mathrm{it}}^{\mathrm{none}} = 1 - \mathrm{pO}_{\mathrm{it}}^{\mathrm{or}}.$$

This implies a likelihood function where,

(4) $$f(\mathrm{CO}_{\mathrm{it}}^{\mathrm{or}}, \mathrm{CO}_{\mathrm{it}}^{\mathrm{none}}|\mathrm{NO}_{\mathrm{it}}) \propto (\mathrm{pO}_{\mathrm{it}}^{\mathrm{or}})^{\mathrm{CO}_{\mathrm{it}}^{\mathrm{or}}} (\mathrm{pO}_{\mathrm{it}}^{\mathrm{none}})^{\mathrm{CO}_{\mathrm{it}}^{\mathrm{none}}}.$$

We assume the latent utility from clicking on the focal firm's organic link ($\mathrm{uO}_{\mathrm{it}}^{\mathrm{or}}$) is determined as:

(5) $$\mathrm{uO}_{\mathrm{it}}^{\mathrm{or}} = \sum_{j=1}^{J} \alpha_j^{\mathrm{or}} \times (\mathrm{rO}_{\mathrm{it}}^{\mathrm{or}} = j) + \mathrm{vO}_{\mathrm{it}}^{\mathrm{or}} + \varepsilon\mathrm{O}_{\mathrm{it}}^{\mathrm{or}},$$

where $\mathrm{rO}_{\mathrm{it}}^{\mathrm{or}}$ denotes the focal firm's organic position; α_j^{or} represents the effect of organic position j on a searcher's utility from clicking on the focal firm's organic link; $\mathrm{vO}_{\mathrm{it}}^{\mathrm{or}}$ captures factors that can be correlated with $\mathrm{uO}_{\mathrm{it}}^{\mathrm{or}}$ as well as $\mathrm{rO}_{\mathrm{it}}^{\mathrm{or}}$, which we shall specify in detail later; $\varepsilon\mathrm{O}_{\mathrm{it}}^{\mathrm{or}}$ is i.i.d. Weibull.

Let $\mathrm{NB}_{\mathrm{it}}$ denote the total number of impressions generated by searches of query i on day t where the focal firm's link is shown in both the organic and the paid listing. For $\mathrm{CB}_{\mathrm{it}}^{\mathrm{or}}$ and $\mathrm{CB}_{\mathrm{it}}^{\mathrm{ad}}$ of those "Both Shown" impressions, searchers clicked on, respectively, the focal firm's link in the organic and the paid listing. For the remaining $\mathrm{CB}_{\mathrm{it}}^{\mathrm{none}}$ $\left(\stackrel{\text{def}}{=} \mathrm{NB}_{\mathrm{it}} - \mathrm{CB}_{\mathrm{it}}^{\mathrm{or}} - \mathrm{CB}_{\mathrm{it}}^{\mathrm{ad}}\right)$ impressions, searchers click on neither the organic nor the paid link of the focal firm.

Similar to the "Organic Shown Only" scenario, we assume that, under the "Both Shown" scenario, the data generating process is multinomial logit where,

(6) $$CB_{it}^{or}, CB_{it}^{ad}, CB_{it}^{none} \sim \text{multinomial}\left(pB_{it}^{or}, pB_{it}^{ad}, pB_{it}^{none} \,|NB_{it}\right),$$

(7) $$pB_{it}^{or} = \frac{e^{uB_{it}^{or}}}{1+e^{uB_{it}^{or}}+e^{uB_{it}^{ad}}},$$

(8) $$pB_{it}^{ad} = \frac{e^{uB_{it}^{ad}}}{1+e^{uB_{it}^{ad}}+e^{uB_{it}^{or}}},$$

(9) $$pB_{it}^{none} = 1 - pB_{it}^{or} - pB_{it}^{ad}.$$

This implies a likelihood function where,

(10) $$f\left(CB_{it}^{or}, CB_{it}^{ad}, CB_{it}^{none}|NB_{it}\right) \propto (pB_{it}^{or})^{CB_{it}^{or}} (pB_{it}^{ad})^{CB_{it}^{ad}} (pB_{it}^{none})^{CB_{it}^{none}}.$$

Under the "Both Shown" scenario, we assume the latent utility from clicking on the focal firm's organic link (uB_{it}^{or}) is determined as:

(11) $$uB_{it}^{or} = \sum_{j=1}^{J} \alpha_j^{or} \times (rB_{it}^{or} = j) + \alpha^{or\_ad} \times rB_{it}^{ad} + \alpha^{or} + vB_{it}^{or} + \varepsilon B_{it}^{or},$$

where α^{or} denotes the intercept; rB_{it}^{or} denotes the focal firm's organic position, and rB_{it}^{ad} its paid position; α_j^{or} and α^{or_ad} represent, respectively, the effects of organic position j and paid position on a searcher's utility from clicking on the focal firm's organic link; vB_{it}^{or} captures factors that can be correlated with uB_{it}^{or} as well as rB_{it}^{or} and rB_{it}^{ad}, which we shall specify in detail later; εB_{it}^{or} is i.i.d. Weibull.

We assume the latent utility from clicking on the focal firm's paid link (uB_{it}^{ad}) is determined as:

(12) $$uB_{it}^{ad} = \sum_{k=1}^{K} \alpha_k^{ad} \times \left(rB_{it}^{ad} = k\right) + \alpha^{ad\_or} \times rB_{it}^{or} + vB_{it}^{ad} + \varepsilon B_{it}^{ad},$$

where rB_{it}^{ad} denotes the focal firm's paid position, and rB_{it}^{or} its organic position; α_k^{ad} and α^{ad_or} represent, respectively, the effects of paid position k and organic position on a searcher's utility from clicking on the focal firm's paid link; vB_{it}^{ad} captures factors that can be correlated with uB_{it}^{ad} as well as rB_{it}^{ad} and rB_{it}^{or}, which we shall specify in detail later; εB_{it}^{ad} is i.i.d. Weibull.

Let NA_{it} denote the total number of impressions generated by searches of query i on day t where the focal firm's link is shown only in the paid listing. We exclude such impressions from our analysis. The "Ad Shown Only" scenario occurs when the focal firm runs PPC campaigns on queries for which it is not ranked organically at all (i.e., absent from not just the first SERP but all SERPs). When NA_{it} is greater than zero, it is very rare to have either NO_{it} or NB_{it} that is greater than zero as well. This is the case because during a short time window it is highly unusual for a firm's link to be both present and absent in the organic listing for searches of the same query. More important, by excluding the "Ad Shown Only" scenario we avoid drawing inferences about consumer click behavior from contrasting two circumstances (i.e., a firm is organically ranked vs. unranked) that could have drastically different underlying conditions.

In summary, we focus on modeling consumer click behavior under the "Organic Shown Only" and the "Both Shown" scenarios. The data generating processes under these two scenarios are assumed to follow, respectively, Equations 1 through 5 and Equations 6 through 12. Once we have the model calibrated, we can predict click through rates under different situations. For example, by holding everything else equal and comparing the organic click through rate under the "Organic Show Only" scenario with the organic click through rate under the "Both Shown" scenario, we can test H1 and H2. Or, under the "Both Shown" scenario, by holding everything else equal and comparing click through rates across different organic and paid positions, we can test H2a and H2b.

Endogeneity Controls

To draw causal inferences by fitting a statistical model to observational data from Google AdWords, we face a key challenge. That is, the focal firm's position in the organic listing, as well as its position in the paid listing (or the lack thereof), can be highly endogenous in the sense that a plethora of factors can be correlated simultaneously with the focal firm's organic/paid positions and organic/paid click through rates (Rutz and Trusov 2011). In Equations 5, 11 and 12, we used $\mathrm{vO}_{\mathrm{it}}^{\mathrm{or}}$, $\mathrm{vB}_{\mathrm{it}}^{\mathrm{or}}$, and $\mathrm{vB}_{\mathrm{it}}^{\mathrm{ad}}$ as placeholders for those factors, some of which may be observable to us while others may not. Conceptually, these factors can be classified into three mutually exclusive and collectively exhaustive categories: a) those that vary across queries but stay the same over time, b) those that vary over time but are the same across queries, and c) those that vary across both queries and time. In the rest of this section, we delineate our empirical strategy for dealing with these factors, as much as we can, but within reason.[3]

Query-variant and time-invariant factors. Search queries differ in many ways that can lead to different click through rates and positions on SERPs. For example, longer queries may have higher click through rates because they may be searched by consumers who have a stronger interest to begin with. Knowing that, a firm may spend more efforts on improving its organic and paid positions (e.g., through SEO and PPC) for longer queries. When that happens and yet one fails to somehow account for the positive correlation between query length and click through rates, one would overestimate the

[3] An alternative to using observational data is to use data collected through field experiments in Google AdWords. Unfortunately, although an advertiser can randomize its PPC campaign schedule, it is impossible for the advertiser to randomize its paid positions, let alone its organic positions, which are the key variables of interest in our study.

impact of positions on click through rates. Because the length of query i (length_i) is directly observable, we shall include it as a covariate in our model.

Besides length, there can be many other query-specific characteristics that can be correlated with click through rates. Although we are not privy to these characteristics, firms may know about them and have acted on them strategically, leading to different organic and paid positions for different queries. To account for such unobserved query-specific factors, we specify two query-specific random effects, $e_i^{\text{or\_query}}$ and $e_i^{\text{ad\_query}}$, which are assumed to be:

$$(13) \qquad \begin{pmatrix} e_i^{\text{or\_query}} \\ e_i^{\text{ad\_query}} \end{pmatrix} \sim N\left(0, \begin{bmatrix} \sigma_1^2 & \rho^{\text{query}}\sigma_1\sigma_2 \\ \rho^{\text{query}}\sigma_1\sigma_2 & \sigma_2^2 \end{bmatrix}\right).$$

By calibrating $e_i^{\text{or\_query}}$ and $e_i^{\text{ad\_query}}$ for query i, our model accounts for the baseline utility from clicking on the focal firm's organic and paid links during searches involving query i. In other words, by including the two query-specific random effects, we control for unobserved heterogeneity across queries in baseline click through rates. Intuitively, this means that when we draw causal inferences about the effects of the focal firm's organic/paid positions on its paid/organic click through rates, we do not rely on cross-query differences in average click through rates. We expect $e_i^{\text{or\_query}}$ and $e_i^{\text{ad\_query}}$ to be positively correlated ($\rho^{\text{query}} > 0$) as queries that have higher baseline organic click through rates should on average have higher baseline paid click through rates.

Time-variant and query-invariant factors. Different days may have different baseline click through rates. For example, click through rates on weekdays may somehow be higher than click through rates on weekends. Knowing that, a firm may run PPC campaigns only on weekdays. When that happens and yet one fails to somehow account for the positive correlation between weekdays and click through rates, one would overestimate the impact of PPC ads on organic click through rates. Because we observe whether day t is a weekday or a weekend, we include a weekend indicator ($\mathrm{weekend}_t$) as a covariate in our model.

Besides weekday versus weekend, there can be many other day-specific factors that can be correlated with click through rates. For example, during holidays or summer consumers might be more likely to click on SERPs. Knowing that, a firm could spend more on PPC campaigns during holidays or summer, resulting in spurious correlation between organic click through rates and paid positions. Or, over time, a firm may become better known among consumers and the increased awareness could result in higher organic positions and higher paid click through rates, hence a spurious correlation between organic positions and paid click through rates. Rather than including additional covariates to capture seasonality or a trend line of arbitrary functional forms in baseline click through rates, we specify two daily random effects, $e_t^{or\_day}$ and $e_t^{ad\_day}$, which are assumed to be:

$$(14) \qquad \begin{pmatrix} e_t^{or\_day} \\ e_t^{ad\_day} \end{pmatrix} \sim N\left(0, \begin{bmatrix} \theta_1^2 & \rho^{day}\theta_1\theta_2 \\ \rho^{day}\theta_1\theta_2 & \theta_2^2 \end{bmatrix}\right).$$

By calibrating $e_t^{or\_day}$ and $e_t^{ad\_day}$ for day t, our model accounts for the baseline utility from clicking on the focal firm's organic and paid links on day t. In other words, by including the two daily random effects, we control for unobserved heterogeneity across days in baseline click through rates. Intuitively, this means that when we draw causal inferences about the effects of the focal firm's organic/paid positions on its paid/organic click through rates, we do not rely on cross-day differences in average click through rates.

We expect $e_t^{or\_day}$ and $e_t^{ad\_day}$ to be positively correlated ($\rho^{day} > 0$) as days that have higher baseline organic click through rates should on average have higher baseline paid click through rates.

Query-variant and time-variant factors. Besides query-specific and day-specific factors, there would be factors that vary by query and day that could influence both the focal firm's positions and click through rates on SERPs. For example, somehow certain queries may become much less popular than the others and receive increasingly lower organic click through rates. Noticing that, the firm may run more PPC campaigns on those queries and obtain higher paid positions, resulting in spurious negative correlation between organic click through rates and paid positions.

Admittedly such factors are the most difficult to account for because there could be any number of them and they could lead to spurious positive and negative correlations. Nevertheless, we include the following covariates in an attempt to minimize such threats: a) the number of impressions generated by query i on day t; b) the number of impressions generated by query i on day t-1; c) the focal firm's SERP positions for query i on day t-1; and d) the number of clicks on the focal firm's link on SERPs for query i on day t-1.

By including the number of current impressions as a control (i.e., NO_{it} and NB_{it}), we can potentially have a proxy for daily query popularity (above and beyond the average search intensity for the query or the day, which is already captured through the query- and day-specific random effects in Equations 12 and 13. For example, anticipating that a particular query is going to be more popular than usual on a particular day, the firm may run a more aggressive PPC campaign for that query on that day, leading to spurious positive correlation between paid positions and click through rates. Another reason that the number of impressions may be correlated with click through rates is that as more consumers search for a particular query on a particular day, the marginal searchers are likely less interested in the query to begin with, thus lowering the average tendency to click, leading to negative correlation between the number of impressions and click through rates.

In addition to current impressions, we include lagged impressions (i.e., $\mathrm{NO}_{\mathrm{it}-1}$ and $\mathrm{NB}_{\mathrm{it}-1}$), lagged positions (i.e., $\mathrm{rO}^{\mathrm{or}}_{\mathrm{it}-1}$, $\mathrm{rB}^{\mathrm{or}}_{\mathrm{it}-1}$, and $\mathrm{rB}^{\mathrm{ad}}_{\mathrm{it}-1}$), and lagged clicks (i.e., $\mathrm{CO}^{\mathrm{or}}_{\mathrm{it}-1}$, $\mathrm{CB}^{\mathrm{or}}_{\mathrm{it}-1}$, and $\mathrm{CB}^{\mathrm{ad}}_{\mathrm{it}-1}$) as controls for factors that vary by query and day that could influence both the focal firm's positions and click through rates on SERPs. The reason for doing so is two-fold. First, firms may adjust their search engine marketing decisions based on historical data, which most likely include impressions, positions and clicks from the past. Second, unobserved query-variant and time-variant factors can be serially correlated due to inertia. Thus, by including the lagged variables we could arguably have good proxies for query-specific trends. To the extent there is strong serial correlation in search result positions and in click through rates, by including the lagged variables as covariates our model provides a conservative test of the hypothesized relationship between current search result positions and current click through rates.

In summary, for factors that can potentially influence consumer click behavior and may (or may not) be correlated with the focal firm's search result positions, we include three types of controls in our model: 1) query-variant and time-invariant, 2) time-variant and query-invariant, and 3) query-variant and time-variant. These endogeneity controls enter into our model through $\mathrm{vO}^{\mathrm{or}}_{\mathrm{it}}$, $\mathrm{vB}^{\mathrm{or}}_{\mathrm{it}}$, and $\mathrm{vB}^{\mathrm{ad}}_{\mathrm{it}}$, the placeholders in Equations 5, 11 and 12. Formally, we assume:

(15) $vO_{it}^{or} = vB_{it}^{or} = \beta_1^{or} \times length_i + e_i^{or\_query} + \beta_2^{or} \times weekend_t + e_t^{or\_day} + \beta_3^{or} \times \ln(NO_{it} + 1) + \beta_4^{or} \times \ln(NB_{it} + 1) + \lambda_1^{or} \times \ln(NO_{it-1} + 1) + \lambda_2^{or} \times \ln(NB_{it-1} + 1) + \lambda_3^{or} \times (NO_{it-1} > 0) + \lambda_4^{or} \times (NB_{it-1} > 0) + \lambda_5^{or} \times rO_{it-1}^{or} + \lambda_6^{or} \times rB_{it-1}^{or} + \lambda_7^{or} \times rB_{it-1}^{ad} + \lambda_8^{or} \times \ln(CO_{it-1}^{or} + 1) + \lambda_9^{or} \times \ln(CB_{it-1}^{or} + 1) + \lambda_{10}^{or} \times \ln\left(CB_{it-1}^{ad} + 1\right)$;

(16) $vB_{it}^{ad} = \beta_1^{ad} \times length_i + e_i^{ad\_query} + \beta_2^{ad} \times weekend_t + e_t^{ad\_day} + \beta_3^{ad} \times \ln(NO_{it} + 1) + \beta_4^{ad} \times \ln(NB_{it} + 1) + \lambda_1^{ad} \times \ln(NO_{it-1} + 1) + \lambda_2^{ad} \times \ln(NB_{it-1} + 1) + \lambda_3^{ad} \times (NO_{it-1} > 0) + \lambda_4^{ad} \times (NB_{it-1} > 0) + \lambda_5^{ad} \times rO_{it-1}^{or} + \lambda_6^{ad} \times rB_{it-1}^{or} + \lambda_7^{ad} \times rB_{it-1}^{ad} + \lambda_8^{ad} \times \ln(CO_{it-1}^{or} + 1) + \lambda_9^{ad} \times \ln(CB_{it-1}^{or} + 1) + \lambda_{10}^{ad} \times \ln\left(CB_{it-1}^{ad} + 1\right)$.[4]

Data

For our empirical analyses, we use Google AdWords data from two firms: a regional custom home builder (CHB) and a national technology service provider (TSP). For over two years, we have information on daily impressions, search result positions[5], and clicks on the desktop platform. Different from previous studies in the literature, our data is broken into three distinct scenarios, depending on whether the focal firm's result is shown only in the paid listing ("Ad Shown Only"), only in the organic listing ("Organic Shown Only"), or in both paid and organic listings ("Both Shown"). As discussed earlier, we exclude from our analyses data generated under the "Ad Shown Only" scenario. In addition, we apply the following two rules to screen the raw Google AdWords data.

[4] When $NO_{it-1} = 0$, $rO_{it-1}^{or} \stackrel{\text{def}}{=} 0$; when $NB_{it-1} = 0$, $rB_{it-1}^{or} \stackrel{\text{def}}{=} 0$, and $rB_{it-1}^{ad} \stackrel{\text{def}}{=} 0$.
[5] In Google AdWords, all raw daily positions are weighted daily averages. We round these daily averages to their nearest integer values.

First, we focus on top search queries that collectively accounted for 95% of each firm's total impressions during the observation window. This rule excludes queries that received relatively low search volumes (among the excluded queries, the most searched had fewer than 318 impressions over two years for the custom home builder, and fewer than 279 impressions for the technology service provider).

Second, for unbranded searches, we focus on observations where the organic position is 8 or higher, and in the "Both Shown" scenario, the paid position is 2 or higher. For branded searches, we focus on observations where the organic position is 1, and in the "Both Shown" scenario, the paid position is 1. This rule allows us to focus on observations that account for 91.4% of clicks for the custom home builder and 90.7% of clicks for the technology service provider.

Table 1 presents descriptive statistics of the data used in our empirical analyses, before and after applying the screening rules. For branded searches, very few impressions and clicks are excluded because the focal firms' paid and organic positions are predominantly 1. For unbranded searches, the large majority of impressions and clicks are retained as well.

Table 2 presents the average click through rates under "Organic Shown Only" and "Both Shown" scenarios and the proportions of data under each scenario.

Table 1 Basic Data Counts

Firm	Unbranded Queries				Branded Queries			
	Days	Obs	Impressions	Clicks	Days	Obs	Impressions	Clicks
Pre-Screen								
CHB	763	21,835	210,504	12,556	763	4,299	11,665	6,710
TSP	782	53,791	545,328	40,872	782	4,208	11,477	5,669
Post-Screen								
CHB	763	13,612	139,678	9,695	763	3,852	11,044	6,258
TSP	782	31,213	411,070	34,453	782	4,194	11,453	5,648

Table 2 Descriptive Statistics

Table 2a Branded Searches

Search Result Type	Proportion	Paid CTR	Organic CTR
Firm CHB			
Organic shown only	77%	0	.462
Both shown	23%	.346	.437
Firm TSP			
Organic shown only	67%	0	.392
Both shown	33%	.285	.398

Table 2b Unbranded Searches

Search Result Type	Proportion	Paid CTR	Organic CTR
Firm CHB			
Organic shown only	69%	0	.054
Both shown	31%	.090	.134
Firm TSP			
Organic shown only	90%	0	.100
Both shown	10%	.060	.120

Notes: Proportion shows the percent of impressions with a certain search result type.

Results

Regional Custom Home Builder

For the regional custom home builder, Table 3 presents the parameter estimates for branded searches. To quantify the cross effect of the focal firm’s presence in the paid listing on its organic CTR, we compare the predicted organic CTR under the "Organic Shown Only" scenario (i.e., pO_{it}^{or} in Equation 2) with the predicted organic CTR under the "Both Shown" scenario (i.e., pB_{it}^{or} in Equation 7). In making those predictions for query i on day t for the branded searches, the organic position is set to 1 and the paid position is set to either absent or 1, holding all the other fixed and random effects equal.

Table 3 Branded Search Parameter Estimates for Firm CHB

Variable	Parameter	Estimate	SE	t Value	P-Value
Main Effect	α_1^{or}	-.432	.122	-3.55	.000
	α^{or_ad}	.589	.115	5.14	<.0001
	α_1^{ad}	.368	.285	1.29	.196
Concurrent Controls in Organic Utility	β_1^{or}	.347	.088	3.94	<.0001
	β_2^{or}	.331	.052	6.43	<.0001
	β_3^{or}	.029	.038	.76	.449
	β_4^{or}	-.051	.066	-.77	.442
Lagged Controls in Organic Utility	λ_1^{or}	-.332	.068	-4.88	<.0001
	λ_2^{or}	-.423	.228	-1.85	.064
	λ_3^{or}	.029	.086	.33	.739
	λ_4^{or}	.155	.167	.93	.353
	λ_8^{or}	.502	.058	8.66	<.0001
	λ_9^{or}	.347	.168	2.06	.040
	λ_{10}^{or}	-.011	.162	-.07	.945
Concurrent Controls in Ad Utility	β_1^{ad}	.190	.211	.9	.366
	β_2^{ad}	.178	.203	.88	.380
	β_3^{ad}	.020	.084	.24	.811
	β_4^{ad}	-.079	.132	-.6	.548

As shown in Figure 2, under the "Both Shown" scenario, the average predicted organic CTR is .396 (the red bar), which is significantly lower ($p < .001$) than the average predicted organic CTR under the "Organic Shown Only" scenario (the blue bar), which is .478. This result is consistent with H1, which posits that a firm's presence in the paid listing decreases its organic CTR for branded searches, suggesting an interaction that is predominantly substitutional.

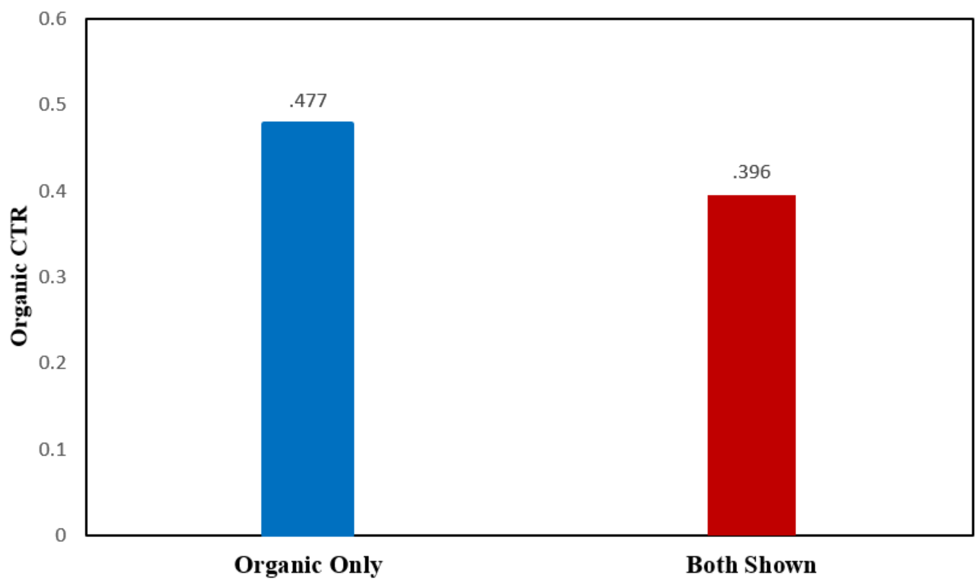

Figure 2 Branded Search Average Predicted Organic CTR for Firm CHB

Table 4 presents the parameter estimates for unbranded searches. To quantify the cross effect of the focal firm's presence in the paid listing on its organic CTR, we again compare the predicted organic CTR under the "Organic Shown Only" scenario (i.e., $\mathrm{pO}_{\mathrm{it}}^{\mathrm{or}}$ in Equation 2) with the predicted organic CTR under the "Both Shown" scenario (i.e., $\mathrm{pB}_{\mathrm{it}}^{\mathrm{or}}$ in Equation 7). In making those predictions for query i on day t for the unbranded searches, the organic position ranges from 1 to 8 and the paid position ranges from either absent or 1 to 2, holding all the other fixed and random effects equal. In total, 24 predicted organic CTRs are obtained for query i on day t under different combinations of organic and paid positions.

Table 4 Unbranded Search Parameter Estimates for Firm CHB

Variable	Parameter	Estimate	SE	t Value	P-Value
Main Effect	α_1^{or}	-1.661	.115	-14.48	<.0001
	α_2^{or}	-1.769	.110	-16.14	<.0001
	α_3^{or}	-2.089	.112	-18.65	<.0001
	α_4^{or}	-2.069	.119	-17.37	<.0001
	α_5^{or}	-2.188	.118	-18.49	<.0001
	α_6^{or}	-2.174	.120	-18.16	<.0001
	α_7^{or}	-2.336	.121	-19.36	<.0001
	α_8^{or}	-2.562	.128	-2.1	<.0001
	α^{or}	.803	.078	1.26	<.0001
	α^{or_ad}	-.032	.050	-.64	.520
	α_1^{ad}	-1.408	.286	-4.92	<.0001
	α_2^{ad}	-1.654	.288	-5.74	<.0001
	α^{ad_or}	-.003	.022	-.13	.897
Concurrent Controls in Organic Utility	β_1^{or}	-.129	.062	-2.08	.037
	β_2^{or}	-.002	.028	-.09	.932
	β_3^{or}	.153	.022	6.9	<.0001
	β_4^{or}	.009	.016	.56	.574
Lagged Controls in Organic Utility	λ_1^{or}	-.206	.027	-7.7	<.0001
	λ_2^{or}	.029	.031	.95	.345
	λ_3^{or}	-.656	.078	-8.37	<.0001
	λ_4^{or}	-.060	.063	-.95	.343
	λ_5^{or}	-.017	.010	-1.68	.093

As shown in Figure 3, the blue bars represent the average predicted organic CTRs under the “Organic Shown Only” scenario. The red and green bars represent the average predicted organic CTRs under the “Both Shown” scenario when the paid position is equal to 1 and 2, respectively. All the blue bars are significantly lower than their red and green counterparts. This result is consistent with H2, which posits that a firm's presence in the paid listing increases its organic CTR for unbranded searches, suggesting an interaction that is predominantly complimentary.

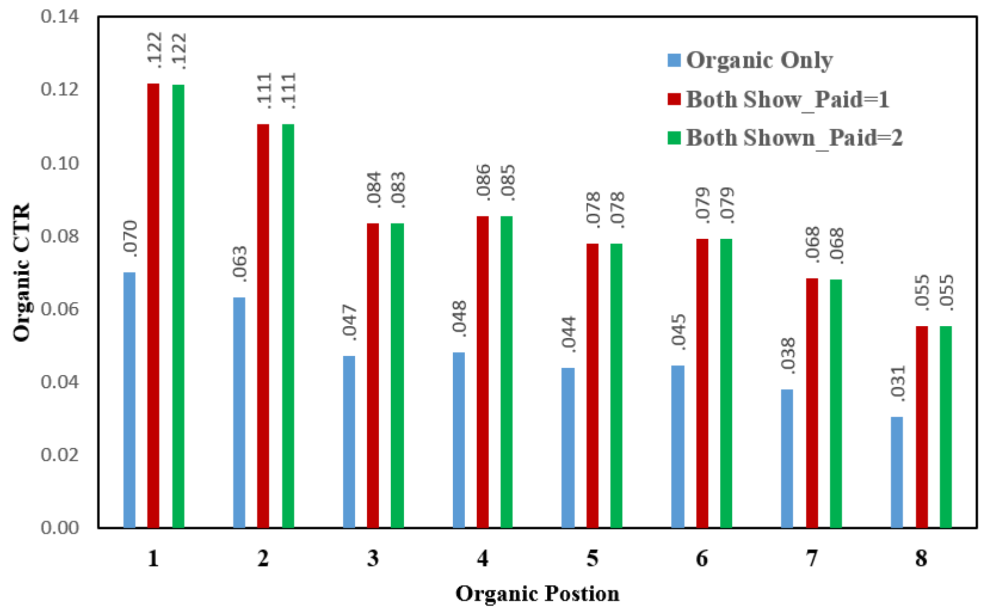

Figure 3 Unbranded Search Average Predicted Organic CTR for Firm CHB

By comparing the red and green bars in Figure 3, we can see how a change of the paid position from 1 to 2 affects the average predicted organic CTR. The differences between the red and green bars turn out to be insignificant. This result does not support H2a, which posits that, for unbranded searches, a decline in a firm's position in the paid listing would decrease its organic CTR. A potential explanation for this empirical finding is that paid positions 1 and 2 are both in general presented on the topmost section of the SERPs and thus generate a similar amount of cross effects on organic CTR via signaling and repetition.

Figure 4 shows the average predicted paid CTRs under the "Both Shown" scenario. The cluster of bars on the left represents paid CTRs when the paid position is 1, while the cluster of bars on the right represents paid CTRs when the paid position is 2. Not surprisingly, the cluster of bars on the left is significantly higher than the cluster on the right, reflecting the fact that paid CTRs are higher when paid position is 1 than when it is 2. Within each cluster, the bars represent paid CTRs for different organic positions, ranging from 1 to 8. Figure 4 shows that, within each cluster, the differences between bars are insignificant. This result does not support H2b, which posits that, for unbranded searches, a decline in a firm's position in the organic listing would decrease its paid CTR. A potential explanation for this empirical finding is that the cross effect from a firm's organic result to its paid CTR is mainly driven by the firm's mere presence in the organic listing on the first SERP, which typically contains organic positions 1 to 8. Beyond the cross effect due to presence, the specific organic position matters little in driving paid CTR.

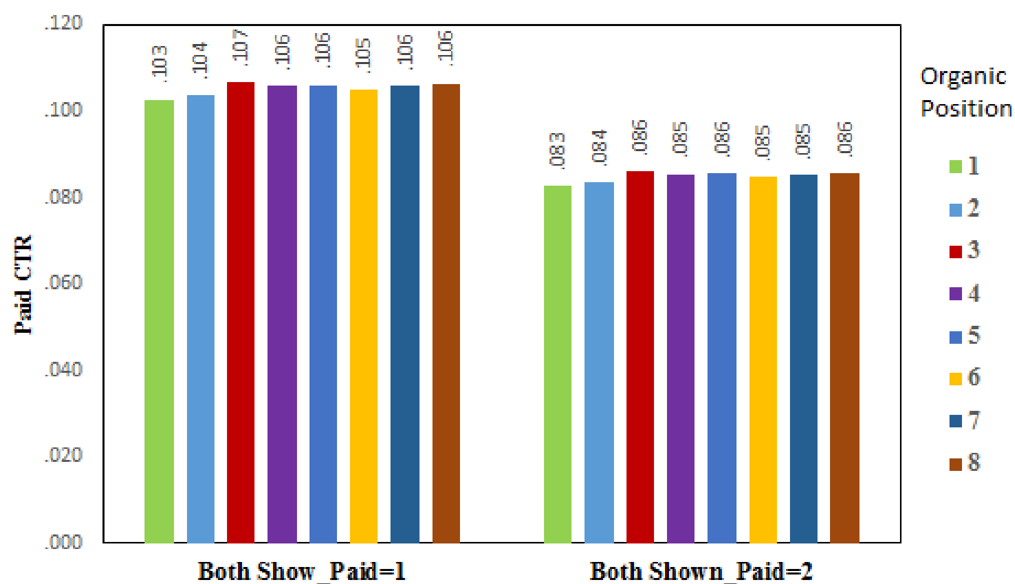

Figure 4 Unbranded Search Average Predicted Paid CTR for Firm CHB

National Technology Services Provider

For the national technology services provider, Table 5 presents the parameter estimates for branded searches. To quantify the cross effect of the focal firm's presence in the paid listing on its organic CTR, we compare the predicted organic CTR under the "Organic Shown Only" scenario (i.e., pO_{it}^{or} in Equation 2) with the predicted organic CTR under the "Both Shown" scenario (i.e., pB_{it}^{or} in Equation 7). In making those predictions for query i on day t for the branded searches, the organic position is set to 1 and the paid position is set to either absent or 1, holding all the other fixed and random effects equal.

Table 5 Branded Search Parameter Estimates for Firm TSP

Variable	Parameter	Estimate	SE	t Value	P-Value
Main Effect	α_1^{or}	-.001	.163	-.01	.995
	α^{or_ad}	.309	.108	2.87	.004
	α_1^{ad}	-.523	.386	-1.35	.176
Concurrent Controls in Organic Utility	β_1^{or}	-.228	.186	-1.23	.221
	β_2^{or}	-.187	.072	-2.61	.009
	β_3^{or}	-.113	.051	-2.19	.029
	β_4^{or}	-.009	.061	-.15	.879
Lagged Controls in Organic Utility	λ_1^{or}	-.057	.046	-1.26	.209
	λ_2^{or}	-.544	.125	-4.34	<.0001
	λ_3^{or}	-.098	.079	-1.24	.216
	λ_4^{or}	.184	.111	1.66	.097
	λ_8^{or}	.201	.053	3.79	.000
	λ_9^{or}	.546	.097	5.61	<.0001
	λ_{10}^{or}	.202	.087	2.33	.020

Table 5 (Continued) Branded Search Parameter Estimates for Firm TSP

Variable	Parameter	Estimate	SE	t Value	P-Value
Concurrent Controls in Ad Utility	β_1^{ad}	.392	.420	.93	.351
	β_2^{ad}	-.567	.172	-3.3	.001
	β_3^{ad}	.291	.134	2.18	.030
	β_4^{ad}	-.080	.094	-.85	.396
Lagged Controls in Ad Utility	λ_1^{ad}	.028	.087	.32	.746
	λ_2^{ad}	-.235	.154	-1.53	.126
	λ_3^{ad}	.211	.217	.97	.330
	λ_4^{ad}	.033	.171	.19	.848
	λ_8^{ad}	.123	.079	1.56	.118
	λ_9^{ad}	.066	.117	.56	.572
	λ_{10}^{ad}	.205	.104	1.96	.050
Random Effect	$\sigma 1$	.401	.126	3.24	.012
	$\sigma 2$	.472	.118	4.00	.004
	ρ^{query}	.928	.121	7.695	<.0001
	$\theta 1$	.408	.114	3.56	.000
	$\theta 2$	.455	.035	12.93	<.0001
	ρ^{day}	.237	.167	1.419	.156

Notes: σ_1 and σ_2 are the standard deviations of query random effect for organic and paid click utility, respectively; θ_1 and θ_2 are the standard deviations of daily random effect for organic and paid click utility, respectively; ρ^{query} and ρ^{day} are the correlation coefficients between organic and paid utility for search query and daily random effect, respectively.

As shown in Figure 5, under the “Both Shown” scenario, the average predicted organic CTR is .343 (the red bar), which is significantly lower ($p < .001$) than the average predicted organic CTR under the “Organic Shown Only” scenario (the blue bar), which is .416. This result provides support for H1, which posits that a firm’s presence in the paid listing decreases its organic CTR for branded searches, suggesting an interaction that is predominantly substitutional. This finding is consistent with what we obtained previously with the regional custom home builder (compare Figures 2 and 5).

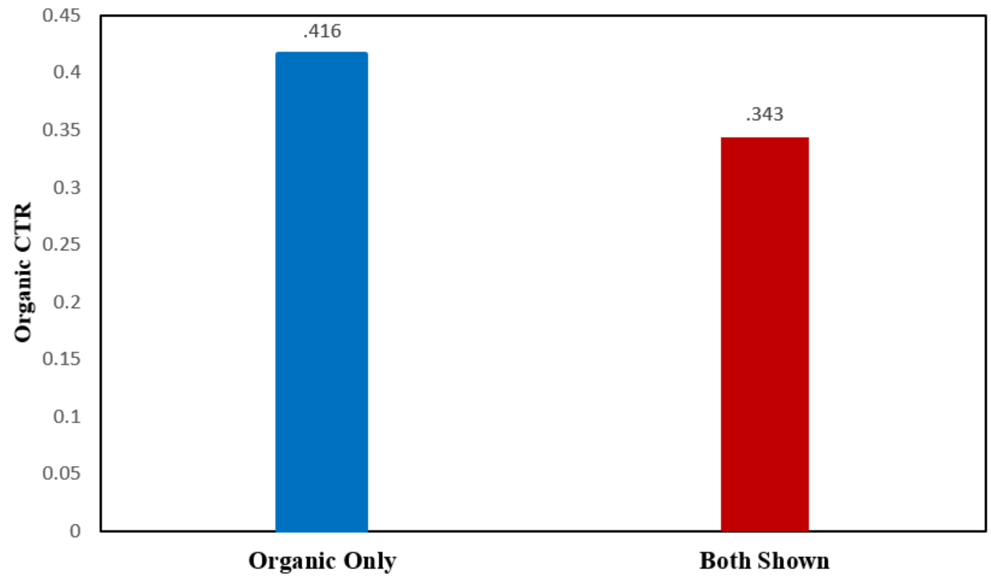

Figure 5 Branded Search Average Predicted Organic CTR for Firm TSP

Table 6 presents the parameter estimates for unbranded searches. To quantify the cross effect of the focal firm's presence in the paid listing on its organic CTR, we compare the predicted organic CTR under the "Organic Shown Only" scenario (i.e., $\mathrm{pO}_{\mathrm{it}}^{\mathrm{or}}$ in Equation 2) with the predicted organic CTR under the "Both Shown" scenario (i.e., $\mathrm{pB}_{\mathrm{it}}^{\mathrm{or}}$ in Equation 7). In making those predictions for query i on day t for the unbranded searches, the organic position ranges from 1 to 8 and the paid position ranges from either absent or 1 to 2, holding all the other fixed and random effects equal. In total, 24 predicted organic CTRs are obtained for query i on day t under different combinations of organic and paid positions.

As shown in Figure 6, the blue bars represent the average predicted organic CTRs under the "Organic Shown Only" scenario. The red and green bars represent the average predicted organic CTRs under the "Both Shown" scenario when the paid position is equal to 1 and 2, respectively. All the blue bars are significantly lower than their red and green counterparts. This result is consistent with H2, which posits that a firm's presence in the paid listing increases its organic CTR for unbranded searches, suggesting an interaction that is predominantly complimentary. This finding is consistent with what we obtained previously with the regional custom home builder (compare Figures 3 and 6).

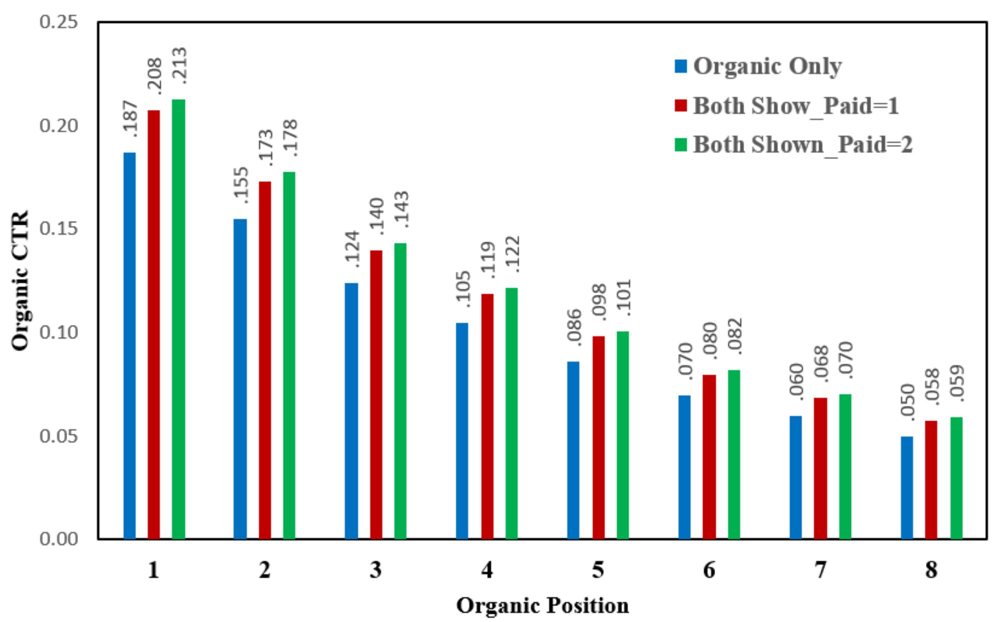

Figure 6 Unbranded Search Average Predicted Organic CTR for Firm TSP

By comparing the red and green bars in Figure 6, we can see how a change of the paid position from 1 to 2 affects the average predicted organic CTR. The differences between the red and green bars turn out to be insignificant. This result does not support H2a, which posits that, for unbranded searches, a decline in a firm's position in the paid listing would decrease its organic CTR. We note this empirical finding, although inconsistent with H2a, is consistent with what we obtained previously with the regional custom home builder (compare Figures 3 and 6). The same potential explanation applies: paid positions 1 and 2 are both in general presented on the topmost section of the SERPs and thus generate a similar amount of cross effects on organic CTR via signaling and repetition.

Finally, for the national technology services provider, Figure 7 shows the average predicted paid CTRs under the “Both Shown” scenario. The cluster of bars on the left represents paid CTRs when the paid position is 1, while the cluster of bars on the right represents paid CTRs when the paid position is 2. Not surprisingly, the cluster of bars on the left is significantly higher than the cluster on the right, reflecting the fact that paid CTRs are higher when paid position is 1 than when it is 2. Within each cluster, the bars represent paid CTRs for different organic positions, ranging from 1 to 8. Figure 7 shows that, within each cluster, the differences between bars are insignificant. This result does not support H2b, which posits that, for unbranded searches, a decline in a firm’s position in the organic listing would decrease its paid CTR. We note this empirical finding, although inconsistent with H2b, is consistent with what we obtained previously with the regional custom home builder (compare Figures 4 and 7). The same potential explanation applies: the cross effect from a firm’s organic result to its paid CTR is mainly driven by the firm’s mere presence in the organic listing on the first SERP, which typically contains organic positions 1 to 8. Beyond the cross effect due to presence, the specific organic position matters little in driving paid CTR.

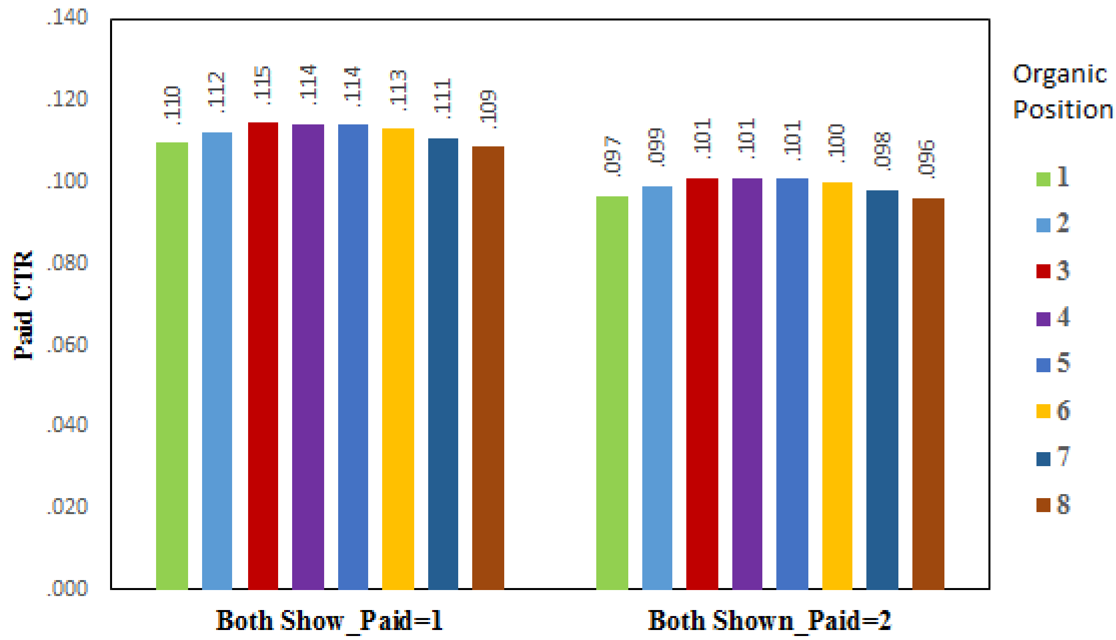

Figure 7 Unbranded Search Average Predicted Paid CTR for Firm TSP

In summary, we applied the same empirical procedure and model in analyzing data from two distinct firms: a regional custom home builder and a national technology services provider. The analysis was carried out independently for these two firms and we obtained highly consistent findings between them, which should enhance the potential generalizability of our findings. The key takeaway lies in that we find strong support for H1 and H2, which posit that a firm's presence in the paid listing can decrease its organic CTR for branded searches, while increase its organic CTR for unbranded searches, a contingency finding that is novel to the literature. Furthermore, conditional on presence in both the organic and paid listings on the first SERP, we find the cross effects between paid and organic results do not vary significantly across specific paid and organic positions.

Conclusion

The interaction between organic and paid search results – specifically, how click-through rates for organic listings are affected by the presence or absence of paid listings for the same firm/brand – has been a matter of great interest in search engine marketing. However, previous findings on this issue have been inconsistent. Some studies have found a complementary relationship between organic and paid results, such that CTRs for organic listings *increase* when paid listings appear for the same firm/brand. Other studies have found a substitute relationship, such that CTRs for organic listings *decrease* when paid listings appear.

We posit that the nature of the interaction between organic and paid listings may be moderated by the nature of the search; in particular, we posit – and find – that the effect of paid listings on organic CTRs is likely to differ between *branded* and *unbranded* searches (i.e., whether the searcher is specifically looking for the brand in question). In examining data from two distinct advertisers and by leveraging a Google Adwords data field that has heretofore been little known to both practitioners and academics, we consistently find that a firm's presence in the paid listing decreases its organic CTR for branded searches, but increases its organic CTR for unbranded searches. This finding may help to explain conflicts in the existing literature, where researchers have found either positive or negative cross effects when they did not separate branded and unbranded searches. We also examines, conditional on the focal firm being present in both the paid and the organic listings on the first SERP, whether different paid/organic positions can have different cross effects on organic/paid CTR. We have found no evidence suggesting that is the case.

Our empirical findings about the interaction between organic and paid search results can have important managerial implications, especially considering the fact that most search engine marketing efforts have been broken into two distinct sub-areas, i.e., SEO vs. PPC, where the former is charged with improving a firm’s organic positions while the latter is charged with optimizing the firm’s paid positions. In practice, SEO and PPC initiatives are more often than not carried out independently. Our finding suggests that firms should coordinate their SEO and PPC initiatives because there can be significant cross effects between paid and organic results.

For example, when it comes to setting PPC budgets for queries that have already been ranked high organically, our finding suggests that, for branded queries, it might be wise for the advertiser to spend less on PPC because its presence in the paid listing would mainly serve as a substitute to its presence in the organic listing, siphoning clicks that would have occurred anyway and for free. However, for unbranded queries, the advertiser might be better off spending more on PPC because its presence in the paid listing would generate a positive cross effect on its organic clicks, above and beyond the paid clicks that would have been generated.

Essay 2

CONSUMER CLICK BEHAVIOR ACROSS DEVICES IN PAID SEARCH ADVERTISING

Introduction

Paid search advertising, as the biggest component of the online advertising channel, accounts for 46% of the online advertising market and it is expected to reach a total market size $142.5 billion in 2021.[6] Because of the popularity of paid search advertising, a significant amount of past research has examined the effectiveness of paid search advertising, the relationship between different paid search metrics and the relationship between paid and organic search results (Ghose and Yang 2009; Rutz , Bucklin and Sonnier 2012; Agarwal, Hosanagar and Smith 2011; Narayanan and Kalyanam 2015; Jeziorski and Moorthy 2015).

These studies have, however, focused primarily on desktop users but ignored mobile users, such as smartphone and tablet users. This is surprising for three reasons. First, the desktop is no longer the primary device for conducting searches on search engine. Mobile searches have overtaken desktop searches since 2015.[7] This trend has become an increasingly important topic that has drawn much attention of practitioners.

Second, prior research has documented that mobile users tend to differ from desktop users in their observed behavior, as they make different choices and have different preferences. For example, Brasel and Gips (2014) found that consumer value items more when shopping on a mobile device because the touch interfaces on mobile devices enhance users' perceived product ownership.[8] Kannan and Li (2017) provided an overview of the research on the effect of digital environment on consumer behavior and

[6] http://www.ironpaper.com/webintel/articles/search-advertising-statistics-trends/
[7] http://searchengineland.com/its-official-google-says-more-searches-now-on-mobile-than-on-desktop-220369
[8] We would give a comprehensive overview of this set of research in the literature part

called for more research on the effect of devices on consumer behavior.

Third, the increasing share of mobile searches poses a new challenge to practitioners. Practitioners are struggling with how to integrate mobile channels into existing strategies for different devices due to a lack of theoretical understanding and empirical evidence about how the mobile channel differs from the desktop channel (Hoehel and Venkatech 2015). Although industry reports showed some preliminary findings, few academic research projects have empirically examined the effect of devices on searcher click behavior in paid search advertising.

This study contributes to the understanding of click behavior across devices in paid search advertising by investigating two major aspects of click behaviors. First, we look at the effect of the device on the tendency to click on the top advertisement. Specifically, we explore whether and how mobile users behave differently from desktop users in terms of the tendency to click on the top advertisement. Second, we look at the effect of the device on the sensitivity to ad position. Specifically, we examine whether and how the responses to changes in position differ between mobile users and desktop users. Furthermore, we separate smartphone users from tablet users and examine whether these two types of mobile device users behave differently in terms of both tendency and sensitivity. It has long been debated whether desktops rather than smartphones are more like tablets in practice.[9] By comparing click behaviors across three types of devices, this study aims to address this question.

Using a two-year data from twenty firms who paid Google for search advertising,

[9] https://blogs.adobe.com/digitalmarketing/advertising/are-tablets-mobile-devices-how-will-googles-changes-in-adwords-impact-advertisers/; http://www.adweek.com/brand-marketing/are-tablets-just-mobile-smartphones-160457/;https://seriouslysimplemarketing.com/are-tablets-considered-mobile-devices/

we conduct a meta-analysis to explore the question of interests. For each firm, we use a binary logit hierarchical model. Our meta-analysis results show that tablet users are more likely to click on the top advertisement compared to desktop users. Furthermore, smartphone users are more likely to click on the top advertisement compared to desktop users only for unbranded, but not for branded searches. With regard to sensitivity to ad position, we find that smartphone and tablet users are more sensitive to ad position compared to desktop users for unbranded searches. Additionally, we find that tablet users are more similar to smartphone users in terms of both tendency to click on the top advertisement and sensitivity to ad position.

This study contributes to the marketing literature in two ways. First, although previous research has examined the effect of the device on consumer behavior, we are among the first to study the effect of the device on click behavior in paid search advertising. Second, most previous research has compared either desktop and tablet or desktop and smartphone. However, little is known about whether tablets are more like desktops compared to smartphones. By separating smartphones from tablets, our study compares all three types of devices. To the best of our knowledge, we are the first to investigate whether tablets are more like desktops compared to smartphones.

The rest of the paper proceeds as follows. First, we discuss the related literature. Next, we describe our data and provide the basic statistics of the data. We then present the model framework, followed by the discussion of the results. In concluding the paper, we summarize our findings and discuss the managerial implications.

Literature

Numerous prior studies have investigated click behaviors in paid search advertising. Some studies looked at how to use query expansion to generate more ad clicks (Bast, Mjumdar and Weber 2007; Cao et al. 2008; Wang et al. 2009). Other studies explored the factors that can explain and predict CTR (Richardson, Dominowska and Ragno 2007; Jeziorski and Segal 2010; Wang et al. 2013; Kim et al. 2014). The majority of them investigated the rank effect. That is, how ad position affects ad CTR. The rank effect exists because browsing the search results starts from the top of the list and scrolling down requires effort (Ghose, Goldfarb and Han 2013; Zheng, Li and Pavlou 2017). Using different approaches and different data sets, these studies consistently found that the CTR is negatively associated with ad position (Ghose and Yang 2009; Agarwal et al. 2011; Rutz and Trusov 2011; Rutz, Bucklin and Sonnier 2012). Specifically, the CTR decreases as ad position increases. However, none of these studies has mentioned the device that consumers use to perform searches.

Prior research has documented how usage of different devices leads to different choices and behaviors. Relying on a data set from the largest e-commerce firm in the world, Xu et al. (2017) demonstrated that the use of tablets spurs causal browsing, which leads to the purchase of more impulse products and a wider diversity of products. Drawing on the Goal-Activation Theory and Decision System Theory, Liu and Wang (2016) proposed that desktops trigger instrumental goals and thus lead to a preference for utilitarian products, while tablets trigger experiential goals and thus lead to a preference for hedonic products. Moutsy and Dass (2014) showed that mobile users are more likely to undertake simple decision-marking tasks. Moreover, the usage of different devices affects specific behaviors. Liu, Abhishek and Li (2017) showed that mobile users are less likely to incur overdraft and credit card penalty fees as compared to the desktop users. Wang et al. (2015) found that mobile users tend to shop for habitual products that they already have a history of purchase.

Effect of Device on a Tendency to Click on the Top Advertisement

A few prior studies have illustrated the characteristics of mobile devices that differ from desktop and may influence consumer behavior. One major feature that distinguishes mobile devices from desktops is that screen sizes are smaller on mobile devices (Ghose and Han 2011; Bang et al. 2013; Xu et al. 2017). Numerous studies have shown that small screen imposes high search costs to users. Chae and Kim (2004) showed that a small screen of the mobile device creates a serious obstacle to users' navigation activities and perceptions. That is to say, the search cost associated with a smaller screen is higher than that with a larger screen. Also, Sweeney and Crestani (2006) found that the limited display capabilities require users to scroll up/down within a page and thus lead to more difficulty to find target information. In other words, the smaller screens result in more search costs.

Seiler (2013) found that search costs play a large role in explaining consumer behavior. Economic theory identifies two types of search costs that influence search behavior: external and cognitive. The external search costs indicate the costs of resources consumers invest in searches, such as monetary costs to acquire information or the opportunity costs of time during acquisitions. The cognitive search costs are the cognitive effort consumers engage in to direct search. The online search environment provides a channel for search without constrained by time and place, and thus reduces external search costs to a great extent (Chiang Kuan-Pin 2006). Therefore, in the context of online search, the search cost mainly refers to the cognitive costs. Since smaller screens are associated with more search costs, searchers are less likely to browse the web on mobile devices (Chen, Ma and Pan 2016).

Another major feature that distinguishes mobile devices from desktops is ubiquity (Shankar et al. 2010; Ghose and Han 2011; Bang et al. 2013; Jung et al. 2014). Ubiquity refers to the ability to access the Internet via mobile devices anytime and anywhere, subject to signal reception. Compared to desktops, the usage of mobile devices is more flexible. Therefore, consumers may use different devices at different locations at different points in time. Song et al. (2013) found that desktop users performed search mostly during working hours (8AM to 5PM), mobile usage peaked during evenings (6PM to 10PM). They also found that the location of usage is different between mobiles and tablets. Specifically, 79% of queries are issued at home for tablet users, whereas only 43% queries are issued at home for mobile users. Both locations of usage and time of usage may affect the tendency to click on the top advertisement.

Effect of Device on the Sensitivity to Ad Position

Ghose, Goldfarb and Han (2012) were among the first to compare sensitivity to ad position between mobile devices and desktop. Using data from a Twitter-like microblogging service, they found that rank effect is higher on mobile devices than on desktops. They pointed out that the underlying theory is also about search cost. Specifically, Brown and Goolsbee (2002) suggested that lower search cost leads to lower price effect. That is, when search cost decreases, price sensitivity decreases as well. If we apply the logic to rank effect in the paid search advertisement, we can infer that lower search costs lead to lower rank effect. Since mobile device comes with higher search cost compared to desktop, mobile users tend to have a higher rank effect than desktop users do.

However, Zheng, Li and Pavlou (2017) found that mobile users have lower rank effect using data from the largest price comparison website in Netherlands. They proposed two possible explanations for their findings. First, consumers may overcome the limitation of smaller screen size of mobile devices as they get used to using mobile devices. Second, consumers have to click a product to see some information because the information on mobile devices is often shrunk or tailored to adapt to the smaller screen.

Other Related Literature

Broadly speaking, our study is related to the literature on mobile marketing. As mobile becomes increasingly prevalent among customers, a body of research has investigated how the adoption of mobile devices affects different aspects of consumer behavior. Wang et al. (2015) found that the adoption of mobile for an Internet-based grocery retailer increases the number of orders and the amount of order in dollars. Liu, Abhishek and Li (2017) showed that the use of mobile channel influences customer demand for digital services. Xu et al. (2014) showed that the introduction of a mobile app leads to a significant increase in demand at the corresponding mobile news website.

Furthermore, Benartzi and Lehrer (2015) presented a lot of examples about how the adoption of mobile devices affects consumer behaviors. One example is that consumers with access to their financial information on mobile tend to spend less and save more. Another example is that consumers tend to order less healthy food on screen because they are less worries about what other people will think of their unhealthy order. In addition, the adoption of mobile affects the use of desktop as well. A handful of papers has focused on if the adoption of smartphone or tablet increases or decreases the use of desktop on digital commerce (Bang et al. 2013; Xu et al. 2017).

Our study is also related to the literature on consumer intent. Previous studies have shown that a consumer intention is the single best predictor of his behavior (Fishbein and Agzen 1975; Morwitzz and Schmittlein 1992). That is to say, consumers with different intents may behave differently. In the context of search marketing, a consumer's intent is inferred from the keywords this consumer is searching on. Some studies categorized search intents into three groups: navigational, informational, and transactional (Bernard and Spink 2008). However, this categorization has not been adopted quite often because of the ambiguous distinction between informational and transaction category. Instead, the marketing literature in recent years has separated branded searches from unbranded searches in analyses and it consistently found that branded searches are associated with higher click-through rate (CTR) compared to unbranded searches (Rutz and Bucklin 2011; Rutz, Bucklin and Sonnier 2012; Ghose and Yang 2009).

Data

We have Google Adwords data from twenty different firms, which ran search campaign from January 1, 2015 to December 31, 2016. These firms belonged to different industries including healthcare, technology service, and others. Some firms are nationwide; while other firms are local.

For each firm, the data includes typical information on keyword, daily number of impressions, clicks, average ad positions, maximum cost-per-click (Max_CPC) and quality score. Impressions refer to the number of times that the focal firm appears in paid listing. Max_CPC refers to the highest amount that an advertiser is willing to pay for a click on the ad. The quality score is an estimate of the quality of the ad, keyword and landing pages, ranging from 1 to 10. It is a major factor that determines ad position in the paid listing.

Different from prior research on paid search advertising, our data is broken into three distinct devices, depending on whether the focal firm's result is shown on a smartphone, or a tablet or a desktop. We apply the following three rules to screen the raw Google Adwords data.

First, we focus on keywords with "exact match" between the user query and ad. The use of exact match (instead of "broad" or "phrase" match) prevents any concerns from possible aggregation biases arising as a result of the absence of data from every single auction that occurred on a given day (Yang and Ghose 2010).

Second, we focus on observations where the position is equal or better than 3. The number of search results on top of organic search results may be different for different devices. However, there are at least three results for all devices. Therefore, this position shrinkage prevents any concerns about possible biases associated with the display variance. In fact, this position shrinkage changes the data a little because most observations have positions equal or better than 3.

Third, we focus on observations where the total number of impressions for a search query is equal to or greater than 100. This allows us to focus on queries that are of key interests to a firm.

Table 6 presents the summary statistics for some key variables across firms. Due to the privacy concern, we replace the firm name with firm ID. We sort firms by impressions, from the highest to the lowest. The total impressions across firms are over ten million. Although we have data over a two-year period, some firms ran search campaign only for a short period during our time window. Accordingly, the number of days varies by firm. With very few exceptions, an average Max_CPC per firm ranges from $3 to $7. Furthermore, the average quality score per firm ranges from 5 to 8.

Table 6 Summary Statistics

Firm ID	# of Days	Impressions	Max_CPC	Quality_Score
1	731	4297244	0.67	7.91
2	728	3306088	1.21	6.34
3	195	575938	2.34	6.52
4	687	507055	3.14	6.22
5	650	414350	3.09	6.58
6	729	322811	6.91	6.30
7	726	288002	5.56	7.24
8	727	276418	3.45	8.29
9	691	219813	6.91	4.91
10	724	205079	3.90	7.30
11	576	198512	6.94	4.77
12	726	151425	3.02	5.99
13	629	134286	10.32	6.21
14	452	114121	5.88	6.61
15	701	71211	5.13	7.96
16	700	56172	74.83	5.15
17	552	42664	8.45	6.28
18	706	26577	5.04	5.62
19	240	21979	3.98	6.71
20	567	9917	4.50	2.74

This study investigates the click behavior by devices. Figure 8 presents the model free CTR by device across positions. It shows that tablet users have the highest CTR regardless of the ad position. Smartphone users have higher CTR compared to desktop users when the ad position is 2 and 3. However, desktop users have higher CTR for the top ad position.

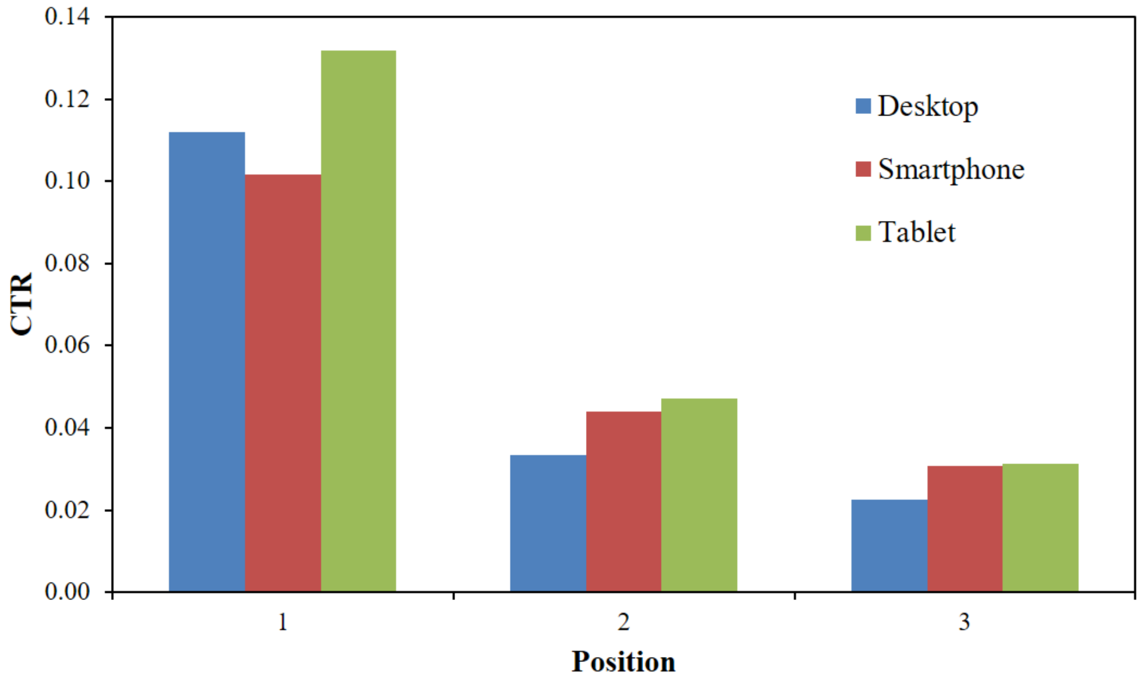

Figure 8 CTR by Device across Position

To investigate the proposed questions in depth, we categorize search queries into two groups: branded and unbranded searches. Branded searches refer to searches with a focal firm's brand name included, whereas unbranded searches refer to searches without a focal firm's brand name included. Marketing literature on search engine typically separates branded searches from unbranded searches in the analyses. Following the literature, we explore the device effect separately for branded and unbranded searches.

The average CTRs for branded and unbranded searches are 0.25 and 0.05, respectively. Table 7 shows the impressions, in percentage, by ad position and query type. Note that ad position is always 1 for branded searches.

Table 7 Percentage Impressions by Ad Position and Query Type

Position	Branded	Unbranded
1	100%	38.28%
2	0%	41.27%
3	0%	20.45%

Table 8 presents impression, in percentage, by device and query type. Overall, 17.67% of all searches are branded searches and 82.33% are unbranded searches. Concerning devices, the shares of searches conducted on desktops, smartphones, and tablets are 48.27%, 38.46% and 13.27%, respectively.

Table 8 Impression Percentage by Device and Query Type

Query Type	Desktop	Smartphone	Tablet	Total Percentage
Branded	7.58%	6.62%	3.47%	17.67%
Unbranded	40.69%	31.84%	9.80%	82.33%
Total Percentage	48.27%	38.46%	13.27%	100%

Note that tablet accounts for the smallest share of searches. For firms without too many searches, the number of tablet searches is too few too be studied. Therefore, we exclude these firms from the study of tablet users. Of all twenty firms, seven firms have only desktop and smartphone searchers.

Model

Let N denote the total number of impressions generated by searches of query i on device d on day t where the focal firm's link appears in the paid listing. From a focal firm point of view, a searcher can either click or not click its paid link. We, therefore, assume that the data generating process is binomial logit where,

(17) $$Clicks_{itd} \sim Binomial\,(P_{itd}, N),$$

(18) $$P_{itd} = \frac{e^{U_{itd}}}{1+e^{U_{itd}}}.$$

We assume that the latent utility from clicking on the focal firm's paid link (U_{itd}) is determined as:

(19) $$U_{itd} = \alpha_d^0 + \alpha_d^1 * (rank_{itd} - 1) + V_{itd} + \varepsilon_{itd},$$

where the intercept and the coefficient is a function of the device as follows:

(20) $$\alpha_d^0 = \beta_0 + \beta_1 * (d = smartphone) + \beta_2 * (d = tablet),$$

(21) $$\alpha_d^1 = \gamma_0 + \gamma_1 * (d = smartphone) + \gamma_2 * (d = tablet).$$

V_{itd} captures factors that can be correlated with both U_{itd} and $rank_{itd}$, which we shall specify in detail later; ε_{itd} is i.i.d Weibull.

We fit this hierarchical logit model to our data firm by firm. For each firm, we have parameter estimates for β_1, β_2, γ_1, γ_2, which are expressed as log odds-ratio and capture the questions of interests. With the estimated coefficients of these focal variables across firms, we conduct a systematic analysis using meta-analysis. Meta-analysis is a widely used method to summarize the results of a set of studies. The idea is to yield a weighted average from the results of the individual studies. In this context, one study corresponds to one firm.

A critical step in meta-analysis is to measure research findings on the same numerical scale, such that the resulting values can be meaningfully compared with each other (Lipsey and Wilson 2001). Since we apply the same model to different firms, we can treat the specific parameter estimate of each firm as an effect size of that firm. The mean effect size is computed by weighting each effect size (ES_i) by the inverse of its optimal variance. The formulas for calculating the mean effect size and its standard error are:

(22) $$\overline{ES} = \frac{\sum W_i * ES_i}{\sum W_i},$$

(23) $$SE_{\overline{ES}} = \sqrt{\frac{1}{\sum W_i}}.$$

Under a fixed effect model, an effect size is assumed to estimate the population effect with a random error that stems only from subject-level sampling error. The meta-analyst believes that there are essentially random differences between studies that cause variations in procedures, settings and the like that go beyond subject-level sampling error.

Under a random effect model, the optimal variance, which is observed effect size variability, includes two components: the portion attributable to subject-level sampling error and the portion attributable to between-study differences. More specifically, the effects are assumed to represent a random sample from a distribution of true effects. The model can be written as:

(24) $$ES_i = \theta_i + \varepsilon_i, \quad where\ \varepsilon_i \sim Normal\ (0, v_i).$$

(25) $$\theta_i = \mu + \delta_i, \quad where\ \delta_i \sim Normal\ (0, \tau^2).$$

Therefore, the optimal variance is:

(26) $$Var(ES_i) = \tau^2 + v_i,$$

and the weight is

(27) $$W_i = \frac{1}{\tau^2 + v_i}.$$

As an alternative method to standardized random effect model, the Bayesian hierarchical model can also estimate the population average of effect size. The model can be written as

(28) $$ES_i \sim Normal(\theta_i, S_i^2),$$

(29) $$\theta_i \sim Normal(\mu, \sigma^2),$$

where $\theta_i$is the effect size of each firm, μ is the population average of the effect size, S_i^2 is the variance of the observed effect size and is considered fixed, and σ^2 is the between firm variance. Here μ and σ^2 are parameter of interest.

For the Bayesian analysis, we need to additionally specify priors for μ and σ^2. Supposed the following noninformative priors are placed on the hyperparameters μ and σ^2:

(30) $$\mu \sim Normal\ (0, sd = 1),$$

(31) $$\sigma^2 \sim igamma(shape = 0.01, scale = 0.01).$$

Endogeneity Controls

A major challenge in modeling click behavior using observational data is how one can control for endogeneity issue. Specifically, the focal firm's paid position can be highly endogenous in the sense that a plethora of factors can be correlated simultaneously with the focal firm's paid click through rates (Rutz and Trusov 2011). In Equations 3, we used V_{itd} as placeholders for those factors, some of which may be observable to us while others may not. Conceptually, these factors can be classified into three mutually exclusive and collectively exhaustive categories: a) those that vary across queries but stay the same over time, b) those that vary over time but are the same across queries, and c) those that vary across both queries and time. In the rest of this section, we delineate our empirical strategy for dealing with these factors, as much as we can, but within reason.

Query-variant and time-invariant factors. Search queries differ in many ways that can lead to different click through rates and positions in paid listing. For example, longer queries may have a higher click through rates because they may be searched by consumers who have a stronger interest to begin with. Knowing that, a firm may spend more efforts on improving its paid positions for longer queries. When that happens and yet one fails to somehow account for the positive correlation between query length and click through rates, one would overestimate the impact of positions on click through rates. Because the length of query i (n_words_i) is directly observable, we shall include it as a covariate in our model.

Besides length, there can be many other query-specific characteristics that can be correlated with click through rates. Although we are not privy to these characteristics, firms may know about them and have acted on them strategically, leading to different paid positions for different queries. To account for such unobserved query-specific factors, we specify a query specific random effect e_i, which is assumed to be:

(32) $$e_i \sim N(0, \sigma^2).$$

Time-variant and query-invariant factors. Different days may have different baseline click through rates. For example, click through rates on weekdays may somehow be higher than click through rates on weekends. Knowing that, a firm may run paid search ad only on weekdays. When that happens and yet one fails to somehow account for the positive correlation between weekdays and click through rates, one would overestimate the impact of paid search ad on paid click through rates. Because we observe whether day t is a weekday or a weekend, we include a weekday indicator ($weekday_t$) as a covariate in our model.

Besides weekday versus weekend, there can be many other day-specific factors that can be correlated with click through rates. For example, during holidays or summer consumers might be more likely to click compared to regular days. Knowing that, a firm could spend more on paid search ad during holidays or summer, resulting in spurious correlation between click through rates and positions. Or, over time, a firm may become better known among consumers and the increased awareness could result in higher paid click through rates, hence a spurious correlation between positions and click-through rates. Rather than including additional covariates to capture seasonality or a trend line of arbitrary functional forms in baseline click through rates, we specify one daily random effect u_t, which is assumed to be:

(33) $$u_t \sim N(0, \varphi^2).$$

Query-variant and time-variant factors. Besides query-specific and day-specific factors, there would be factors that vary by query and day that could influence both the focal firm's positions and click-through rates in paid listing. For example, somehow certain queries may become much less popular than the others and receive increasingly lower paid click through rates. Noticing that, the firm may run more paid search ad on those queries and obtain higher paid positions, resulting in a spurious negative correlation between click through rates and positions. To address this concern, we include the following covariates in the model: a) the number of impressions generated by query i on device d on day t $Impressions_{itd}$; b) the maximum cost per click Max_CPC_{itd}; c) the quality score QS_{itd}; d) the number of impressions generated by query i on device d on day t-1 $Impressions_{itd-1}$; e) the focal firm's paid positions for query i on day t-1 $Position_{itd-1}$; and f) the number of clicks on the focal firm's link in paid listing for query i on device d on day t-1 $Clicks_{itd-1}$. In addition, we specify a query by date random effect v_{it}, which is assumed to be:

(34) $$v_{it} \sim N(0, \omega^2).$$

In summary, for factors that can potentially influence consumer click behavior and may (or may not) be correlated with the focal firm's search result positions, we include three types of controls in our model: 1) query-variant and time-invariant, 2) time-variant and query-invariant, and 3) query-variant and time-variant. These endogeneity controls enter into our model through V_{itd}, which is specified as follows:

(35) $$V_{itd} = \alpha^2 * \ln(Impressions_{itd}) + \alpha^3 * weekday_t + \alpha^4 * n\_words_i$$
$$+\alpha^5 * Max\_CPC_{itd} + \alpha^6 * (Max\_CPC_{itd} = 0) + \alpha^7 * QS_{itd} + \alpha^8 * (QS_{itd} = 0)$$
$$+ \alpha^9 * ln(Impressions_{itd-1}) + \alpha^{10} * ln(Clicks_{itd-1}) + \alpha^{11} * Position_{itd-1}$$
$$+ \mathrm{e}_i + u_t + v_{it}.$$

Results

As mentioned before, we conduct the meta-analysis separately for branded and unbranded searches. Figure 9 presents the parameter estimates on devices in equation 4 for unbranded searches. The figure on the left captures the difference between smartphone and desktop users in tendency. Every circle dot represents an effect size of a firm. Although the effect sizes for some firms are insignificant, most firms have significantly positive effect size. The triangle on the bottom represents the mean effect size obtained from the meta-analysis across firms. The mean effect size on the left figure is significantly positive, indicating that smartphone users are more likely to click on the top advertisement compared to desktop users for unbranded searches. The figure on the right captures the difference between tablet and desktop users in tendency. The effect sizes for all firms are significantly positive. Accordingly, the positive mean effect size suggests that tablet users are more likely to click on the top advertisement compared to desktop users for unbranded searches.

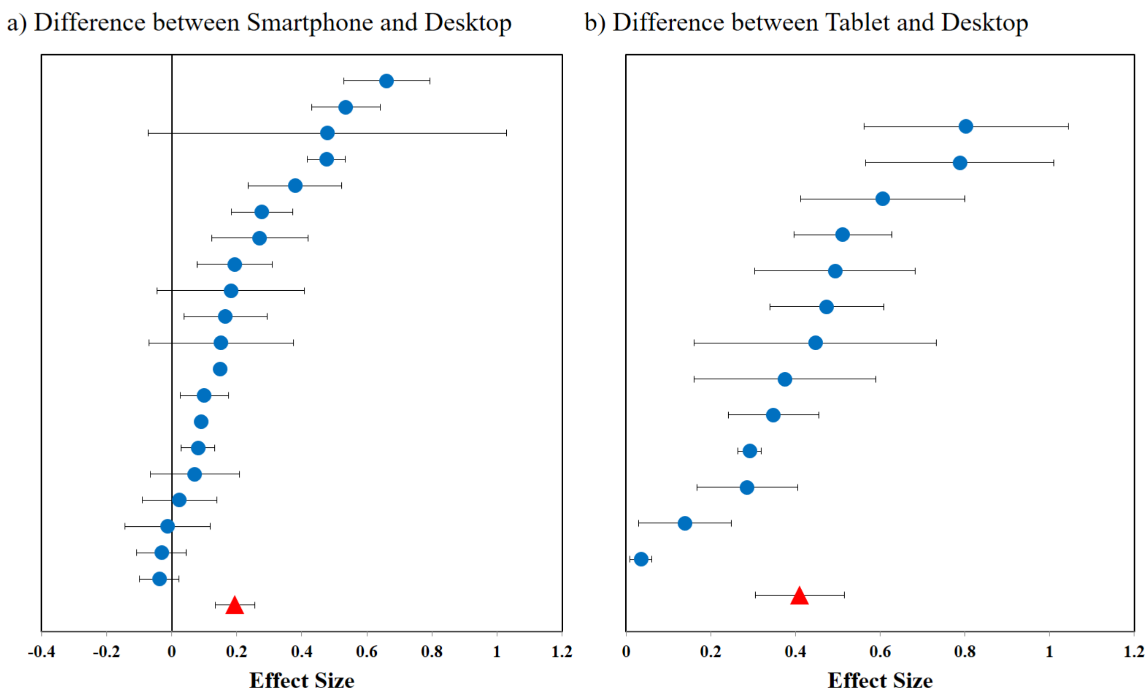

Figure 9 Meta-Analysis of Tendency for Unbranded Searches

Figure 10 presents parameter estimates on devices in equation 4 for branded searches. For some firms, the effect sizes are positive, while other firms, they are negative. Consistent with unbranded searches, the mean effect size in the right figure is significantly positive. However, the mean effect size in the left figure is insignificant, suggesting that there is no significant difference between smartphone and desktop users in the tendency to click on the top advertisement for branded searches.

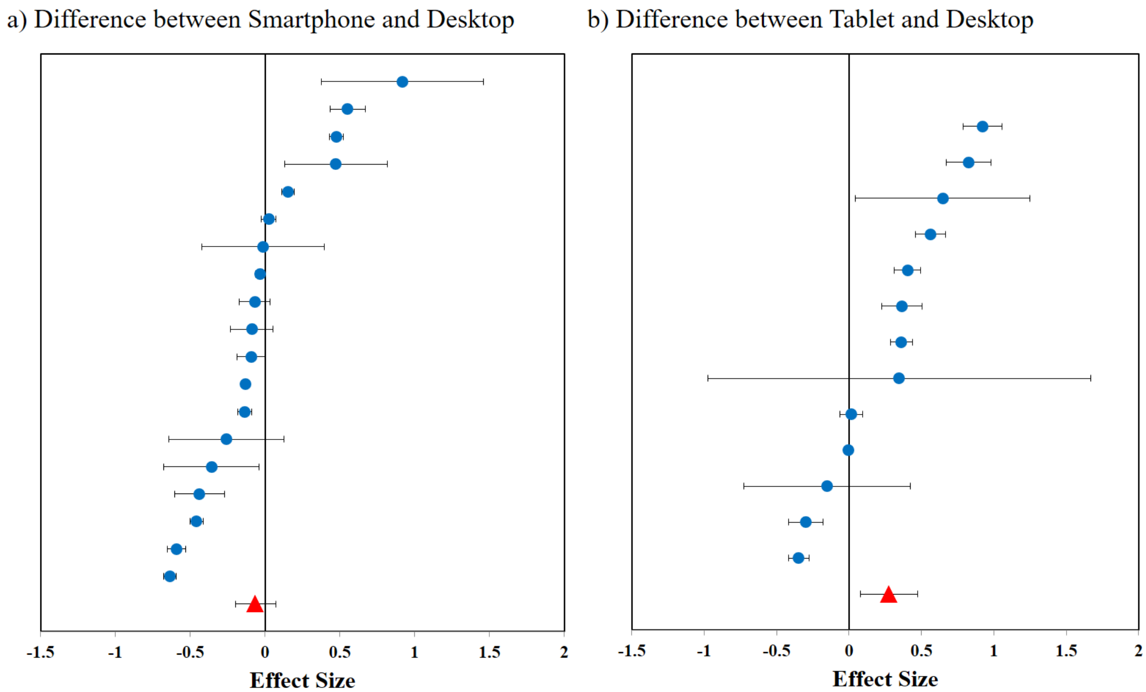

Figure 10 Meta-Analysis of Tendency for Branded Searches

Since we have the difference between smartphone and desktop and the difference between tablet and desktop, we can compare smartphone users and tablet users. Specifically, the differences between $\beta_1$and β_2 in equation 4 capture the differences between smartphone users and tablet users. Based on the parameter estimates of differences across firms, we can obtain the mean effect size of the difference using random effect meta-analysis. For unbranded searches and branded searches, the mean effect size is significantly negative. This means that smartphone users are less likely to click on the top advertisement compared to tablet users for both unbranded and branded searches.

Next, we address the question of whether tablet users are more similar to desktop or smartphone users. Two major findings emerged for unbranded searches: 1) mobile users (both smartphone and tablet) are more likely to click on the top advertisement compared to desktop users; 2) tablet users are more likely to click on the top advertisement compared to smartphone users. Therefore, we can infer that tablet users are more similar to smartphone users for unbranded searches in terms of clicking on the top advertisement. By applying the same logic to branded searches, we can infer that tablet users are more similar to smartphone users in terms of the tendency to click on the top advertisement.

Figure 11 presents the parameter estimates on devices in equation 5 for unbranded searches. The figure on the left captures the difference between smartphone and desktop users on sensitivity. The mean effect size in the left figure is significantly negative, indicating that smartphone users are more sensitivity to ad position compared to desktop users for unbranded searches. Similarly, the mean effect size in the right figure is also significantly negative. Therefore, we can infer that tablet users are more sensitive to ad position compared to desktop users for unbranded searches. Note that the mean effect sizes in the left and right figures are only slightly different from 0. That is, the differences across devices are not very significant.

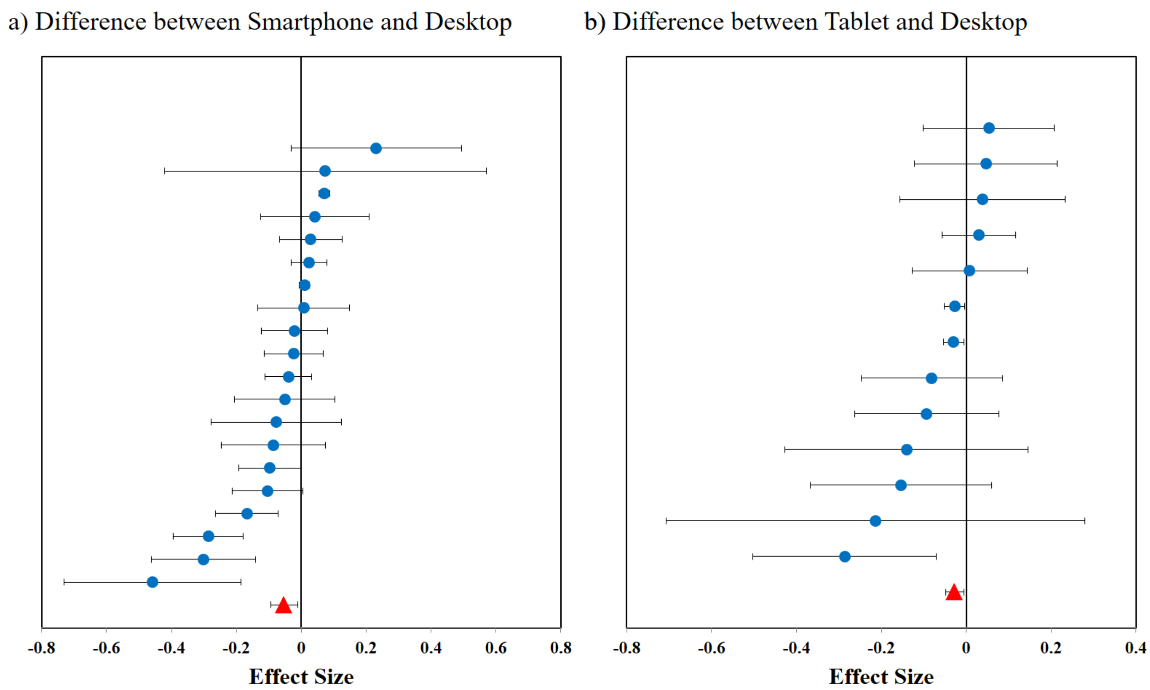

Figure 11 Meta-Analysis of Sensitivity for Unbanded Searches

Same as before, we can compare smartphone users and tablet users on the sensitivity to ad position. Based on the estimated differences across firms, we can obtain the mean effect size of the difference using random effect meta-analysis. For unbranded searches, the mean effect size is insignificantly negative. This means that there is no significant difference between smartphone and tablet users in the sensitivity to ad position.

This finding can help us understand whether tablet users are more similar to desktop or smartphone users. For unbranded searches, the previous findings showed that mobile users (both smartphone and tablet users) are more sensitive to ad position compared to desktop users. Since difference between smartphone and tablet users is insignificant, we can infer that tablet users are more similar to smartphone users for unbranded searches in terms of the sensitive to ad position.

Besides the focal parameters of interests, we have a set of parameter estimates corresponding to a set of control variables. Most of these estimates don't exhibit consistent patterns. For example, some firms have positive values while other firms have negative values for the parameter corresponding to the number of words. Not surprisingly, the rank effect exhibits a consistent pattern. That is, the CTR decreases as the ad position increases.

As mentioned before, we also use the Bayesian hierarchical model to estimate the population average of effect size. The results are consistent with the standardized random effect model. Table 9 presents the details of the effects and the corresponding standard errors across query type and different methods.

Table 9 Comparison of Meta-Analysis Results between Methods

Query Type	**Parameter**	**Standardized Random Effect**		**Bayesian Hierarchical**	
		Effect	SE	Effect	SE
Branded	β_1	-0.06	0.07	-0.06	0.09
	β_2	0.27	0.10	0.27	0.13
	$\beta_1 - \beta_2$	-0.40	0.08	-0.40	0.08
Unbranded	β_1	0.19	0.03	0.20	0.04
	β_2	0.41	0.05	0.41	0.07
	$\beta_1 - \beta_2$	-0.20	0.06	-0.20	0.07
	γ_0	-0.20	0.02	-0.20	0.02
	γ_1	-0.05	0.02	-0.06	0.03
	γ_2	-0.03	0.011	-0.04	0.03
	$\gamma_1 - \gamma_2$	0.01	0.03	0.01	0.04

Conclusion

Mobile devices have recently become the primary device for the Internet search. While it has been widely documented that mobile users tend to differ from desktop users in their observed behavior, little is known about how desktop and mobile users differ in click behavior on paid search advertising. This study contributes to the understanding of click behavior on paid search advertising across devices by investigating searchers' tendency to click on the top advertisement and their sensitivity to ad position.

Table 10 presents the summary of the findings of this study. The first column lists two types of search query. The second and third column are two major aspects of click behavior that we investigate. With regard to the click tendency, we find that tablet users are more likely to click on the top advertisement compared to desktop users for branded and unbranded searches. However, our findings suggest that smartphone users are more likely to click on the top advertisement compared to desktop users only for unbranded searches, but not for branded searches. These findings highlight the importance of separating smartphone users and tablet users in terms of the click behavior in paid search advertising. Broadly speaking, mobile users are more likely to click on the top advertisement compared to desktop users. This finding is consistent with the common belief in industry. In other words, as the first academic study on differences between devices in paid search advertising, this study confirms the conventional wisdom in industry.

Table 10 Summary of Findings

Query Type	Tendency	Sensitivity
Branded	Tablet> Desktop Smartphone ≈ Desktop	N/A
Unbranded	Tablet> Desktop Smartphone>Desktop	Tablet>Desktop Smartphone>Desktop

With regard to sensitivity, we find that smartphone and tablet users are slightly more sensitive to ad position compared to desktop users for unbranded searches. Our findings on the sensitivity to ad position provide insights into the conflicts in the existing literature, which reported either smaller or bigger rank effect for desktop users compared to mobile users. Our systematic analyses show that both smaller or bigger rank effects are possible. The meta-analysis suggests that smaller rank effect is slightly more significant compared to bigger rank effect. That is, desktop users are less sensitive to ad position than are smartphone and tablet users.

In addition to comparing mobile and desktop users, this study also shows that tablet users are more similar to smartphone users than to desktop users in terms of both tendency and sensitivity. This finding is inconsistent with the common belief in the industry, which suggests that tablets are used more like desktops rather than smartphones because tablet users and desktop users share usage location. Specifically, a Google study showed that the most popular places to use tablets are couch, bed, table, and kitchen at home. Since tablets are more similar to smartphones than to desktops in terms of screen size, we may infer that tendency and sensitivity are driven more by screen size than by usage location.

Our empirical findings about device differences in paid search advertising can have important managerial implications. Since click behaviors differ across devices, advertisers should consider different paid search strategies for different devices. In practice, advertisers tend to use the one-size fits all approach in paid search advertising, especially since they have not been able to separate tablet and desktop in Google Adwords until recently. The recent update in Adwords allows advertisers to come up with different strategies for different devices. Therefore, advertisers should take advantage of this feature to optimize their paid search advertising. For example, in terms of setting the bidding prices, advertisers would be better off if they consider different bidding prices for different devices.

Moreover, advertisers should be aware that the effect of being first is more salient for mobile users compared to desktop users, as mobile users are more likely to click on the top advertisement and more sensitive to ad position compared to desktop users. In addition, it is important for advertisers to separate branded searches from unbranded searches, as the device effects are different for different searches.

LIMITATION AND FUTURE WORK

Our study has several limitations. For the first essay, one major limitation concerns endogeneity issue. The effect of the paid ad presence is the focal interest of the first essay. However, the presence of paid ad may be a strategic decision made by firms because being present or absent is entirely under the firm's control. Although we include strong controls in our model, these controls don't address all concerns on the endogeneity issue. In our future work, we will turn to a field experiment to address this concern. We have the data from a firm which turned off the paid search ad by accident for several days due to credit card problem. This gives us the opportunity to study the effect of the paid ad presence without confounding effects from a firm's strategic decision.

Another key limitation of the first essay concerns the generalizability of the findings. Since our current empirical analysis is restricted to the data from two firms, the generalizability of the findings to other firms need to be empirically verified. To deal with this problem, we plan to collect data from many more firms and conduct a systematic analysis of the question of interest.

Besides addressing the limitations, we also plan to extend the contribution of our current study by investigating the research question across devices. Starting in 2017, our current data can be broken into three different devices: smartphone, tablet and desktop. With this new feature, we are able to examine how the interaction between organic and paid search results differs by device.

The major limitation of the second essay lies in the hidden behavior mechanism behind our empirical findings. Our empirical findings show that different device users behave differently in terms of click behaviors on SERP. This might be because searchers use different devices at different times of the day, which might lead to different behaviors, or because different searchers use different devices at different locations. Alternatively, it could be because different device usages lead to different behaviors. With our current data, we are not able to examine these possibilities. Future research could be conducted experimentally in a lab to explore the theory behind different click behaviors across devices.

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