Competition and Crowd-out for Brand Keywords in Sponsored Search

Andrey Simonov
University of Chicago (Booth)

Chris Nosko
University of Chicago (Booth)

Justin M. Rao
Microsoft Research

September 8, 2016
First draft: September 4, 2015

Abstract

On search keywords with trademarked terms, the brand owner (“focal brand”) and other relevant firms compete for consumers. For the focal brand, paid clicks have a direct substitute in the organic links below the paid ad(s). The proximity of this substitute depends on whether competing firms are bidding aggressively to siphon off traffic. We study the returns to focal brands and competitors using large-scale experiments on Bing with data from thousands of brands. When no competitors are present, we find a positive, statistically significant impact of brand ads of 1-4%, with larger brands having a smaller causal effect. In this case, the effective “cost per incremental click” is significantly higher than focal brands typically pay on other keywords. If the focal brand is not present in the top slot, competitors “steal” 18-42% of clicks on average, indicating there is a strong causal effect of position. Brand owners can eliminate almost all click stealing by occupying the top ad slot—competitors get a modest 1-5% of clicks in this case. More competitors dramatically shift focal brand’s organic traffic to the paid link, raising costs. Nonetheless, since the defense is highly effective, the ROI on defensive advertising appears to be strongly positive.

*We thank Christian Perez, Matthew Goldman, Giorgos Zervas, and the participants of 2015 QME (MIT) for helpful comments. Most of this work was completed when Simonov was an intern at Microsoft Research. All opinions represent our own and not those of our employers.
1 Introduction

In sponsored search advertising, queries that include a company’s trademarked name form a substantial portion of advertising expenditure. At first glance this practice seems sensible: consumers learn about products through a variety of channels and seek them out online using a search engine. Entering a specific brand signals product awareness and click-through rates (CTR) tend to be higher than on similar non-brand keywords. Further, since bidding on another firm’s trademarked term is legal, competing firms can step in and siphon off traffic and focal brands may want to bid aggressively to minimize “traffic stealing” (as in theoretical model of Sayedi et al. (2014)). On the other hand, there is evidence that advertising on brand keywords might be ineffective. Since the focal brand’s website is the most relevant to the query, it almost always occupies the first “organic” result, which is shown just below the paid link(s), creating the possibility that the paid link crowds-out free clicks. A recent paper, Blake, Nosko and Tadelis (2015, herein “BNT”), find almost complete crowd-out for a single, well-known brand, eBay. Using a controlled experiment, they document that when eBay stopped bidding on its own keywords 99.5% of traffic was retained via the organic link.

In this paper we aim to deepen our understanding of brand search in light of these considerations. We do so using a large-scale field experiment run on Bing. At the time of the experiment, the maximum allowable number of ads placed above the organic results on both Bing and Google was four. In the experiment, this cap was exogenously reduced to 0, 1, 2 or 3, which allows us to study user behavior in the absence of paid search advertising all together and with an exogenous cap placed on the number of ads. We focus our analysis on the 2,500 most searched brands, which provides a sample with rich variance in measures of brand capital.

Our analysis reveals that the most important consideration for the focal brand is whether or not competitors are currently bidding on its branded keywords. In BNT, eBay was not typically facing competitors on searches containing “ebay,” meaning that if eBay did not advertise, the top link on the page would be eBay’s organic link. As we will explain in detail, our estimates indicate that the causal effect of an own-brand ad differs by an order of magnitude when competitors are present as compared to when they are absent. Accordingly, we will address these two cases separately, starting with the case of no competitors.
A focal brand facing no competitors can experimentally estimate ad effectiveness by pausing ads on branded queries at random times or in random geo-locations (eBay used both strategies). Our experiments produce similar variation by randomizing at the user level. We estimate causal effects for 824 firms that consistently advertised on their own-brand queries using the experimental conditions “Cap 0” (no paid links) and “Cap 1” (one paid link). We find that the results in BNT are a bit of an outlier. In our sample of firms, sponsored links on branded search queries drive significant incremental traffic—total clicks to focal brands increase by 2-3 percentage points on average. This effect is significantly larger for lesser known brands, while the strongest brands in our sample show effects closest to that of eBay. Even for smaller firms, the incremental traffic is still relatively modest, but the “crowd-out” of free clicks tends to be quite large—the addition of a brand ad shifts nearly half of the clicks on the focal brand’s organic link(s) to the paid ad—exceeding the causal effect by more than a factor of ten.¹

We now examine what happens when competitors advertise on branded queries. While prominent firms have fought legal battles to block competitors from bidding on their branded keywords, courts have consistently upheld the legality of the practice. If one or more competitors clear the reserve price and the focal brand submits a bid as well we observe that the focal brand almost always occupies the top slot.² The competitors appear below the top ad but above the organic results. We measure the impact on the focal brand from two channels: 1) click “stealing” and 2) increasing the cannibalization of free clicks. We estimate both quantities by fixing the set of focal brands and comparing the “Cap 1” condition to “Cap 2”, “Cap 3” and the control. We find that competitors are able to steal only 1-5% of clicks, with the magnitude dependent on the number of competitors present and brand attributes. The addition of competing ads has a much larger impact on crowd-out rates. When facing no competitors (Cap 1), 60% of total clicks to the focal brand’s website are paid (the rest are free). When we randomly add in competitors, the fraction of paid clicks increases by 10% for the first competitor added, 9% for the second and 5% for the third, reaching 84% for a full slate of competitors.

The final case to consider is when competitors advertise and the focal brand does not. For a fully randomized comparison, we would need to remove focal brands while keeping

¹Focal brands in our sample always occupy the top organic slot in brand search results.
²It is exceedingly rare that a brand bids and does not occupy the top slot. This is due to the bidding behavior of focal brands the because high relevancy and CTR are rewarded by the scoring function in the generalized second price (GSP) auction.
the ads of competitors. Since the experiment always preserved the auction ranking for business considerations, we do not have such variation. Our approach is to use cases where competitors advertise and the focal brand consistently chooses not to. To control for brand strength and characteristics, we place brands in three categories based on their CTR in the no ads condition. The high CTR group matches the case of those brands that choose to advertise on their own keywords and here we find that a single competing advertiser in the top position acquires 15–20% of searchers. This large impact of ad position is consistent with the recent finding that position is more important when consumers are less familiar with the firm (Narayanan and Kalyanam, 2015) and theoretical work also predicts this pattern (Jerath et al., 2011). Interestingly, the effect size is nearly identical for the other two CTR groups. The key difference is that for the low CTR group (often corresponding to brands that are sold be licensed resellers), most of these clicks come at the expense of other firms on the results page, not the focal brand. The middle group lies between the high and low, with about half the clicks coming at the expense of the focal brand. In all scenarios, click stealing increases substantially as more competitors are exogenously added to the page, which is consistent with our first set of findings that additional competing ads lower CTR on the organic links.

It is important to note that we are not exogenously determining which focal brands advertise. Since we are controlling for baseline clickability, the brands in the set that do not advertise are equally attractive to searchers when no ads are present. Still, there could be bias based on unobservables. Since focal brands may choose not to advertise when they believe competitors ads are ineffective, we believe the most natural direction of this bias is towards zero. Since we find effects here that are an order of magnitude larger than the case when no competitors are present and that are relatively uniform across the brands we study, we are confident in the thrust of our findings.

Our final finding is that competing firms tend to be much smaller than focal brands. For the 564 firms that face competition consistently, the median Alexa website rank (across all websites for US-located visitors) for the focal brand is 8,000, whereas it is 80,000 for the top ranked competitor, 145,000 for the second and 178,000 for the third. These already-drastic differences become larger if converted to page views, since the page view distribution is “heavy tailed” (Kumar and Tomkins, 2010). This reveals that small competitors are “piggy backing” off the awareness of their much larger rivals—brands they aspire to associate with—in a form of targeting. When firms are of similar size, it is a well-known result that allowing
firms to target each other’s customers with special offers enhances competition by putting
tfirms in a prisoner’s dilemma (Thisse and Vives, 1988), which has been explicitly tied to the
context of sponsored search as well (Desai et al., 2014). Given the repeated nature of the
interaction we might expect that cooperative “live and let live” strategies could be supported
in equilibrium. Yet in practice we see that the size asymmetry greatly limits the focal brand’s
ability to punish, which helps explain the continued prevalence in the marketplace.

Putting all the pieces together, in the absence of competitors, the average focal-brand
ad causally increases total page CTR by 2.8% and shifts about half of free clicks to the paid
link. This means that for each incremental paid click, the firm must pay for about sixteen
clicks that would have been free, though this varies with brand strength. We compute “cost
per incremental click” for focal brands and find that it tends to be higher than the CPC
they pay on searches in which they do not have a high organic ranking. While this does
not show that these purchases are mistakes, for instance the value of a brand click could be
higher than on a regular query, our practical guidance to marketing managers is to carefully
consider whether the terms of this tradeoff are favorable. In the presence of competition,
our results suggest that own-brand ads play an important “defensive” role as competitors
stand to siphon off a considerable fraction of traffic if they are allowed to occupy the top
position(s) above the focal brand’s organic link(s). Increasing the number of competitors
causally raises the CTR on the focal brand’s paid link at the expense of free clicks, raising the
cost of defense. Nonetheless, because the defense is very effective, the implicit ROI versus
the counterfactual of not advertising appears to be positive, endorsing the practice of using
brand ads defensively. Finally, this defense is largely against much smaller brands that are
using the awareness of the focal brand as means to gain consideration for themselves.

2 Context and Related Literature

We define brand keywords as queries that consist of a trademarked term and where the
trademark holder occupies the top organic slot. Competitors using a trademarked term
to guide their bidding is a contentious practice. Focal brands dislike the fact that their
competitors can target a user that has expressed an explicit interest in them. Indeed these
firms may raise brand awareness with other forms of advertising with the goal of monetizing
this awareness via search (Lewis and Nguyen, 2014), and competitors entering the equation
makes this more difficult. Despite many trademark infringement lawsuits using these lines of reasoning, courts have consistently upheld the legality of showing competing ads on branded queries. However, the use of trademarked terms in a competitor’s ad text is not allowed, though an exception was granted in 2009 to licensed resellers.\(^3\) Chiou and Tucker (2012) study this change and find that it did not damage the focal brand because it made the competing resellers less distinct.

In sponsored search, advertisers pay for “consideration,” as measured by clicks, and clicks are thus the central unit of analysis in sponsored search.\(^4\) Early experimental evidence on click substitution patterns comes from Reiley et al. (2010), which showed that organic links and ads are substitutes for each other. This substitution pattern is overwhelmingly present in our experimental data as well and has also been found in structural work (Jeziorski and Segal, 2014).\(^5\) Reiley et al. (2010) further show that more ads can increase total CTR for the ad placed in the top slot because organic links act as slightly better substitutes for ads. As discussed in the introduction, Blake et al. (2015) ran a large experiment with eBay and the results of the experiments led the firm to discontinue brand search ads. In the experimental period, eBay did not face competing ads.

The next relevant strand of the literature studies how position on the page impacts user choice. Craswell et al. (2008) uses fully randomized experiments of algorithmic results (shuffling links exogenously) to show that “position effects”—the causal influence of position on the page—can be large near the top of the page. Agarwal et al. (2011) conduct a field experiment with a retailer and find a strong causal effect of position on CTR. Narayanan and Kalyanam (2015) study position effects in the ad slate with a regression discontinuity approach, which uses the fact that position is determined by a continuous “rank score.” They find position effects can be quite large, especially at the top of the page, but vary considerably depending on a user’s experience with the focal brand, are smaller for the focal brand than competitors and stronger when the advertiser is smaller. Granka et al. (2004) presents eye-tracking evidence that most users use a “top-down cascade” approach to searching the page. Later work has shown that search is more complex than simple top-down traversals but an

\(^3\)For example, while travel website Expedia is free to bid on “priceline,” it cannot include, for example, “better than priceline” in their ad text.

\(^4\)Our study uses focuses on clicks. Past work has consistently linked clicks to conversions, though conversion rate may vary by position on the page (Rutz and Bucklin, 2011; Agarwal et al., 2011; Goldman and Rao, 2014).

\(^5\)One paper, Yang and Ghose (2010), sharply diverges from this result. Using a structural model, they assert that there is a positive interdependence between organic ranking and search click-through rate.
overall top-down pattern still predominates (Dupret and Piwowarski, 2008).

The final relevant piece of the literature models bidding in sponsored search. Desai et al. (2014) model interactions between competitors on brand keywords and discuss the prisoner’s dilemma nature of the interaction. Yang et al. (2013) model auction entry and show that increased competition tends to hurt incumbent advertisers but help the search platform. Jerath et al. (2011) present a related theoretical model where there are low- and high-quality firms and show that inferior firms have a greater incentive, all else equal, to locate at the top of the page yet the superior firms may get more clicks even though they occupy lower positions. In our setting this occurs when the brand’s organic link still gets the majority of clicks when rival ads above it.6

3 Empirical Setting

In this section we describe our informal model and provide details of the experiments, data and estimation.

3.1 An Informal Model

Drawing on past work in marketing and economics, we present a stylized model of brand search to ground our investigation. We posit that consumers engage in search to achieve an end objective, such as buying a good that serves a particular function. In our study we observe two key steps in this process: 1) Searching a branded term signals awareness of the focal brand and intention to find the brand online; 2) Clicking a link involves consideration. Awareness does not imply consideration, a consumer can choose to visit a competing brand or opt to not consider any of the firms. Since competing firms may be able to satisfy a user’s end objective, they have an incentive to intercept consumers with links in the search results. Indeed this seems like it would be a useful form of targeting for lesser-known products that have similar functionality. The main way to do this is by bidding on paid links for keywords containing branded terms since they are unlikely to have sufficient relevance to branded

6We do not, however, observe brands occupying the lower advertising slots. The context of brand search is somewhat different than generic product search, so we would not expect all the predictions to be borne out.
queries to appear high in the organic results.

We assume consumer \( i \) examines the first \( N_i \) links on the page and choose the one with highest expected utilities, where \( N_i \) can differ by consumers. This model of search is consistent with past work using eye-tracking (Granka et al., 2004; Dupret and Piwowarski, 2008) and papers studying the causal influence of position on the page (Craswell et al., 2008; Narayanan and Kalyanam, 2015). Incomplete search provides an additional incentive for firms to use paid listings because it allows their link to enter the awareness sets of more searchers and face a smaller number of competing alternatives in expectation. Further, the model suggests that if competitors are able to get clicks when the focal brand occupies the top ad slot, then at least some consumers opted to consider them despite their initial awareness of the focal brand. Position effects derive from incomplete search—the fewer links users consider, the higher returns from “defensive positions” at the top of the page. In the absence of competing firms, a focal brand ad can impact choices by shifting the organic results of competitors down the page and through any additional information that increases the chance of gaining consideration.

3.2 Experiment Description

The data in our study come from a series of randomized experiments on the Bing search engine. On Bing, the sponsored listings that appear at the top of the page, above the organic listings, are known as the “mainline.” A maximum of four mainline ads are shown on a given query, the same practice employed by Google. Absent experimentation, the number of ads and their composition is endogenously determined by firms’ bids, the reserve price and the hard cap at four. A cross-sectional regression that looked at differences in the number of advertisements by keyword would conflate true effectiveness of advertisements with differing environments across keywords. We use the experimental variation to control for these confounding factors.

The experiments were conducted on a small fraction of U.S.-located users over nine days in January of 2014 with randomization at the user level. Four experiments took place, in which the maximum number of mainline ads was limited to 0, 1, 2, and 3. Each experiment had a balanced control group, which corresponded to the maximum of 4 mainline ads, the typical production setting. This is standard practice in online experimentation, as it provides
a check that each experimental “line” was executed correctly.

The treatment limited the number of ads that could be shown, but often this cap did not bind. For instance, in the treatment group that limited mainline ads to a maximum of 3 (“Cap 3” to employ the terminology we will use throughout), if there were not enough bidders that met the reserve price to fill the 3 slots, then fewer than 3 ads were shown. We carefully control for this issue by selecting only queries that matched into bidding data where an ad would have been shown in the absence of the experiment. See the Appendix A for more details on this process.

3.3 Data Description

To identify brands, we extracted 87,000 retailer and brand names from the Open Directory Project. A search is characterized as a brand query if and only if (1) the query is on this list, meaning it is a verified firm brand, and (2) the query matches the domain name in the first organic position. We focus only on brands that are in the first organic link because this selects true brand queries. Queries that for brands that are not in the first organic position might be searches of a different nature, perhaps not meant to get directly to the brand page, but to a broader set of sites. Figure 1 provides an example of a brand query. Queries are simplified using standard techniques, e.g. we treat “Macy’s,” “macys.com,” “macys,” and “macy’s” as the same query. We focus on searches with 0 or 1 clicks on the page, ignoring rare instances of 2 or more clicks.

Table 1 gives the number of brands binned by the number of observations for those brands in all control conditions combined. 64.7% of all brands in the control group have less than 10 exposures but represent only 0.19% of all traffic, whereas 96% of traffic comes from the 1045 brands that have 1000 or more exposures. We keep the 2517 companies with over 350 exposures, which cover 98.7% of market activity. Out of the selected 2517 companies, 824 of companies advertise on their own brand keywords more than 90% of the time. In estimating

--

7 dmoz.org, the project uses volunteer annotators to “classify the web.”

8 In these occurrences, the searcher often visits all advertisers, making it less interesting to study. Further, search engines often refund clicks from such patterns.

9 With this selection rule we are balancing the number of firms against the inclusion of brands that don’t provide meaningful information because they are so small. We have done substantial robustness around this threshold and the results are not materially impacted.
This example has two mainline ads: own brand ad in mainline 1 and competitor’s ad in mainline 2.
the direct returns to brand search advertising we focus on these 824 brands. More detailed information on all the firms is given in the Appendix A, Figure 9.

Table 1: Ad coverage in the control condition

<table>
<thead>
<tr>
<th>Number of exposures in Control</th>
<th>Number of brands in Control</th>
<th>Percentage of brands (%)</th>
<th>Percentage of traffic (%)</th>
<th>Percentage of own ads in ML1 (%)</th>
<th>Percentage of competitor’s ads in ML1 (%)</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>4869</td>
<td>23.1</td>
<td>0.02</td>
<td>3</td>
<td>30.6</td>
</tr>
<tr>
<td>2</td>
<td>2773</td>
<td>13.1</td>
<td>0.02</td>
<td>4.1</td>
<td>32.4</td>
</tr>
<tr>
<td>3</td>
<td>1686</td>
<td>8</td>
<td>0.02</td>
<td>6.3</td>
<td>30.8</td>
</tr>
<tr>
<td>4 - 10</td>
<td>4315</td>
<td>20.5</td>
<td>0.12</td>
<td>10.2</td>
<td>34.5</td>
</tr>
<tr>
<td>11 - 100</td>
<td>4200</td>
<td>19.9</td>
<td>0.64</td>
<td>19.8</td>
<td>34.6</td>
</tr>
<tr>
<td>101 - 1000</td>
<td>2202</td>
<td>10.4</td>
<td>3.6</td>
<td>42.64</td>
<td>28.5</td>
</tr>
<tr>
<td>&gt; 1000</td>
<td>1045</td>
<td>5</td>
<td>95.6</td>
<td>43.8</td>
<td>13.6</td>
</tr>
<tr>
<td>Total</td>
<td>21090</td>
<td>100</td>
<td>100</td>
<td>14.4</td>
<td>31.4</td>
</tr>
</tbody>
</table>

Percentage of ads is computed across companies. For example, companies with 4 exposures and companies with 10 exposures are given the same weight in group 4-10. Total frequency is also computed across companies, unweighted.

3.4 Estimation

For each brand \( j \), we observe a number of brand searchers in each experimental condition \( c, N_{jc} \). For each search, among other things we observe the URLs of organic links shown on the page, URLs of paid links shown, and click decisions of consumers. We classify the URLs as belonging to the focal brand if it matches the brand name and belonging to competitors otherwise. We estimate the probability of clicking on a focal brand’s link across experimental conditions using a simple frequency estimator:

\[
\hat{Pr}(\text{click } j \text{ in } c) = \frac{1}{N_{jc}} \sum_{i} I(i \text{ clicks } j \text{ in } c)
\]

where \( I(i \text{ clicks } j \text{ in } c) \) follows a Bernoulli distribution. The estimator has expectation of \( p_{jc} \) and the variance of \( \frac{p_{jc}(1-p_{jc})}{N_{jc}} \), where \( p_{jc} \) is the true probability of a click. Similarly, we estimate the probability of clicking on competing firms, \( j' \), after searching for brand \( j \) in the experimental condition \( c \) as \( \hat{Pr}(\text{click } j' \text{ in } c) \).

We compute \( \hat{Pr}(\text{click } j \text{ in } c) \) for each combination of brand \( j \) and experimental condition.
Experimental conditions were balanced to compare treatment and control groups. In the results section, we compare treatment conditions to each other, e.g., comparing Cap 0 to Cap 1 allows to isolate the effect of own brand advertising in the absence of competitors in positions 2, 3 and 4. To make sure different conditions can be compared without bias, we check that the associated control conditions do not differ from each other. Appendix B presents the click probability estimates for the focal brands/competitors organic/paid web links, along with the 95% confidence intervals around these estimates. We do not find any statistically significant differences in these comparisons.

4 Results

In this section we separate our analysis by competitive scenario, starting with the case of no competitors present, moving to the case where a focal brand and competitors are present, and then the case where only competitors are present. We then present data on costs in order to infer ROI and close by examining competitor attributes.

4.1 Ad Effect without Competitors Present

We examine the effectiveness of advertising in the absence of competing firms by comparing focal brand click probabilities in the Cap 0 and Cap 1 conditions. This corresponds to the probability that an individual arrives at the website of the searched brand. Subfigure (a) in Figure 2 plots the average estimate of these probabilities across 824 firms, as well as the corresponding 95% confidence interval. The figure shows that advertising on one’s own keyword drives an incremental 2.27 percentage points of traffic. This estimate is overwhelmingly statistically significant, but note that the y-axis is “zoomed in.”

Subfigure (b) shows the traffic to the focal brands’ website by link type. In Cap 0, all traffic navigates to the focal brand’s website through the organic links. In Cap 1, about half of the traffic goes through the paid ad on top of the page, reflecting “cannibalization” or “crowd-out.” In Appendix E, we show that most of this traffic would have gone through the first organic result, but we document statistically significant crowd-out for the first six slots (the focal brand often occupies many of the organic results), with the effect size declining.
Figure 2: The Effect of Advertising on One’s Own Keyword

(a) Incremental Effect
(b) Effect by Paid/Organic Traffic

The error bars give +/- two standard errors.

with position, which is the prediction of our informal model. The difference in the overall bar height represents incremental clicks, which shows that while there is a causal effect of the focal brand’s ad, the majority of paid clicks are those that were crowded-out from the organic channel.

We now examine if ad effectiveness differs across brands. We focus our analysis on a sub-sample of 493 brands which have a sufficient amount of traffic for reliable brand-specific estimates. Figure 3 shows a histogram of the brand-specific estimates with an overlaid normal density calibrated to the data. The empirical distribution has heavier tails than the normal density and we formally test and readily reject the hypothesis that the observed heterogeneity is driven by sampling variation alone.

We decompose this heterogeneity using brand prominence, which we proxy for with the

---

10 We keep companies with more than 80 exposures in each condition. Results are not sensitive to the choice of the threshold.

11 We perform a series of standard tests for normality, including Shapiro-Wilk, Jarque-Bera, DÁgostino and other tests. All of them reject normality of the distribution. Figure 14 in the Appendix shows the empirical CDF of brand-specific estimates and further confirms these tests.
Figure 3: The Distribution of Brand-Specific Heterogeneity

![Graph showing the distribution of effect on probability to get a click.](image)

Blue line corresponds to the implied normal density

website ranking among US-located users from Alexa.com, a widely used website ranking service. We also considered log global rank, “bounce rate” (the probability of a visit less than 30 seconds), the fraction of traffic from search engines, pages viewed per day and time spent per day, which are summarized in Table 6 in Appendix C. Specification (1) in Table 2 regresses the advertising causal effect estimate on log US rank. Brands with a higher ranking (closer to 1) tend to have a smaller advertising effect. On average, the regression predicts the ad effect for a very well-known company is 2 percentage points lower than for the median company in our sample, meaning we would predict a near-zero effect for such firms.

We now examine the mechanism behind this effect. More prominent brands could gain less from advertising on brand search because they have higher brand loyalty/knowledge or because they already occupy more space on the page (competitors have a lower position because the brand has richer organic results). Specification (2) examines if the effectiveness of advertising is correlated with the number of organic links for the focal brand. We do not find a statistically significant relationship. Specification (3) examines the correlation between the effectiveness of advertising and the space occupied by top organic result on the page. This space is measured by the number of “deep links” (sub-links below the first organic results) and “detail cards” (detailed informational panels including things like maps
Table 2: Relationship between brand capital and advertisement effectiveness

<table>
<thead>
<tr>
<th></th>
<th>(1)</th>
<th>(2)</th>
<th>(3)</th>
<th>(4)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Dependent variable</td>
<td>Effect of focal brands ad</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>log(us)</td>
<td>0.004**</td>
<td>0.004***</td>
<td>0.002</td>
<td>0.002</td>
</tr>
<tr>
<td></td>
<td>(0.001)</td>
<td>(0.001)</td>
<td>(0.001)</td>
<td>(0.001)</td>
</tr>
<tr>
<td>Number of own organic links</td>
<td>0.001</td>
<td></td>
<td>-0.001</td>
<td></td>
</tr>
<tr>
<td></td>
<td>(0.002)</td>
<td></td>
<td>(0.002)</td>
<td></td>
</tr>
<tr>
<td>Deeplinks</td>
<td></td>
<td>-0.002</td>
<td>-0.002</td>
<td></td>
</tr>
<tr>
<td></td>
<td></td>
<td>(0.001)</td>
<td>(0.001)</td>
<td></td>
</tr>
<tr>
<td>Dcard</td>
<td></td>
<td>-0.002***</td>
<td>-0.002***</td>
<td></td>
</tr>
<tr>
<td></td>
<td></td>
<td>(0.0005)</td>
<td>(0.0005)</td>
<td></td>
</tr>
<tr>
<td>Observations</td>
<td>493</td>
<td>493</td>
<td>493</td>
<td>493</td>
</tr>
<tr>
<td>R²</td>
<td>0.013</td>
<td>0.014</td>
<td>0.062</td>
<td>0.063</td>
</tr>
<tr>
<td>Adjusted R²</td>
<td>0.011</td>
<td>0.010</td>
<td>0.057</td>
<td>0.055</td>
</tr>
</tbody>
</table>

Note: *p<0.1; **p<0.05; ***p<0.01

Brands with detail cards have a significantly lower advertising effect. The coefficient on log US rank becomes insignificant in this specification, suggesting that the mechanism behind the higher effectiveness for smaller brands is the size and nature of the content of the first organic result. Specification (4) includes all measures of how much space the focal brand’s results occupy on the page and confirm the importance of top result. Indeed, 99% of organic traffic going to the focal brands website navigates through the top organic link on the page. Still, there is a small fraction of consumers who decide to scroll down the page and navigate to the focal brand’s website through links at the lower positions.

4.2 The Role of Competitors in Positions 2-4

We now shift our focus to the case when one or more competitors clears the auction’s reserve price while the focal brand still occupies the top slot. In this case, the role of focal brand’s ad is defensive: in the absence of the ad, competitors would occupy top paid position on the page and ratings). Appendix D provides a more detailed description and example of deeplinks and dcards.

It is exceedingly rare for the focal brand to occupy slots 2–4. Auction data reveal that if they choose to bid, they win the auction easily.
For the 824 companies analyzed above, 564 face 3 competitors advertising in positions 2-4 at least once in all experimental conditions. For these companies, we can compare the traffic to the focal brand’s website without any competing firms present in the paid links (Cap 1) to the case with one competing firm (Cap 2), two competing firms (Cap 3) and three competing firms (Controls) present. We use the bidding data to keep only the cases when competing firms would have advertised in the absence of the experiment.

Figure 4 (a) displays the impact of competing firms in positions 2–4 on overall traffic for the focal brand. The first point displays the probability of navigating to the brand’s website when only the brand ad is present. The second through fourth points display the traffic to the brand’s website adding in competitors to slots 2 through 4, respectively. Focal brands are split by the median website traffic ranking. The relationship is downward sloping and significant. However, the magnitude is modest: the full slate of competitive ads reduces the traffic to the focal brand by an average of 4.3 percentage points. The lower brand capital firms show a level shift down in CTR but a similar pattern with respect to competing ads.

Figure 4: The effect of competitive ads in mainline slots 2-4

Subfigure (b) of Figure 4 shows the effect of competing firms on crowd-out of organic traffic. When only the focal brand’s ad is present, 60% of traffic navigates through the paid link.\textsuperscript{14} This fraction increases to 70%, 78% and 84% with one, two and three competing

\textsuperscript{14}This is higher than estimates for all 824 companies; this is because brand’s which face competitors
firms respectively.

4.3 Impact of Competitors in the Absence of a Focal Brand Ad

We now examine the case when competing firms occupy the top paid position. Due to the nature of the experiment, this occurs for a different set of focal brands: “Cap” conditions exogenously remove ads from below but not from above. We identify brands for which competing firms occupied the top paid position more than 90% of the time during our sample period. There are 181 such brands in the sample. By construction, this set of brands does not overlap with the 824 brands we have used for the analysis above. Figure 5 presents histograms of click probability in the Cap 0 condition, which removes the impact of the ads themselves, for brands with competitors in the top position and focal brands in the top position. For brands that decide to advertise, we observe click probabilities that usually exceed 70%, whereas lower organic click probabilities are more common when a competitor occupies the top slot. To help us make more reliable comparisons, we categorize brands by the amount of traffic they get in the absence of any ads: 1) “low” CTR segment for CTR less than 50% (77 firms) 2) “medium” segment when CTR is between 50% and 70% (59 firms) 3) “high” segment for CTR greater than 70% (45 firms).

Figure 6 Subfigure (a) shows the increase in traffic to competitors in position 1 by firm type. Interestingly, competing firms get 17-18% of traffic for all three types of focal brands. Subfigure (b) shows that this traffic comes from different places as compared to the counterfactual of no ads, given by our Cap 0 condition. For the high traffic firms, almost all 18 percentage points come at the expense of the focal brand. 12.5 and 8.5 percentage points come at the expense of the focal brand for the medium and low CTR segments respectively, reducing the incentive for “defense.” Indeed we see it is less common to advertise in these cases. Averaged across all firms, focal brands lose 12 percentage points of clicks and all quoted figures in this paragraph are statistically significant well beyond the 0.01 level.

To get a rough idea of how additional competitors affect traffic to the focal brand we use the 35 focal brands in the high CTR segment that faced up to 4 competitors at least once. Figure 7 Subfigure (a) shows that the probability a consumer navigates to the focal brand’s tend to be less prominent, and for them the effect of brand search advertising is stronger, leading to higher crowd-out.
Figure 5: Heterogeneity in firms that do not bid on their own brand keywords

(a) Competing firm in top paid position
(b) Focal brand in top paid position

Figure 6: Effect of competing firms advertising in top paid position on the page, by level of traffic to focal brand’s website

(a) Competitor’s Paid Traffic
(b) Focal Brand’s Traffic

Error bars give +/- two standard errors.
website decreases from 61 percentage points in case of 1 competitor to 50 percentage points in case of 2 competitors, 49 percentage points in case of 3 competitors, and 45 percentage points in case of 4 competitors, resulting in competitors intercepting 42% of traffic as compared to the no ads condition. Subfigure (b) shows the analogous change in the fraction of traffic to competitors’ websites.

Figure 7: Effect of competing firms advertising in top paid position on the page, by level of traffic to focal brand’s website

(a) Focal Brand’s Traffic
(b) Competitor’s Paid Traffic

Error bars give +/- two standard errors.

4.4 Costs and ROI

In the absence of competing firms, a focal brand a produces 2.27 extra clicks and 36.4 paid clicks per 100 searches. Since a firm is paying for about 16 clicks per incremental click, “cost per click” (CPC, the standard pricing metric reported by online advertising platforms) will sharply diverge from the true “cost per incremental click” (CPIC). We define CPIC as the cost of getting 1 incremental click and compute it as follows:

\[ CPIC = \frac{Pr(i \text{ clicks paid link of focal brand})}{Pr(i \text{ clicks links of focal brand}|\text{Ad}) - Pr(i \text{ clicks links of focal brand}|\text{No Ad})} \]

where the numerator is the probability a click goes through the paid link of a focal brand and the denominator is the incremental effect of paid link on focal brand’s traffic.
The CPIC/CPC ratio is a natural measure of crowd-out. Our informal estimate of 16 is actually a lower bound on the average ratio because CPIC/CPC is a convex function in ad effect size. Jensen’s inequality tells us that a convex function evaluated at average values is strictly less than the average value of the function. While focal brands are effectively paying a high multiple on their nominal CPC, it turns out that their CPCs tend to be very low because of how the GSP auction rewards relevance. To get a better idea of effective costs, we focus on the subset of companies which rarely face competing firms advertising and with enough data to compute the brand-specific advertising effects, leaving us with 268 brands.\(^{15}\) Table 3 presents a detailed summary of the costs paid per click by these brands and competing firms on the branded keywords. Average nominal CPC for focal brands is between $0.06–0.15 depending on the sample (all vs. those with a statistically significant ad effect) and the weighting. Competitors pay much higher prices, between $0.47–0.86 on average, despite occupying lower positions.

<table>
<thead>
<tr>
<th>Measure</th>
<th>Unweighted average</th>
<th>Weighted average(^\dagger)</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>All brands</td>
<td>Significant</td>
</tr>
<tr>
<td>(C_{\text{P}}C_{\text{brand}}) ($)</td>
<td>0.15</td>
<td>0.15</td>
</tr>
<tr>
<td>(C_{\text{P}}C_{\text{compet}}) ($)</td>
<td>0.86</td>
<td>0.78</td>
</tr>
<tr>
<td>(C_{\text{P}}C_{\text{brand}} - \text{other}) ($)</td>
<td>1.36</td>
<td>1.43</td>
</tr>
<tr>
<td>(CPIC_{\text{brand}}) ($)</td>
<td>3.50*</td>
<td>1.12</td>
</tr>
<tr>
<td>(CPIC_{\text{brand}} &gt; CPIC_{\text{compet}}) (%)</td>
<td>51.2</td>
<td>92.7</td>
</tr>
<tr>
<td>(CPIC_{\text{brand}} &gt; CPIC_{\text{own}} - \text{other}) (%)</td>
<td>55.9</td>
<td>90.6</td>
</tr>
<tr>
<td>(N)</td>
<td>268</td>
<td>43</td>
</tr>
</tbody>
</table>

\(^{\dagger}\) Weighted by number of searches

\(^\dagger\) CPC paid by the brand on other keywords when they are not high in the organic listing. It is computed for 85% of companies with data coverage.

\(^\ast\) Lower bound computed with average values as described in the text.

For firms with a significant ad effect, average CPIC is $1.12 unweighted and $1.42 weighted by searches. The lower bound on CPIC for all firms is $3.50 unweighted and $2.52 weighted. Both are substantially higher than the CPC of competitors. A second natural comparison point is the CPC focal brands pay on keywords when they do not occupy a high organic position and thus nearly all clicks are marginal. Even for the firms with a significant

\(^{15}\) Competitors are present less than 20% of the time in control conditions, the results are not sensitive to this threshold.
ad effect, CPIC exceeds the relevant comparison 93% of the time weighted by searches and 51% unweighted. We are unable to make firm-level comparisons when the effect size is not significant, but note that the lower bound given by evaluating the CPIC at average values exceeds the comparison measures of CPC on average. Taken together, the evidence indicates that brands which do not face competition tend to pay more for incremental clicks on their own brand keywords than they do elsewhere or their competitors pay on average. While these conditions do not always hold nor are they direct evidence of mistakes per se, it does suggest this type of expenditure should be critically examined.

The story completely changes when competitors are advertising. Using the point estimate that 18 percentage points of clicks would be stolen from a high traffic brand by a single competitor, focal brand ads have a strong ROI. This is because the defense is highly effective (the total CTR returns almost to the case when there is no advertising) and even though the focal brands must pay for 50 clicks to get 18 incremental clicks, their CPC is about 10 times less than they pay on other queries. Putting the pieces together, the implied CPIC is in an attractive range and indeed better than usual. Additional competing firms shift the focal brand’s organic link further down the page, which significantly increases crowd-out rates but also the click stealing that would be expected to occur if the focal brand was not present; the numbers work out so that ROI still appears to be positive.

It is important to keep in mind that ROI is positive relative to a counterfactual of a competitor stealing clicks. If competitors are not present, the returns to advertising are much lower and indeed most brands choose not to advertise. It is thus clear why brands have fought legal battles to ban competing firms from bidding on their trademarked terms. Smaller rivals use the focal brand’s awareness as a form of targeting, which then creates the need for defensive positions. As discussed in theoretical models, this enhances competition in a way that smaller firms, who get very little search traffic themselves, and the platform tend to like and larger firms tend to dislike (Yang et al., 2013; Sayedi et al., 2014).

4.5 Strength of Focal Brand and Competitors

To understand the relative strength of competing firms versus focal brands, we plot the difference in the log US website rank in Figure 8. The distribution is centered around -3, which corresponds to the focal brand having $e^3 (=20)$ times higher rank. The red vertical
line indicates when competitors have equal popularity as the relevant focal brand—very little mass lies to the right of this point. For the 564 firms that face competition consistently, the median Alexa rank of website popularity (across all websites for American visitors) is 8,000, whereas it is 80,000 for the top competitor, 145,000 for the second and 178,000 for the third. It has been previously shown that website traffic displays heavy tails (Kumar and Tomkins, 2010), meaning that having 20 times lower rank corresponds to a much larger differential in terms of page views. Overall the evidence clearly points to competitors consistently being much less prominent than focal brands.

Figure 8: Distribution of the Difference in Log Rank between Focal Brand and Competitors

5 Discussion and Conclusion

Our results provide a deeper understanding of why (and why not) firms should advertise in brand search. In the absence of competing firms, focal brands can still improve the positions of their web links on the page by running a brand search advertisement. On average, focal brands get just over 2 extra clicks out of 100 searches. The size and content of the first organic result modulates the effect size—since smaller firms tend to have less rich search results they benefit more from brand ads.
Competing firms greatly affect the market. When a focal brand occupies the top position, competitors steal a modest 1–5 clicks out of 100 searches. But when a focal brand is not present, competing firms consistently acquire a relatively large fraction of clicks. Whether these clicks come at the expense of the focal brand or other firms depends on the baseline traffic level of the focal brand. Even though the comparison across competitive scenarios involves different firms, we highlight that the impact competitors have with no focal brand present is ten times higher than when the focal brand blocks competitors by occupying the top slot and the magnitude of click stealing is stable across firm segments. In our informal model, this corresponds to competitors being relatively good substitutes for the focal brand and users examining a small number of links, which combine to produce strong position effects. These factors imply that focal brand ads play a defensive role, which greatly limits the ability of competitors to exploit strong position effects.

We discussed that while CPC is widely used and easy to understand, it often does not capture true marginal costs of traffic. Indeed CPC is similar for focal brands in the presence and absence of competitors, but our results indicate that true ROI hinges on their presence. The alternative metric we propose, CPIC, is economically sound but computing it requires the relevant counterfactual, which may not be easily observable, can change over time or may be an unfamiliar concept to decision makers. We do, however, observe evidence that many firms broadly understand these complexities. For example, advertising on brand keywords is much more common when competitors are present. Nonetheless, when we have the resolution to study behavior at the firm level, there is evidence that the depth of these complexities is either not fully understood or captured by within-firm incentives.

Finally our results reveal that firm heterogeneity is critical to understanding sponsored search. Smaller focal brands benefit more from ads even in the absence of competitors. More strikingly, competitors are far less prominent than their associated focal brand—these small firms use brand search as a way of directly competing with their larger, more well-known rivals. Since these competing firms tend to get very little search traffic themselves, there is little fear of a reprisal in the form of bids on their keywords. The focal brand can almost, but not entirely, eliminate traffic stealing by placing an ad in the top position. Even in this case, given how small competing firms are, the traffic they do manage to attract could still be meaningful, revealing brand search to be an important form of competitive advertising.
References


6 Appendices

6.1 Appendix A: Experiment and Auction Data

The experiment we use randomly restricts the number of possible paid links on top of the search page. The control group corresponds do the default, which is a maximum of 4 advertisements in the mainline (Cap 4). There are 4 experimental conditions: Cap 0, 1, 2 and 3. The idea is similar to the control: e.g. Cap 0 does not allow any advertisements in the mainline, and Cap 3 allows at most 3 advertisements in the mainline.

This design of the experiment restricts us to studying only the cases where an advertisement is eligible to be shown in the mainline, which means that in the absence of experiment advertisement will be shown in the mainline. E.g. we cannot study the effect of advertisement for a company that does not advertise on its own keyword: there will be no own brand advertisements in both Cap 0 and Cap 1 condition.

Thus, we restrict our attention to cases where companies advertise. We are still facing a challenge: if a company advertises only 50% of the time on a given query and selects search traffic where the effect will be higher\textsuperscript{16}, we cannot compare occasions with the advertisement to the treatment condition where the ad will be removed. E.g. if we would like to estimate the effect of own brand advertisement in mainline 1 when in 50% of the cases company advertises, and in 50% of the cases there is no advertisement, comparing occasions in Cap 1 conditions with a paid link shown to the entire Cap 0 conditions will bias the estimates.

To find the right treatment group, we need to allocate the occasions where the ad was actually removed from the mainline. In the example above, we would like to compare occasions with own brand paid link in Cap 1 to occasions in Cap 0 when own brand paid link would have been shown. To find such occasions, we collect the auction data for the search queries in the experiment. The allocation of positions in mainline follows the standard GSP auction rules: players submit the bids for a price of a click, platform computes the “rankscore” of a given player, and players are allocated the positions in mainline based on their rankscores. Given that the reservation level is cleared, a company with the highest rankscore gets position 1, a company with the second highest rankscore gets position 2, etc. Rankscore is

\textsuperscript{16}E.g. using geo-targeting
proportional to the bid and a probability of click on the ad as computed by the platform

\[ RS_j \propto b_j p_{\text{click}} j^{\alpha} \]  

(1)

where \( b_j \) is a bid of company \( j \), \( p_{\text{click}} j \) - a probability of company \( j \) to get a click, and \( \alpha \) is the tuning parameter.

This implies that knowing the rankscores of bidders and reservation level for a search query allows saying which advertisement would be shown in the mainline in the absence of the experiment. To get this information, we exploit auction data collected by the advertising team. Experiment that we use was designed by removing the potential advertising slots from mainline, but bidding data was still collected.

Table 4: Summary of matching of the experimental and auction data

<table>
<thead>
<tr>
<th>Condition</th>
<th>Searches Total</th>
<th>Searches Matched</th>
<th>% of eligible ads in ML 1</th>
<th>ML 2</th>
<th>ML 3</th>
<th>ML 4</th>
</tr>
</thead>
<tbody>
<tr>
<td>Cap 0</td>
<td>3162615</td>
<td>1506827</td>
<td>47.6</td>
<td>30.6</td>
<td>9.2</td>
<td>4.6</td>
</tr>
<tr>
<td>Cap 1</td>
<td>6342073</td>
<td>3568054</td>
<td>56.3</td>
<td>41.8</td>
<td>11.2</td>
<td>4.7</td>
</tr>
<tr>
<td>Cap 2</td>
<td>6338914</td>
<td>3568918</td>
<td>56.3</td>
<td>41.8</td>
<td>10.9</td>
<td>6.1</td>
</tr>
<tr>
<td>Cap 3</td>
<td>6348311</td>
<td>3577819</td>
<td>56.4</td>
<td>41.9</td>
<td>11</td>
<td>5.7</td>
</tr>
<tr>
<td>Control</td>
<td>22209220</td>
<td>12506083</td>
<td>56.3</td>
<td>41.9</td>
<td>11</td>
<td>5.7</td>
</tr>
</tbody>
</table>

Table 4 presents the summary of matching experimental data and collected auction data for Cap 0-4. For Cap 1, 2, 3 and 4, around 56.3% of search queries in experimental data were matched with the auction data. A search query will not be recorded in the auction data if no advertiser submitted a non-trivial bid\(^\text{17}\), so the unmatched data can correspond to queries with no bidders. The majority of unmatched queries correspond to occasions where no advertisements were shown, which supports this explanation.

Cap 0 condition has a higher percentage of unmatched search queries. This indicates the problem with the matching, given that the experiment was constructed to be balanced between the treatment and control groups. We further find that percent of advertisement eligible for the mainline 1 position in Cap 0 is substantially different from the percent of advertisements eligible for mainline 1 position in Cap 1, 2, 3 and 4.

\(^{17}\)As defined by the platform
This creates a potential problem for using the occasions with eligible brand advertisements for Cap 0 condition. Consider the case of estimating the effect of own brand advertisement in mainline 1. Using the matched data, we would like to compare occasions with the own brand advertisement from Cap 1 condition to occasions with the eligible own brand advertisement from Cap 0 conditions. We know that some occasions with the eligible own brand advertisement are missing from Cap 0. If this mismatch is correlated with the probability of a click on the own brand weblink, our estimate of the advertisement effect will be biased.

To check if there is a selection problem in Cap 0 matching, we estimate the effect of own brand advertisement in mainline 1 for companies which always advertise in mainline 1 on their own keyword\textsuperscript{18}. For these companies, comparison of Cap 0 to Cap 1 provides the casual effect of own brand advertisement: we know that, if not the experiment, search results in Cap 0 will have their own brand advertisement in mainline 1. We also can estimate the effect using only eligible own advertisement occasions in Cap 0 and Cap 1. If the estimates of the effect based on two methods are different, we can confirm that the occasion in Cap 0 which have the eligible own brand advertisement in mainline 1 are correlated with the probability of click on the focal brand’s website.

Table 5: Effect of own brand ad in mainline 1 is significantly underestimated when using eligible ads

<table>
<thead>
<tr>
<th></th>
<th>All queries</th>
<th>When own ad is eligible</th>
</tr>
</thead>
<tbody>
<tr>
<td>$N_{comp}$</td>
<td>391</td>
<td>391</td>
</tr>
<tr>
<td>$\hat{p}_{\text{own0}}$</td>
<td>0.7867</td>
<td>0.8115</td>
</tr>
<tr>
<td></td>
<td>(0.0022)</td>
<td>(0.0029)</td>
</tr>
<tr>
<td>$\hat{p}_{\text{own1}}$</td>
<td>0.8035</td>
<td>0.8179</td>
</tr>
<tr>
<td></td>
<td>(0.0015)</td>
<td>(0.0015)</td>
</tr>
<tr>
<td>$\hat{p}<em>{\text{own1}} - \hat{p}</em>{\text{own0}}$</td>
<td>0.0168</td>
<td>0.0063</td>
</tr>
<tr>
<td></td>
<td>(0.0027)</td>
<td>(0.0033)</td>
</tr>
</tbody>
</table>

$\hat{p}_{\text{own0}}$ is the probability of a click on own brand link in Cap 0
$\hat{p}_{\text{own1}}$ is a similar probability in Cap 1

Table 5 presents the estimation results. The ad effect estimate based on all traffic is 1.68 percent points. The effect estimated based only on traffic with the eligible own advertisement

\textsuperscript{18}Companies that have their own brand advertisement in mainline 1 more than 99% of the time
is 0.63 percent points. The difference in two estimates is statistically significant\textsuperscript{19}.

We thus confirm that the occasions of eligible own brand ads in mainline 1 in Cap 0 are correlated with the probability to get a click on the own brand weblink. This restricts us from using the eligible advertisements occasions to compare Cap 0 and Cap 1. Instead, we focus only on companies that have a paid link in mainline 1 more than 90\% of the time. For these companies, comparison of Cap 0 and Cap 1 gives a causal effect of advertisement.

Figure 9 shows that around 50\% of companies advertise at least 10\% of the time, with around 33\% advertising more than 90\% of the times. Restricting the analysis to the latter group gives us 824 companies which always advertise on their keyword.

\textsuperscript{19}Difference in estimates is 0.0105, with a standard error of the difference being 0.0043, which corresponds to a t-stat of 2.46
Figure 9: Frequency of ads in mainline 1 for 2517 most popular brand queries

(a) Frequency of own ads in ML1

(b) Frequency of competitor’s ads in ML1

(c) Frequency of ads in ML1
6.2 Appendix B: Comparison of Control Conditions

Figure 10 presents the estimates of the probabilities to click on focal brand’s/competitors organic/paid web links, along with the 95% confidence intervals around these estimates, for the control conditions. Estimates are pulled for 824 brands used for the analysis. We do not find any statistically significant difference in either comparison in the controls. We conclude that treatment conditions can be compared directly.

Figure 10: Estimates of probability to get a click on focal brand’s/competitors organic/paid web links, control conditions

The bars are two standard deviations around the estimates, corresponding to the 95% confidence interval
For comparison, Figure 11 presents the estimates of the probabilities to click on focal brand’s/competitors organic/paid web links for all experimental conditions.

Figure 11: Estimates of probability to get a click on focal brand’s/competitors organic/paid web links, all conditions

(a) Focal Brand’s Organic Links
(b) Focal Brand’s Paid Links
(c) Competitors’ Organic Links
(d) Competitors’ Paid Links

The bars are two standard deviations around the estimates, corresponding to the 95% confidence interval
## 6.3 Appendix C: Brand Capital Measures

<table>
<thead>
<tr>
<th>Measures</th>
<th>Mean</th>
<th>Standard deviation</th>
</tr>
</thead>
<tbody>
<tr>
<td>$\log(\text{expos})$</td>
<td>7.59</td>
<td>1.41</td>
</tr>
<tr>
<td>$\log(\text{Rank}_{\text{global}})$</td>
<td>10.52</td>
<td>2.14</td>
</tr>
<tr>
<td>$\log(\text{Rank}_{\text{US}})$</td>
<td>9.05</td>
<td>1.96</td>
</tr>
<tr>
<td>Bounce rate, (%)</td>
<td>35.1</td>
<td>14.3</td>
</tr>
<tr>
<td>Time spent per day (minutes)</td>
<td>4.6</td>
<td>2.98</td>
</tr>
<tr>
<td>Pages viewed per day</td>
<td>4.5</td>
<td>2.76</td>
</tr>
<tr>
<td>Search traffic (%)</td>
<td>19.85</td>
<td>9.19</td>
</tr>
</tbody>
</table>
6.4 Appendix D: Deeplinks and Dcard Example

Figure 12: Deeplinks example
6.5 Appendix E: Organic Traffic by Page Position

Figure 13 presents the estimates of probabilities of a click on focal brand’s organic links by their positions. We find that multiple organic links are affected by the cannibalization: we could find a significant change in the probability to click focal brand’s organic links in top 6 positions on the page.
The bars are two standard deviations around the estimates, corresponding to the 95% confidence interval.
Appendix F: Additional Figures

Figure 14: Heterogeneity in the effectiveness of brand search advertising

Black line corresponds to the implied average brand search ad effect estimate; red, green and blue lines correspond to the 95% confidence interval of the estimates of focal brand’s ad effect.