Competitive Advertising on Brand Search: Traffic Stealing, Adverse Selection, and Customer Confusion*

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June 30, 2018

Abstract

We study the effectiveness of competitive advertising on brand search using a large-scale randomized ad allocation on Bing. Competitors can steal traffic from the focal brand, and they steal more (6-20%) if they occupy the top paid position on the results page than if a focal brand is advertising in the top paid position (1-3%). However, these "stolen" clicks are of low quality, with 42.6% of consumer returning to Bing in less than 30 seconds after clicking competitors' ad ("quick back" event), compared to 3.6-6% quick back probability after a click on the focal brand's link. This high quick back rate is due to both adverse selection of consumers (14.8 percentage points) and an incremental increase consistent with customer confusion (27.8 percentage points). More relevant competitors get more clicks with lower quick back probability. Using these results, we derive the implied costs of incremental traffic for focal brands, propose an exclusive ad placement mechanism for the platform, decompose the estimates to the effects of page position and link type on consumer choices, and discuss the degree of customer confusion and social costs imposed by competitive advertising.

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1 Introduction

Brand search, consumers' practice of searching for a particular brand on a search engine like Google or Bing, is very common.[1] It is often cited as the prime example of navigational search (Broder, 2002), in which the consumer's sole search objective is to navigate to the searched-for ("focal") brand's website, presumably making all other links on the page irrelevant. However, another common practice is competitive advertising on brand search. Competitors bid to be shown in the top positions on the search engine results page (SERP) in the hopes of intercepting some of the focal brand's website traffic. This practice has been encouraged by practicioners[2] and deemed legal by courts,[3] despite its contrast to the navigational nature of brand search and the persistent claims of trademark owners that competitors are confusing their prospective customers. The core argument for allowing competitive advertising on brand search is that it informs or reminds the searchers about other products and brands, bringing into question the definition of brand search as having solely a navigational purpose. The legality of competitive advertising has forced focal brands to "protect" their traffic by advertising on their own brand name and occupying the top paid position on the results page, pushing competitors' ads down the page (Desai et al., 2014).[4]

We aim to inform this debate by measuring the effectiveness of competitive advertising on brand search. First, we ask if competitors can steal a substantial share of traffic from the focal brand by occupying the top paid position on the search results page? Such traffic stealing would cast doubt on brand search as having a strictly navigational goal and validate the defensive advertising of focal brands. Second, we ask if there is traffic stealing, what is the quality of the traffic that competitors are able to capture? Perhaps competitors

[1]For example, all of the top-10 search queries on Google in May 2018 were brand names, with "youtube" and "facebook" leading the list: `https://ahrefs.com/blog/top-google-searches/`

[2]Multiple search advertising resources available online discuss this practice; for example, see `http://www.wordstream.com/blog/ws/2012/12/10/three-types-of-search-queries` and `https://3qdigital.com/google/should-you-bid-on-your-own-brand-name-in-adwords`.

[3]The most prominent cases include *Rescuecom Corp. v. Google Inc. 562 F.3d 123 (2nd Cir. 2009)* and *Rosetta Stone v. Google, 676 F.3d 144 (4th Cir. 2012)* in the US, and *Court of Justice of the EU, Google France v. Louis Vuitton Malletier, Mar. 23, 2010, Joint Cases C-236/08 to C-238/08, ECR 2010, I-02417* in the European Union. See `https://trademarkwell.com/trademarked-keywords-am-i-infringing-or-not/` for a broader overview of related cases (March 2017), Bechtold and Tucker (2014) for an overview of the related literature, or Gilson (2014); McCarthy (2014) for a more fundamental treatment of legal aspects of trademarks.

[4]If the focal brand decides to advertise, it almost always gets the top paid position due to the high relevance of its ad.

steal traffic with their paid ads, but these customers visit competitors' websites for only several seconds before they return to the search engine ("quick back" event). Further, if the quality of competitors' traffic is indeed low, is it due to adverse selection of customers (lower "quality" of customers clicking on a competitor's link) or to a mismatch of customers' needs and competitors' offerings on the linked website? The former would signal that competitive advertising is more likely to attract less loyal customers, while the latter would support the argument of customer confusion due to competitive advertising.

To answer these questions, we need estimates of competitive ad effectiveness with and without focal brands' ads, which is challenging due to the familiar problem of endogeneity of ad occurrences in observational data. To overcome this problem, we rely on a randomized ad allocation performed by Bing search engine for its own business purposes. This ad allocation manipulates (1) the number of ads in the top ("mainline") slot and (2) the order of ads shown on the results page. Such rich variation in the realization of ads allows us to observe cases with and without focal brands' protective ads, as well as cases with different competitors in the paid positions. We run the analysis on a set of 1,459 popular brand names for which the focal brands advertise on their brand traffic during the period from several months in 2017.

Our first result is that competitors can steal a substantial share of traffic from focal brands. When the focal brand's ad is not shown in the top paid position, one-four competitors can get 6-20% of the focal brand searches; in contrast, when the focal brand occupies the top position, competitors' steal only 1-3% of the focal brand searches. These results support the defensive nature of brand search described by Desai et al. (2014) and suggested by previous work, although the magnitude of traffic stealing by competitors in the top page position is two times lower than suggested by an across-brands comparison (Simonov et al., 2017). More generally, competitors in the top paid positions get more clicks as the focal brand's links (both paid and organic) move down the page, supporting the dependence of click-through rates (CTR) of ads on the surrounding links (Jeziorski and Segal, 2015).

The traffic stealing of competitors differs by their paid position and prominence. Competitors that are (randomly) shown in the top paid position steal the vast majority of clicks, varying from 4.2 to 9 percentage points for the cases of one-four competitors' paid links, while competitors in positions 2-4 get only 0-2.8 percentage points of traffic. Such strong position effects justify advertisers' intense competition to be shown in the top paid position. If the most relevant competitor, defined as the competitor with the second highest auction rank score after the focal brand, that occupies the top paid position, traffic stealing increases on average by 4.4 percentage points, indicating that the identity of competitors matters for consumer click choices.

While competitors enjoy a relatively high CTR in the absence of the focal brand's ad, this "stolen" traffic suffers from a high "quick" back" rate, which is the probability that a consumer returns to the search engine's results page less than 30 seconds after making a click.[5] When competitors occupy the top paid position on the page, their quick back probability is around 42.6%, substantially higher than the 6.2% quick back rate of clicks on focal brands' links. Such high quick back probability is due to both adverse selection of consumers, accounting for 14.8 out of 42.6 percentage points, and an incremental increase in the number of quick backs, accounting for the remaining 27.8 percentage points. As the number of competitors' paid links increases from zero to four, the quick back rate on the focal brand's clicks decreases from 6.2% to 3.5%, allowing us to measure adverse selection. At the same time, with an increase in the number of competitors, the total quick back rate also increases, from 6.1% to 11.2%, reflecting the share of incremental quick backs. The nature of the competitor in the top paid position matters; when the most relevant competitor occupies the top paid position, the quick back probability on competitors' clicks is 4.8 percentage points lower compared to an average competitor in this position.

These results have implications for all market participants. For competitors, our results imply that outbidding the focal brand on brand search is potentially valuable in terms of the traffic increase, but the "quality" of clicks that competitors get is lower than the average focal brand's traffic. For focal brands, our results imply that a "defensive" advertising strategy indeed helps to "protect" their traffic, even though the quality of traffic that navigates to competitors' website is of lower quality than the traffic that remains with the focal brand. However, this "defense" can be fairly expensive: Simonov et al. (2017) found that the average cost per incremental click (CPIC) focal brands pay on their traffic varies from \$0.6 to \$1.03, depending on the number of competitors advertising below the focal brand ad, compared to a nominal cost per click (CPC) of \$0.23. If the focal brands care equally about paid and organic traffic, these estimates of the cost per incremental click reveal their willingness to pay (WTP) for traffic. Search engines can use these WTP estimates and the CPCs

[5] "Quick back" events are considered to be a measure of the "success" of a click on the SERP; Goldman and Rao (2014) showed that they have a strong negative correlation with click conversion rates, making quick back probability a good proxy for traffic quality.

that competitors pay to design a simple exclusive ad allocation mechanism that removes competitors' ads while charging focal brands a premium for "owning" their search results.

The richness of variation in links' positions on the results page allows us to measure the effect of the type of link and page position on consumers' search process. To examine the relative importance of these factors for consumers, we decompose the click probability estimates to the primitives of the expected utility of clicking a link on the page. The effect of the position of the focal brand's link on click probability has a near-linear functional form, with the odds ratio $\frac{\text{Prob(click a link in position x)}}{\text{Prob(click a link in position 1)}}$ decreasing from 1 to 0.54 as the position x of the focal brand's link decreases from 1 to 5. Results are different for the effect of competitor's link position on click probability, with the odds ratio decreasing from 1 to 0.24 once a competitor's link moves from position 1 to position 2, and then near-linearly decreasing from 0.24 to 0.081 as a competitor's link decreases to position 4. Such differences in position effects cannot be explained by the simple mechanism of the "cost of scrolling" down the page, suggesting that consumers either extract a signal from a competitor's link occupying the top position or make the mistake of clicking the first link and assuming that it will be for the focal brand. We also find that consumers have a slight preference for the organic link (over the paid link) of the focal brand, with this difference in preference compensated for by moving the organic link from the first to the third position on the page.

Finally, our results have implications for the regulators who must decide whether to allow or ban competitive advertising on brand search. The results are mixed. On the one hand, we show that brand search is hardly *only* navigational, or limited to consumers willing to go only to the focal brand's website. Competitors steal a substantial share of traffic, signaling that some consumers extract value from competitors' websites. On the other hand, the presence of competitors on the top of the results page significantly increases the overall quick back probability, implying that fewer consumers are satisfied with the search results. The estimates of an increase in quick back probabilities allow us to derive an upper bound on customer confusion and do a back of the envelope calculation on the additional social costs imposed by competitors' ads on searchers, measured by the time it takes to navigate to the focal brand's website.[6] We go through these computations in section 4.2 and discuss them in section 4.3.4. Further, Appendix 6.1 shows that competitors that mention the focal

[6]First, even if consumers navigate correctly to the focal brand's website after a quick back on a competitor's link, they lose around 3-12 seconds per search. Second, in Appendix 6.3, we show that the presence of competitors increases consumers' time on the search results page.

brand's name in their title tend to steal more but lower quality clicks (higher quick back probability), suggesting that mentioning the focal brand's name in the competitors' ad title leads to additional consumer confusion.

The rest of the paper is organized as follows. Section 2 discusses the related literature. Section 3 discusses the randomization, data, and estimation. Section 4 presents the empirical results and discusses the implications for market participants. Section 5 concludes.

2 Related Literature

We study the effectiveness of competitive advertising on brand search, looking at both the volume of traffic stealing by competitors' ads and "quality" of the stolen traffic. Regarding the volume of traffic stealing, the current empirical evidence is mixed. On the one hand, it is well-established that moving a link to a higher position on a page increases the number of clicks it receives, as documented in the domains of search engine results (Narayanan and Kalyanam, 2015; Jeziorski and Moorthy, 2017), hotel listings (Ursu, 2017), and TV channels (Martin and Yurukoglu, 2017). Simonov et al. (2017) show that competitors can steal 2% to 3% of a brand's traffic when shown below the focal brand's ad and suggest that competitors can steal an order of magnitude more clicks if the focal brand does not advertise. If this is the case, focal brands are faced with a prisoner's dilemma and forced to advertise on their own traffic to "defend" it from competitive stealing (Sayedi et al., 2014; Desai et al., 2014). These results are supported by recent work by Coviello et al. (2017), who replicate the experimental design of Blake et al. (2015) for a less well-known company than eBay, Edmunds.com. On the other hand, Golden and Horton (2017) show that a direct competitor does not measurably benefit from moving one position higher on their competitor's brand search results, suggesting that all brand search is navigational, which is consistent with the results of Blake et al. (2015), who show that the focal brand's ad mainly crowds out its own organic link clicks.

We show that competitive traffic stealing is common, and that the focal brands' defensive advertising is an effective strategy to reduce such traffic stealing, supporting the theoretical results of Sayedi et al. (2014) and Desai et al. (2014). The position effects that we find are of a lower degree than suggested by Simonov et al. (2017) but significantly higher than zero (Golden and Horton, 2017), generalizing the measurement of competitive traffic stealing by Coviello et al. (2017). Further, our estimates of competitive traffic stealing allow us to measure the cost of the focal brand's "defense" from competitors by computing the "cost per incremental click" measure in the case of competition (Simonov et al., 2017). Using these estimates, we propose a simple exclusive ad allocation mechanism for brand search advertising (Jerath and Sayedi, 2015).

We believe this paper is the first to examine the quality of stolen traffic in the context of competitive advertising on brand search. Using the "quick back" events (returns to Bing SERP less than 30 seconds after the click) as a proxy for the click's success (Goldman and Rao, 2014), we show that the quality of competitors' traffic is of an order of magnitude lower quality than the focal brand's traffic, and decompose the lower quality into the effects of adverse selection (Akerlof, 1970; Puelz and Snow, 1994; Lewis, 2011; Handel, 2013; Polyakova, 2016; Jeziorski et al., 2018)[7] and incremental increase in the quick back probability. The incremental increase in quick back probabilities is consistent with the argument that competitive advertising on brand search might be confusing customers, although it can also be explained by the deliberate search of consumers. Thus, our results inform a legal debate on whether competitors' ads should be allowed on brand search[8] and a broader debate on the legality of trademark usage by competitors (Chiou and Tucker, 2012; Bechtold and Tucker, 2014).

More broadly, our work fits into the literature on search advertising (Yao and Mela, 2011; Choi and Mela, 2016) and measuring advertising effectiveness. Similar to Goldman and Rao (2014), we exploit a randomized ad allocation to estimate the effectiveness of search advertisements. We confirm the results in Jeziorski and Segal (2015) that the CTR of paid links depends on the surrounding ads, rejecting simpler models of Edelman et al. (2007) and Varian (2007), and estimate the expected utility primitives. We confirm that position effects generalize to competitors advertising on searches for another brand (Narayanan and

[7]Most empirical work on adverse selection is done in the context of insurance markets; the work of Jeziorski et al. (2018) is the closest to our context as it shows the adverse selection in customer poaching in the context of the car insurance market in Portugal.

[8]The most prominent cases include *Rescuecom Corp. v. Google Inc. 562 F.3d 123 (2nd Cir. 2009)* and *Rosetta Stone v. Google, 676 F.3d 144 (4th Cir. 2012)* in the US, and *Court of Justice of the EU, Google France v. Louis Vuitton Malletier, Mar. 23, 2010, Joint Cases C-236/08 to C-238/08, ECR 2010, I-02417* in the European Union. See `https://trademarkwell.com/trademarked-keywords-am-i-infringing-or-not/` for a broader overview of related cases (March 2017), and Gilson (2014); McCarthy (2014) for a more fundamental treatment of legal aspects of trademarks.

Kalyanam, 2015; Ursu, 2017; Martin and Yurukoglu, 2017; Jeziorski and Moorthy, 2017) and extend a more broad work on measuring advertising effectiveness online (Ghose and Yang, 2009; Reiley et al., 2010; Goldfarb and Tucker, 2011a,b; Rutz and Bucklin, 2011; Lewis and Reiley, 2014; Lewis and Rao, 2015; Sahni, 2015; Sahni and Nair, 2016; Johnson et al., 2015, 2016a,b; Gordon et al., 2016) and offline (Lodish et al., 1995; Ackerberg, 2001; Shapiro, 2016; Tuchman, 2016; Stephens-Davidowitz et al., 2017; Hartmann and Klapper, 2017).

3 Empirical Setting

3.1 Randomization Description

The key empirical challenge in measuring search ad effectiveness with observational data is the usual endogeneity problem. First, companies self-select into advertising on particular queries, potentially choosing more effective ad allocations. Second, the auction mechanism is designed to put more relevant ads higher on the search results page: for each ad, the platform computes a "rank score", a metric that combines bids, expected CTRs, and other ad relevance variables, and the top rank score ads are shown in up to four "mainline" slots (above the organic search results), as long as they clear the query-specific reservation level.

To overcome this challenge, we use a randomized ad allocation run by the Bing search engine for its own business purposes. Bing subjects a small fraction of its traffic to a "random flight" condition, which manipulates the order, type, and number of paid links shown in the "mainline".[9] More specifically, the randomization occurs in four steps:

1. Set the reservation level of rank scores on this search to zero;
2. Randomly select the number of eligible mainline ad positions, m_{elig};
3. For all m ads with a non-zero rank score, randomize the rank score;
4. If $m > m_{\text{elig}}$, show the m_{ML} ads with the highest rank score in the mainline; if $m \leq$

[9]We cannot disclose the exact share of the randomized traffic since it could reveal the overall traffic volume on Bing.com.

m_{elig}, show the m ads.[10]

This randomization has multiple features useful for studying the effect of competitors' ads on brand search. The second step shifts the number of ads shown on the page, allowing assessment of the effect of paid listings on consumers' behavior. The third step shuffles the rank scores of the eligible ads, potentially putting competitors' ads at the top of the page even when the focal brand bids to protect its traffic. A combination of these two steps allows us to study both the position effects of competitors' ads and their overall effectiveness.

The main limitation of this randomization is that it is done by Microsoft for product purposes and is not structured as an experiment. First, the randomized conditions do not have balanced control groups. Instead, the probability that a query will be allocated to a random condition is driven by product needs, such as learning an advertisers' expected CTR. Second, the number of eligible "mainline" ads in the experiment, m_{elig}, is not recorded in the data; we have information on the number of ads shown, which could be m_{elig} or m.

We overcome these challenges in two ways. First, we focus only on the brand-day pairs for which the focal brand was advertised in the top paid position for more than 90% of searches in the normal ad allocation condition. This way, we ensure that the brand traffic is valuable for the focal brand (it decides to advertise) and that the focal brand's ad almost always *would have been* in the top paid position in the absence of randomization. Second, we use the information on bids, expected CTR estimates, and other ad characteristics to reconstruct which competitors *would have been* shown on the page without the "random flight." We then find the right "control" group for the random flight queries in the non-randomized traffic.

3.2 Data

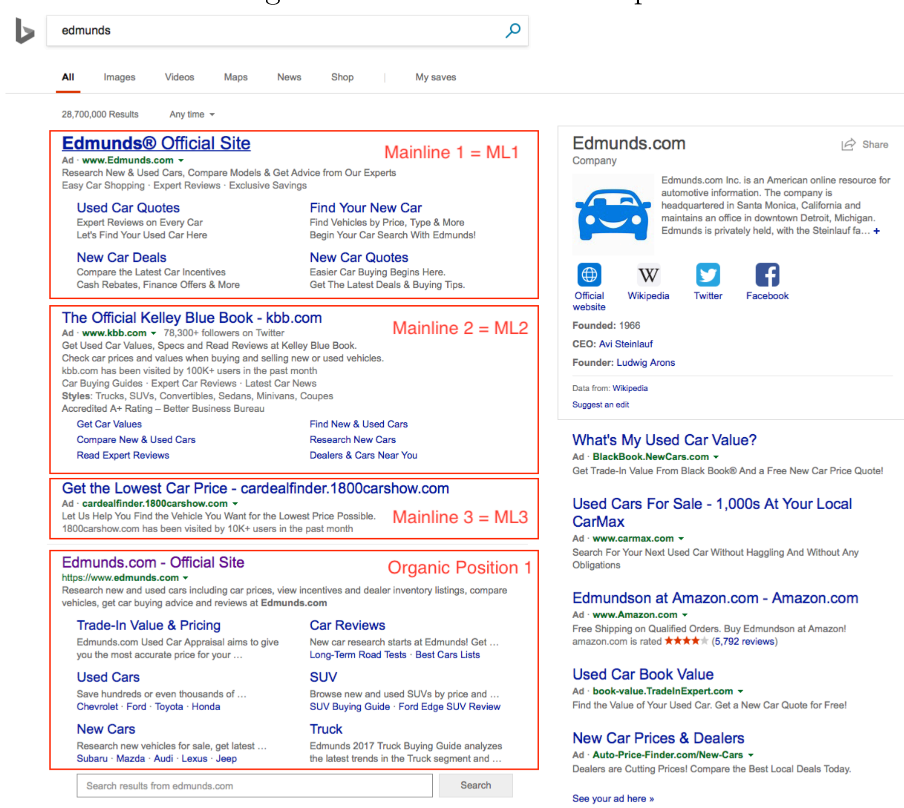
For our main analysis, we use data from Bing's search logs, which includes information about what is shown on the search results page and records of consumers' behavior. The unit of observation in this data is a search occasion. Among other things, we observe information about paid and organic web links on the results page, consumer click decisions, and "dwell

[10] Actual randomization involves two additional steps that randomize showing ad product listings and site links, both with a probability of 50%. We do not use this variation in our estimation.

time" of a consumer after clicking a link, which is the time before this consumer returns to Bing's search page.

To define brand search, we follow the procedure described in Simonov et al. (2017). We define a brand search as a search query if and only if (1) it is on the Open Directory Project list of 87,000 brand names and (2) it matches the domain name of the first organic result on the search results page.[11] The first step is necessary to exclude non-branded searches, and the second step is necessary to ensure a particular brand's website is the most relevant search result. Notice that by defining the brand search this way, we restrict our attention to queries that contain only the name of the brand. We simplify queries by removing punctuation marks and website-related strings of text such as "www" and "http".

Figure 1: Brand search example.



This example has three mainline ads: the first ad, ML1, is for the focal brand Edmunds, while the second and thirds ads, ML2 and ML3, are from competitors.

[11]The Open Directory Project, dmoz.org, discontinued its work as of March 2017. We use the same list of brands as in Simonov et al. (2017).

Figure 1 presents an example of brand search. The focal brand, Edmunds, occupies the top paid position on the page, or the "mainline 1" (ML1) position, and the first organic position. Two competitors are advertising on the focal brand, "KBB" and "1800carshow", occupying paid positions ML2 and ML3, respectively.

We focus our attention on brand searches during the period of several months in 2017. To ensure that a query is not a random word typed in by a mistake, we focus our attention only on relatively prominent brands. More specifically, we use only brand-day pairs in which a brand is searched for more than 80 times.[12] There are 575,357 brand-day pairs with 3,703 unique brand names that match this criterion.

Given that our counterfactual of interest corresponds to cases in which a competitor's ad occupies the top paid position on the page instead of the focal brand's ad, we further restrict this set to cases of brand-day pairs in which the focal brand's ad occupies the top paid position at least 90% of the time in the absence of randomization, meaning that the focal brand is consistently advertising on its brand name. This results in 161,302 brand-day pairs with 1,459 unique brands that satisfy this criterion. For these brand-day combinations, there are, on average, 1.86 ads in the top paid positions on the page, with a competitor's ad in the second paid position 43.79% of the time, the third position 27.59% of the time, and the fourth position 15.35% of the time.[13] We also restrict our attention to cases of zero or one click on the results page, removing rare occasions of two or more clicks on the page.[14]

We match the resulting brand-day pairs to the randomized ad data. There are 90,867 brand-day pair matches with 1,291 unique brands in the randomized ad allocation data for the corresponding data period, for a total of 586,762 brand searches.

As discussed above, the randomized ad allocation is not a balanced experiment as it was done for product reasons, such as expected CTR estimation. Thus, for each brand search in the "random flight", we need to find the right comparison group. To do so, we reconstruct which ads *would have been* shown in the top paid positions, if any, in the absence of the randomization. To find these "eligible" ads, we predict their "true" rank scores using the

[12] The threshold of 80 searches per day ensures a sufficient amount of data per brand per day so that we can estimate whether the focal company has advertised on its brand name. Our results are robust to changing this threshold.

[13] We remove rare cases of the focal brand advertising but not occupying the top paid position on the page.

[14] Cases of zero and one click cover more than 98% of brand searches available in the data, in both the normal and randomized ad allocation conditions.

non-randomized data and ad information such as bids, expected CTR estimates for each ads, and other ad characteristics S, and then reconstruct the ad allocation process using the predicted rank scores and observed (for us) reservation levels. We correctly reconstruct the presence of competitors in paid positions 2-4 in 93.5-95.6% of the cases.[15]

Table 1: Summary statistics of brand search data in the randomized ad allocation condition.

Randomized condition		# of bidders			Share of eligible competitors' ads in			
# of ML ads	Focal brand's ad	Non-zero rank score	Below reserve	# Eligible ads mainline	ML2	ML3	ML4	Search occasions
0	–	2.056	1.066	0.990	0.126	0.038	0.015	244,069
1	–	3.832	2.600	1.232	0.312	0.128	0.063	83,156
1	ML1	1.517	0.491	1.027	0.076	0.018	0.007	81,800
2	–	5.523	3.953	1.570	0.434	0.232	0.131	48,510
2	ML1	3.519	2.010	1.509	0.355	0.111	0.049	14,068
2	ML2	3.510	2.008	1.502	0.360	0.105	0.042	13,856
3	–	6.760	4.923	1.838	0.513	0.322	0.198	37,222
3	ML1	5.608	3.695	1.913	0.522	0.257	0.136	6,060
3	ML2	5.542	3.674	1.868	0.514	0.239	0.116	5,966
3	ML3	5.525	3.636	1.889	0.529	0.245	0.119	5,867
4	–	7.844	5.792	2.051	0.578	0.388	0.252	30,362
4	ML1	6.926	4.716	2.210	0.619	0.369	0.222	3,975
4	ML2	7.148	4.961	2.187	0.616	0.358	0.215	4,073
4	ML3	7.040	4.886	2.153	0.617	0.341	0.195	3,883
4	ML4	7.059	4.889	2.170	0.610	0.355	0.205	3,895
Total:		3.428	2.158	1.270	0.255	0.118	0.064	586,762

Table 1 presents the summary statistics of the "random flight" brand searches split by the randomized ad allocation realizations. There are 15 different realizations, which vary by the number of mainline ads and position of the focal brand's ad, if it is shown. The last column presents the number of brand search occasions that fall into each condition. More brand searches fall under the conditions with fewer mainline ads, reflecting (1) the fact that not all brands have four competitors bidding on the focal brand's name, and (2) the overall design of the "random flight." Columns 3–8 show summaries of brand searches' characteristics, such as number of bidders and number of eligible (present in the absence of randomization) competitors in the top paid positions. These results support the idea that randomized conditions are not directly comparable; for example, in the no mainline ads condition (row 1), 12.4% of brand searches have a competitor advertising in ML2, whereas this figure is 57.8% for the randomized condition with four competitors in the mainline position. We thus need to control for the search query (brand name) and exact combination of eligible advertisers on the query, a combination of which we denote as market conditions m, to estimate correct treatment effects. Notice also that brand searches with the same

[15] We implement the predictive exercise on a sample of 100 million ads on the brand searches in the non-randomized condition. For proprietary reasons, we cannot report the results of or details about the prediction mechanism.

number of mainline ads and the focal brand's ad in one of the positions are balanced in terms of their observed characteristics, such as number of eligible ads and number of search occasions, giving us an additional test of whether we constructed the comparison groups appropriately.

3.3 Estimation

Consumers search for brand j in the market condition m on an occasion k, pursuing some objective. As a result of this search, they observe a page with search results, including the advertising positions of the focal (searched-for) brand and its competitors at the top of the page, $\{X^s_{jmk}, X^c_{jmk}\}$, respectively. Consumers then decide whether to click on the focal brand's search result, competitors' search results, or not to click on any links on the page. These click decisions depend on the brand- and market-condition-specific results on the page, α_{jm}, the advertising positions of the focal brand and competitors, $\{X^s_{jmk}, X^c_{jmk}\}$, and idiosyncratic shock, which can be expressed as ϵ_{jmk},

$$y_{jmk} = \alpha_{jm} + f_{jm}(X^o_{jmk}, X^c_{jmk}) + \epsilon_{jmk},$$

where y_{jmk} is a binary variable capturing the click decision.

We are interested in the effect of the presence and positions of the focal brand's and competitors' ads at the top of the brand search results page. With regular search results, $\{X^s_{jmk}, X^c_{jmk}\}$ are completely determined by the brand and market conditions, α_{jm}, given that companies decide on which brands and in which market conditions to advertise. The randomized ad allocation provides us observations where $\{X^s_{jmk}, X^c_{jmk}\}$ is random conditional on the brand and marketing conditions, α_{jm}. Notice that we need to condition on α_{jm} since the randomization does not completely remove the correlation between α_{jm} and $\{X^s_{jmk}, X^c_{jmk}\}$, as it allocates only ads with a non-zero rank score on the brand query. However, we are able to reconstruct the identities and order of the ads shown on the page *in the absence* of the experiment, giving us measures of the market conditions, α_{jm}, and thus allowing us to control for any relevant differences across the searches.

The last thing we need to define is the $f_{jm}(\cdot)$ function. Luckily, there is a finite and small number of ad allocation conditions; there are at most four ad positions at the top of the search page, and at most one focal brand ad, giving 15 possible combinations of ads for the top of the page.[16] We thus define $f_{jm}(\cdot)$ as $\sum_{i=1}^{15} \gamma_{i,jm} \mathbb{1}(\text{ad condition } i)$, where $\gamma_{i,jm}$ is the effect of a randomized ad condition i for brand j and in market condition m.

The amount of data that we have restricts us from estimating separate treatment effects for each brand j and market condition m. We fall back on estimating an average treatment effect, γ_i, by pulling the effect estimates across the brands. Notice that if we treat all the observations similarly, we get an average treatment effect that is weighted by the probability of the appearance of brand j and market condition m in each of the treatment groups, determined by brand prominence and Bing's randomization. In the results section, we test whether there is a detectable heterogeneity in the treatment effects across companies and manipulate the observation weights to get the average treatment effect unaffected by randomized ad allocation.

Given the definitions above, we estimate the effect of the focal brand's and competitors' ads on page behavior, such as consumer clicks and quick back probability, using the following regression:

$$y_{jmk} = \sum_{i=1}^{15} \gamma_i \mathbb{1}_{jmk}(\text{ad condition } i) + Z_{jm}\beta + \epsilon_{jmk}, \tag{1}$$

where γ_i are the average treatment effects of interest and Z_{jm} represent the controls, such as query, eligible ads, or overall market condition fixed effects.

4 Results

4.1 Level of Traffic: Clicks

We start with the results on the volume of traffic stealing by competitors. Figure 2 shows estimates of the share of clicks on the focal brands' and competitors' links (sum of paid and

[16] These combinations are defined as an interaction of five advertising levels (0,1,2,3,4) and an indicator of the presence of the focal brand's ad. Cases with more than one focal brand ad at the top of the page are extremely rare ($< 0.1\%$) and are likely due to ad allocation mistakes, so we remove these cases from the analysis.

organic) under different numbers and compositions of mainline ads.[17] When there are no ads in the mainline (column 1), an average focal brand receives 86.6% (s.e. 0.07%) of the clicks.[18] As we add competitors to the top paid positions, the share of the focal brands' clicks decreases (red line), with one competitor reducing the focal brand's traffic by 6.05 (0.14) percentage points and four competitors reducing the focal brand's traffic by 20.7 (0.24) percentage points. These changes in the focal brand's traffic are statistically significant and economically meaningful, with the focal brand losing 23.9% of its traffic when facing four competitors.

The results are drastically different if the focal brand's ad is in the top paid position on the page (blue line). In this case, one to three competitors in other paid positions reduce the focal brand's traffic by only 1.3-2.6 percentage points, which is consistent with the small traffic stealing effects of competitors presented by Simonov et al. (2017). This difference in traffic stealing supports the "defensive" role of focal brands advertising in paid position 1.

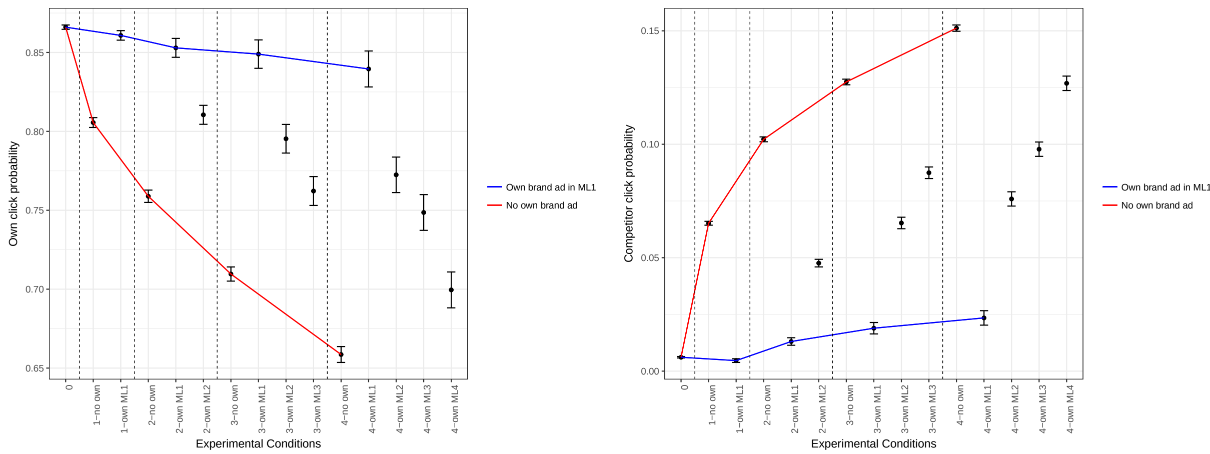
In practice, the focal brand's ad almost always appears in the top paid position on the page due to its relevance, conditional on the focal brand's bidding on its keyword. However, the randomized ad allocation results in occasions of the focal brand occupying mainline positions 2-4 while competitors advertise in the mainline 1 position. These cases confirm the strong position effects of ads on brand search. In cases of two mainline ads, shifting the focal brand's ad from mainline 1 to mainline 2 reduces the focal (total) brand's traffic by 4.24 (0.4) percentage points. Similarly, a shift of the focal brand's ad to position 3 reduces the focal brand's traffic by 8.67 (0.6) percentage points, and a shift to position 4 reduces it by 14 (0.8) percentage points, for cases with three and four mainline ads, respectively. The similarity in position effect estimates across comparisons further validates our design of comparison groups (inclusion of the market condition fixed effects) across unbalanced randomized conditions.

In Figure 2, we present the results for the pooled paid and organic traffic of the focal

[17] Estimation is done using regression (1), with an interaction of brands and an exact set of advertiser fixed effects as controls. Tables 4 and 5 in Appendix 6.4 present the regression results under this and alternative specifications.

[18] The estimates correspond to the weighted average treatment effect, with the weights proportional to the frequency of brand search for each company and brands' allocation to randomized conditions. Columns 5 and 6 in Tables 4 and 5 in Appendix 6.4 re-weight the observations to account for the difference in random conditions assignment probabilities and difference in brand prominence and find qualitatively similar results. For example, the results from column 5 are summarized in Figure 12 in Appendix 6.4.

Figure 2: Estimates of the probability of a consumer clicking on the focal brand's web link.



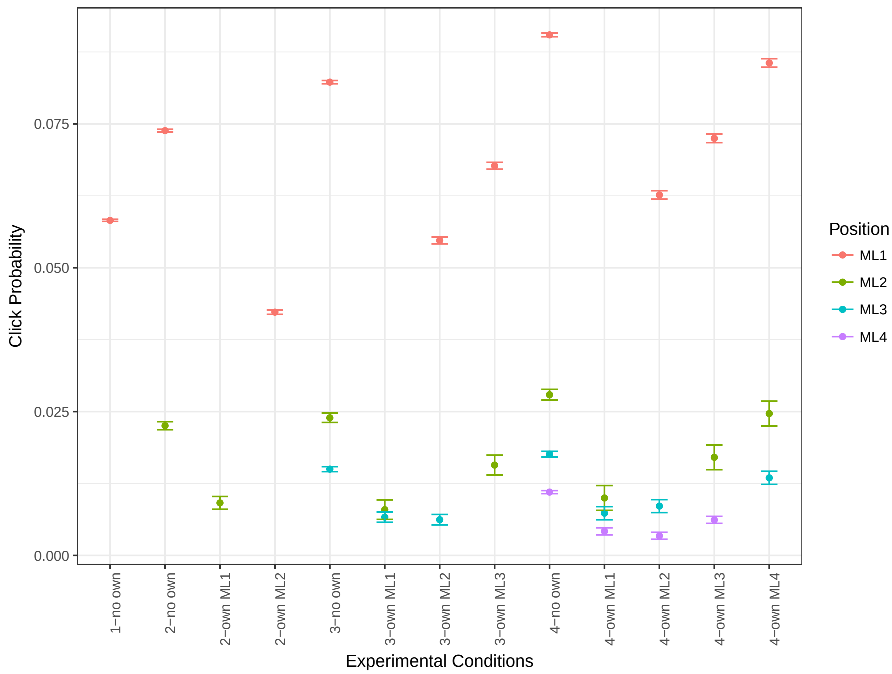
(a) Competitors' Clicks (b) Competitors' Clicks

Randomized conditions are described as "Y number of mainline ads – own (focal) brand's mainline position Y". For example, "3-own ML3" means that there are three ads in the mainline position, and the focal brand's ad is in the third position from the top. The estimates are based on the results of regression (1) (Tables 4 and 5 in Appendix 6.4, specifications 4), with an interaction of brands and an exact set of advertiser fixed effects as controls. The dependent variable is an indicator of a click on the focal brand's (a) or competitors' (b) web links, in organic or paid positions. We take the average click probability in the randomized condition with no ads as a baseline for the click probability.

brands and their competitors. Figures 3 and 4 break down this traffic by type and positions of links. Figure 3 presents the estimated CTRs of the competitors' ads by their position, across the randomization conditions. The competitor in paid position 1 steals the highest share of the focal brand's traffic, varying from 4.22 (0.02) to 9.04 (0.02) percentage points of clicks for the randomized conditions with one to four competitors. This corresponds to the vast majority of competitors' clicks. We note that competitors benefit from the presence of other competitors in the mainline; both competitors in mainline 1 and 2 get more clicks as the number of competitors increases.

Figure 4 splits the focal brand's traffic by paid and organic web links. This difference is crucial for focal brands, given a potentially large crowd-out of organic clicks by a paid web link, as found by previous research (Blake et al., 2015; Simonov et al., 2017). Our estimates confirm these results. The levels of the bars in subfigure (a) correspond to the overall share of clicks of the focal brand, similar to the results presented in Figure 2. Without competitors' ads, 37.85% (0.18) of the focal brand's traffic navigates through the paid link. Adding competitors below the focal brand's ad increases the cannibalization rates, with 70.5% (0.85) of the focal brand's traffic going through the paid link in the case of three

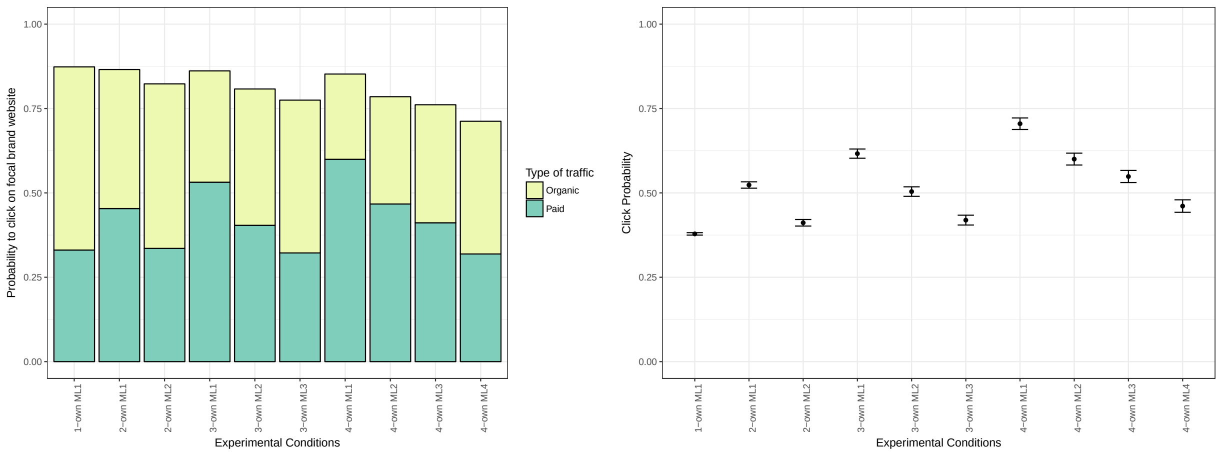
Figure 3: Estimates of the probability of a consumer clicking on the focal brand's web link.



Randomized conditions are described as "Y number of mainline ads – own (focal) brand's mainline position Y". For example, "3-own ML3" means that there are three ads in the mainline position, and the focal brand's ad is in the third position from the top. The estimates are based on the results of regression (1) (Tables 17 and 18 in Appendix 6.4, specification 4), with an interaction of brands and an exact set of advertiser fixed effects as controls. The dependent variable is an indicator of a click on a competitor's web link in mainline positions one through four.

competitors in mainlines 2-4, supporting the results in Simonov et al. (2017). As the focal brand's ad moves down the page, from mainline 1 to mainline 4, the share of paid traffic decreases from 70.5% (0.85) to 46.1% (0.92).

Figure 4: Estimates of the probability of a consumer clicking on the focal brand's paid and organic web links, by type



(a) Focal Brand's Traffic

(b) Share of Paid Traffic

Randomized conditions are described as "Y number of mainline ads – own (focal) brand's mainline position Y". For example, "3-own ML3" means that there are three ads in the mainline position, and the focal brand's ad is in the third position from the top. The estimates are based on the results of regression (1) (Tables 15 and 16 in Appendix 6.4, specification 4), with an interaction of brands and an exact set of advertiser fixed effects as controls. The dependent variables are indicators of a click on the focal brand's paid or organic web links. We take the average click probability in the randomized condition with one mainline ad of the focal brand ("1-own ML1") as a baseline for the click probability.

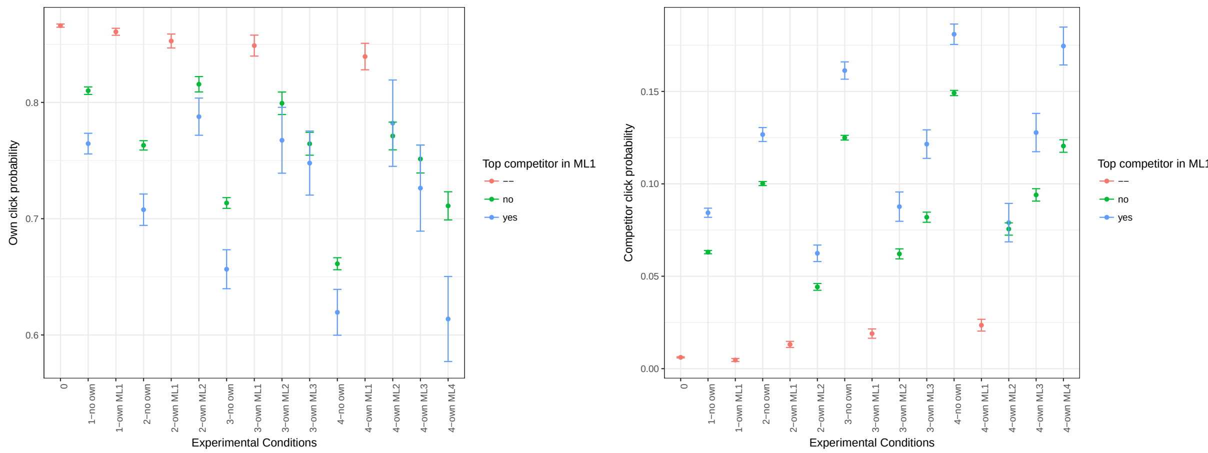
We can conclude that competitors can steal the focal brand's traffic, and can steal more if the focal brand's ad does not occupy mainline 1. However, the randomization that we use puts an average competitor of the focal brand in mainline 1, not the most relevant competitor. In practice, if the focal brand stops advertising, the most relevant competitor occupies mainline 1, so perhaps the nature of the competitor in the top position influences the degree of traffic stealing.

To test whether results differ for the most relevant competitor, we separate out the conditions when such a competitor is in the top paid position.[19] The most relevant competitor is defined as the competitor usually shown in the second mainline position, immediately after the focal brand's ad. Figure 5 presents the click probabilities split by the type of competitor

[19]We focus only on competitors in the top position of the results page since (1) the majority of competitors' traffic goes to the top competitor, as shown in Figure 3, and (2) estimates become too noisy if broken down by type of competitor in the second through fourth top positions.

in the top paid position. A more relevant competitor can indeed steal more traffic from the focal brand; if the most relevant competitor occupies the top paid position, one to four competitors can decrease a focal brand's traffic by 10.1 (0.43) to 24.7 (0.98) percentage points, compared to 6.6 (0.15) to 20.5 (0.25) percentage points if the top paid web link is not of the most relevant competitor.

Figure 5: Estimates of the probability of clicking on the focal brand's (a) and competitors' (b) web links, by relevance of the competitor in the top paid position on the page.



(a) Focal Brand's Clicks

(b) Competitors' Clicks

Randomized conditions are described as "Y number of mainline ads – own (focal) brand's mainline position Y". For example, "3-own ML3" means that there are three ads in the mainline position, and the focal brand's ad is in the third position from the top. The estimates are based on the results of regression (1) (Table 9 in Appendix 6.4, specification 4), with an interaction of brands and an exact set of advertiser fixed effects as controls. The dependent variables are indicators of a click on the focal brand's (a) and competitors' (b) web links, in organic or paid positions. We take the average click probability in the randomized condition with no ads as a baseline for the click probability.

4.2 Quality of Traffic: Quick Backs

We have shown that competitors are able to steal the focal brand's traffic and that this traffic stealing depends on competitors' relevance, prominence, competitive nature, and title. Do these incremental clicks reflect loyal customers of the focal brand switching to competitors? Or are these less loyal "comparison shoppers" who tend to explore various websites without completing a purchase?

In this section, we explore these questions by measuring the "quality" of competitors' and the focal brand's traffic. We do not have access to click conversions so we instead focus on "quick back"events, which occur when a consumer returns to the SERP in less than 30 seconds after clicking on a search result. Quick back events are considered to be a measure of the "success" of a click for search engines; Goldman and Rao (2014) showed that they have a strong negative correlation with click conversion rates.

Table 2: Estimates of quick back probability of clicks on the focal brand's, competitors', and all links.

	Quick Back Probability, %		
Randomized	Clicks		
Ad Conditions	Focal Brands	Competitors	Total
"0 – no own"	6.18	23.98	6.12
	(0.05)	(1.1)	(0.05)
"1 – no own"	4.79	43.48	8.01
	(0.12)	(1.69)	(0.12)
"2 – no own"	4.19	41.79	9.27
	(0.16)	(1.72)	(0.15)
"3 – no own"	4.15	42.87	10.60
	(0.19)	(1.74)	(0.17)
"4 – no own"	3.48	42.59	11.21
	(0.22)	(1.76)	(0.19)

The estimates are based on the results of regression (1), with an interaction of brands and an exact set of advertiser fixed effects as controls (Table 6 in Appendix 6.4, specification 4). Dependent variables are indicators of a "quick back" event on clicks on the focal brand's, competitors', and all web links, in organic or paid positions. We take the average quick back probability in the randomized condition with no ads as a baseline for the click probability.

Table 2 presents estimates of the quick back probability for clicks on the focal brand's, competitors', and all web links.[20] Several results in the table are notable. First, clicks on the focal brand's links (column 1) have a lower chance of a quick back than clicks on competitors' ads (column 2). For example, with one competitor in the mainline slots, clicks on the focal brand's weblink have a 4.79% probability of being a quick back event, while clicks on a competitor's weblink have a 43.48% probability. This indicates that competitors' clicks are of a much lower "quality" than the focal brand's clicks.

Second, the quick back probability of the focal brands' clicks decreases from 6.18% to 3.48% as the number of competitors in the top paid positions increases from zero to four. This implies that the traffic that switches away from the focal brand to competitors has a

[20]We present only estimates for conditions with no focal brand ads due to the noisy estimates of the other conditions. Table 6 in Appendix 6.4 presents full estimation results. Further, we note that links in the "Total" column include the focal brand's and competitors' links as well as a small fraction of other links (e.g., page answer links). This explains why the "total" quick back probability (column 3) is slightly different from the weighted sum of focal brands' and competitors' quick back probabilities.

higher "baseline" quick back probability (lower quality) than the traffic that "stays" with the focal brand. Such adverse selection signals that, on average, it is less loyal customers who are more likely to click on competitors' links.

Third, as the number of competitors in the top paid positions increases from zero to four, the quick back probability of all clicks increases from 6.12% to 11.21%. This increase implies that competitors' ads generate incremental quick back events; in other words, competitors have a negative impact on the overall quality of clicks on the SERP.

What share of the high (42-43%) quick back rate for competitors clicks is due to adverse selection versus an incremental increase in quick back events? We can use the level of clicks and quick back rate estimates to decompose this effect. For instance, with four competitors in the mainline position, 42.59% of competitors' clicks result in a quick back event. Four competitors steal 20.7 of 86.6 percentage points of the focal brand's traffic, meaning that 65.9 percentage points of consumers stay with the focal brand. The quick back probability of all (86.6 percentage points) of the focal brand's traffic is 6.18%, and the quick back probability of the remaining 65.9 percentage points is 3.48%, meaning that the baseline quick back probability of "switching" traffic is $(6.18\% - \frac{65.9}{86.6} * 3.48\%) * \frac{86.6}{20.7} = 14.78\%$. This implies that the remaining $42.59 - 14.78 = 27.81$ percentage points of competitors' quick backs are incremental.

There are two potential interpretations for the incremental increase in quick back events. On the one hand, consumers may click on one of the top links on the page assuming that they are navigating to the focal brand's website. Once they realize they are on the wrong website, they return to the SERP. This explanation of quick back events implies some form of customer confusion.[21] On the other hand, consumers may notice competitors in the top paid positions and decide to learn more about them, interpreting their high position as a signal of quality. After clicking, they realize that the competitor's link does not satisfy their immediate need and decide to return to the SERP. While the click is still not satisfactory, consumers may have learned something about the competitor via the clicked link, corresponding to a deliberate search process.

It is challenging to disentangle these two potential stories since a direct test for customer

[21]The legal literature refers to this case as initial interest confusion, a temporary confusion that is resolved before making a purchase (e.g., Rothman, 2005).

confusion would involve either surveying consumers or examining their full browsing histories, both of which are inaccessible to us.[22] Instead, we further exploit the available data to look for empirical support for either theory.

First, we examine the overall distribution of dwell times after a click on a competitor's ad conditional on a quick back event. Subfigure (a) of Figure 6 presents the implied histogram. The distribution of clicks is bimodal, with a small mass of consumers leaving just a couple of seconds after making a click (likely due to a long loading time) and most quick backs occurring in the interval of 3-12 seconds. Thus, it either takes at least several seconds for consumers to realize they are on the wrong website, or consumers exercise a deliberate search and then bounce back to Bing to search again. Given that it takes consumers only tens or hundreds of milliseconds to recognize brand dilution (Tushnet, 2007), reaction of 3-12 seconds is more consistent with a deliberate search story.[23] Compare this to Subfigure (b), which shows the distribution of dwell times after a click on a focal brand's link conditional on a quick back event. The majority of the focal brand's quick backs happen in the first couple of seconds, likely due to page loading problems, and the rest of the histogram is only slightly skewed to the right.

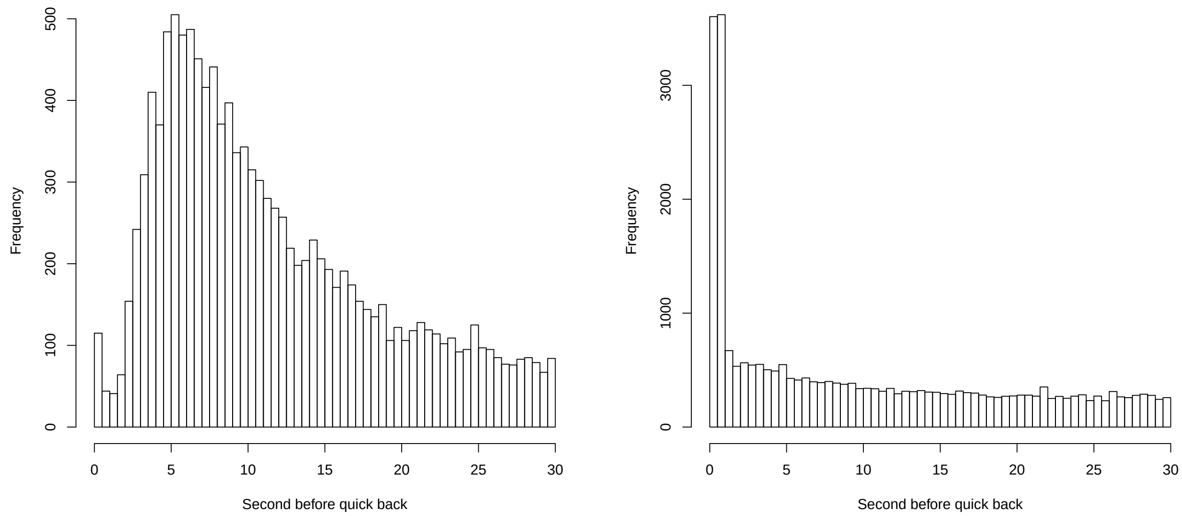
Second, we test whether more relevant competitors get clicks with lower quick back probability (higher quality). Such a data pattern is more consistent with the deliberate search story, since, almost by definition, more relevant competitors are more likely to satisfy a searcher's needs. Figure 7 splits quick back probability estimates by the type of competitor in the top paid position. While the estimates are noisy, they indicate that when the most relevant competitor is in the top position, competitors' traffic has a lower quick back probability. When we combine data from different conditions, we find that the presence of the most relevant competitor in the first paid position decreases the quick back probability of all competitors' clicks by 4.83 (1.06) percentage points.[24] These results show that the relevance

[22]Bing data contains individual-level request histories, which could approximate browsing histories. However, extracting these histories of requests for all consumers in the sample is not feasible due to computational constraints that we face. Even if the requests histories were pulled, they are less satisfactory than browsing histories since we would not observe direct navigations.

[23]Important caveat is that reaction time results described in (Tushnet, 2007) are based on the evidence from the lab experiments, recently reconsidered by (Beebe and Steckel, 2019). In practice, it might take more time for consumers to realize they are on the wrong website. Still, given the order of magnitude difference in the response time, we interpret the results as more consistent with a deliberate search process.

[24]Estimates are presented in Table 10 in Appendix 6.4. Given that most traffic goes to a competitor in the top paid position (Figure 3), this result is driven by the higher-quality clicks on the most relevant competitor.

Figure 6: Distribution of dwell times conditional on a quick back event.



(a) Competitors' Quick Backs

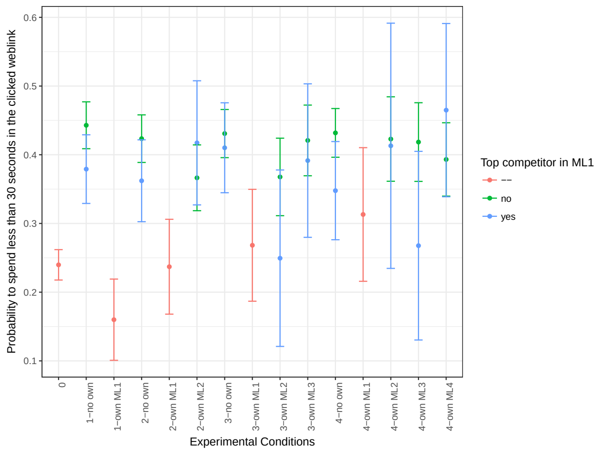
(b) Focal Brand's Quick Backs

Based on randomized ad allocation data.

of competitors in the top paid positions indeed matters, suggesting that either more relevant competitors are less likely to confuse customers or that incremental quick backs are due to consumers' deliberate searching and not to confusion.

Overall, we conclude that competitors are more likely to siphon off less loyal customers of the focal brand ("comparison shoppers") and that they do increase the quick back probability on the SERP; the data is more consistent with the deliberate search process but is inconclusive overall since we cannot formally disentangle customer confusion and deliberate search. However, there are two interpretations of our results that allow to assess the potential degree of customer confusion and social cost from competitive advertising on brand search. First, using the incremental quick backs and assuming that people would realize the website confusion in 30 seconds, we can derive an upper bound on the degree of customer confusion generated by competitive advertising. The measure of 27.81 incremental quick backs implies that, at most, 27.81% of customers who click on competitors' paid links were "confused" and returned to the search engine. Given that four competitors' ads in the top paid positions siphon off 20.6% of the focal brand's traffic, at most $0.206 * 27.81\% = 5.7\%$ of consumer searching for the focal brand end up being confused. While imperfect, this measure suggests

Figure 7: Estimates of the quick back probability of clicks on competitors' web links, by relevance of the competitor in the top paid position on the page.



Randomized conditions are described as "Y number of mainline ads – own (focal) brand's mainline position Y". For example, "3-own ML3" means that there are three ads in the mainline position, and the focal brand's ad is in the third position from the top. The estimates are based on the results of regression (1) (Table 11 in Appendix 6.4, specification 4), with an interaction of brands and an exact set of advertiser fixed effects as controls. The dependent variables are indicators of a quick back event on competitors' clicks, in organic or paid positions. We take the average click probability in the randomized condition with no ads as a baseline for the click probability.

that the vast majority of customers searching for the focal brand are either unaffected or find some value in competitive advertising, arguing against its ban.

Second, we can interpret incremental quick backs as an additional time cost incurred by the society in the presence of competitors' ads on brand search. Given that (a) almost all (87%) of quick backs on competitors' ad results in another search for the focal brand,[25] (b) with four competitors' ads 5.7% of brand searchers result in an incremental quick back, and (c) on average it takes consumers 10 seconds to make a quick back after competitors' ad click, if we put four competitors on top of the Google's top 100 brand search keywords (1,614,914,000 searches in 1 month[26]) the resulting societal time cost would be 255,698 hours (29.19 years), converting to $6.88 million using a $26.92 per hour wage rate.[27] Notice that this number represents the worst-case scenario since most focal brands (especially prominent ones) do not face four competitors on their brand search (e.g. "Google" or "Facebook"), and most (66% based on Rao and Simonov (2016)) focal brands advertise defensively on their keywords, which prevents almost all of the traffic stealing (thus dramatically reducing the

[25]Based on 1 day of data for which we are able to extract subsequent searchers of consumers after a competitors' ad click resulting in a quick back.

[26]Based on `https://ahrefs.com/blog/top-google-searches/`.

[27]Data for the US for May 2018: `https://ycharts.com/indicators/average_hourly_earnings`.

societal time costs). We further discuss the policy implications of our results in Section 4.3.4.

4.3 Implications

4.3.1 Focal Brands: Cost per Incremental Click

The results discussed above show that competitors are able to steal the focal brand's traffic and that the focal brand can effectively "defend" its traffic by occupying the top paid position on the SERP. How expensive is such a "defense" for the focal brand? To assess this, we use the estimates presented in Figures 2 and 4 to compute the cost per incremental click (CPIC) for the focal brand (Simonov et al., 2017). CPIC measures how much money the focal brand should pay to get one incremental click:

$$CPIC = \frac{\#\text{ paid clicks}}{\#\text{ incremental clicks}} CPC$$

In our scenario with competitors' ads, focal brands pay the cost per click (CPC) for each of their paid clicks and benefit primarily from reducing traffic stealing by competitors. If a focal brand faces one competitive ad in the mainline position and chooses not to advertise, it loses 10.1 (0.43) percentage points of its traffic.[28] If the focal brand does advertise, it loses virtually no clicks but pays for 45.36 (0.46) percentage points of its traffic. Thus, the CPIC for a focal brand facing one competitor is approximately $\frac{45.36}{10.1} * CPC = 4.49 * CPC$, where CPC is the cost per click of the focal brand. Similarly, the CPIC for a focal brand facing two competitors is approximately $\frac{53}{15.8} * CPC = 3.35 * CPC$, and for a focal brand facing three competitors, it is approximately $\frac{60}{22.8} * CPC = 2.63 * CPC$. The implied CPICs for a company with median CPC of \$0.23 are \$1.03, \$0.77, and \$0.60 for the cases of one, two, or three competitors in the mainline, respectively. For comparison, a median competitor in the second mainline position pays \$0.92 per click, meaning that a focal brand often pays the same amount per incremental click as competitors, a drastically different conclusion compared to the case of nominal measures of CPC. However, given the high quick back rates on competitors' clicks, the focal brands tend to pay less per "high quality" incremental click (i.e., an incremental click that does not result in a quick back event).

[28]Given that the right counterfactual would put the most relevant competitor in the top position, we use the results in Figure 5 for this analysis.

4.3.2 Search Engines: A Mechanism for Exclusive Ad Placement

As shown above, focal brands sometimes pay more for their incremental customers than their competitors do. This result relates to a broader discussion on exclusive search ad placement, a mechanism in which the search engine allows one advertiser to be "exclusive" for a query (Jerath and Sayedi, 2015). If the high CPIC of focal brands correctly signals high willingness to pay for traffic, this indicates some focal brands are willing to pay more for incremental traffic than competitors are currently paying.[29] In such cases, the search engine (e.g., Bing) can offer exclusive ad placement to focal brands and charge them based on their implied CPIC. Because the CPIC of the focal brand is higher than the CPC of competitors, this should be optimal for both the focal brand (they would get incremental clicks for the same price as they are currently willing to pay) and Bing (they would get more money for incremental clicks). The process can be operationalized by setting a second reservation level for the focal brand's ad in the existing auction; if the focal brand bids above this "exclusive threshold", the platform serves an exclusive ad, and both the platform and the focal brand benefit.

At the same time, there are at least two reasons why Bing and Google might be reluctant to implement an exclusive ad mechanism. First, this procedure would require automatically computing the CPIC of the focal brand over time, which could become problematic if competitors are not shown on the page and the right counterfactual is not observed. This problem can be solved by running an experiment on a small fraction of the traffic, but even then the platform needs the most relevant competitors to continue bidding even though they are almost never shown on the SERP.

Second, and perhaps more importantly, exclusive ads of the focal brand will very likely have a negative impact on the focal brand's nominal paid traffic metrics, since (1) in the absence of competitors, the crowd-out of the focal brand decreases (per Figure 4), so the volume of paid traffic is lower, and (2) because of this lower paid traffic, the platform will have to charge higher exclusive CPCs to equate the real metric of CPICs that the focal brand pays. If a company is tracking only the volume of paid and not total traffic, it will seem like it is paying more for a lower volume of traffic, which is the opposite of what is desired.

[29] Here, we assume that the clicks competitors get would go to the focal brand if competitors stopped advertising. Our results are too noisy to confirm this, but Simonov et al. (2017) found that this was true using a large experiment in a similar context.

There are several reasons why companies may wish to maximize paid instead of total traffic, including the difficulty of measuring changes in the focal traffic and potential principle-agent problems within the company.[30]

4.3.3 Consumers: Expected Utility Decomposition

Given the rich variation in the identity and position of ads, we can decompose the estimated click probabilities into the effects of position and type of link (paid or organic, and focal brand or competitor) on the results page. Brand search can be interpreted as a sequential search problem, which is typical for other types of searches (Jeziorski and Segal, 2015). Given that consumers almost always make at most one click on the SERP, consumers' decision problem can be approximated by a discrete-choice problem. After searching for a brand j, a consumer lands on the results page with realizations of the focal brand's and competitors' links, $\{X^s_{jm}, X^c_{jm}\}$. Consumers' expected utility, or the net search costs (e.g., scrolling the page), of clicking on link l on the search results page is

$$u_i = v(\text{type}_l) - c(\text{position}_l, \text{type}_l) + \zeta_{ig} + (1-\sigma)\epsilon_{il},$$

where α is the mean expected utility of the link depending on its type (focal brand's organic, focal brand's ad, or competitor's ad), $c(\cdot)$ is the function of competitors' cost depending on the link's position and type, and $\zeta_{ig} + (1-\sigma)\epsilon_{il}$ is the l's group and observation-specific shock, distributed as an extreme-value random variable, leading to a nested logic structure (McFadden, 1981; Cardell, 1997).[31] The focal brand's paid and organic links are in one group, and all other options (competitors' links and the "no click" option) are in another group.

Given the limited number of types and page positions of the links, we can reduce $v(\text{type}_l)$

[30] Anecdotally, many companies have different divisions or hire different ad agencies that are responsible for paid and organic traffic. Set-ups such as this misalign managers' incentives and make them compete for paid and organic traffic. Since search ads are more likely to be bought by the team managing paid traffic, they are likely to maximize paid traffic. Rao and Simonov (2016) documented suggestive evidence for this principle-agent problem by looking at the different reactions of firms to public and private information.

[31] We chose the nested logit formulation of the model since we have strong expectations of the types of links that should be grouped together. For such a setting, the results in Berry (1994) allow a simple decomposition of the estimates into parameters of consumers' utility.

to three states and $c(\text{position}_l, \text{type}_l)$ to seven states:

$$v(\text{type}_l) = \alpha + \alpha_{\text{ad}} I(\text{type}_l = \text{own ad}) + \alpha_{\text{compet}} I(\text{type}_l = \text{compet})$$

$$-c(\text{position}_l, \text{type}_l) = \sum_{x \in \{2,3,4,5\}} \gamma_{\text{own},x} I(\text{type}_l = \text{own}, \text{position}_l = x) +$$

$$+ \sum_{x \in \{2,3,4\}} \gamma_{\text{compet},x} I(\text{type}_l = \text{compet}, \text{position}_l = x)$$

where $\text{type}_l = \text{own}$ includes cases of both a focal brand's ad and its organic links.[32] Coefficients α capture the expected utility consumers get from clicking the focal brand's paid and organic links and competitors' paid links in the top position on the page. Coefficients γ capture the decrease in the expected utility from moving the focal brand's and competitors' links down the page.

Applying the inversion defined by Berry (1994), we note the difference in log click probabilities as

$$ln(\text{Prob}_{lk}) - ln(\text{Prob}_{0k}) = \alpha(\text{type}_l) - c(\text{position}_l, \text{type}_l) + \sigma ln(\text{Prob}_{l/g,k}) + \xi_{lk}$$

where $\text{Prob}_{l/g,k}$ is the link's l choice probability within its group g on occasions k, and ξ_{lk} represents the residual variation in log click probabilities. Our parameterization of v and c above implies that we need to estimate 11 coefficients (10 of α and γ and the within-group correlation σ).[33]

Table 3 presents the resulting decomposition of consumers' expected utility by link type and page position. Expectedly, consumers prefer the focal brand's organic link ($v = 1.8636$) to its paid link ($v = 1.8636 - 0.1907 = 1.6729$) and strongly prefer either to competitors' links ($v = 1.8636 - 2.7063 = -0.8427$). Also as expected, the correlation in the utility shocks of paid and organic links of the focal brand, σ, is positive and high, reflecting the similarity of the focal brand's links. Costs increase with the position of the link on the page, and they increase faster for competitors. To interpret the scale of the coefficients, Figure 8 plots the odds ratios of the probability of a consumer's click on the focal brand's and a

[32]We focus only on aid competitors' links and only on clicks on the top organic link since the traffic going to other organic links is very low.

[33]Results virtually do not change if we instrument for $ln(\text{Prob}_{l/g,k})$ with the positions of other links of the same group on the SERP.

Table 3: Decomposition of estimates into the parameters of consumers' expected utility.

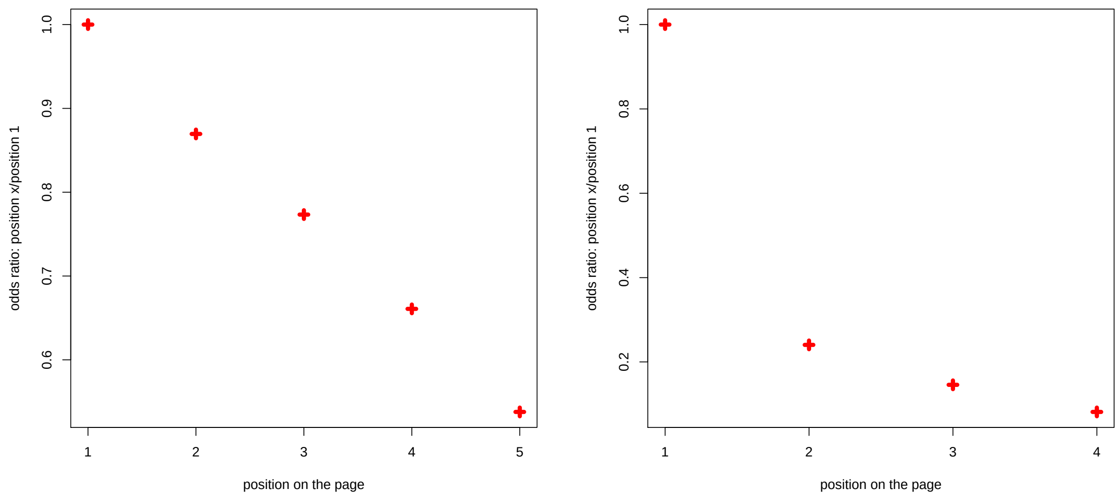
	Estimate	Std. Error
α	1.8636	0.1464
α_{ad}	-0.1907	0.1203
α_{compet}	-2.7063	0.1644
$\gamma_{\text{own},2}$	-0.1398	0.1514
$\gamma_{\text{own},3}$	-0.2571	0.1580
$\gamma_{\text{own},4}$	-0.4143	0.1707
$\gamma_{\text{own},5}$	-0.6202	0.1992
$\gamma_{\text{compet},2}$	-1.4251	0.1086
$\gamma_{\text{compet},3}$	-1.9257	0.1165
$\gamma_{\text{compet},4}$	-2.5074	0.1398
σ	0.7236	0.1295
Observations	55	
R^2	0.985	
Adjusted R^2	0.982	

Decomposition based on the estimates from Figures 2-4.

competitor's link in positions 1-5 to the probability of clicking the same link in position 1, $\frac{\text{Prob(click in position x)}}{\text{Prob(click in position 1)}}$. Subfigure (a) shows that as the focal brand's link moves down the page, the odds ratio decreases from 1 to 0.54, implying that the probability of clicking the focal brand's link in position 5 is 46% lower than in position 1. Notably, the decrease in the odds ratios is virtually linear, reinforcing the interpretation of page position as a cost of scrolling down the page. Subfigure (b) presents the odds ratios for competitors' links; there is a dramatic decrease in click probability as a competitor's link moves from position 1 to position 2 and a close-to-linear decrease for the move to lower positions. There are multiple ways to interpret this non-linearity, including a top-to-bottom sequential consumer search process (if the focal brand is in position 1, many consumers stop searching), a signal of the value of a competitor's link in the top position, or consumers' "clicks by confusion" that go to the top page position. The drastic difference between position effects on the focal brand's and competitors' links is inconsistent with a simple sequential search story, suggesting that part of the effect of a link's position affects the click probability through signaling or customer confusion.

The results in Table 3 also allow us to compare the importance of the type of the focal brand's link (paid or organic) to the link's page position. Figure 10 in Appendix 6.2 presents the odd ratios of the click probability of the focal brand's organic to paid links, by the

Figure 8: Odds ratios of the probability of a click by position of focal brand's and competitors' links.



(a) Focal Brands (b) Competitors

Estimates of $\frac{\text{Prob(click on a link in position x)}}{\text{Prob(click on a link in position 1)}}$.

organic link's position. If both links are in the top position on the results page, consumers are 21% more likely to click the organic link. As the organic link falls to position 2 on the page, the click probabilities become close to equal, and once the organic link falls to position 5, consumers' are 35% less likely to click it compared to the paid link in the top position.

4.3.4 Regulators: Consumers' Confusion and the Social Costs of Competitors' Ads

Given our results, should competitive advertising on brand search be allowed? The evidence that we have presented so far is mixed. On the one hand, we can conclude that competitors' ads provide value to *some* customers, since a substantial share of consumers click on competitors' links, and the majority of those clicks are "successful", meaning that consumers do not return to the search engine in less than 30 seconds. On top of this, more relevant competitors are able to steal more and higher quality traffic, which cannot be explained by misclicks of consumers due to confusion. All of this supports the argument that competitive advertising brings value to some of the focal brand's searchers, meaning that a ban on competitive advertising would deprive consumers of useful information and thus restrict their choice set.

At the same time, some of our results are consistent with the existence of customer confusion as a result of competitive advertising. The presence of competitors' ads at the top of the results page significantly increases the overall quick back probability, implying that more consumers are not satisfied with the search results in this case. Since higher quick back probability is also consistent with consumers' deliberate search, our estimates allow to determine only an upper bound on the degree of customer confusion, namely that around a quarter of consumers who click competitors' links do so due to confusion, corresponding to the 5.7% of searchers of the focal brand. While imperfect, this measure suggests that the vast majority of customers searching for the focal brand are either unaffected or find some value in competitive advertising.

An alternative way to think about the higher quick back probabilities is that it takes extra time for the unsatisfied consumers to find their way to the focal brand's website. Thus, competitors' ads on brand search create additional societal time cost. As we show in the last paragraph of section 4.2, these time costs can be substantial.[34]However, most of the focal brands (especially prominent ones) do not face competitors on their brand search, and most (66% based on Rao and Simonov (2016)) focal brands advertise defensively on their keywords, which prevents almost all of the traffic stealing and thus dramatically reduces the societal time costs. We conclude that under the status quo, the (costly) burden of customer protection lies completely with the focal brands. Interestingly, the incentives of search engines and regulators are at least partly aligned in this case, since both want the focal brands to show up in the top paid position, preventing customer dissatisfaction.

A separate issue that is often discussed in the court cases in relationship to customer confusion is whether the competitor confuses a customer by mentioning the focal brand's

[34]On top of the time costs arising from the incremental quick back events, the mere presence of competitors in the top of the SERP increases the time it takes a consumer to make a click, with the share of consumers making a click in less than 10 seconds decreasing from 83.4% (0.08) without ads to 67.9% (0.31) with four competitors in the top paid positions as we show in Appendix 6.3. Most of the increase in this time-to-click measure comes from consumers who eventually click on the focal brand's link, which is shown after the competitors' ads, implying that the presence of competitors creates additional costs for consumers whose brand search purpose is purely navigational.

name in its ad title.[35] In Appendix 6.1, we distinguish between the cases of competitive ads that mention the focal brand's name in their title and the rest of the competitive ads. On average, when a competitor's ad mentions the focal brand's name, it steals 4.68 (0.04) percentage points more clicks, and these clicks have a 7.9 (0.64) percentage points higher quick back probability, consistent with additional customer confusion. However, we note that our randomization procedure does not manipulate the text of ads, only which ads are shown at the top of the page. Accordingly, we cannot claim that the effect we measure is causal; perhaps companies that mention the focal brand's name in their ad titles are of a different type than those that do not mention it. One theory is that competitors that mention the focal brand in their title are more likely to be resellers of the focal brand; however, in this case, higher quick back probabilities suggest customer confusion even more strongly, since resellers should be more relevant to the searcher than direct competitors of the focal brand.

5 Conclusion

Brand search is considered the prime example of navigational search query, bringing into doubt competitive advertising on brand search as an effective traffic stealing strategy. Our results show that brand search is hardly *only* navigational. Competitors can steal a substantial share of focal brands' traffic. While this traffic is of lower quality, near 60% of consumers do not immediately return to the SERP, implying that they find something of value on competitors' websites. Moreover, more relevant competitors are able to get more and "higher quality" traffic, confirming that they find more value on the websites of more relevant competitors. Our results thus validate the practice of competitive advertising on brand search; there are cases of brand search where consumers make a search to satisfy a general informational or transactional objective, and competitors are able to acquire traffic because they can also satisfy this objective.

We discuss the implications of these findings for all sides of the market. Focal brands that practice "defensive" advertising should be aware of the implied costs per increment of traffic. Search engines can use these results to price exclusive ads for focal brands. On the consumer side, we discuss the relative importance of the type of link and its position on the

[35] See `https://trademarkwell.com/trademarked-keywords-am-i-infringing-or-not/`, Bechtold and Tucker (2014) or Gilson (2014); McCarthy (2014).

results page. Finally, we provide food for thought for regulators, showing that competitors create value for some consumers but potentially confuse and increase search costs for others.

While to our knowledge this is the first empirical work that generalizes competitive traffic stealing in a universe of prominent brands, there are several directions of work that can extend our results. First, while the data from the search engine side allow us to study page position and use randomized ad allocation for a sample of brands, we do not observe the actual conversions and must proxy for them with quick back events (Goldman and Rao, 2014). More work like Coviello et al. (2017) and Golden and Horton (2017), which looks at competitive advertising from the firm side and has access to consumer conversions, would allow a better understanding of the subsequent actions of consumers in reaction to competitive advertising on brand search. Second, competitive advertising potentially has long-term implications for focal brands, for example, creating awareness of competitors among focal brand customers (Rutz et al., 2011). Finally, we provide suggestive evidence for the degree of customer confusion on brand search, but our results are far from conclusive. For example, incremental quick backs caused by competitors can either come from comparison shoppers who are likely to go to competitors anyway or from customers who always click the first link and thus easily make mistakes. More detailed evidence, potentially tracking consumers' browsing histories before and after they are (experimentally) exposed to competitive ads, would allow us to make conclusions about customer confusion more decisively. Of course, such a study puts high demands on the size of the experiment (Lewis and Rao, 2015), presenting an empirical challenge that has not yet been resolved.

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6 Appendix

6.1 Appendix A: Competitors Using a Focal Brand's Trademark

One of the key considerations in court cases about the legality of competitive advertising is whether the usage of the focal brand's trademark in a competitor's ad title creates confusion among consumers.[36] While our randomization does not manipulate the text of ads, it does manipulate whether an ad that contains the focal brand's name in its title is shown at the top of the page. Thus, we can examine whether competitors' ads that mention the focal brand's name siphon off more traffic and determine the quick back rate on this traffic.

Figure 9 presents focal brands' and competitors' click probability estimates, split by whether the competitor in the top paid position mentions the focal brand's name. The results indicate that competitors that mention the focal brand's name steal more clicks than competitors that do not. Considering all the differences together, having a competitor that mentions the focal brand's name in the top paid position decreases the focal brand's traffic by an extra 3.17 (0.15) percentage points and increases competitors' traffic by 4.68 (0.04) percentage points.[37]

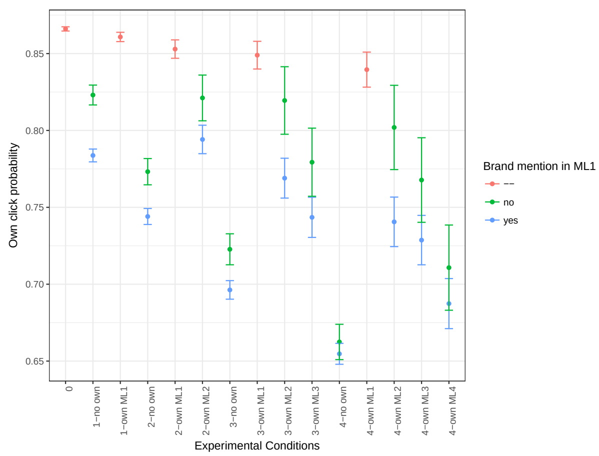
While competitors that mention the focal brand's name in their title steal more of its traffic than other competitors, the quality of this traffic is low. When such a competitor occupies the top paid position, the quick back probability on clicks on competitors' web links is 7.9 (0.64) percentage points higher compared to the case when there is a competitor in the top position that does not mention the focal brand.[38] This higher quick back probability suggests customer confusion due to competitors' mentions of the focal brand's name in their titles. At the same time, we note that the majority of competitors' clicks do not have a quick back event, suggesting that many customers still find value in these competitors' websites.

[36]See `https://trademarkwell.com/trademarked-keywords-am-i-infringing-or-not/` for a March 2017 overview.

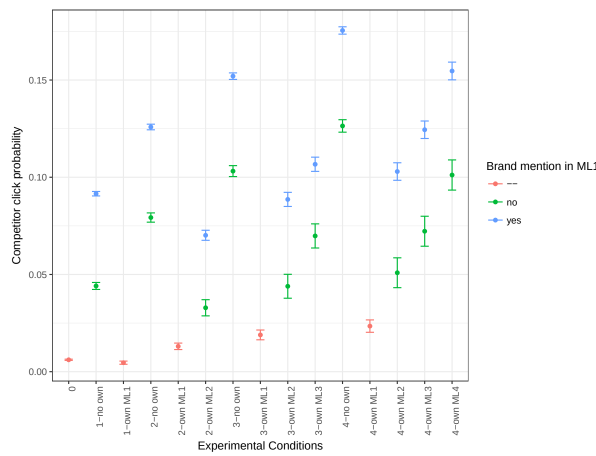
[37]Estimates are presented in Table 12 in Appendix 6.4.

[38]Estimates are presented in Table 14 in Appendix 6.4.

Figure 9: Estimates of the probability of clicking the focal brand's (a) and competitors' (b) web links, by whether the competitor in the top paid position mentions the focal brand's name.



(a) Focal Brand's Clicks

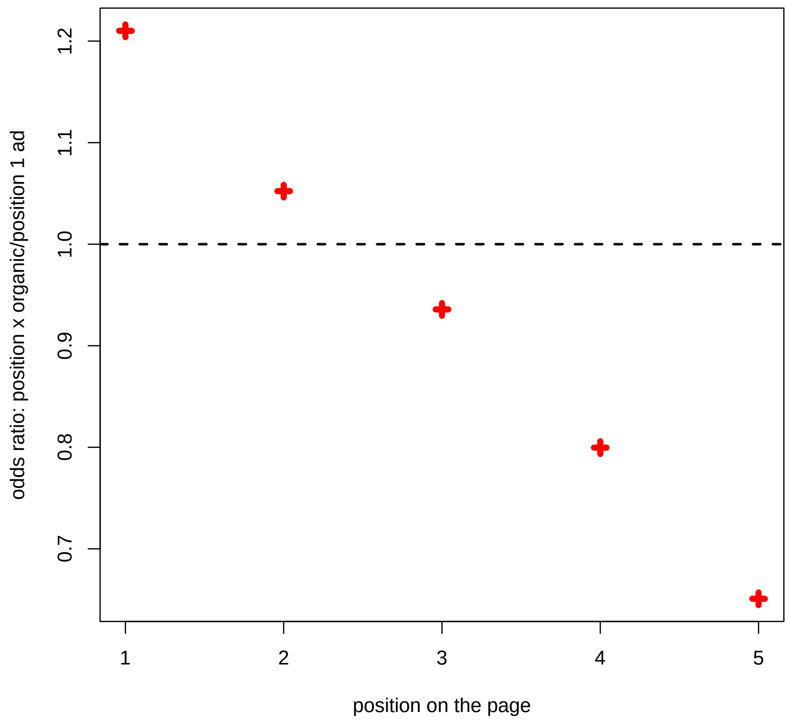


(b) Competitors' Clicks

Randomized conditions are described as "Y number of mainline ads – own (focal) brand's mainline position Y". For example, "3-own ML3" means that there are three ads in the mainline position, and the focal brand's ad is in the third position from the top. The estimates are based on the results of regression (1) (Table 13 in Appendix 6.4, specification 4), with an interaction of brands and an exact set of advertiser fixed effects as controls. The dependent variables are indicators of a click on the focal brand's (a) and competitors' (b) web links, in organic or paid positions. We take the average click probability in the randomized condition with no ads as a baseline for the click probability.

6.2 Appendix B: Odds Ratios of Position and Type of Link

Figure 10: Odds ratios of the probability of a click on the focal brand's organic versus paid links, by the organic link's page position.

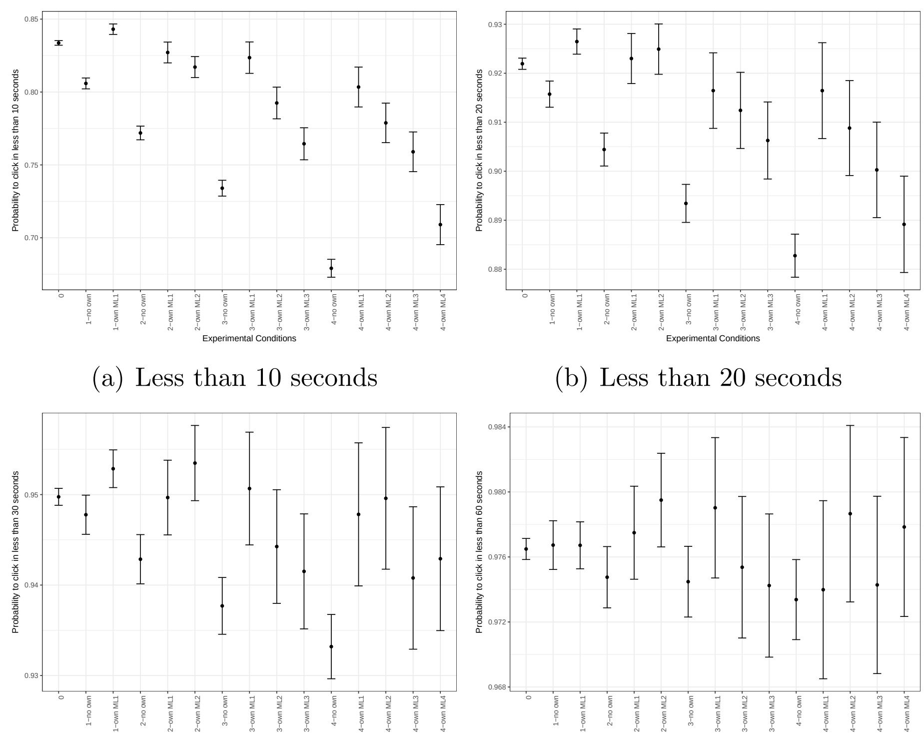


Estimates of $\frac{\text{Prob(click on organic link in position x)}}{\text{Prob(click on paid link in position 1)}}$.

6.3 Appendix C: Time-to-Click

Apart from decreasing click quality, competitors' ads in the mainline position may confuse consumers by simply increasing the time they need to click on the web link of their choice. Figure 11 presents estimates of the probability of a click on any web link on the results page in less than 10, 20, 30, or 60 seconds under different randomized conditions. Competitors' paid links increase time-to-click, with one to four competitors decreasing the number of consumers who click on any web link in less than 10 seconds from 83.36% (0.08) to 80.59% (0.19)–67.91% (0.31), in less than 20 seconds from 92.19% (0.06) to 91.57% (0.13)–88.27% (0.22), and in less than 30 seconds from 94.97% (0.05) to 94.77% (0.11)–93.32% (0.18).

Figure 11: Estimates of the probability of a click on any web link in less than 10–60 seconds.



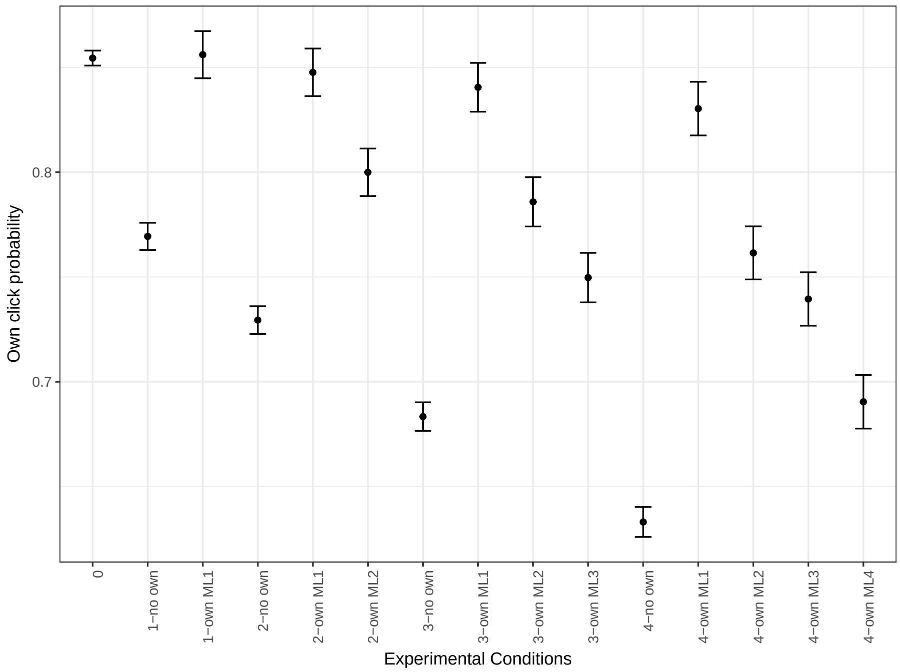
(a) Less than 10 seconds (b) Less than 20 seconds

(c) Less than 30 seconds (d) Less than 60 seconds

Randomized conditions are described as "Y number of mainline ads – own (focal) brand's mainline position Y". For example, "3-own ML3" means that there are three ads in the mainline position and the focal brand's ad is in the third position from the top. The estimates are based on the results of regression (1) (Tables 7 and 8 in Appendix 6.4, specification 4), with an interaction of brands and an exact set of advertiser fixed effects as controls. The dependent variables are indicators of the occasions of spending less than X=10 (a), 20 (b), 30 (c), or 60 (d) seconds on the search results page. We take the average probability of spending more than X minutes in the randomized condition with no ads as a baseline.

6.4 Appendix D: Robustness and Results Tables

Figure 12: Estimates of the probability of a consumer clicking the focal brand's web link, with observations weighted by the likelihood of falling into each randomized condition.



Randomized conditions are described as "Y number of mainline ads – own (focal) brand's mainline position Y". For example, "3-own ML3" means that there are three ads in the mainline position, and the focal brand's ad is in the third position from the top. The estimates are based on the results of regression (1) (Table 4, specification 5), with an interaction of brands and an exact set of advertiser fixed effects as controls. The dependent variable is an indicator of a click on a focal brand's web links, in organic or paid positions. We take the average click probability in the randomized condition with no ads as a baseline for the click probability.

Table 4: Estimates of changes in the probability of a consumer clicking on the focal brand's web link, paid or organic.

Randomized condition		Δ Click Probability					
# of ML ads	Focal Brand's Ad	(1)	(2)	(3)	(4)	(5)	(6)
1	–	-8.54	-7.35	-6.67	-6.05	-5.98	-6.51
		(0.14)	(0.13)	(0.13)	(0.14)	(0.14)	(0.14)
1	ML1	0.74	0.2	-0.52	-0.52	-0.69	-0.55
		(0.14)	(0.13)	(0.13)	(0.13)	(0.13)	(0.15)
2	–	-14.67	-12.59	-11.8	-10.72	-10.57	-10.78
		(0.17)	(0.16)	(0.17)	(0.18)	(0.18)	(0.17)
2	ML1	-0.02	0.16	-1.2	-1.31	-1.43	-1.3
		(0.29)	(0.29)	(0.29)	(0.29)	(0.25)	(0.29)
2	ML2	-4.37	-4.31	-5.66	-5.56	-5.68	-5.62
		(0.29)	(0.29)	(0.29)	(0.29)	(0.25)	(0.29)
3	–	-19.83	-17.46	-16.64	-15.64	-15.32	-15.72
		(0.19)	(0.18)	(0.19)	(0.21)	(0.22)	(0.2)
3	ML1	-1.65	-0.22	-1.88	-1.71	-2.12	-1.69
		(0.44)	(0.43)	(0.43)	(0.45)	(0.39)	(0.41)
3	ML2	-6.9	-5.5	-7.09	-7.07	-7.02	-7.07
		(0.44)	(0.43)	(0.43)	(0.45)	(0.39)	(0.42)
3	ML3	-10.67	-9.23	-10.83	-10.38	-10.39	-10.32
		(0.45)	(0.44)	(0.44)	(0.45)	(0.4)	(0.42)
4	–	-25.82	-23.31	-22.5	-20.75	-20.53	-20.44
		(0.21)	(0.2)	(0.2)	(0.24)	(0.26)	(0.22)
4	ML1	-5.12	-3.57	-5.5	-2.65	-2.43	-2.55
		(0.54)	(0.53)	(0.53)	(0.57)	(0.52)	(0.52)
4	ML2	-8.9	-7.31	-9.2	-9.36	-9.24	-8.98
		(0.53)	(0.52)	(0.52)	(0.56)	(0.51)	(0.51)
4	ML3	-12.41	-10.78	-12.65	-11.74	-11.86	-11.85
		(0.55)	(0.54)	(0.54)	(0.56)	(0.52)	(0.52)
4	ML4	-17.44	-15.63	-17.48	-16.65	-15.91	-16.11
		(0.55)	(0.54)	(0.54)	(0.56)	(0.52)	(0.52)
Controls:							
Query FE		No	Yes	Yes	No	No	No
Eligible Ads FE		No	No	Yes	No	No	No
Market Condition FE		No	No	No	Yes	Yes	Yes
Weights:							
Balance the number of potential advertisers		No	No	No	No	Yes	No
Inverse log(US ranking)		No	No	No	No	No	Yes
R^2		0.006	0.039	0.040	0.062	0.062	0.079
Adjusted R^2		0.006	0.039	0.040	0.050	0.050	0.067

The dependent variable is a click on the focal brand's web link, paid or organic. Observations are brand search occasions. We do not reveal the overall number of observations as it might allow inference of the volume of searches on Bing (which is proprietary information). The baseline case is a randomized condition of no advertisements in the mainline position. "Eligible Ads FEs" are indicator variables for how many and what type of ads (focal brand's or competitors') would be shown in the mainline position in the absence of randomization. "Market Condition FEs" are indicator variables for the searched-for query and the exact set of ads that would have been shown in the absence of randomization. Weights based on the number of potential advertisers re-weight the observations so that a search is equally likely to appear in any condition regardless of the number of eligible advertisers. One exception is cases of three or fewer advertisers that cannot be allocated to a randomized condition with four mainline ads.

Table 5: Estimates of changes in the probability of a consumer clicking on a competitor's web link, paid or organic.

Randomized condition		Δ Click Probability					
# of ML ads	Focal Brand's Ad	(1)	(2)	(3)	(4)	(5)	(6)
1	–	6.79	6.52	6.34	5.91	5.89	6.2
		(0.04)	(0.04)	(0.04)	(0.04)	(0.04)	(0.04)
1	ML1	-0.28	-0.16	-0.1	-0.15	-0.13	-0.23
		(0.04)	(0.04)	(0.04)	(0.04)	(0.04)	(0.05)
2	–	11.42	10.94	10.53	9.61	9.51	9.57
		(0.05)	(0.05)	(0.05)	(0.05)	(0.05)	(0.05)
2	ML1	0.63	0.59	0.66	0.69	0.67	0.67
		(0.08)	(0.08)	(0.08)	(0.08)	(0.07)	(0.09)
2	ML2	4.23	4.19	4.26	4.15	3.83	4.49
		(0.08)	(0.08)	(0.08)	(0.08)	(0.07)	(0.09)
3	–	14.22	13.64	13.03	12.13	12.01	12.1
		(0.05)	(0.05)	(0.05)	(0.06)	(0.06)	(0.06)
3	ML1	1.55	1.24	1.3	1.28	1.24	1.3
		(0.12)	(0.12)	(0.12)	(0.12)	(0.11)	(0.13)
3	ML2	6.36	6.09	6.14	5.92	5.55	5.81
		(0.13)	(0.12)	(0.12)	(0.13)	(0.11)	(0.13)
3	ML3	8.58	8.27	8.32	8.13	7.9	8.04
		(0.13)	(0.13)	(0.13)	(0.13)	(0.11)	(0.13)
4	–	17.2	16.56	15.79	14.51	14.66	14.3
		(0.06)	(0.06)	(0.06)	(0.07)	(0.07)	(0.07)
4	ML1	1.9	1.57	1.61	1.73	1.59	1.75
		(0.15)	(0.15)	(0.15)	(0.16)	(0.15)	(0.16)
4	ML2	7.47	7.1	7.14	6.98	6.33	6.95
		(0.15)	(0.15)	(0.15)	(0.16)	(0.14)	(0.16)
4	ML3	9.95	9.61	9.65	9.17	9.1	9.14
		(0.15)	(0.15)	(0.15)	(0.16)	(0.15)	(0.16)
4	ML4	12.97	12.58	12.61	12.08	11.1	11.75
		(0.15)	(0.15)	(0.15)	(0.16)	(0.15)	(0.16)
Controls:							
Query FE		No	Yes	Yes	No	No	No
Eligible Ads FE		No	No	Yes	No	No	No
Market Condition FE		No	No	No	Yes	Yes	Yes
Weights:							
Balance the number of potential advertisers		No	No	No	No	Yes	No
Inverse log(US ranking)		No	No	No	No	No	Yes
R^2		0.029	0.043	0.044	0.107	0.107	0.114
Adjusted R^2		0.029	0.043	0.044	0.095	0.095	0.102

Based on regression (1). The dependent variable is a click on a competitors' web link, paid or organic. Observations are brand search occasions. We do not reveal the overall number of observations as it might allow inference of the volume of searches on Bing (which is proprietary information). The baseline case is a randomized condition of no advertisements in the mainline position. "Eligible Ads FEs" are indicator variables for how many and what type of ads (focal brand's or competitors') would be shown in the mainline position in the absence of randomization. "Market Condition FEs" are indicator variables for the searched-for query and the exact set of ads that would have been shown in the absence of randomization. Weights based on the number of potential advertisers re-weight the observations so that a search is equally likely to appear in any condition regardless of the number of eligible advertisers. One exception is cases of three or fewer advertisers that cannot be allocated to a randomized condition with four mainline ads.

Table 6: Estimates of changes in quick back probabilities, by traffic type.

Randomized condition		Δ Quick Back Probability											
		Competitors' Clicks				Focal Brand's Clicks				All Clicks			
# of ML ads	Focal Brand's Ad	(1)	(2)	(3)	(4)	(1)	(2)	(3)	(4)	(1)	(2)	(3)	(4)
1	–	24.97	21.15	21.59	19.5	-1.16	-1.3	-1.36	-1.39	2.33	2.19	2.11	1.89
		(1.12)	(1.1)	(1.11)	(1.28)	(0.11)	(0.11)	(0.11)	(0.11)	(0.1)	(0.1)	(0.1)	(0.11)
1	ML1	-6.76	-5.36	-5.63	-7.9	0.25	0.35	0.4	0.27	0.19	0.28	0.33	0.19
		(2.56)	(2.54)	(2.54)	(2.74)	(0.1)	(0.1)	(0.1)	(0.1)	(0.1)	(0.1)	(0.1)	(0.1)
2	–	21.15	18	19	17.81	-1.83	-1.98	-2.02	-1.99	3.54	3.39	3.27	3.14
		(1.13)	(1.11)	(1.11)	(1.32)	(0.14)	(0.14)	(0.14)	(0.15)	(0.13)	(0.13)	(0.13)	(0.14)
2	ML1	6.31	2.92	2.93	-0.19	0.04	-0.08	0	-0.08	0.24	0.14	0.21	0.11
		(3.1)	(3.06)	(3.06)	(3.27)	(0.22)	(0.22)	(0.22)	(0.23)	(0.22)	(0.22)	(0.22)	(0.22)
2	ML2	19.69	15.66	15.76	13.89	-0.49	-0.59	-0.51	-0.65	1.43	1.32	1.4	1.21
		(1.81)	(1.78)	(1.78)	(1.95)	(0.23)	(0.23)	(0.23)	(0.23)	(0.22)	(0.22)	(0.22)	(0.22)
3	–	20.99	18.3	19.64	18.89	-2.04	-2.11	-2.12	-2.03	4.67	4.59	4.45	4.48
		(1.13)	(1.12)	(1.12)	(1.35)	(0.16)	(0.16)	(0.16)	(0.18)	(0.14)	(0.14)	(0.14)	(0.16)
3	ML1	4.27	2.32	2.59	2.95	0.95	0.64	0.72	0.33	1.27	0.97	1.04	0.69
		(3.54)	(3.48)	(3.49)	(3.92)	(0.34)	(0.34)	(0.34)	(0.35)	(0.33)	(0.33)	(0.33)	(0.34)
3	ML2	21.21	17.77	18.03	10.99	-0.27	-0.46	-0.38	-0.69	2.61	2.43	2.5	1.94
		(2.15)	(2.12)	(2.12)	(2.42)	(0.35)	(0.35)	(0.35)	(0.36)	(0.33)	(0.33)	(0.33)	(0.34)
3	ML3	22.77	19.46	19.68	17.73	-0.93	-1.26	-1.18	-1.29	3.15	2.88	2.95	2.79
		(1.95)	(1.92)	(1.93)	(2.17)	(0.36)	(0.36)	(0.36)	(0.37)	(0.33)	(0.33)	(0.33)	(0.34)
4	–	20.66	18.31	19.86	18.61	-2.75	-2.75	-2.75	-2.7	5.59	5.59	5.44	5.09
		(1.14)	(1.12)	(1.12)	(1.37)	(0.18)	(0.18)	(0.18)	(0.22)	(0.16)	(0.16)	(0.16)	(0.19)
4	ML1	9.02	6.1	6.46	7.43	-0.87	-1.09	-1.01	-0.85	-0.39	-0.54	-0.49	-0.18
		(4.01)	(3.95)	(3.95)	(4.73)	(0.42)	(0.42)	(0.42)	(0.44)	(0.4)	(0.4)	(0.4)	(0.43)
4	ML2	21.92	18.2	18.51	18.3	-1.41	-1.38	-1.31	-1.16	2.19	2.2	2.25	2.41
		(2.37)	(2.33)	(2.33)	(2.75)	(0.43)	(0.43)	(0.43)	(0.46)	(0.4)	(0.4)	(0.4)	(0.43)
4	ML3	24.31	20.66	20.98	15.79	-1.81	-1.94	-1.86	-2.12	3.26	3.13	3.19	2.65
		(2.17)	(2.13)	(2.14)	(2.48)	(0.45)	(0.45)	(0.45)	(0.47)	(0.41)	(0.41)	(0.41)	(0.43)
4	ML4	21.77	17.85	18.28	16.48	-1.21	-1.33	-1.25	-1.26	4.82	4.71	4.76	4.75
		(1.97)	(1.94)	(1.94)	(2.29)	(0.46)	(0.46)	(0.46)	(0.48)	(0.41)	(0.41)	(0.41)	(0.43)
Controls:													
Query FE		No	Yes	Yes	No	No	Yes	Yes	No	No	Yes	Yes	No
Eligible Ads FE		No	No	Yes	No	No	No	Yes	No	No	No	Yes	No
Market Condition FE		No	No	No	Yes	No	No	No	Yes	No	No	No	Yes
R^2		0.017	0.049	0.049	0.222	0.0004	0.017	0.017	0.030	0.0003	0.015	0.015	0.030
Adjusted R^2		0.017	0.048	0.049	0.077	0.0004	0.017	0.017	0.017	0.0003	0.015	0.015	0.017

Based on regression (1). The dependent variable is an indicator of a quick back event. Observations are focal brand's, competitors', and total web links clicks in the data. We do not reveal the overall number of observations as it might allow to infer the volume of searches on Bing (proprietary information). The baseline case is a randomized condition of no advertisements in the mainline position. "Eligible Ads FEs" are indicator variables for how many and what type (focal brand or competitor) of ads would be shown in the mainline in the absence of randomization. "Market Condition FEs" are indicator variables for the searched-for query and the exact set of ads that would have been shown in the absence of randomization.

Table 7: Estimates of changes in the probability of a consumer making a click in less than 10 or 20 seconds.

Randomized condition		Δ Probability to Click in Less Than							
		10 seconds				20 seconds			
# of ML ads	Focal Brand's Ad	(1)	(2)	(3)	(4)	(1)	(2)	(3)	(4)
1	–	-3.97	-2.95	-3.04	-2.78	-1.2	-0.67	-0.69	-0.62
		(0.16)	(0.16)	(0.16)	(0.17)	(0.11)	(0.11)	(0.11)	(0.12)
1	ML1	1.4	0.89	1.12	0.94	0.65	0.38	0.47	0.45
		(0.16)	(0.16)	(0.16)	(0.16)	(0.11)	(0.11)	(0.11)	(0.12)
2	–	-8.55	-7.09	-6.88	-6.18	-2.86	-2.08	-1.98	-1.75
		(0.2)	(0.2)	(0.2)	(0.22)	(0.14)	(0.14)	(0.14)	(0.16)
2	ML1	-1.21	-0.73	-0.5	-0.66	-0.17	0.08	0.16	0.11
		(0.34)	(0.34)	(0.34)	(0.35)	(0.25)	(0.24)	(0.24)	(0.25)
2	ML2	-2.18	-1.74	-1.49	-1.66	0.01	0.24	0.33	0.3
		(0.35)	(0.35)	(0.35)	(0.35)	(0.25)	(0.25)	(0.25)	(0.25)
3	–	-12.98	-11.2	-10.79	-9.96	-4.35	-3.4	-3.22	-2.85
		(0.22)	(0.22)	(0.22)	(0.26)	(0.16)	(0.16)	(0.16)	(0.19)
3	ML1	-2.45	-1.17	-1.11	-1.01	-1	-0.31	-0.3	-0.55
		(0.52)	(0.51)	(0.51)	(0.53)	(0.37)	(0.37)	(0.37)	(0.38)
3	ML2	-5.35	-4.43	-4.34	-4.12	-1.62	-1.12	-1.09	-0.95
		(0.52)	(0.52)	(0.52)	(0.54)	(0.37)	(0.37)	(0.37)	(0.38)
3	ML3	-8.36	-7.31	-7.23	-6.92	-2.31	-1.74	-1.71	-1.57
		(0.53)	(0.53)	(0.53)	(0.54)	(0.38)	(0.38)	(0.38)	(0.39)
4	–	-19.74	-17.81	-17.25	-15.46	-5.34	-4.34	-4.09	-3.92
		(0.25)	(0.25)	(0.25)	(0.3)	(0.18)	(0.18)	(0.18)	(0.21)
4	ML1	-6.72	-5.46	-5.57	-3.02	-4.5	-3.84	-3.88	-0.55
		(0.64)	(0.63)	(0.63)	(0.68)	(0.45)	(0.45)	(0.45)	(0.49)
4	ML2	-5.93	-4.71	-4.79	-5.49	-1.73	-1.11	-1.14	-1.31
		(0.63)	(0.63)	(0.63)	(0.67)	(0.45)	(0.45)	(0.45)	(0.48)
4	ML3	-8.77	-7.57	-7.61	-7.47	-2.65	-2	-2.02	-2.17
		(0.65)	(0.64)	(0.64)	(0.68)	(0.46)	(0.46)	(0.46)	(0.48)
4	ML4	-14.13	-12.94	-12.99	-12.46	-4.21	-3.55	-3.57	-3.28
		(0.65)	(0.65)	(0.65)	(0.68)	(0.46)	(0.46)	(0.46)	(0.49)
Controls:									
Query FE		No	Yes	Yes	No	No	Yes	Yes	No
Eligible Ads FE		No	No	Yes	No	No	No	Yes	No
Market Condition FE		No	No	No	Yes	No	No	No	Yes
R^2		0.003	0.017	0.017	0.035	0.001	0.008	0.008	0.026
Adjusted R^2		0.003	0.017	0.017	0.022	0.001	0.008	0.008	0.012

Based on regression (1). The dependent variable is an indicator variable of whether the click was made in less than 10 or 20 seconds. Observations are all click occasions in the data. We do not reveal the overall number of observations as it might allow inference of the volume of searches on Bing (which is proprietary information). The baseline case is a randomized condition of no advertisements in the mainline position. "Eligible Ads FEs" are indicator variables for how many and what type of ads (focal brand's or competitors') would be shown in the mainline position in the absence of randomization. "Market Condition FEs" are indicator variables for the searched-for query and the exact set of ads that would have been shown in the absence of randomization.

Table 8: Estimates of changes in the probability of a consumer making a click in less than 30 or 60 seconds.

Randomized condition		Δ Probability to Click in Less Then							
		30 seconds				60 seconds			
# of ML ads	Focal Brand's Ad	(1)	(2)	(3)	(4)	(1)	(2)	(3)	(4)
1	–	-0.54	-0.18	-0.2	-0.2	-0.09	0.08	0.06	0.02
		(0.09)	(0.09)	(0.09)	(0.1)	(0.06)	(0.06)	(0.06)	(0.07)
1	ML1	0.45	0.27	0.32	0.31	0.08	-0.01	0.01	0.02
		(0.09)	(0.09)	(0.09)	(0.09)	(0.06)	(0.06)	(0.06)	(0.06)
2	–	-1.52	-1	-0.95	-0.69	-0.39	-0.14	-0.17	-0.17
		(0.11)	(0.11)	(0.11)	(0.13)	(0.08)	(0.08)	(0.08)	(0.09)
2	ML1	-0.2	-0.03	0.01	-0.01	-0.05	0.04	0.03	0.1
		(0.2)	(0.2)	(0.2)	(0.2)	(0.14)	(0.14)	(0.14)	(0.14)
2	ML2	0.21	0.37	0.41	0.37	0.2	0.28	0.28	0.3
		(0.2)	(0.2)	(0.2)	(0.2)	(0.14)	(0.14)	(0.14)	(0.14)
3	–	-2	-1.38	-1.28	-1.21	-0.42	-0.13	-0.17	-0.2
		(0.13)	(0.13)	(0.13)	(0.15)	(0.09)	(0.09)	(0.09)	(0.1)
3	ML1	-0.25	0.2	0.2	0.09	0.01	0.23	0.2	0.25
		(0.3)	(0.3)	(0.3)	(0.31)	(0.21)	(0.21)	(0.21)	(0.21)
3	ML2	-0.99	-0.65	-0.65	-0.55	-0.33	-0.15	-0.17	-0.11
		(0.3)	(0.3)	(0.3)	(0.31)	(0.21)	(0.21)	(0.21)	(0.22)
3	ML3	-1.26	-0.87	-0.86	-0.82	-0.4	-0.19	-0.22	-0.22
		(0.3)	(0.3)	(0.3)	(0.31)	(0.21)	(0.21)	(0.21)	(0.22)
4	–	-2.45	-1.82	-1.69	-1.66	-0.66	-0.39	-0.43	-0.31
		(0.14)	(0.14)	(0.14)	(0.17)	(0.1)	(0.1)	(0.1)	(0.12)
4	ML1	-3.98	-3.54	-3.58	-0.19	-3.77	-3.55	-3.6	-0.25
		(0.37)	(0.37)	(0.37)	(0.39)	(0.25)	(0.25)	(0.25)	(0.27)
4	ML2	-0.43	-0.01	-0.04	-0.02	-0.05	0.16	0.11	0.22
		(0.36)	(0.36)	(0.36)	(0.39)	(0.25)	(0.25)	(0.25)	(0.27)
4	ML3	-1.38	-0.94	-0.96	-0.9	-0.57	-0.35	-0.39	-0.22
		(0.37)	(0.37)	(0.37)	(0.39)	(0.26)	(0.26)	(0.26)	(0.27)
4	ML4	-1.2	-0.75	-0.77	-0.68	-0.33	-0.1	-0.14	0.14
		(0.37)	(0.37)	(0.37)	(0.39)	(0.26)	(0.26)	(0.26)	(0.27)
Controls:									
Query FE		No	Yes	Yes	No	No	Yes	Yes	No
Eligible Ads FE		No	No	Yes	No	No	No	Yes	No
Market Condition FE		No	No	No	Yes	No	No	No	Yes
R^2		0.0004	0.004	0.004	0.022	0.0001	0.001	0.001	0.017
Adjusted R^2		0.0004	0.004	0.004	0.008	0.0001	0.001	0.001	0.003

Based on regression (1). The dependent variable is an indicator variable of whether the click was made in less than 30 or 60 seconds. Observations are all click occasions in the data. We do not reveal the overall number of observations as it might allow inference of the volume of searches on Bing (which is proprietary information). The baseline case is a randomized condition of no advertisements in the mainline position. "Eligible Ads FEs" are indicator variables for how many and what type of ads (focal brand's or competitors') would be shown in the mainline position in the absence of randomization. "Market Condition FEs" are indicator variables for the searched-for query and the exact set of ads that would have been shown in the absence of randomization.

Table 9: Estimates of changes in the probability of a consumer clicking on the focal brand's and competitors' web links, with interaction of the relevance of the competitor in ML1, by condition.

Randomized condition		Δ Probability to Get a Click							
		Focal Brand				Competitors			
# of ML ads	Focal Brand's Ad	(1)	(2)	(3)	(4)	(1)	(2)	(3)	(4)
1	–	-8.24	-7.08	-6.13	-5.59	6.42	6.16	6	5.69
		(0.14)	(0.14)	(0.14)	(0.15)	(0.04)	(0.04)	(0.04)	(0.04)
1	ML1	0.74	0.2	-0.52	-0.53	-0.28	-0.16	-0.1	-0.14
		(0.14)	(0.13)	(0.13)	(0.13)	(0.04)	(0.04)	(0.04)	(0.04)
2	–	-14.14	-12.12	-11.19	-10.3	10.83	10.38	10.03	9.4
		(0.18)	(0.17)	(0.17)	(0.19)	(0.05)	(0.05)	(0.05)	(0.05)
2	ML1	-0.02	0.16	-1.2	-1.32	0.63	0.59	0.66	0.7
		(0.29)	(0.29)	(0.29)	(0.29)	(0.08)	(0.08)	(0.08)	(0.08)
2	ML2	-4.13	-4.02	-5.08	-5.04	3.89	3.86	3.91	3.81
		(0.33)	(0.32)	(0.32)	(0.32)	(0.09)	(0.09)	(0.09)	(0.09)
3	–	-19.57	-17.2	-16.29	-15.25	13.88	13.32	12.77	11.89
		(0.2)	(0.19)	(0.19)	(0.22)	(0.06)	(0.06)	(0.06)	(0.06)
3	ML1	-1.65	-0.22	-1.88	-1.72	1.55	1.24	1.3	1.29
		(0.44)	(0.43)	(0.43)	(0.45)	(0.12)	(0.12)	(0.12)	(0.12)
3	ML2	-6.62	-5.23	-6.68	-6.68	5.97	5.71	5.76	5.6
		(0.47)	(0.47)	(0.47)	(0.48)	(0.13)	(0.13)	(0.13)	(0.13)
3	ML3	-10.56	-9.15	-10.58	-10.16	8.06	7.78	7.82	7.58
		(0.48)	(0.47)	(0.47)	(0.49)	(0.14)	(0.14)	(0.14)	(0.14)
4	–	-25.28	-22.77	-21.92	-20.48	16.43	15.8	15.11	14.3
		(0.21)	(0.21)	(0.21)	(0.25)	(0.06)	(0.06)	(0.06)	(0.07)
4	ML1	-5.12	-3.57	-5.5	-2.66	1.9	1.57	1.61	1.74
		(0.54)	(0.53)	(0.53)	(0.57)	(0.15)	(0.15)	(0.15)	(0.16)
4	ML2	-9.08	-7.46	-9.23	-9.49	7.42	7.05	7.09	6.94
		(0.57)	(0.56)	(0.56)	(0.59)	(0.16)	(0.16)	(0.16)	(0.17)
4	ML3	-12.15	-10.6	-12.35	-11.47	9.59	9.27	9.31	8.79
		(0.58)	(0.57)	(0.57)	(0.6)	(0.17)	(0.16)	(0.16)	(0.17)
4	ML4	-16.49	-14.64	-16.37	-15.5	12.23	11.82	11.85	11.43
		(0.58)	(0.57)	(0.57)	(0.6)	(0.17)	(0.16)	(0.16)	(0.17)
Interaction with the most relevant competitor in ML1									
1	–	-2.68	-2.42	-4.97	-4.55	3.38	3.26	3.14	2.13
		(0.37)	(0.37)	(0.37)	(0.41)	(0.11)	(0.1)	(0.11)	(0.12)
2	–	-5.26	-4.61	-6.07	-5.53	5.77	5.47	5	2.65
		(0.51)	(0.5)	(0.5)	(0.64)	(0.14)	(0.14)	(0.14)	(0.18)
2	ML2	-1.29	-1.55	-3.06	-2.79	1.81	1.76	1.85	1.82
		(0.73)	(0.72)	(0.72)	(0.73)	(0.21)	(0.21)	(0.21)	(0.2)
3	–	-2.79	-2.75	-3.8	-5.7	3.54	3.39	2.81	3.63
		(0.6)	(0.59)	(0.59)	(0.81)	(0.17)	(0.17)	(0.17)	(0.23)
3	ML2	-2.08	-1.99	-3.06	-3.18	2.91	2.8	2.86	2.56
		(1.28)	(1.26)	(1.26)	(1.33)	(0.36)	(0.36)	(0.36)	(0.37)
3	ML3	-0.73	-0.57	-1.7	-1.66	3.5	3.34	3.4	3.96
		(1.24)	(1.22)	(1.22)	(1.29)	(0.35)	(0.35)	(0.35)	(0.36)
4	–	-6.06	-5.93	-6.55	-4.18	8.52	8.4	7.73	3.18
		(0.67)	(0.66)	(0.66)	(0.95)	(0.19)	(0.19)	(0.19)	(0.27)
4	ML2	1.54	1.29	0.33	1.1	0.43	0.41	0.44	0.34
		(1.65)	(1.62)	(1.62)	(1.76)	(0.47)	(0.46)	(0.46)	(0.49)
4	ML3	-2.15	-1.47	-2.43	-2.51	2.9	2.74	2.75	3.37
		(1.66)	(1.63)	(1.63)	(1.75)	(0.47)	(0.47)	(0.47)	(0.49)
4	ML4	-7.51	-7.79	-8.82	-9.73	5.86	5.96	5.99	5.41
		(1.63)	(1.6)	(1.6)	(1.73)	(0.46)	(0.46)	(0.46)	(0.48)
Controls:									
Query FE		No	Yes	Yes	No	No	Yes	Yes	No
Eligible Ads FE		No	No	Yes	No	No	No	Yes	No
Market Condition FE		No	No	No	Yes	No	No	No	Yes
R^2		0.006	0.039	0.040	0.062	0.029	0.043	0.044	0.107
Adjusted R^2		0.006	0.039	0.040	0.050	0.029	0.043	0.044	0.095

Based on regression (1). The dependent variable is a click on the focal brand's or competitors' web link, paid or organic. Observations are brand search occasions. We do not reveal the overall number of observations as it might allow inference of the volume of searches on Bing (which is proprietary information). The baseline case is a randomized condition of no advertisements in the mainline. "Eligible Ads FEs" are indicator variables for how many and what type (focal brand or competitor) of ads would be shown in the mainline in the absence of randomization. "Market Condition FEs" are indicator variables for the searched-for query and the exact set of ads that would have been shown in the absence of randomization.

Table 10: Estimates of changes in quick back probabilities of competitors' clicks, with an interaction of the relevance of the competitor in ML1.

Randomized condition		Δ Quick Back Probability			
# of ML ads	Focal Brand's Ad	(1)	(2)	(3)	(4)
1	–	26.06	22.15	22.41	20.11
		(1.13)	(1.11)	(1.11)	(1.29)
1	ML1	-6.76	-5.36	-5.67	-7.97
		(2.56)	(2.54)	(2.54)	(2.74)
2	–	22.17	18.95	19.75	18.25
		(1.13)	(1.11)	(1.12)	(1.32)
2	ML1	6.31	2.92	2.88	-0.26
		(3.1)	(3.06)	(3.06)	(3.27)
2	ML2	21.43	17.27	16.99	14.84
		(1.81)	(1.79)	(1.79)	(1.96)
3	–	21.8	19.04	20.21	19.28
		(1.14)	(1.12)	(1.12)	(1.35)
3	ML1	4.27	2.32	2.52	2.86
		(3.54)	(3.48)	(3.49)	(3.92)
3	ML2	22.5	18.96	18.92	11.67
		(2.16)	(2.12)	(2.13)	(2.42)
3	ML3	24.16	20.73	20.65	18.43
		(1.96)	(1.93)	(1.93)	(2.18)
4	–	21.57	19.15	20.5	18.96
		(1.14)	(1.12)	(1.13)	(1.37)
4	ML1	9.02	6.1	6.4	7.35
		(4.01)	(3.95)	(3.95)	(4.73)
4	ML2	22.77	18.99	19.08	18.68
		(2.37)	(2.33)	(2.33)	(2.75)
4	ML3	25.38	21.64	21.71	16.38
		(2.17)	(2.13)	(2.14)	(2.48)
4	ML4	22.99	18.98	19.12	17.03
		(1.97)	(1.94)	(1.94)	(2.3)
Most relevant competitor in ML1		-7.03	-6.48	-5.22	-4.83
		(0.69)	(0.68)	(0.69)	(1.06)
Controls:					
Query FE		No	Yes	Yes	No
Eligible Ads FE		No	No	Yes	No
Market Condition FE		No	No	No	Yes
R^2		0.017	0.049	0.049	0.222
Adjusted R^2		0.017	0.048	0.049	0.077

Based on regression (1). The dependent variable is an indicator of a quick back event. Observations are competitors' web link click occasions in the data. We do not reveal the overall number of observations as it might allow inference of the volume of searches on Bing (which is proprietary information). The baseline case is a randomized condition of no advertisements in the mainline. "Eligible Ads FEs" are indicator variables for how many and what type of ads (focal brand's or competitors') would be shown in the mainline in the absence of randomization. "Market Condition FEs" are indicator variables for the searched-for query and the exact set of ads that would have been shown in the absence of randomization.

Table 11: Estimates of changes in quick back probabilities of competitors' clicks, with an interaction of the relevance of the competitor in ML1, by condition.

Randomized condition		Δ Quick Back Probability			
# of ML ads	Focal Brand's Ad	(1)	(2)	(3)	(4)
1	–	26.41	22.72	22.96	20.31
		(1.14)	(1.12)	(1.13)	(1.3)
1	ML1	-6.76	-5.36	-5.67	-7.98
		(2.56)	(2.54)	(2.54)	(2.74)
2	–	22.39	19.15	19.9	18.37
		(1.15)	(1.13)	(1.13)	(1.33)
2	ML1	6.31	2.92	2.87	-0.27
		(3.1)	(3.06)	(3.06)	(3.27)
2	ML2	18.99	15.01	14.91	12.67
		(2)	(1.97)	(1.97)	(2.12)
3	–	21.19	18.46	19.64	19.11
		(1.15)	(1.13)	(1.14)	(1.36)
3	ML1	4.27	2.32	2.52	2.85
		(3.54)	(3.48)	(3.49)	(3.92)
3	ML2	22.79	18.93	19.03	12.79
		(2.33)	(2.3)	(2.3)	(2.6)
3	ML3	22.44	19.08	19.16	18.11
		(2.12)	(2.09)	(2.09)	(2.32)
4	–	22.02	19.36	20.7	19.21
		(1.15)	(1.14)	(1.14)	(1.39)
4	ML1	9.02	6.11	6.39	7.33
		(4.01)	(3.95)	(3.95)	(4.73)
4	ML2	22.73	18.98	19.17	18.31
		(2.5)	(2.46)	(2.46)	(2.87)
4	ML3	26.6	22.59	22.8	17.87
		(2.31)	(2.28)	(2.28)	(2.64)
4	ML4	21.79	17.82	18.13	15.34
		(2.11)	(2.08)	(2.08)	(2.43)
Interaction with the most relevant competitor in ML1					
1	–	-9.24	-10.1	-8.69	-6.38
		(1.36)	(1.35)	(1.35)	(1.82)
2	–	-8.5	-7.88	-6.26	-6.13
		(1.44)	(1.42)	(1.42)	(2.43)
2	ML2	2.81	2.66	3.17	5.09
		(3.48)	(3.42)	(3.42)	(3.83)
3	–	-1.75	-1.33	-0.23	-2.07
		(1.64)	(1.62)	(1.62)	(2.76)
3	ML2	-8.61	-6.32	-5.85	-11.83
		(4.93)	(4.85)	(4.85)	(5.77)
3	ML3	1.69	1.94	2.31	-2.93
		(4.21)	(4.14)	(4.14)	(4.96)
4	–	-10.43	-8.11	-6.78	-8.41
		(1.57)	(1.55)	(1.55)	(3.1)
4	ML2	-6.71	-6.36	-6.01	-0.98
		(6.56)	(6.45)	(6.45)	(8.38)
4	ML3	-15.09	-12.78	-12.48	-15.08
		(5.36)	(5.27)	(5.27)	(6.24)
4	ML4	-0.11	0.18	0.44	7.18
		(4.46)	(4.39)	(4.39)	(5.71)
Controls:					
Query FE		No	Yes	Yes	No
Eligible Ads FE		No	No	Yes	No
Market Condition FE		No	No	No	Yes
R^2		0.017	0.049	0.049	0.222
Adjusted R^2		0.017	0.048	0.049	0.077

Based on regression (1). The dependent variable is an indicator of a quick back event. Observations are competitors' web link click occasions in the data. We do not reveal the overall number of observations as it might allow inference of the volume of searches on Bing (which is proprietary information). The baseline case is a randomized condition of no advertisements in the mainline. "Eligible Ads FEs" are indicator variables for how many and what type of ads (focal brand's or competitors') would be shown in the mainline in the absence of randomization. "Market Condition FEs" are indicator variables for the searched-for query and the exact set of ads that would have been shown in the absence of randomization.

Table 12: Estimates of changes in the probability of a consumer clicking on the focal brand's and competitors' web links, with an interaction of cases when the title of the competitor's ad in ML1 mentions the focal brand.

Randomized condition		Δ Probability to Get a Click							
		Focal Brand				Competitors			
# of ML ads	Focal Brand's Ad	(1)	(2)	(3)	(4)	(1)	(2)	(3)	(4)
1	–	-5.43	-5.56	-4.99	-4.64	4.28	4.18	3.99	3.82
		(0.15)	(0.15)	(0.15)	(0.16)	(0.04)	(0.04)	(0.04)	(0.04)
1	ML1	0.74	0.2	-0.52	-0.52	-0.28	-0.16	-0.1	-0.15
		(0.14)	(0.13)	(0.13)	(0.13)	(0.04)	(0.04)	(0.04)	(0.04)
2	–	-11.27	-10.63	-9.96	-9.16	8.67	8.38	7.96	7.3
		(0.18)	(0.18)	(0.18)	(0.2)	(0.05)	(0.05)	(0.05)	(0.06)
2	ML1	-0.02	0.16	-1.2	-1.31	0.63	0.59	0.66	0.69
		(0.29)	(0.29)	(0.29)	(0.29)	(0.08)	(0.08)	(0.08)	(0.08)
2	ML2	-1.61	-2.72	-4.17	-4.31	2	2.12	2.18	2.3
		(0.3)	(0.29)	(0.29)	(0.3)	(0.09)	(0.08)	(0.08)	(0.08)
3	–	-16.42	-15.5	-14.79	-14.07	11.46	11.08	10.45	9.8
		(0.2)	(0.2)	(0.2)	(0.23)	(0.06)	(0.06)	(0.06)	(0.06)
3	ML1	-1.65	-0.22	-1.88	-1.71	1.55	1.24	1.3	1.28
		(0.44)	(0.43)	(0.43)	(0.45)	(0.12)	(0.12)	(0.12)	(0.12)
3	ML2	-3.57	-3.58	-5.29	-5.56	3.67	3.59	3.63	3.68
		(0.45)	(0.44)	(0.44)	(0.45)	(0.13)	(0.13)	(0.13)	(0.13)
3	ML3	-7.34	-7.31	-9.03	-8.87	5.88	5.77	5.81	5.89
		(0.45)	(0.44)	(0.44)	(0.46)	(0.13)	(0.13)	(0.13)	(0.13)
4	–	-22.36	-21.31	-20.62	-19.15	14.4	13.95	13.18	12.14
		(0.22)	(0.21)	(0.21)	(0.25)	(0.06)	(0.06)	(0.06)	(0.07)
4	ML1	-5.12	-3.57	-5.49	-2.65	1.9	1.57	1.61	1.73
		(0.54)	(0.53)	(0.53)	(0.57)	(0.15)	(0.15)	(0.15)	(0.16)
4	ML2	-5.45	-5.32	-7.33	-7.84	4.68	4.51	4.54	4.73
		(0.54)	(0.53)	(0.53)	(0.56)	(0.15)	(0.15)	(0.15)	(0.16)
4	ML3	-9	-8.81	-10.8	-10.19	7.19	7.04	7.07	6.87
		(0.55)	(0.54)	(0.54)	(0.57)	(0.16)	(0.15)	(0.15)	(0.16)
4	ML4	-14.09	-13.7	-15.67	-15.13	10.26	10.06	10.08	9.82
		(0.55)	(0.54)	(0.54)	(0.57)	(0.16)	(0.15)	(0.15)	(0.16)
Competitor in ML1 mentions focal brand		-6.92	-3.99	-3.74	-3.17	5.59	5.2	5.23	4.68
		(0.14)	(0.14)	(0.14)	(0.15)	(0.04)	(0.04)	(0.04)	(0.04)
Controls:									
Query FE		No	Yes	Yes	No	No	Yes	Yes	No
Eligible Ads FE		No	No	Yes	No	No	No	Yes	No
Market Condition FE		No	No	No	Yes	No	No	No	Yes
R^2		0.006	0.039	0.040	0.062	0.030	0.044	0.044	0.107
Adjusted R^2		0.006	0.039	0.040	0.050	0.030	0.044	0.044	0.095

Based on regression (1). The dependent variable is a click on the focal brand's or competitors' web link, paid or organic. Observations are brand search occasions. We do not reveal the overall number of observations as it might allow inference of the volume of searches on Bing (which is proprietary information). The baseline case is a randomized condition of no advertisements in the mainline. "Eligible Ads FEs" are indicator variables for how many and what type of ads (focal brand's or competitors') would be shown in the mainline in the absence of randomization. "Market Condition FEs" are indicator variables for the searched-for query and the exact set of ads that would have been shown in the absence of randomization.

Table 13: Estimates of changes in the probability of a consumer clicking on the focal brand's and competitors' links, with an interaction of the title of the competitor's ad in ML1 mentioning the focal brand, by condition.

Randomized condition		Δ Probability to Get a Click							
		Focal Brand				Competitors			
# of ML ads	Focal Brand's Ad	(1)	(2)	(3)	(4)	(1)	(2)	(3)	(4)
1	–	-5.04	-5.17	-4.63	-4.3	4.17	4.08	3.9	3.8
		(0.17)	(0.17)	(0.17)	(0.18)	(0.05)	(0.05)	(0.05)	(0.05)
1	ML1	0.74	0.2	-0.52	-0.52	-0.28	-0.16	-0.1	-0.15
		(0.14)	(0.13)	(0.13)	(0.13)	(0.04)	(0.04)	(0.04)	(0.04)
2	–	-10.97	-10.37	-9.67	-9.29	8.66	8.38	7.95	7.32
		(0.23)	(0.22)	(0.22)	(0.25)	(0.06)	(0.06)	(0.06)	(0.07)
2	ML1	-0.02	0.16	-1.2	-1.31	0.63	0.59	0.66	0.69
		(0.29)	(0.29)	(0.29)	(0.29)	(0.08)	(0.08)	(0.08)	(0.08)
2	ML2	-2.09	-3.05	-4.49	-4.49	2.56	2.66	2.73	2.68
		(0.38)	(0.37)	(0.37)	(0.37)	(0.11)	(0.11)	(0.11)	(0.1)
3	–	-16.92	-16.04	-15.32	-14.33	11.4	11.02	10.37	9.7
		(0.25)	(0.25)	(0.25)	(0.29)	(0.07)	(0.07)	(0.07)	(0.08)
3	ML1	-1.65	-0.22	-1.88	-1.71	1.55	1.24	1.3	1.28
		(0.44)	(0.43)	(0.43)	(0.45)	(0.12)	(0.12)	(0.12)	(0.12)
3	ML2	-3.03	-2.95	-4.63	-4.66	4.04	3.94	3.99	3.78
		(0.61)	(0.6)	(0.6)	(0.62)	(0.17)	(0.17)	(0.17)	(0.17)
3	ML3	-7.56	-7.52	-9.22	-8.67	6.56	6.44	6.5	6.37
		(0.62)	(0.61)	(0.61)	(0.62)	(0.17)	(0.17)	(0.17)	(0.17)
4	–	-23.15	-22.14	-21.47	-20.36	14.3	13.83	13.05	12.03
		(0.28)	(0.28)	(0.28)	(0.34)	(0.08)	(0.08)	(0.08)	(0.09)
4	ML1	-5.12	-3.57	-5.49	-2.65	1.9	1.57	1.61	1.73
		(0.54)	(0.53)	(0.53)	(0.57)	(0.15)	(0.15)	(0.15)	(0.16)
4	ML2	-5.3	-5.09	-7.02	-6.41	5.02	4.8	4.84	4.48
		(0.75)	(0.74)	(0.74)	(0.77)	(0.21)	(0.21)	(0.21)	(0.22)
4	ML3	-8.8	-8.56	-10.52	-9.83	7.01	6.87	6.91	6.61
		(0.76)	(0.75)	(0.75)	(0.79)	(0.22)	(0.22)	(0.22)	(0.22)
4	ML4	-14.76	-14.14	-16.12	-15.53	10.13	9.91	9.94	9.5
		(0.76)	(0.74)	(0.74)	(0.78)	(0.21)	(0.21)	(0.21)	(0.22)
Interaction with competitor in ML1 mentions focal brand									
1	–	-7.79	-4.86	-4.55	-3.93	5.84	5.43	5.43	4.74
		(0.24)	(0.23)	(0.23)	(0.25)	(0.07)	(0.07)	(0.07)	(0.07)
2	–	-7.52	-4.51	-4.33	-2.91	5.6	5.2	5.26	4.66
		(0.31)	(0.3)	(0.3)	(0.34)	(0.09)	(0.09)	(0.09)	(0.09)
2	ML2	-5.72	-3.18	-2.94	-2.7	4.2	3.85	3.83	3.73
		(0.59)	(0.58)	(0.58)	(0.58)	(0.17)	(0.16)	(0.16)	(0.16)
3	–	-5.92	-2.89	-2.66	-2.64	5.72	5.32	5.39	4.88
		(0.35)	(0.34)	(0.34)	(0.4)	(0.1)	(0.1)	(0.1)	(0.11)
3	ML2	-8.05	-5.29	-5.1	-5.05	4.81	4.48	4.47	4.47
		(0.87)	(0.86)	(0.86)	(0.89)	(0.25)	(0.25)	(0.25)	(0.25)
3	ML3	-6.46	-3.56	-3.34	-3.58	4.18	3.8	3.78	3.68
		(0.88)	(0.87)	(0.87)	(0.89)	(0.25)	(0.25)	(0.25)	(0.25)
4	–	-5.34	-2.34	-2.04	-0.77	5.8	5.44	5.47	4.91
		(0.39)	(0.38)	(0.38)	(0.46)	(0.11)	(0.11)	(0.11)	(0.13)
4	ML2	-7.21	-4.44	-4.37	-6.14	4.91	4.62	4.62	5.21
		(1.06)	(1.04)	(1.04)	(1.11)	(0.3)	(0.3)	(0.3)	(0.31)
4	ML3	-7.33	-4.5	-4.33	-3.91	5.97	5.55	5.55	5.22
		(1.08)	(1.06)	(1.06)	(1.12)	(0.31)	(0.31)	(0.31)	(0.31)
4	ML4	-5.53	-3.08	-2.81	-2.34	5.86	5.51	5.5	5.35
		(1.08)	(1.06)	(1.06)	(1.12)	(0.31)	(0.3)	(0.3)	(0.31)
Controls:									
Query FE		No	Yes	Yes	No	No	Yes	Yes	No
Eligible Ads FE		No	No	Yes	No	No	No	Yes	No
Market Condition FE		No	No	No	Yes	No	No	No	Yes
R^2		0.006	0.039	0.040	0.062	0.030	0.044	0.044	0.107
Adjusted R^2		0.006	0.039	0.040	0.050	0.030	0.044	0.044	0.095

Based on regression (1). The dependent variable is a click on the focal brand's or competitors' web link, paid or organic. Observations are brand search occasions. We do not reveal the overall number of observations as it might allow inference of the volume of searches on Bing (which is proprietary information). The baseline case is a randomized condition of no advertisements in the mainline. "Eligible Ads FEs" are indicator variables for how many and what type of ads (focal brand's or competitors') would be shown in the mainline in the absence of randomization. "Market Condition FEs" are indicator variables for the searched-for query and the exact set of ads that would have been shown in the absence of randomization.

Table 14: Estimates of changes in quick back probabilities of competitors' clicks, with an interaction of cases when the title of the competitor's ad in ML1 mentions the focal brand.

Randomized condition		Δ Quick Back Probability			
# of ML ads	Focal Brand's Ad	(1)	(2)	(3)	(4)
1	–	21.38	18.1	18.72	14.46
		(1.17)	(1.15)	(1.15)	(1.34)
1	ML1	-6.76	-5.36	-5.63	-7.93
		(2.56)	(2.54)	(2.54)	(2.74)
2	–	17.77	15.12	16.27	12.93
		(1.17)	(1.15)	(1.15)	(1.38)
2	ML1	6.31	2.92	2.92	-0.21
		(3.1)	(3.06)	(3.06)	(3.27)
2	ML2	16.32	12.8	13.05	9.15
		(1.83)	(1.8)	(1.81)	(1.99)
3	–	17.72	15.52	16.99	14.14
		(1.17)	(1.15)	(1.16)	(1.4)
3	ML1	4.27	2.32	2.58	2.94
		(3.54)	(3.48)	(3.49)	(3.92)
3	ML2	17.58	14.69	15.11	5.86
		(2.18)	(2.14)	(2.15)	(2.45)
3	ML3	19.47	16.65	17.02	13.1
		(1.97)	(1.94)	(1.95)	(2.2)
4	–	17.43	15.56	17.24	13.93
		(1.17)	(1.15)	(1.16)	(1.42)
4	ML1	9.02	6.1	6.45	7.41
		(4.01)	(3.95)	(3.95)	(4.73)
4	ML2	18.31	15.13	15.6	13.11
		(2.39)	(2.35)	(2.35)	(2.78)
4	ML3	20.79	17.66	18.14	10.77
		(2.19)	(2.15)	(2.16)	(2.51)
4	ML4	18.48	15.06	15.63	11.88
		(1.99)	(1.96)	(1.96)	(2.32)
Competitor in ML1 mentions focal brand		5.55	4.73	4.47	7.92
		(0.5)	(0.49)	(0.49)	(0.65)
Controls:					
Query FE		No	Yes	Yes	No
Eligible Ads FE		No	No	Yes	No
Market Condition FE		No	No	No	Yes
R^2		0.017	0.049	0.049	0.222
Adjusted R^2		0.017	0.048	0.049	0.077

Based on regression (1). The dependent variable is an indicator of a quick back event. Observations are competitors' web link click occasions in the data. We do not reveal the overall number of observations as it might allow inference of the volume of searches on Bing (which is proprietary information). The baseline case is a randomized condition of no advertisements in the mainline. "Eligible Ads FEs" are indicator variables for how many and what type of ads (focal brand's or competitors') would be shown in the mainline in the absence of randomization. "Market Condition FEs" are indicator variables for the searched-for query and the exact set of ads that would have been shown in the absence of randomization.

Table 15: Estimates of changes in the probability of a consumer clicking on the focal brand's paid link.

Randomized condition		Δ Click Probability			
# of ML ads	Focal Brand's Ad	(1)	(2)	(3)	(4)
2	ML1	14.61	18.05	11.64	12.3
		(0.44)	(0.43)	(0.42)	(0.43)
2	ML2	2.97	6.16	-0.25	0.49
		(0.44)	(0.43)	(0.43)	(0.43)
3	ML1	21.08	27.98	18.88	20.1
		(0.64)	(0.63)	(0.62)	(0.64)
3	ML2	8.61	15.08	6.42	7.32
		(0.65)	(0.63)	(0.62)	(0.64)
3	ML3	-0.23	6.62	-2.08	-0.85
		(0.65)	(0.64)	(0.63)	(0.65)
4	ML1	26.89	34.42	22.93	26.88
		(0.78)	(0.76)	(0.75)	(0.8)
4	ML2	14.05	21.51	10.44	13.65
		(0.78)	(0.75)	(0.74)	(0.79)
4	ML3	9.71	17.05	5.89	8.09
		(0.79)	(0.77)	(0.76)	(0.8)
4	ML4	0.7	8.34	-2.63	-1.16
		(0.79)	(0.77)	(0.76)	(0.8)
Controls:					
Query FE		No	Yes	Yes	No
Eligible Ads FE		No	No	Yes	No
Market Condition FE		No	No	No	Yes
R^2		0.062	0.112	0.137	0.157
Adjusted R^2		0.062	0.112	0.137	0.146

Based on regression (1). The dependent variable is a click on the focal brand's paid link. Observations are brand search occasions. We do not reveal the overall number of observations as it might allow inference of the volume of searches on Bing (which is proprietary information). The baseline case is a randomized condition with focal brand's ad in the top paid position and no other mainline ads. "Eligible Ads FEs" are indicator variables for how many and what type of ads (focal brand's or competitors') would be shown in the mainline in the absence of randomization. "Market Condition FEs" are indicator variables for the searched-for query and the exact set of ads that would have been shown in the absence of randomization.

Table 16: Estimates of changes in shares of traffic navigating to the focal brand's website through the paid channel.

Randomized condition		Δ Share of Paid Traffic			
# of ML ads	Focal Brand's Ad	(1)	(2)	(3)	(4)
2	ML1	17.21	20.56	13.63	14.49
		(0.45)	(0.44)	(0.43)	(0.44)
2	ML2	5.97	9.22	2.46	3.29
		(0.47)	(0.46)	(0.45)	(0.45)
3	ML1	25.88	32.42	22.59	23.78
		(0.67)	(0.65)	(0.64)	(0.66)
3	ML2	14.43	20.6	11.58	12.54
		(0.69)	(0.68)	(0.66)	(0.68)
3	ML3	5.38	12.1	2.81	4.08
		(0.72)	(0.7)	(0.68)	(0.7)
4	ML1	35.72	42.87	31.07	32.65
		(0.83)	(0.81)	(0.8)	(0.84)
4	ML2	22.78	29.83	17.86	22.16
		(0.84)	(0.82)	(0.81)	(0.86)
4	ML3	19.8	26.84	15.29	17.01
		(0.88)	(0.86)	(0.84)	(0.88)
4	ML4	10.96	18.26	7.02	8.25
		(0.91)	(0.89)	(0.87)	(0.91)
Controls:					
Query FE		No	Yes	Yes	No
Eligible Ads FE		No	No	Yes	No
Market Condition FE		No	No	No	Yes
R^2		0.091	0.140	0.170	0.188
Adjusted R^2		0.091	0.140	0.170	0.178

Based on regression (1). The dependent variable is a click on the focal brand's paid link. Observations are all clicks on the focal brand's web links. We do not reveal the overall number of observations as it might allow inference of the volume of searches on Bing (which is proprietary information). The baseline case is a randomized condition with the focal brand's ad in the top paid position and no other mainline ads. "Eligible Ads FEs" are indicator variables for how many and what type of ads (focal brand's or competitors') would be shown in the mainline in the absence of randomization. "Market Condition FEs" are indicator variables for the searched-for query and the exact set of ads that would have been shown in the absence of randomization.

Table 17: Estimates of changes in the probability of a consumer clicking on competitors' paid links in ML1 and ML2.

Randomized condition		Δ Probability to Click Competitor's link in							
		ML1				ML2			
# of ML ads	Focal Brand's Ad	(1)	(2)	(3)	(4)	(1)	(2)	(3)	(4)
1	–	6.43	6.43	6.33	5.82	0	-0.08	-0.11	-0.01
		(0.01)	(0.01)	(0.01)	(0.01)	(0.03)	(0.03)	(0.03)	(0.03)
1	ML1	0	0	0.03	0.01	0	0.04	0.05	0.01
		(0.01)	(0.01)	(0.01)	(0.01)	(0.03)	(0.03)	(0.03)	(0.03)
2	–	8.33	8.32	8.1	7.38	2.51	2.37	2.29	2.26
		(0.01)	(0.01)	(0.01)	(0.01)	(0.03)	(0.03)	(0.03)	(0.03)
2	ML1	0	0	0.03	0.01	0.91	0.89	0.92	0.91
		(0.02)	(0.02)	(0.02)	(0.02)	(0.06)	(0.06)	(0.06)	(0.06)
2	ML2	4.34	4.34	4.37	4.23	0	-0.01	0.02	0.03
		(0.02)	(0.02)	(0.02)	(0.02)	(0.06)	(0.06)	(0.06)	(0.06)
3	–	9.14	9.13	8.8	8.23	2.79	2.63	2.49	2.39
		(0.01)	(0.01)	(0.01)	(0.01)	(0.04)	(0.04)	(0.04)	(0.04)
3	ML1	0	-0.01	0.01	0	0.89	0.79	0.8	0.8
		(0.03)	(0.03)	(0.03)	(0.03)	(0.08)	(0.08)	(0.08)	(0.08)
3	ML2	5.72	5.71	5.73	5.47	0	-0.07	-0.06	-0.02
		(0.03)	(0.03)	(0.03)	(0.03)	(0.08)	(0.08)	(0.08)	(0.09)
3	ML3	6.9	6.9	6.91	6.77	1.7	1.61	1.62	1.57
		(0.03)	(0.03)	(0.03)	(0.03)	(0.09)	(0.08)	(0.08)	(0.09)
4	–	10.61	10.6	10.19	9.05	3.13	2.94	2.76	2.79
		(0.02)	(0.02)	(0.02)	(0.02)	(0.04)	(0.04)	(0.04)	(0.05)
4	ML1	0	0	0.01	0.01	1.03	0.94	0.94	1
		(0.04)	(0.04)	(0.04)	(0.04)	(0.1)	(0.1)	(0.1)	(0.11)
4	ML2	6.36	6.36	6.37	6.27	0	-0.12	-0.12	-0.08
		(0.04)	(0.04)	(0.04)	(0.04)	(0.1)	(0.1)	(0.1)	(0.11)
4	ML3	7.75	7.75	7.76	7.25	1.78	1.68	1.68	1.71
		(0.04)	(0.04)	(0.04)	(0.04)	(0.1)	(0.1)	(0.1)	(0.11)
4	ML4	8.99	8.98	8.99	8.56	2.59	2.48	2.48	2.47
		(0.04)	(0.04)	(0.04)	(0.04)	(0.1)	(0.1)	(0.1)	(0.11)
Controls:									
Query FE		No	Yes	Yes	No	No	Yes	Yes	No
Eligible Ads FE		No	No	Yes	No	No	No	Yes	No
Market Condition FE		No	No	No	Yes	No	No	No	Yes
R^2		0.128	0.128	0.131	0.339	0.013	0.018	0.018	0.072
Adjusted R^2		0.128	0.128	0.131	0.330	0.013	0.018	0.018	0.060

Based on regression (1). The dependent variable is a click on competitors' paid mainline 1 or mainline 2 links. Observations are brand search occasions. We do not reveal the overall number of observations as it might allow inference of the volume of searches on Bing (which is proprietary information). The baseline case is a randomized condition of no advertisements in the mainline. "Eligible Ads FEs" are indicator variables for how many and what type of ads (focal brand's or competitors') of ads would be shown in the mainline in the absence of randomization. "Market Condition FEs" are indicator variables for the searched-for query and the exact set of ads that would have been shown in the absence of randomization.

Table 18: Estimates of changes in the probability of a consumer clicking on competitors' paid links in ML3 and ML4.

Randomized condition		Δ Probability to Click Competitor's link in							
		ML3				ML4			
# of ML ads	Focal Brand's Ad	(1)	(2)	(3)	(4)	(1)	(2)	(3)	(4)
3	–	1.72	1.65	1.63	1.5	0	-0.02	-0.02	0
		(0.02)	(0.02)	(0.02)	(0.02)	(0.01)	(0.01)	(0.01)	(0.01)
3	ML1	0.78	0.75	0.75	0.67	0	-0.01	0	-0.01
		(0.04)	(0.04)	(0.04)	(0.04)	(0.02)	(0.02)	(0.02)	(0.02)
3	ML2	0.65	0.63	0.64	0.62	0	-0.01	-0.01	0
		(0.05)	(0.05)	(0.05)	(0.05)	(0.02)	(0.02)	(0.02)	(0.02)
3	ML3	0	-0.03	-0.02	-0.01	0	-0.01	-0.01	-0.01
		(0.05)	(0.05)	(0.05)	(0.05)	(0.02)	(0.02)	(0.02)	(0.02)
4	–	1.97	1.9	1.87	1.76	1.16	1.13	1.13	1.1
		(0.02)	(0.02)	(0.02)	(0.02)	(0.01)	(0.01)	(0.01)	(0.01)
4	ML1	0.7	0.67	0.68	0.73	0.48	0.47	0.47	0.42
		(0.06)	(0.06)	(0.06)	(0.06)	(0.03)	(0.03)	(0.03)	(0.03)
4	ML2	0.96	0.93	0.93	0.86	0.44	0.43	0.44	0.34
		(0.05)	(0.05)	(0.05)	(0.06)	(0.03)	(0.03)	(0.03)	(0.03)
4	ML3	0	-0.03	-0.03	0.01	0.72	0.71	0.72	0.62
		(0.06)	(0.06)	(0.06)	(0.06)	(0.03)	(0.03)	(0.03)	(0.03)
4	ML4	1.49	1.45	1.45	1.35	0	-0.02	-0.01	0.01
		(0.06)	(0.06)	(0.06)	(0.06)	(0.03)	(0.03)	(0.03)	(0.03)
Controls:									
Query FE		No	Yes	Yes	No	No	Yes	Yes	No
Eligible Ads FE		No	No	Yes	No	No	No	Yes	No
Market Condition FE		No	No	No	Yes	No	No	No	Yes
R^2		0.009	0.012	0.012	0.091	0.006	0.008	0.008	0.114
Adjusted R^2		0.009	0.012	0.012	0.079	0.006	0.008	0.008	0.102

Based on regression (1). The dependent variable is a click on competitors' paid mainline 3 or mainline 4 links. Observations are brand search occasions. We do not reveal the overall number of observations as it might allow inference of the volume of searches on Bing (which is proprietary information). The baseline case is a randomized condition of no advertisements in the mainline. "Eligible Ads FEs" are indicator variables for how many and what type of ads (focal brand's or competitors') would be shown in the mainline in the absence of randomization. "Market Condition FEs" are indicator variables for the searched-for query and the exact set of ads that would have been shown in the absence of randomization.