

When Does Brand Bidding Pay Off (Even) If Website Competition Is Low?

Research-in-Progress

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Abstract

Many companies place advertisements on search engine result pages, a practice referred to as search engine advertising (SEA). If their website also appears among the organic results, it is questionable whether SEA makes sense: Free clicks may be substituted by costly clicks on the advertisement (paid result). We propose a model that determines when paid results complement organic results and when they cannibalize them. The model explains both interaction effects by the characteristics of the triggering keyword and the specificity of the advertisement. We evaluate the model in a field experiment in the context of a quasi-monopolistic company and approx. nine million search queries that contain its brand names (brand bidding). This helps to reduce possible biases from competition and user heterogeneity. Preliminary results suggest that superior net effects can be achieved by placing ads for search queries that indicate a navigational or transactional search intention compared to informational searches.

Keywords: Search Engine Advertising, Brand Bidding, Cannibalization

Introduction

Search engine advertising (SEA), the practice of placing advertisements on search engine result pages (SERPs), has become the primary form of online marketing in the last years. In 2013, US advertisers spent almost half (43%) of their total online advertising budget of \$42.78 billion on SEA and other search-engine related marketing forms (IAB 2014).

Basically, SEA works as follows: First, advertisers create an ad at the SEA platform of a search engine. The ad consists of a title, an ad text, and a link to the target website. Then, they specify which search queries should trigger this ad by assigning it *keywords* (e.g., “jogging shoes”). Each keyword may contain several words as in the example. Each time a user enters a search query (e.g., “red jogging shoes”) into the search engine, all ads with keywords matching this search query (to some degree) are candidates for display. The presence of an ad consequently depends on the user’s search query and is called a *paid result*, in contrast to the so-called *organic results* created on the basis of website content and other criteria. To determine if and in which position on the SERP to display the ad, a ranking mechanism is defined. For this purpose, most search engines employ a real-time auction, i.e., they rank the ads based on monetary bids placed by advertisers for the triggering keyword. Since it is one of the main goals of search engines to present relevant results, they often adjust the advertisers’ bids by an estimate of the target website’s relevance to the user, the *quality score*, and some other criteria before ordering the ads. Some candidate ads may not be displayed at all if their adjusted bid is too low (from the search engine’s point of view). If more ads should be displayed than fit on one SERP, they are placed on the next page. Usually, advertisers do not have to pay the search engine for mere *impressions* of their ad but rather for each click of a user (*pay per click*, PPC). The actual *cost per click* (CPC) depends on the ad position assigned by the search engine and the cost for the next lower ad position. It is usually lower than the maximum bid placed by the advertiser.

Brand bidding refers to bidding on keywords that contain a brand name, therefore called *branded keywords* (e.g., “nike jogging shoes”). Note that we focus in this paper on advertisers bidding only on brand names that they own but it is also possible and legal in many countries to bid on brand names of competitors. On one hand, only a few advertisers engage in this strategy referred to as “piggybacking” (Rosso and Jansen 2010), so that the competition for branded keywords is usually lower than for non-branded or *generic keywords*. Furthermore, search engines consider advertisers’ target websites as more relevant if the user’s search query contains their brand name, leading to higher quality scores (Abou Nabout and Skiera 2012a). Low competition and high quality scores afford a low CPC. On the other hand, branded keywords typically generate more clicks, more conversions and higher revenues (Abou Nabout and Skiera 2012b). This might be due to a spill-over effect (Rutz and Bucklin 2011): Users searching for branded keywords are usually in a later state of their conversion process, having searched for generic keywords in an earlier step.

With branded keywords leading to higher revenues and a lower CPC, it may be surprising why not all advertisers who engage in SEA also engage in brand bidding. One possible explanation is that search engines usually rank the organic results according to their estimated relevance to the user (e.g., Vaughan 2004). Since, as mentioned earlier, advertisers’ target websites are considered as more relevant if the user’s search query contains their brand name, they typically will rank high among the organic results. If advertisers still engage in brand bidding, the user is confronted with two prominently posed results (organic and paid) linking to the same website (although possibly to a different *landing page* within this website). In this situation, both results may interact in the following way (see also Abou Nabout and Skiera 2012b): On one hand, the paid result may attract users who in its absence would not click on the organic result. This is called the *addition effect* and can lead to an increase in the overall clicking probability and thus, *ceteris paribus*, also to an increase in advertisers’ expected revenues. On the other hand, the paid result may lure some users who would otherwise click on the organic result. This so-called *cannibalization effect* may increase advertisers’ costs, assuming a PPC compensation scheme, because they have to pay for clicks that they could have had for free.

It is not obvious whether the increase in revenues due to the addition effect or the increase in costs due to the cannibalization effect will outweigh and, therefore, whether engaging in brand bidding is a profitable strategy for advertisers. First empirical findings (Abou Nabout and Skiera 2012b) suggest that this is the case despite the existence of considerable cannibalization of both, clicks and conversions. These results are just averages over a few different keywords and a single ad text. Thus, it remains unclear how different keyword characteristics and the ad text influence the interaction effects. This knowledge would be of great use for advertisers because it would first enable them to select the keywords for which brand bidding pays off most and second support their decision on the ad text and their bid for given keywords. This is the research gap we aim to address with this work. For this purpose, we develop and test a model of users’ behavior that allows a direct explanation of both interaction effects on three levels: clicks, conversions, and profit. So far, however, we only have addressed the click level.

We decided to conduct a field experiment in the real environment of a popular search engine (Google) and a well-known advertiser. We chose an advertiser who is a monopolist in the sense that his products cannot be bought on any other website. Competitive products exist but our partner is the market leader. The reason for our choice is the following: Users searching with branded keywords are usually in a late state of their conversion process, as mentioned above; hence, they can be assumed to have a clear desire (e.g., to buy jogging shoes). This desire can, furthermore, be assumed to be related to the advertiser’s brand at this stage so that there is little substitutability in the user’s mind (e.g., Nike jogging shoes will not be substituted by Adidas jogging shoes or vice versa). However, because we consider a monopolistic advertiser whose target website is the only website where they can fulfil this desire (unlike Nike shoes, which can be bought from many retailers), they finally must visit this website. The only remaining variable is whether they do this by clicking on the organic result or by clicking on the paid result. In this sense, we can attempt for the first time a “pure” evaluation of both interaction effects that is neither affected by user heterogeneity in form of a user’s long-term preferences (e.g., store preference) nor by short-term competition among retailers (e.g., sale actions). These factors have been shown to influence the performance of a SEA campaign (e.g., Gauzente 2009; Gauzente 2010; Animesh et al. 2011) but usually cannot be directly observed (Yang and Ghose 2010). Hence, it is helpful to exclude their variances from econometric estimations.

To summarize, we extend previous research first by investigating how keyword characteristics and the ad text drive the interaction effects. Second, our experiment permits for the first time a pure evaluation of these interaction effects. Further, our dataset enables us to undertake a third extension of prior research because the conversion-related data can be broken down by product and specific consumer behavior as follows: With respect to products, we are able to test whether an ad promoting a specific product increases the number of orders of this product (compared to a general ad text) and how this relates to the number of orders of other products. As far as consumers are concerned, we can test the effects of brand bidding on their site registration behavior. Further analyses of consumer characteristics in this context were not possible due to strong data privacy rules kept by the company.

Our results are relevant for all advertisers who consider engaging in brand bidding.

Previous Work

In a broad context, this paper relates to all studies investigating the interaction between SEA and other instruments from online marketing (Gopal et al. 2011; Kireyev et al. 2013) or offline marketing (Goldfarb and Tucker 2011). More specifically, we focus on the interplay between SEA and organic search engine results. This relates to several papers that investigate how user behavior is affected by the simultaneous presence of organic and paid results. It has been found that users in this situation strongly prefer the organic results (Jerath et al. 2013), although the paid results had practically the same relevance (Jansen et al. 2007). This may be because some users are negatively biased against paid results (Jansen 2007), which has a significant impact on their clicking intention and behavior (Gauzente 2009).

Against this background, some studies have analyzed the interaction between an organic and a paid result from the same advertiser (as it is the case for brand bidding). Yang and Ghose (2010) find a complementary relationship between both results, i.e., a positive correlation between the corresponding clicking probabilities. Furthermore, they find in a field experiment that the total number of clicks per impression, the total number of conversions per click, and the total revenue are higher if a paid result is present. Agarwal et al. (2011) confirm that the presence of an organic result increases the total probability of a click but report a decrease in the probability of a conversion. However, as we argue in the section on assumptions, these results do not necessarily apply to the situation of brand bidding (by a well-known advertiser). Furthermore, they only relate to the addition effect (although the effect is not specified in the same way). Even if clicks, conversions, or revenues rise, the effect of SEA cannot be precisely controlled without consideration of cannibalization effects as we do below. Addressing this issue, Abou Nabout and Skiera (2012b) conduct a field experiment in a brand bidding context. They pause the paid result for some weeks and measure both interaction effects by simple performance comparisons between the periods with and without the paid result being present. With their approach, they are able to judge the overall interaction effects, but they do not attempt to identify the drivers behind them. In this work, keyword characteristics are considered as one driver of interaction effects. Thereby, it also adds up to a stream of research investigating which keyword characteristics explain users' click and purchase behavior (e.g., Ghose and Yang 2009).

Some other studies, mostly using game theory, have dealt with the effects of the presence of organic results on the optimal bid for advertisers (e.g., Katona and Sarvary 2010; Xu et al. 2012). This is not the only decision an advertiser has to make, however: First, he has to decide for which keywords he should bid at all. Our work contributes to the literature on this task (e.g., Rutz and Bucklin 2007; Thomaidou and Vazirgiannis 2011) by enabling advertisers to select keywords that improve the increment of their profit by engaging in SEA. This increment can be calculated by the interaction effects. Our work additionally provides alternative keyword performance measures as mentioned in the introduction. Second, advertisers have to decide about which ad text to choose (e.g., Animesh et al. 2011). Regarding this task, Danescu-Niculescu-Mizil et al. (2010) have investigated how the similarity of an ad to the organic result influences the clicking probabilities. Besides, Jansen et al. (2011) have found that the combination of branded keywords with ad texts containing brand information leads to 15 times more revenue than any other combination. We extend these results by analyzing the influence of similarity between an ad and the corresponding organic result as another driver of interaction effects in the context of brand bidding.

The influence of brand bidding on specific products and the interaction of user registration behavior and brand bidding have not been studied yet, to the best of our knowledge.

Model

Interaction Effects

To quantify the addition and the cannibalization effect, we first have to define how these effects can be modeled and operationalized. We begin by considering both interaction effects with respect to clicks. At this level, we measure the addition effect by the conditional probability $p_{k,d}^{add}$ that a user searching with keyword k on day d will click (on any result) when the ad is shown, given that he would not have clicked on the organic result if the ad were not shown. Similarly, we measure the cannibalization effect by the conditional probability $p_{k,d}^{cann}$ that a user who would have clicked on the organic result in the absence of the paid result will switch to clicking on the paid result in its presence.

Previous research (e.g., Danescu-Niculescu-Mizil et al. 2010; Yang and Ghose 2010) has found the search intention of users as assumed on the basis of the triggering keyword k to be an important determinant of the probability of a click. Hence, we allow both interaction effects to depend on the user's search intention by employing a taxonomy that classifies search queries into three categories: *informational*, *navigational*, and *transactional* (Broder 2002). These categories are associated with the intention to gain a certain piece of information, to reach a certain website, or to perform a certain action (resp.). We define three corresponding dummy variables Informational_k , Navigational_k , and Transactional_k that take the value 1 if and only if k belongs to the respective category. Since the classification of k cannot always be determined objectively, we apply the following classification rules: If k contains parts of the URL of the target website or similar terms (e.g., misspellings), it is assumed to be navigational (82 keywords in our experiment). If it is related to a product, it is assumed to be transactional (42 keywords). Else, it is considered informational (94 keywords). In the following, informational keywords act as reference category.

In order to investigate the influence of the specificity of an ad on the interaction effects, we also include a dummy variable $\text{SpecificAd}_{k,d}$ in our model that takes the value 1 if the ad shown on day d for keyword k advertises a specific product and the value 0 otherwise. Correspondingly, we define another dummy variable SpecificProduct_k taking the value 1 if the keyword k contains the name of the product advertised and the value 0 otherwise. Note that $\text{SpecificProduct}_k = 1$ implies $\text{Transactional}_k = 1$. In our dataset, it also implies $\text{SpecificAd}_{k,d} = 1$ due to a requirement described later; thus, we cannot include an interaction term between these two variables.

To account for the advertiser's choice of words in the ad text and the decision on his bid for a keyword, we add two variables that relate to these decisions to our model: the relevance of the ad to the user ($\text{PaidRelevance}_{k,d}$) and the (daily average of the) position of the ad ($\text{PaidPosition}_{k,d}$). We operationalize $\text{PaidRelevance}_{k,d}$ by the percentage of words in the keyword k that the ad shown on day d for k contains. For the explanation of the cannibalization effect, we also include two analogous variables, OrgRelevance_k and $\text{OrgPosition}_{k,d}$. These variables account for the relative importance of the organic result compared to the paid result that users evaluate when deciding on which result to click. Remember that for $\text{PaidPosition}_{k,d}$ and $\text{OrgPosition}_{k,d}$, lower values correspond to a higher position on the SERP with 1 being the best value. Note that these variables are endogenous since they result from the calculation of the search engine (e.g., Agarwal et al. 2011). So far, we do not account for this endogeneity, however, since this would greatly complicate the estimation of our model without being expected to change the results significantly (as the variation of both variables can be assumed to be relatively low in our context).

Finally, we control for possible industrial dynamics by adding a linear time trend $\text{Time}_d = d$ (Yang and Ghose 2010) and for possible weekend effects (Hemant and Ramachandran 2011) by a dummy variable Weekend_d that takes the value 1 on weekends and the value 0 otherwise. Assuming a logistic regression model, these rationales lead to the following equations:

$$\log\left(\frac{p_{k,d}^{add}}{1-p_{k,d}^{add}}\right) = \beta_0 + \beta_1 \cdot \text{Navigational}_k + \beta_2 \cdot \text{Transactional}_k + \beta_3 \cdot \text{SpecificProduct}_k + \beta_4 \cdot \text{PaidRelevance}_{k,d} + \beta_5 \cdot \text{PaidPosition}_{k,d} + \beta_6 \cdot \text{SpecificAd}_{k,d} + \beta_7 \cdot \text{Weekend}_d + \beta_8 \cdot \text{Time}_d, \quad (1)$$

$$\log\left(\frac{p_{k,d}^{\text{cann}}}{1-p_{k,d}^{\text{cann}}}\right) = \gamma_0 + \gamma_1 \cdot \text{Navigational}_k + \gamma_2 \cdot \text{Transactional}_k + \gamma_3 \cdot \text{SpecificProduct}_k + \gamma_4 \cdot \text{OrgRelevance}_k \\ + \gamma_5 \cdot \text{OrgPosition}_{k,d} + \gamma_6 \cdot \text{PaidRelevance}_{k,d} + \gamma_7 \cdot \text{PaidPosition}_{k,d} + \gamma_8 \cdot \text{SpecificAd}_{k,d} \\ + \gamma_9 \cdot \text{Weekend}_d + \gamma_{10} \cdot \text{Time}_d. \quad (2)$$

Assumptions and Estimation

To simplify estimation, we make three assumptions about user behavior:

1) We assume that each user clicks at most once per impression; i.e., repeated clicks (on the same result) and dual clicks (clicks on both results) do not occur. This is reasonable because the user has no incentive to click multiple times, given that both results usually link to the same website. Alternative assumptions, such as the independence of clicks on both results as posited by Yang and Ghose (2010), could be made easily without an essential change of the model. However, due to the lack of user-level data, none of these assumptions can be tested; hence, the best one can do is to assume a plausible user behavior.

2) We assume that the sheer presence of an ad does not discourage users from clicking (on any result). This is consistent with the observation that users consider paid results less intrusive than other internet advertising forms (e.g., banner) because they are related to their search queries (e.g., Gauzente 2009; Ghose and Yang 2009). Therefore, there seems to be no reason why a user willing to click in the absence of an ad should change his mind and not click at all just because an ad is displayed. Furthermore, as reasoned earlier, users in a quasi-monopolistic context finally need to visit the advertiser's target website in order to fulfill their desire (as implied by their use of branded keywords).

3) We assume that users who are newly attracted by a paid result reach the target website by actually clicking on the paid result. To justify this, it can be argued that if a user prefers to click on the organic result instead, it is unlikely that he would not have done so if no ad were present. While in prior research (Yang and Ghose 2010), engaging in SEA has also increased the number of clicks on the organic result, we expect this to happen only very rarely (if at all) in the context we investigate because of the following rationale: Highly positioned organic results increase brand awareness, especially for less known goods or services (Dou et al. 2010). This can also be expected for paid results that appear on top of a SERP. Thus, in case of less known websites that achieve lower organic ranks, a paid result may support the organic result so that users better recall the product/company when they encounter it in a lower position. This increases the likelihood that they click on this less known link. In case of strong brands, however, this effect is negligent for two reasons: First, the corresponding website is almost always visible, usually taking one of the top spots on the SERP. Second, a paid result seldom changes the awareness of a brand that almost "everybody" knows. A spillover to the organic result is almost nonexistent in this case.

Assumptions 2) and 3) have implicitly also been made by previous research (e.g., Abou Nabout and Skiera 2012b). In any case, these working assumptions can be relaxed in the future by using a more complex econometrical model. Note, however, that they are also not critical for our current model; their violation may only introduce a small bias in the results as our analyses have shown.

Under assumption 1), users who are presented a SERP with an organic result and a paid result from the same advertiser have three possibilities: To click on the organic result, to click on the paid result, or not to click at all. Correspondingly, their behavior can be described by a random variable that follows a multinomial distribution with the number of impressions (of both results), $Impressions_{k,d}$, as the number of trials and $p_{k,d,ad=1}^{org}$, $p_{k,d,ad=1}^{paid}$, and $1 - p_{k,d,ad=1}^{click}$ with $p_{k,d,ad=1}^{click} = p_{k,d,ad=1}^{org} + p_{k,d,ad=1}^{paid}$ as the probabilities of the respective click events. Since the absolute numbers of clicks on each result are observed, these probabilities can be calculated easily via Maximum Likelihood.

Our approach for identifying $p_{k,d}^{add}$ and $p_{k,d}^{cann}$ is to relate them to $p_{k,d,ad=1}^{click}$ and $p_{k,d,ad=1}^{org}$. For this purpose, we first consider the users who click on any result in the presence of the paid result. Under assumption 2), they recruit themselves on the one hand from all users who would also have clicked if only the organic result had been present. Let us denote the corresponding probability as $p_{k,d,ad=0}^{click}$. On the other hand, the users newly attracted by the ad due to the addition effect add up to $p_{k,d,ad=1}^{click}$, which, therefore, is given by

$$p_{k,d,ad=1}^{click} = p_{k,d,ad=0}^{click} + (1 - p_{k,d,ad=0}^{click}) * p_{k,d}^{add}. \quad (3)$$

Note that the identification of the addition effect does not require assumption 3) because to calculate (3), only the total probabilities of a click are necessary. Additionally assuming 3), we can express $p_{k,d,ad=1}^{org}$ as

$$p_{k,d,ad=1}^{org} = p_{k,d,ad=0}^{click} * (1 - p_{k,d}^{cann}). \quad (4)$$

(4) states that the users clicking on the organic result in the presence of the paid result are the users who in its absence would also have clicked on the organic result and whose clicks are not cannibalized.

By (3) and (4), $p_{k,d}^{add}$ and $p_{k,d}^{cann}$ could be identified if $p_{k,d,ad=0}^{click}$ were observable when an ad is displayed. Since this is not possible, however, we calculate it by the logistic model

$$\log\left(\frac{P_{k,d,ad=0}^{click}}{1 - P_{k,d,ad=0}^{click}}\right) = \delta_0 + \delta_1 \cdot \text{Navigational}_k + \delta_2 \cdot \text{Transactional}_k + \delta_3 \cdot \text{SpecificProduct}_k + \delta_4 \cdot \text{Competition}_k + \delta_5 \cdot \text{OrgRelevance}_k + \delta_6 \cdot \text{OrgPosition}_{k,d} + \delta_7 \cdot \text{Weekend}_d + \delta_8 \cdot \text{Time}_d \quad (5)$$

and estimate the corresponding parameter vector δ by observations made when only the organic result is displayed. In this situation, $p_{k,d,ad=0}^{click}$ is identified by $\text{Impressions}_{k,d}$ and the absolute number of clicks on the organic result similarly to $p_{k,d,ad=1}^{org}$ when an ad is displayed. Based on the resulting estimate $\hat{\delta}$ of δ , we impute $p_{k,d,ad=0}^{click}$ for each observation in the presence of an ad so that it is known in (3) and (4).

In addition to all variables from (1) and (2) that are not specific to the paid result, we included Competition_k in (5), a value that is correlated with the number of advertisers who bid for the keyword k and, hence, a proxy for the number of (paid) results that could distract the user from clicking on the organic result of the advertiser under consideration. Competition_k is reported by Google as a moving average with a seemingly long period so that we found very little daily variation in this value during our experiment for the great majority of keywords. Therefore, it is sufficient to observe Competition_k as an average value over the whole experiment period in this case.

Field Experiment and Dataset

As described in the introduction, our dataset stems from a field experiment conducted in cooperation with a big, quasi-monopolistic company as advertiser. Due to the confidentiality of the data, we cannot reveal the company's name, industry branch, or products. We can only reveal that the products are a commodity, not very expensive, and therefore very well suited for online sales (Keisidou et al. 2011).

The identification of the interaction effects requires observing user behavior with and without an ad being present. Ideally, one would need pairs of observation that only differ in this respect (i.e., the same SERP and the same ads are displayed to "twin" users at the same time). This is not possible in a field experiment with a widely used search engine. In a lab, a randomized controlled experiment can be conducted but it would be difficult to collect millions of human searches. Therefore, we partitioned the whole observation period into a treatment period, during which the ad is displayed, and a control period, during which it is not displayed. Thereby, the observations made during the control period can be used to estimate the performance that the organic result would have achieved if it was shown solely during the treatment period. Following previous work (e.g., Yang and Ghose 2010), we employed a repeated measures design to mitigate the influence of unobservable variables that potentially could change between the treatment period and the control period: The ad was first displayed for one week and paused for the next week. This setting was repeated in the third and the fourth week for the same set of keywords, resulting in a total observation period of four weeks. We chose a period in fall 2013 without any national holidays or other expected special events that could influence the data. Also, luckily for the experiment, no unexpected events (e.g., a major weather disaster) took place at this time.

Bids worth a US\$ five-digit budget were placed for 218 different keywords. All of the keywords have been used by the advertiser before and, since our focus is on brand bidding, contain one of his brand names. Furthermore, each keyword was specified as "exact", i.e., to trigger an ad if and only if it matches the user's search query exactly. This way, we avoid aggregation biases that potentially could arise from the lack of data on each keyword auction during the observation period (Yang and Ghose 2010).

In order to enable testing of the influence of an ad's content on its performance, we created two different ads: The first one is rather general and could, in principle, substitute the organic result because it has a similar structure and makes use of so-called *sitelinks* (links to subpages that are placed below the ad text as an extension of the ad) to highlight popular areas of the website. In contrast, the second ad specifically promotes one of the company's products and highlights offers related to this product in its sitelinks. Therefore, it can be considered as rather complementary to the organic result and it increases the diversity on the SERP. To separate the effects of both ads, we isolated them into two different SEA campaigns that we alternated on each day, starting with the general ad on the first day of the first week and the specific ad on the first day of the third week. An exception was made for 20 keywords that contain the name of the product that the specific ad promotes: For these keywords, the specific ad was shown on each day within the treatment period due to the wish of the advertiser, who suspected that the general ad would not perform well for these keywords.

For each keyword, we can observe off-site performance data (impressions, clicks, and costs) as well as on-site performance data (conversions, which we define as orders, and revenues) for each displayed result separately on a daily aggregated basis. In total, our dataset contains 4 weeks * 7 days * 218 keywords = 6,104 aggregated observations, of which one half belongs to the control period and the other half belongs to the treatment period. They are based on approx. 9 million individual searches. Unfortunately, due to a Google policy established in 2011, the on-site performance data of users who have clicked on the organic result cannot be tracked (and thus, observed) if they use a secure connection (https). This issue is referred to as the "not provided"-problem in practice. However, there are no indications to assume that this loss of data does not occur at random (i.e., that https-users systematically behave differently than http-users in the context of this study); therefore, it should not bias the results.

The on-site performance data can be broken down by a consumer dimension and by product: We know how many users created new accounts for ordering, used an existing account, or ordered without registering, which is also possible at the website. Furthermore, we know how often each product was ordered and how much revenue this generated. Thereby, we are able to analyze potential differences in the interaction effects stemming from described user or product differences, something that was not carried out in previous work.

Preliminary Results and Interpretations

A small number of observations had to be eliminated before model estimation. The most common reason (354 cases) was that no user searched with the keyword on that day. The remaining 5,696 observations were used to estimate the model by the BFGS-algorithm (Broydon 1970; Fletcher 1970; Goldfarb 1970; Shanno 1970). Table 1 presents the results, which should be considered as preliminary.

As could be expected, the probability $p_{k,d,ad=0}^{click}$ of a click on the organic result (without a paid result) increases with a high relevance and a good position of the organic result as well as low competition. Furthermore, it is higher for navigational and transactional keywords than for informational keywords; however, the increase is smaller for product-specific keywords.

Regarding the addition effect, we first find that $p_{k,d}^{add}$ increases with a high relevance of the ad. This is plausible since users who would not consider the advertiser's target website as fulfilling their desire based on the organic result only are more likely to do this based on the paid result if the ad's content matches their search query to a higher degree. $p_{k,d}^{add}$ also increases with a good position of the paid result. This could be for one thing because users may value websites higher that rank top among the paid results (in analogy to the ranking of organic results). For another thing, they may get less distracted by competitors' results when evaluating the results top down. Furthermore, we find $p_{k,d}^{add}$ to be significantly higher for transactional keywords than for informational and navigational keywords, for which no significant difference was found. This result can possibly be explained by considering the corresponding high coefficient of $p_{k,d,ad=0}^{click}$: The great magnitude of users searching with transactional keywords would have also clicked on the organic result. The few remaining ones may consider the ad to be targeting their goal closer than the organic result. Therefore, they click on the ad when it is present. Next, we find $p_{k,d}^{add}$ to be lower for the specific ad than for the general ad. This can be expected because the specific ad does not directly fit the users' desire for most keywords. However, quiet surprisingly, even for keywords relating to

the product advertised by the specific ad, $p_{k,d}^{add}$ is still lower than for other transactional keywords. This may be based on the hope of users searching for certain products to get a special offer when clicking on an ad (Jansen et al. 2007). This expectation may be more pronounced if the ad relates to another product because users assume that this occurs to grab their attention to a special deal for the advertised product.

	Logit of $p_{k,d,ad=0}^{click}$	Logit of $p_{k,d}^{add}$	Logit of $p_{k,d}^{cann}$
(Intercept)	0.561 (0.005)***	0.555 (0.231)*	-0.467 (0.051)***
Navigational _k	1.190 (0.002)***	0.018 (0.012)	-0.256 (0.008)***
Transactional _k	1.378 (0.014)***	1.144 (0.032)***	-0.310 (0.018)***
SpecificProduct _k	-0.760 (0.014)***	-0.886 (0.050)***	1.589 (0.023)***
Competition _k	-2.901 (0.048)***	-	-
OrgRelevance _k	0.650 (0.004)***	-	0.193 (0.011)***
OrgPosition _{k,d}	-0.919 (0.003)***	-	0.598 (0.011)***
PaidRelevance _{k,d}	-	0.978 (0.021)***	0.356 (0.013)***
PaidPosition _{k,d}	-	-1.887 (0.227)***	-0.294 (0.049)***
SpecificAd _{k,d}	-	-0.386 (0.010)***	-1.710 (0.006)***
Weekend _d	-0.058 (0.002)***	0.302 (0.008)***	0.124 (0.005)***
Time _d	0.002 (0.000)***	0.011 (0.001)***	0.006 (0.000)***

Standard errors are given in brackets. Significance (likelihood ratio): *** $p < 0.001$, ** $p < 0.01$, * $p < 0.05$.

Table 1. Parameter Estimates

The cannibalization effect, $p_{k,d}^{cann}$, increases with the relevance of the ad. Users may switch to the ad if they have the feeling that they will reach the desired page at the advertiser's website faster using the ad's landing page than the organic result. This is reinforced by $p_{k,d}^{cann}$ increasing with a weaker position of the organic result and a good position of the paid result: Instead of going through all organic results until the desired one is found, users click on the paid result to reach the advertiser's website faster. Furthermore, $p_{k,d}^{cann}$ is higher for the specific ad than for the general ad. This makes sense since the ad will cannibalize clicks more probably if it fits the users' desire more closely. For keywords related to the product advertised by the specific ad, the effect correspondingly diminishes almost completely. Finally, $p_{k,d}^{cann}$ is lower for navigational keywords than for informational keywords and lower for transactional keywords than for navigational keywords. This may be because for navigational and transactional keywords, the organic result usually has a good position; i.e., there is little incentive for users to switch to the paid result.

$p_{k,d,ad=0}^{click}$ and both interaction effects are subject to a significant but very small time trend. Interestingly, both interaction effects were found to be stronger on weekends than on weekdays, suggesting that the appeal of the paid result is greater on weekends. This is supported by a negative weekend effect on $p_{k,d,ad=0}^{click}$. The reason may be that users have different search intentions on weekends (e.g., because of surfing at home) or that the composition of users during the weekend is different than on weekdays (e.g., due to a higher percentage of less experienced users).

Conclusion and Future Work

In conclusion, based on the first results shown in Table 1, one would advise advertisers to engage in brand bidding foremost for navigational and transactional keywords since they exhibit a lower cannibalization effect while increasing or not affecting the addition effect. For the same reason, they should bid on keywords for which the organic result has a relatively poor position or does not seem relevant. The specificity, the position, and the relevance of the ad are found to affect both interaction effects in the same

way. This means that addition and cannibalization both increase (or decrease) with an unpredictable net result with respect to the number of clicks.

We assume that if brand bidding pays off for quasi-monopolists, it should also pay off for non-monopolists: For the latter, we expect the addition effect to be greater since their paid result will attract not only users who would not have clicked at all in its absence but also users who would have clicked on a competitor's result.

Since the main financial goal of an advertiser is to increase his profit, our next steps are to extend the analysis to conversions, revenues, and profit. The effects of brand bidding on the number of specific products sold and the number of new users become especially important at these levels and will be analyzed in this context. Furthermore, we plan to define more complex models that relax our assumptions about user behavior and allow for endogenous relationships of variables.

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