Do Organic Results Help or Hurt Sponsored Search Performance?

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Abstract

We study the impact of changes in the position of competing listings in organic search results on the performance of sponsored search advertisements. Using data for several keywords from an online retailer's ad campaign, we measure the impact of organic competition on both click-through rate and conversion rate of sponsored search ads for these keywords.

We find that changes in the position of competing listings in organic results do not impact the click performance of the advertiser. We also find that competing organic listings in higher positions have a negative impact on conversion performance for generic keywords, but may help conversion performance for more specific keywords.

Our results inform advertisers on how the presence of organic results influence the performance of their sponsored advertisements. Our results also provide insight into consumer behavior in sponsored search settings. Specifically we show that consumers pay different levels of attention to search results depending on their search stage, and that this can result in differential impact of organic results on click and conversion performance of sponsored search advertisements..

Keywords: *Sponsored search, Organic search, ad placement, hierarchical Bayesian estimation, online advertising, online auctions, search engine marketing*

Introduction

Internet advertising spend is currently growing faster than any other form of advertising, and is expected to grow from $31 billion in 2011 to $49.5 billion in 2015[1]. Moreover, 40% of this advertising spend occurs on sponsored search, where advertisers pay to appear alongside the regular search results of a search engine. Search engines function as a 2-sided market, providing a relevant match between information providers and consumers. Most search engines, including Google, Yahoo, and MSN, use auctions to sell their ad space inventory. In these auctions, advertisers submit bids on specific keywords based on their willingness to pay for a click from a consumer searching on that (or a closely related) keyword. Search engines use a combination of the submitted bid and past click performance to set the position (rank) of the advertisement in the sponsored search results.

The presence of competition in organic (regular) results can affect the performance of sponsored search advertisements. Advertisers can attain a top position in sponsored search results by submitting high bids. In contrast, organic results are determined by the search engine based on the relevance and the popularity of the page for the given keyword, and are not influenced by advertiser bids. Because of this, consumers may trust organic results more than sponsored search results, causing negative effect on sponsored search performance (Jansen and Resnick 2006). Indeed, eye tracking studies have shown that consumers tend to focus more on organic results than they do on sponsored search results.[2] Given this observation, when setting advertising strategies, it is important for advertisers to understand how organic results influence both click-through rate and conversion rate in sponsored search advertisements.[3] Likewise, when setting their ranking algorithms for sponsored search auctions, it is important for search engines to understand the drivers of click and conversion performance so that they can accurately represent the relative quality of different advertisers in their search results.

[1] http://www.emarketer.com/blog/index.php/tag/paid-search/

[2] http://www.webcitation.org/5FmwyPgDv

[3] The term "conversion" is more commonly used in the industry than "order" because the definition of successful customer acquisition varies by firm. For example, for some firms, such as a free email service provider, user registration is referred to as a conversion

Previous theoretical work on sponsored search (Katona and Sarvary, 2010; and Xu et al. 2012) has considered the influence of organic results in evaluating the outcome for search engine performance. However, there is very little empirical analysis of this question. Previous empirical work has focused primarily on the influence of ad position (Agarwal, Hosanagar, and Smith 2011; Ghose and Yang 2009) and text properties (Rutz and Trusov 2011) on click and conversion performance. Yang and Ghose (2010) find that an advertiser's organic listing has a complementary effect on its own sponsored listing: an increase in the click probability of an organic listing of an advertiser increases the click probability of the sponsored listing. However, Danescu-Niculescu-Mizil et al. (2010) find that an increase in the click probability of top organic listing is also accompanied by an increase in the click probability of top sponsored listing, irrespective of the identity of the firm.

Thus, it is not clear whether and how competing listings in organic results will impact sponsored search advertisements. Note that the impact of competing listings is applicable regardless of the presence or absence of the advertiser's own organic listing. Additionally, studies in the existing literature have only considered the effect of organic listings on click-throughs — not conversions. Conversions may be important because a recent study has shown that user conversion behavior can look very different from click behavior (Agarwal, Hosanagar and Smith 2011). Animesh, Viswanathan and Agarwal (2011) have studied the impact of competitive intensity on the click performance; and Jeziorski and Segal (2012) show that relative ordering of advertisements affects the click performance of advertisements, an effect that can be attributed to difference in the quality of the corresponding advertisers. However, these studies do not consider conversion behavior or the influence of organic results on click performance.

In this paper we extend the existing literature by empirically analyzing how competition from organic search results impacts click and conversion performance in sponsored search. We do this using the results of a field experiment to generate a unique panel dataset of daily clicks, orders, and costs for multiple keywords in a sponsored search advertising campaign for an online retailer. Our experiment systematically varies the position of the ad in the list of sponsored search results, and captures the resulting daily clicks, orders, and cost for the keywords used in the campaign. We also use a web crawler to capture competing organic search results displayed alongside our advertisements. We use a hierarchical Bayesian model to analyze the probabilities for clicking and converting (i.e. purchasing) in this environment. We define competition as organic listings from firms selling similar products. We represent the effect of competition in terms of the average position of the competing organic listings, and weigh these positions with the popularity of the listing (a proxy for its perceived quality). The average position of the competition changes over time for every keyword in our sample. We also account for the endogeneity of the competition in organic results. We validate our results with alternate measures of competition and several other robustness measures.

We have three main findings. First, we find that clicking consumers do not pay attention to the position of competition in organic results. We attribute this to the search behavior of information seekers who are primarily responsible for the click performance. These users appear to be following simplified decision rules in their search process, and may not consider attributes on which the firms compete. Thus, click performance is not affected by relative changes in the order of organic listings for a given position of the sponsored search advertisement, as they are still arranged in a decreasing order of relevance.[4] Second, we find that organic competition affects the conversion performance of keywords, which suggests that buyers pay more attention to competition in organic results. Third we find that the impact of competition in organic results depends on the specificity of the keyword. While competing organic listings in a high position always have a negative impact on conversion performance of generic keywords, they can have a *positive* impact on conversion rates for more specific keywords. This could be because, for generic keywords, consumers are less informed and tend to search less. As a result, competing organic listings in a higher position cause the consumer to terminate their search early, leading to lower conversion rates. For specific keywords, consumers are more informed and tend to search more (White and Morris, 2007; White Dumais and Teevan 2009). When the position of the organic competing listings improves, these consumers are more likely to evaluate advertisers towards the end of the list. As a result,

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[4] A site can improve its ranking using Search Engine Optimization techniques which will make its site appear more relevant. So if a non competing listing for an ad shows up higher in the ranking, users may still think it is relevant.

they end up buying more from the advertiser due to a recency effect (Agarwal, Hosanagar, and Smith, 2011).

We believe our paper makes several contributions to the literature. First, it provides key managerial insights for advertisers. Many websites do not appear in organic results, or appear only for a few keywords, and need to establish a sponsored search marketing strategy to advertise their products. These advertisers can face competition from sites appearing in organic results and selling similar products. Competing organic listings can improve their ranking by investing in search engine optimization to make their pages more relevant for search results. Our results suggest that this may not impact the click performance of the advertiser. Given that branding is driven primarily by clicks (Rutz and Bucklin, 2011) whereas transactional revenues are driven by conversions, advertisers interested only in branding may not need to worry about changes in competition in organic results. Conversion performance, however, is influenced by competing listings in organic results. Interestingly, this competition might in fact help increase conversions for some keywords. Thus, advertisers may have to consider different responses to competition, depending on the type of keywords in their advertising campaign.

Our finding that conversion behavior can look very different from click behavior also has implications for search engines. Current search engine algorithms use click information to compare performance across advertisers. Given that consumers evaluate competing listings differently when deciding whether to click or convert, click rates alone can be incomplete or misleading indicators of an advertisement's performance. Our results also suggest that search engines should consider the impact of organic results on the manner in which consumers evaluate sponsored advertisements. Given that consumers show a preference for organic results when searching for information, it may not be desirable to over-emphasize ads when relevant listings already appear in organic results. A recent move by Google to show ads below organic search results for certain searches is consistent with this finding.[5]

[5] http://adwords.blogspot.com/2011/11/new-ad-placements-on-search.html

Finally, our results provide important insights into consumer behavior in sponsored search environments. Our results suggest that consumer response to a sponsored search advertisement can be influenced by competing listings displayed in organic results. Moreover, the performance outcome is different for clicks and conversions, and this can be attributed to the search intent. Clicks are primarily driven by consumers in an information seeking mode. These consumers use simple rules to make their click decisions and may not be influenced by the changing order of listings because they trust the search engine to provide most relevant results in the order of relevance. Thus, a change in the position of competing organic listings does not affect their response to sponsored advertisements and does not affect overall click through rate. Conversions are primarily driven by consumers in a buying mode. Our results show that these consumers evaluate seller listings more carefully than information seekers do. As a result, they are less likely to visit and buy from an advertisement if the competing organic listings appear in high positions. Our results also suggest a recency effect in consumer choice behavior in this environment as reflected by the increase in the conversion rate for more specific keywords. Buyers using these keywords tend to buy more from the advertiser when competing organic listings appear at the top of the list, as they are more likely to visit advertisers toward the end of the list.

We also note that search engines continuously innovate to provide better search results to users. For example, they recently started providing geo targeting and more personalization of results. However, the question of how users evaluate ads in presence of regular search results is still valid. As long as the search engine continues to co-list both organic and sponsored results, our results will still be applicable.

Literature Review

Our research is most closely related to the literature on consumers' online search and purchase behavior, with an emphasis on message ordering and the impact of competition. Our research is also closely related to the literature on advertisers' performance in sponsored search markets. We review these two literatures below.

Consumers' online search and purchase behavior

Prior work in traditional media has demonstrated that message ordering influences ad persuasion (Rhodes et al. 1973, Brunel and Nelson, 2003). Similar results have been shown in online environments. Hoque and Lohse (1999) find that consumers are more likely to choose advertisements near the beginning of an online directory than they are when using paper directories. Ansari and Mela (2003) have found that in an email campaign, higher position listings lead to a higher probability of clicking. There is also some evidence for this in the context of search engine. Feng et al. (2007) find that clicks decrease exponentially with position and attribute this to the decay in user attention as one proceeds down a list. Similarly, Ghose and Yang (2009) find that the click through rate of an advertisement decreases with position. As both organic and sponsored search results are ordered lists, an important question is how the position of competing listings in organic results influences an ad's performance. Using eye tracking analysis, Granka et al. (2004) find that users generally investigate search results sequentially, from top to bottom and from left to right. Danescu-Niculescu-Mizil et al. (2010) find that the top organic listing has a higher click through rate as compared to the top sponsored listing even if the sponsored listing shows above the organic listing. This suggests that users are more likely to visit organic results first.

Another important consideration is the search characteristics of different consumers. Online consumers include both buying consumers and information seekers (Moe 2003, Moe and Fader, 2004; Montgomery, Li, Srinivasan, and Lietchy, 2004). Moe (2003) shows that there is heterogeneity in search patterns of consumers on a website. Using path analysis, Montgomery, Li, Srinivasan, and Lietchy (2004) show that consumers with directed search have a higher probability of purchase than other consumers. Moe (2006) shows that consumers tend to use simplified decision rules, and may not consider certain attributes in the initial stage of purchase. A similar pattern might exist in sponsored search: consumers may be heterogeneous in terms of their purchase intent and resulting search behavior. Information seekers may not consider all attributes while making their click decisions. On the other hand, focused search on the part of buying consumers may reflect more selectivity in clicking and buying from advertisements. Information seekers and buyers may respond differently to the presence of competing organic listings in the top position. As a consequence, the presence of competing listings in the top organic positions may have a different effect on click and conversion behavior.

Search behavior of buyers can also be influenced by the relevance of the results presented to them. Users are expected to search until the utility of the products already searched meets their reservation utility (Haubl et al. 2010). If users find more relevant choices earlier in their search then they are more likely to stop their search earlier. The presence of competing organic listings in the top positions would provide more relevant choices to the buyers for a given position of the advertiser. As a result, users are less likely to visit an advertiser if competing organic listings appear in the top position.

Search behavior can also be different across buyers. Urbany et al. (1989) show that consumers with higher uncertainty about information for alternatives are likely to search less, while consumers with uncertainty about choice search more. Brucks (1985) and Srinivasan and Ratchford (1991) show that product knowledge increases search. Similarly, Moorthy, Ratchford and Talukdar (1997) show that consumers with low expertise are likely to search less than other consumers. The keywords used by consumers can potentially reflect expertise. For example, a common belief in the industry is that the use of more specific keywords may reflect a higher proportion of buyers as compared to less specific keywords. White and Morris (2007) and White, Dumais and Teevan (2009) confirm that advanced users submit longer, more specific queries and click further down into search results. As a result, if competing organic listings appear at the top, the search behavior would be less affected for buyers using more specific keywords than for buyers using less specific keywords.

Advertiser revenues depend on both clicks and conversion probability. Traditional advertising studies have demonstrated primacy effects in the recall of brand and product information (e.g., Pieters and Bijmolt 1997). In sponsored search, the consumer cannot perfectly recall product information from all visited web-sites, as they may have to view several pages across each website to get to the product of interest. Wyer and Srull (1986) show the existence of recency effects under conditions of high information load. Wedel and Pieters (2000) also find a recency effect in the recall of advertisements in a print magazine. Haubl, Benedict and Bas (2010) show that, in the context of sequential choice, consumers are disproportionately influenced by the attractiveness of the most recently evaluated product. This would suggest that the consumers who are likely to buy are more likely to do so from the website evaluated last rather than the website evaluated early in their sequential search. The presence of competing organic listings in the top of a list may influence the order in which buyers evaluate an advertisement, and in turn the conversion performance. Thus conversion behavior may differ across keywords in response to the changing position of organic listings.

Sponsored search markets

Existing work in sponsored search has focused on auction design, consumer behavior, and advertiser strategy. In terms of consumer behavior, Ghose and Yang (2009) and Agarwal, Hosanagar and Smith (2011) study the impact of ad position on click and conversion performance. Rutz and Trusov (2011) study the impact of ad textual properties on consumer click propensity. However, none of these studies considers the impact of organic results on consumer behavior. In this regard, Jansen and Resnick (2006) find a negative bias for sponsored search ads versus organic search results. In their theoretical work, Katona and Sarvary (2010) and Xu et al. (2012) have assumed a preference for organic results on the part of consumers. Yang and Ghose (2010) find complementarity between an advertiser's own organic listing and its sponsored listing. However, these papers do not consider the impact of competing organic listings on sponsored search results. Additionally, while modeling clicks, Yang and Ghose (2010) do not explicitly study the effect of organic results on conversion performance. Prior research suggests that consumer conversion behavior can differ significantly from their click behavior (Agarwal, Hosanagar and Smith 2011). As the conversion rate in sponsored search is very low, clicking performance primarily depends on information seekers, while conversion performance depends on serious buyers.

Animesh, Viswanathan and Agarwal (2011) show that competitive intensity has a different impact on click performance depending on the unique selling proposition of the advertiser. This highlights the importance of studying competitive intensity. Jeziorski and Segal (2012) find that advertisers appearing higher in search results impose a negative externality on the click performance of advertisements in lower positions, and attribute this effect to information satiation. Thus, higher competitive intensity in top positions may result in lower click performance of an advertiser. However, these authors focus on queries where users are primarily seeking information such as 'weather' which can be completely satisfied by a single site. They do not focus on keywords where the user's goal is to obtain information about products where different sites may provide differentiated information. Additionally, they do not investigate the effect of higher position of competing listings in organic results. Thus, the direction of the impact of competing organic listings is not well established in the literature. Likewise, the impact of competing listings in organic results, on conversion is not known. These topics are the subject of this study.

Data

Our main dataset was generated through a field experiment with a pet product company's sponsored search ad campaign on Google. The data were generated by submitting randomized bids for several keywords and measuring consumer response in terms of clicks and orders for different positions of the ads corresponding to the keywords. These keywords were randomly chosen from a set of keywords in the campaign related to the food product category that had generated clicks and at least one order for the retailer in the past 60 days. We used an automated web crawler to determine the organic results that consumers would see in response to search queries corresponding to the experimental keywords.[6] Google allows advertisers to use 'broad,' 'exact' or 'phrase' match for their keywords. One issue with broad and phrase match is that the exact set of competitors may vary based on the exact search query and the matching choices of competitors. An 'exact' match ensures that the search query exactly matches the chosen keywords, and to ensure replicability, we have only used keywords with an 'exact' match in our sample.

Organic search results for every keyword can include listings of firm websites selling related products as well as listings for purely information oriented sites such as wikis and information portals. We identify competing listings as the ones which are selling a similar product to our focal advertiser. Additionally, we

[6]Our web crawler extracted search results on an hourly basis during the panel period. Our webcrawler program ran on two different servers in different geographic locations: Pittsburgh and Austin. Search results obtained from both servers were similar indicating that users were likely to see the same search results.

have verified the list of competitors with our advertiser. Consumers show a preference for organic results over sponsored results (Granaka et al. 2004, Danescu-Niculescu-Mizil et al. 2010). Thus, consumers could be evaluating several organic listings before considering the sponsored listings. In order to account for this, we represent organic competition in terms of the daily average position of the competing organic listings. The relative position of the organic listings changes over time as firms make changes to their websites in order to rank their sites higher in search results. Figure 1 shows the variation in the average position of competing organic listings for each of the keywords in our sample for the duration of the experiment. It may not suffice to use the average position of competing listings because it is possible that competing listings may just swap positions with each other without affecting their overall average position of the competition. From a user's perspective, however, there is still a change in the relative ordering of competing listings which can influence their click and conversion behavior if they perceive these listings to be of different quality. Similarly, if a listing with higher perceived quality changes position, it can have a larger impact on user choices as compared to a listing with lower perceived quality. In order to account for such differential effect of competing sites we normalize the position of each competing listing with a measure of their perceived quality. Following the literature, we use corresponding Alexa rank obtained from alexa.com as the measure of perceived quality for competitor listings appearing in organic search results (Brynjolfsson and Smith 2000, Palmer 2002, Animesh et al. 2010). Note that we use the average Alexa rank of each website during the panel period of the experiment. We calculate organic competition using the formula at the bottom of Table 1. Thus, a higher Alexa rank of a competing listing (lower value of the Alexa Rank) would lead to a higher position (lower value) of that listing. Note that the competing listings in the organic results for a keyword do not change during the panel period, only their relative position changes. In the robustness section, we show results for other measures of organic competition.

In order to account for other factors that may influence consumer click behavior on sponsored results, we also capture the quality score measure maintained by Google and available to the advertiser (LQscore). This measure represents the click propensity of an advertiser and is calculated by Google based on several metrics including the relative click performance of the advertiser for the keyword, the relative overall click performance of the advertiser, the relative quality of the ad and the relevance of the ad for the focal keyword. Google uses a sliding window to determine the value of the quality score. However, this value remained unchanged during the course of the experiment for our keywords.

Our resulting data set consists of 1440 observations of daily impressions, clicks, and orders for 36 keywords over a 40-day period from June 2009 to July 2009. Table 1 provides summary statistics for our data. Note that the observations represent daily aggregate data for advertisements corresponding to the sample keywords for our advertiser, and that the dataset is typical of the information received by sponsored search advertisers. We do not have information on the performance of competing advertisements or detailed information on how an individual consumer makes a choice during a search session, information that would not typically be available to an advertiser.

Simultaneous Model

Consider an advertiser placing bids for a keyword in order to ensure its advertisements are visible in the list of sponsored results for queries related to that keyword. The search engine uses this bid, and the expected ad performance, to determine the advertisement's position in the list of sponsored search ads. The search engine also shows the corresponding organic results. Consumers see the organic results and advertisements, and decide to click on some of the ads, and subsequently decide whether to make a purchase. Thus, the search engine's decisions influence both the position of our advertiser, as well as that of competition, in the organic results. We simultaneously model consumers' click-through and conversion behavior, and use an IV approach to address the endogeneity of ad position and the position of competing organic results.

Click through Rate per Impression (CTR)

A consumer's choice of clicking on an advertisement can be modeled in terms of the latent utility of clicking. This in turn depends on the position of the advertisement and the quality of the advertiser, as well as the competition from organic results (Ghose and Yang, 2009). As mentioned earlier, we consider the average position of the competing listings in the organic results as a measure of the organic competition. While doing so we also normalize the position of competing listings in organic results with their corresponding Alexa Rank. (Subsequently, we analyze the sensitivity of our results to alternate measures of organic competition.)

In order to account for other factors such as ad relevance and the quality of the landing page, we use the quality score measure provided by the search engine. The advertiser's own listing can appear in the organic results for certain keywords. We control for this by using a variable representing the actual organic position of the advertiser's listing. If the listing is not present, then we use a suitably large number to represent the organic position.[7] Our unit of analysis is a keyword because the search engine auction is keyword specific. Keyword characteristics are an indication of underlying search behavior, which varies across consumers. For example, the keyword 'shirt' is less specific and indicates an initial stage of information search, while more specific keywords (e.g., 'levi shirt', 'formal blue shirt') indicate a more advanced and directed stage of information search. To account for these differences across keywords, we capture how specific a keyword is using two different measures: 'specificity' and 'brand.' The specificity of a keyword is based on the nearness of the its landing page to the product. For example, a top level such as 'men's clothing' would have the specificity value of 0, a second level representing products such as 'shirts' would have the specificity value of 1. Brand is indicated by the presence of a well-recognized manufacturer brand name in the keyphrase. This approach for representing keyword heterogeneity is similar to the one adopted by Agarwal, Hosanagar, and Smith (2011), Ghose and Yang (2009), and Yang and Ghose (2010).

We use a hierarchical model to capture the effect of keyword characteristics. This provides a flexible random component specification that allows us to incorporate both observable and unobservable keyword-specific heterogeneity, given the small number of observations for each keyword. Hierarchical models are commonly used to draw inferences on individual level characteristics (e.g., Rossi and Allenby,

[7] In our analysis we use a value of 20 to indicate that it is beyond the first page of search results. We have separately verified that our results are robust for other values.

2003). HB models have also recently been applied to study sponsored search data with keywords as a unit of analysis (Ghose and Yang 2009; Yang and Ghose 2010; Agarwal, Hosanagar, and Smith 2011; Rutz et al. 2012).

In our model we assume an i.i.d. extreme value distribution of the error term for individual choices and use a logit model to represent the click probability for a keyword k at time t as follows

(1) $$\Lambda_{k,t}^{CTR} = \frac{exp\,(U_{kt}^{CTR})}{1+exp\,(U_{kt}^{CTR})}$$

where U_{kt}^{CTR} is the latent utility of clicking. For a keyword k at time t, the latent utility of clicking can be expressed as

(2) $$U_{kt}^{CTR} = \theta_0^k + \theta_1^k AdPos_{kt} + \theta_2^k Organic\_Comp_{kt} + \theta_3^k OrganicPos_{kt} + \theta_4 LQScore_{kt} + \theta_t Time_{kt} + \varepsilon_{kt}^{\theta}$$

$$\theta^k = \Delta^{\theta} z_k + u_k^{\theta} \qquad u_k^{\theta} \sim N(0, V^{\theta})$$

where AdPos represents the position of the ad in sponsored search results,

OrganicPos is the position of the advertiser's organic listing for keyword k and time t and is the actual position when the listing is present or a large number otherwise,

Organic_Comp is the competition in organic results,

LQScore is the quality score of the ad,

Time controls for time dynamics in the auction,

$\varepsilon_{kt}^{\theta}$ represents the time varying unobserved keyword attributes that are common for all consumers,

z_k represents keyword specific characteristics: brand and specificity. Δ^{θ} is a matrix capturing the relationship between keyword characteristics and the mean values of coefficients,

and u_k^{θ} represents the unobservable heterogeneity for each keyword, which we assume is normally distributed with a mean 0 and covariance matrix V^{θ}

Conversion Rate per Click (CONV)

Conversion rate (probability) refers to the fraction of clicks that generate orders. Assuming an i.i.d. extreme value distribution of the error term for individual choices, we can express the conversion probability as

(3) $$\Lambda_{kt}^{CONV} = \frac{exp(U_{kt}^{CONV})}{1+exp(U_{kt}^{CONV})}$$

where U_{kt}^{CONV} is the latent utility of conversion, which may depend on the position of the advertisement. As above, organic competition can influence the conversion probability. For keyword k at time t, this latent utility can be expressed as

(4) $$U_{kt}^{CONV} = \beta_0^k + \beta_1^k AdPos_{kt} + \beta_2^k Organic\_Comp_{kt} + \beta_3^k OrganicPos_{kt} + \beta_t Time_{kt} + \varepsilon_{kt}^{\beta}$$

$$\beta^k = \Delta^{\beta} z_k + u_k^{\beta} \qquad u_k^{\beta} \sim N(0, V^{\beta})$$

We also include controls for the advertiser's own listing in the organic results, as well as for time dynamics.

Ad Position

The search engine determines the position of an advertisement for a keyword based on the product of the current bid and the quality of the advertisement relative to competing ads. As mentioned earlier, this relative quality measure is called the 'quality score' and is available to advertisers through Google. The dependence of ad position on bid and quality score introduces two sources of endogeneity: that related to the advertiser's bid decision and that related to the search engine's ad position decision. Advertisers can influence the position of their advertisements by changing their bids (for example to optimize performance). As a consequence, position is endogenously determined. Further, search engines might assign advertisers to specific positions that yield the search engine the highest revenues.

In order to control for this potential endogeneity, we have to account for the advertiser's bid choices as well as the position assigned by the search engine. In our setup, bids were randomized for the sample keywords. Thus the bid amounts are, by design, exogenous during the field experiment, taking away any strategic effect of our advertiser. Using a wide range of random bids also ensures that even if other advertisers are bidding using their own objective functions, the advertisements in our experiment are exposed to consumers over a wide range of positions.

Endogeneity is also introduced because search engines use ad performance data to compute an ad's position. In order to account for this, we use an Instrumental Variables (IV) approach and model ad position as a function of the randomized bid, adding controls to our model for the effect of the quality score. Similar approaches have been used by Ghose and Yang (2009) and Agarwal, Hosanagar, and Smith (2011). As a result, we express the ad position for a keyword k at time t as

$$(5)\ ln(AdPos_{kt}) = \gamma_0^k + \gamma_1^k ln(bid_{k,t}) + \gamma_2 ln(LQscore_{k,t}) + \gamma_{Time} Time_{kt} + \varepsilon_{kt}^{\gamma}$$

$$with\ \gamma^k = \Delta^{\gamma} z_k + u_k^{\gamma}\ and\ u_k^{\gamma} \sim N(0, V^{\gamma})$$

Note that the position of the advertisement is the daily average position, and is a continuous variable. This functional form ensures that the bid and the listed quality score, LQscore, are required to determine the ad position, and it explicitly incorporates the fact that the ad position is not randomized even if advertiser bids are random.

Organic Competition

Variation in the organic competition can arise from several factors. Firms continuously strive to improve their sites to increase their relevance, and thereby improve their position in search results. However, they can also do this systematically in response to an external event such as promotion, which may increase the consumer response. Additionally, the search engine can also strategically change the position of organic listings in response to events in order to ensure that it maximizes its revenue from the sponsored ads. As a consequence, the effect of organic competition on click and conversion performance can be biased.

We use an IV approach to correct for this potential endogeneity bias. For every keyword in our sample, we consider the competing firms in the organic listing and determine their daily average organic position for other non related keywords.[8] We use this average daily position across all organic competition for a keyword as an instrument for its organic competition. If a firm tries to improve its

[8] Our webcrawler data collection was for a large number of keywords. However, the bid randomization was possible only for a smaller set which form the focal keywords in our analysis.

organic position for different keywords, it would require similar effort from the cost perspective. For example, if a firm shows up in organic results for keywords 'shirt' and 'shoes' then any attempt made by the firm to improve its listing position for these keywords would have common cost components which would lead to correlation between the position of the organic listing of the firm for these keywords. At the same time, the consumer valuations would be independent across keywords and hence, the underlying products. So the demand shocks such as promotions should be independent. In that case, the position of one keyword can be used as an instrument for the position of a non-related keyword. Note that the consumer valuation can be also correlated if the firm has same promotions across multiple products. However, this is more likely to be the case for related products. By selecting the position of non related keywords we minimize the impact of such correlation. This is similar to the approach adopted by Hausmann et al. (1996), Nevo (2001) and more recently Ghose, Ipeirotis, and Li (2012) to use prices of the product in other markets as an instrument.

Using this approach the organic competition can be specified as a function of the IV variable as follows

(6) $Organic\_Comp_{kt} = \alpha_0^k + \alpha_1^k z_{kt} + \varepsilon_{kt}^{\alpha}$

$with\ \alpha_0^k = \Delta^{\alpha} z_k + u_k^{\alpha}\ and\ u_k^{\alpha} \sim N(0, V^{\alpha})$

z_{kt} is the average daily position of organic competition for non related keywords. In the robustness section, we validate our results with two alternate instruments

Finally, as the position of the advertisement as well as organic competition are endogenous, the unobservable time varying keyword attributes for the equations representing consumer decisions will be correlated with error terms for the equations representing position and organic competition. As such, we use the following distribution to account for correlation between the error terms:

(7) $$\begin{bmatrix} \varepsilon_{kt}^{\beta} \\ \varepsilon_{kt}^{\theta} \\ \varepsilon_{kt}^{\gamma} \\ \varepsilon_{kt}^{\alpha} \end{bmatrix} \sim N(0, \Omega) \text{ where } \Omega = \begin{bmatrix} \Omega_{11} & \Omega_{12} & \Omega_{13} & \Omega_{14} \\ \Omega_{21} & \Omega_{22} & \Omega_{23} & \Omega_{24} \\ \Omega_{31} & \Omega_{32} & \Omega_{33} & \Omega_{34} \\ \Omega_{41} & \Omega_{42} & \Omega_{43} & \Omega_{44} \end{bmatrix}$$

Identification

The above set of simultaneous equations represent a triangular system, which has been addressed by authors in classical (Lahiri and Schmidt 1978, Hausman 1975, Greene 1999) and Bayesian econometrics (Zellner 1962). It can be represented as follows:

$$U_{kt}^{CTR} = f(\text{Ad Position}, \text{Organic Competition}, X1, \varepsilon_{kt}^{\theta})$$

$$U_{kt}^{CONV} = f(\text{Ad Position}, \text{Organic Competition}, X2, \varepsilon_{kt}^{\beta})$$

$$\text{Ad Position} = f(X3, \varepsilon_{kt}^{\gamma})$$

$$\text{Organic Competition} = f(X4, \varepsilon_{kt}^{\alpha})$$

In this setup, Ad Position (AdPos) and Organic Competition (Organic_Comp) are endogenous, while the variables X1-X4 are exogenous. Identification arises from the fact that position is determined by the exogenous variables: bid and LQScore. As noted above, the bid for each keyword is randomized (exogenous) in our setup, and LQScore is a value internally calculated by the search engine for each keyword, and remains stable for the short period of our experiment, unless the advertisers change their ads or landing pages to influence the quality score. Similarly, Organic Competition is completely determined by the instrumental variable, which is not correlated with the error term. Position and Organic Competition in turn influence click and conversion performance.

Thus the rank and order conditions are satisfied for identification purposes (Greene, 1999). Lahiri and Schmidt (1978) have shown that the parameter estimates for a triangular system can be fully identified using Generalized Least Squares. Hausman (1975) shows that the likelihood function for a triangular system is the same as for Seemingly Unrelated Regressions. Zellner (1962) has addressed triangular systems from a Bayesian point of view, and shows that the posterior probability distribution function is the same as in a Seemingly Unrelated Regressions setting. Triangular systems have been estimated using the classical approach (Elberse and Eliashberg 2003; Godes and Mayzlin 2004) and more recently in sponsored search using the Bayesian approach (Ghose and Yang 2009; Yang and Ghose 2010; Agarwal, Hosanagar and Smith 2011).

We estimate the model using a Bayesian approach, applying Markov Chain Monte Carlo sampling due to the non-linear characteristics of our model (Rossi and Allenby 2005). A more detailed discussion of the priors and conditional posteriors of this model is given in Online Appendix. For the HB Models, we run the MCMC simulation for 80,000 draws and discard the first 40,000 as burn-in. In order to ensure that our parameter estimates are accurate we have simulated the clicks, orders, Ad position and Organic Competition using our estimates. By repeating the estimation with this simulated dataset we were able to recover our parameter estimates, indicating that our parameters are fully identified.

Results

Click through rate (CTR)

Table 2 provides the mean values for the posterior distribution of the Δ^{θ} matrix and the covariance matrix V^{θ} from equation 2. The coefficient for organic competition (organic_comp) is not significant. This suggests that, in general, consumers clicking on our advertiser's ads are not influenced by variation in the position of the competing listings in the organic results. This can be attributed to the search mode of the majority of consumers driving the clicks. As the conversion rate is very low, most of these consumers are in an information-seeking mode. These consumers may use simplified decision rules (Moe 2006) and just rely on the position of organic results to make their choice of clicking. As a consequence, their choice of clicking is not impacted by whether or not the organic listing is a competing retailer. Yang and Ghose (2010) find complementarity in click performance between an advertiser's listing in the organic and sponsored search results. This may suggest that competing organic listings may act as substitutes. However, our result shows that this may not be the case, as click performance is not affected by changes in the position of the competing organic listings.

The coefficient for ad position (AdPos) is negative and significant, indicating that click performance decays with position. This is similar to findings in the extant literature (Ghose and Yang, 2009; Yang and Ghose, 2010) and shows that click through rate decays with the position of the ad.

The coefficient for OrganicPos is insignificant. This is potentially due to the fact that very few keywords in our sample have the advertiser's own listing in the organic search result, and the small variation in the position of the organic listing for our advertiser is not sufficient to influence the consumer's click behavior. The coefficient of LQScore is positive and significant indicating that keywords with a higher LQScore have higher clickthrough rates than other keywords. This is consistent with expectations, because LQScore accounts for factors such as ad quality. The covariance matrix shows the significance of heterogeneity in this setup.

We also note that our results may not hold if the search engine organic results change so that non-relevant listings can also end up in very high positions. This scenario could arise if the search engine started to prioritize the ads in order to get higher revenue. It could also happen if the non-relevant sites improve their position by trying to manipulate the search engine results without improving their quality.[9] In that case, users may be able to recognize these listings and may start relying on the ads for their information needs. This would lead to a decrease in the click through rates for ads when true competing organic listings are shown in prominent positions. Thus, our results should be interpreted in view of the search engine's stated design objective of showing the most relevant listings in the organic results.

Conversion rate (CONV)

Table 3 provides the mean values for the posterior distribution of the Δ^{β} matrix and the covariance matrix V^{β} in equation 4. The coefficient for Organic_Comp is not significant, implying that, on average, conversion rate is not affected by changes in organic competition. However, the coefficient for the interaction between Organic_Comp and specificity is negative and significant. As our variable 'specificity' is mean centered, this suggests that the lower position of competing organic listings (higher value) has a negative effect on conversion rate for highly specific keywords and a strong positive effect on more general keywords.

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9 http://www.searchenginejournal.com/why-seo-is-best-in-recession/43354/

Buyers using less specific keywords are usually in an initial stage of information search. They are less informed. As a consequence, they are likely to search less (White and Morris 2007; White, Dumais and Teevan 2009). If competing organic listings appear in lower positions, these consumers are more likely to visit the advertiser and also buy from it. However, when the position of the competing organic listings improves, these buyers are more likely to visit the competing organic listings. Given that such buyers do not engage in deep search, these buyers are less likely to visit the advertiser. This in turn leads to lower conversion rates for generic keywords.

On the other hand, buyers using more specific keywords are usually further along in the search process, and are generally more informed. These consumers also tend to search more than other buyers do. As a consequence, these buyers may visit an advertiser even if other organic listings appear in higher positions. Thus, the number of buyers visiting the advertiser's landing page may not be affected as much by organic listings being placed higher. Further, an improvement in the position of competing organic listings would lead these buyers to visit these listings first followed by the visit to the ads. If the product offerings are similar, they may be more likely to buy from the advertiser due to a recency effect. It is also possible that the presence of competing organic listings in the top positions may improve the quality perception of the advertiser as the results appear more relevant. In short, deeper search for more specific keywords may imply that the choice set is not adversely affected if competing organic listings show up higher. Finally, a recency bias may lead to a higher conversion rate for the advertiser. Such recency bias has been reported in the literature in the context of advertising (Wedel and Pieters 2000), sequential search (Haubl, Benedict and Bas 2010), and in sponsored search (Agarwal, Hosanagar and Smith 2011).

The coefficient for AdPos is positive and significant, indicating that on an average conversion rate increases with position. This result is similar to the finding by Agarwal, Hosanagar, and Smith (2011) and suggests that serious buyers are visiting lower positions more than information seekers, and are buying from these positions. Note that this holds for only the top few positions, which is the case for our dataset (which only contains the top 10 positions).

Ad Position & Organic Competition

Table 4 provides the mean values for the posterior distribution of the Δ^{γ} matrix and V^{γ} from equation 5. In these results, higher bids lead to higher current position (lower value of position). This is reasonable as bid is one of the primary inputs used to compute ad position, and higher values of bids should move the ad higher in the list of returned results. The coefficient for LQscore is negative and significant. Thus, a higher LQScore also leads to higher current position. This is expected as a higher LQScore for a keyword should help the ad be placed higher in the sponsored results. Table 5 provides the mean values for the coefficient of the instrument. As expected, the coefficient for the instrument for Organic Competition is positive and significant.

Finally, Table 6 shows the covariance between unobservables for CTR, CONV, ad position, and Organic Competition from equation 7. Covariance between the unobservables for CONV and CTR is statistically significant. This indicates that the unknown factors influencing consumer clicks also influence subsequent conversion behavior. The covariance between the unobservables for CONV and Organic Competition is also statistically significant. As error terms for CTR and CONV are also correlated, this suggests that the unobservables influencing Organic_Comp are influencing CTR. Similarly, the covariance between the unobservables for CONV, CTR, and Ad position are statistically significant. This suggests that the unobservables influencing position are also influencing CTR and CONV, meaning that position and Organic_Comp are endogenous and the proposed simultaneous equation model helps to capture the effect of this endogeneity.

Robustness of Results

In this section we outline several steps we have taken to evaluate the robustness of our results.

Holdout Sample Analysis

As one test of robustness, we have attempted to verify the prediction accuracy of our results using a holdout sample. To do this, we consider data for the first 4 weeks for each keyword as the estimation sample and the data for the same keywords for the remaining two weeks as the holdout sample. We use mean absolute percentage error (MAPE) for daily CTR and CONV values at the aggregate level and at the keyword level. The error values are reported in Table 7 and indicate that the model prediction accuracy is similar for both the estimation and holdout samples. This suggests that our model estimates are robust.

<u>Model with Alternate Instruments for Organic Competition</u>

Lagged Organic Competition: We followed Villas-Boas and Winer (1999), Archak et al. (2011) and Ghose, Ipeirotis, and Li (2012) by using the lagged value of organic competition as an instrument for organic competition in conjunction with Google Trends data specifying search volume for each keyword. The lagged variable may not be an ideal instrument since the common demand shocks that can influence organic competition may be correlated over time. Nevertheless, common demand shocks that are correlated through time are essentially trends. Controlling for trends through our use of search volume data for different keywords should alleviate most, if not all, such concerns. The corresponding results for CTR and CONV are shown in Tables 8 & 9 and are qualitatively similar to our main result. We use harmonic mean (Newton and Raftery, 1994) to calculate the log-marginal density based on the MCMC output. We report log-marginal densities in Table 10.

Latent Instrumental Variable: We also apply the latent instrumental variable (LIV) approach developed by Ebbes et al. (2005, 2009). In this approach a binary unobserved IV partitions the endogenous variable (in our case organic competition) into two components, one uncorrelated and the other correlated with the error term in the main model (the models for click through rate and conversion rate). Ebbs et al. (2005) show that all model parameters are identifiable, that one discrete instrument is sufficient in most cases, and that this specification is robust under various nonnormal distributions of the true instrument. However, there is some loss of efficiency compared with a situation in which a true discrete instrument is used (see Ebbes et al. 2009). This approach has been adopted by Zhang et al. (2009) to address the endogeneity issues related to the impact of ad characteristics on sales. Similarly, Rutz and Trusov (2011) and Rutz et al. (2012) use the LIV approach to address the endogeneity of position in sponsored search ads. Using this approach the organic competition can be specified as a function of the LIV variable as follows

(8) $Organic\_Comp_{kt} = \alpha_0^k + \alpha_1 \pi_{kt} + \varepsilon_{kt}^{\alpha}$

$with\ \alpha_0^k = \Delta^{\alpha} z_k + u_k^{\alpha}\ and\ u_k^{\alpha} \sim N(0, V^{\alpha})$

π_{kt} is the discrete LIV which takes a value of 0 or 1, and α_1 is its effect on organic competition. Similar to the approach used by Zhang et al. (2009) we assume that π_{kt} follows a Bernoulli distribution $\pi_{kt} \sim B(p^{\pi})$ where p^{π} is the probability of the instrument ($\pi_{kt} = 1$), and α_0^k is the keyword specific constant term.

The corresponding results for CTR and CONV are shown in Tables 8 & 9 and are qualitatively similar to our main result. The posterior mean for α_1 is -1.65 (0.08) and that of p^{π} is 0.54 (0.02)

.Model with Fixed Effect for Keywords

We also use a fixed effects approach to control for keyword specific effects. Using this approach we find that both CTR and CONV are impacted by the organic competition (Tables 8 & 9). Higher values of organic competition (lower position) result in an increase in CTR as well as CONV. However, higher values of organic competition result in a decrease in the conversion performance for more specific keywords. Additionally, the average magnitude of the impact of organic competition is larger for CONV than for CTR. This again suggests that buyers are more likely to be influenced by the changes in the organic competition than are information seekers. Table 10 shows the marginal density of this model and suggests that the model has a poor fit as compared to our main model.

Alternative Measures of Organic Competition

We have also verified our results with two alternate measures of organic competition. For a keyword at time t, we consider the average position of the competing organic listings at time t without any normalization as a measure of its organic competition. In that case the organic competition is

$$Organic\_Competition = \frac{1}{n} \sum Organic\ Position\ of\ Competing\ Organic\ Listing$$

We also use another measure where we consider the position of the top competing organic listing for each keyword as a measure of competition. We identify the top competing organic listing as the one which has the highest average normalized position in organic listings for a keyword during the our panel period. For normalization, we again use the relative Alexa rank. We have also verified top competitor for each keyword with our advertiser. For each keyword, we use the average daily position of organic listings of the top competitor for non related keywords as an instrument for its organic position.

Results using these measures are shown in Tables 8 and 9. The results are qualitatively similar to our main analysis. The coefficient for Organic_Comp for CTR is not significant (Table 8), suggesting no influence of organic competition on click performance. For CONV, the coefficient of Organic_Comp is negative and significant for all keywords for the model with no normalization of position for organic competition (Table 9). However, the coefficient for more specific keywords is also negative and significant. The net outcome is that an increase in the position of organic competition leads to an increase in the conversion rate for generic keywords and decrease in the conversion rate for specific keywords. For the model with the top organic listing as a measure of organic competition, the coefficient for organic competition is positive and significant. However, the coefficient is negative and significant for more specific keywords. This again suggests that buyers using more specific keywords are more likely to buy when the competing organic listings are in higher positions. However, buyers using generic keywords are less likely to buy when the competing organic listings are in higher positions.

Discussion and Conclusion

In our research we analyze how the position of competing organic results affects the performance of sponsored search advertisements. Practitioners rarely evaluate the organic results landscape in planning their sponsored search strategies. The most that is typically done prior to bidding is to investigate whether one's own organic result shows up in the results. Ours is the first research we are aware of to systematically investigate the impact of competition in organic results on sponsored search performance.

To do this, we use a unique dataset derived from a field experiment with an online retailer's advertising campaign on Google. In this experiment we systematically (and exogeneously) varied the advertiser's bid, and captured the position of the ad and the daily impressions, clicks, orders, and costs resulting from this position. We also use a web-crawler to capture the search results from competing organic listings returned by these keywords. We analyze our data using a hierarchical Bayesian model, and accounting for the endogeneity of the ad position and organic competition. Our results show that a change in the position of competing organic listings has no impact on the click-through rate of our retailer's ads. However, these changes do impact the conversion rate of the retailer's ads. Further, we find that the impact of competition in organic listings can be different for different types of keywords. While competition from organic listings hurts conversion rates for generic keywords, it surprisingly helps increase conversion rates for more specific keywords.

These results are important for several reasons. From a practitioner perspective, our results emphasize the importance of analyzing competition in organic results when designing sponsored search campaigns. Our results suggest that advertiser response to organic competition depends on whether the advertiser is interested in clicks or conversions or both. Our finding that competition may help increase conversion rates for specific keywords also suggest that advertisers should evaluate the role of competition differently based on the type of keyword.

For search engines, the design and display of sponsored search results should account for the role of organic results in the consumers' evaluation of sponsored ads. Further, search engines should recognize that conversion performance may not mirror click performance, and thus clickthrough rates alone may not be sufficient as performance measures for ads.

Finally, our results inform the academic literature regarding consumer behavior in sponsored search environments. First, our results provide additional evidence that consumer response to sponsored search advertisements differs significantly as a function of consumer intent. In our data, click-through rate is not influenced by changing positions of competing organic listings, whereas conversion rate is influenced by these changes. This suggests that consumers with strong purchase intent pay more attention to organic listings. Our results suggest the possibility of recency effect in choices made by buyers. We show that these recency effects can also be driven by changing positions of competing organic listings for a given position of the sponsored ad.

As with any empirical analysis there are several limitations of our study. While, our results explain some information search behavior of consumers at an aggregate level, the aggregate nature of our data limits our ability to account for the actions of individual consumers. This calls for future research using click stream data to empirically evaluate the behavior of different types of consumers in sponsored search environments. Additionally, our analysis of orders is based on measurements conducted by the SEM firm employed by the advertiser, wherein consumer action is tracked during the entire search session. This potentially underreports sales resulting from an advertisement, because consumers may click on an advertisement, visit the advertiser's landing page without converting but return later (even using a different search engine query) to then buy the product. In these instances, the future purchases are not properly attributed to the original keyword. While we are able to evaluate the impact of organic search results, we do not have data to evaluate the reverse effect: the impact of sponsored search on organic results. Yang and Ghose (2010) evaluate the clicking propensity for organic results as a function of the clicking propensity for sponsored results. However, they do not explicitly study the conversion performance of organic results. Future research should investigate the combined effect of both organic and search results on the overall performance and suggest strategies to optimize the extent of advertiser participation in sponsored search.

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Table 1: Keyword Performance Summary Statistics

Variable	Mean	St. Dev.	Min	Max
Impressions	72.8	159	1	1666
Clicks	1.1	2.2	0	24
Orders	0.03	0.2	0	3
AdPos	3.47	1.7	1	9.78
OrganicPos	17.8	5	3	20
Organic_Comp	6.4	2.1	1.2	11.6
Organic_Comp without Normalization	6.1	1.8	1.5	9.75
Top Organic Listing as Competition	2.5	1.2	0.5	7.1
IV	7	1.2	2.9	11.1
IV for Organic_Comp without Normalization	6.5	1	3.5	9
IV for Top Organic Listing as Competition	6.1	1.8	1	12.7
LQScore	8	1.5	6	10
Brand	0.6	0.5	0	1
Specificity	0.4	0.7	0	1
Bid	0.5	0.3	0.08	2

$$Organic\_Competition = \frac{1}{n}\sum \frac{(Organic\ Position\ of\ Competing\ Organic\ Listing)\, x\, log(Alexa\ rank\ of\ Competing\ Organic\ Listing)}{\log(Alexa\ Rank\ of\ our\ Advertiser\ )}$$

Table 2: Estimates for the CTR

	Intercept	Brand	Specificity
Const	-3.44 (0.54)***	0.86 (1.13)	2.31 (1.05)**
AdPos	-1.56 (0.1)***	-0.77 (0.22)***	-0.46 (0.26)*
Organic_Comp	-0.03 (0.07)	0.23 (0.16)	0.03 (0.2)
OrganicPos	-0.02 (0.07)	-0.13 (0.16)	-0.14 (0.2)
Quality Score	0.18 (0.03)***		
Time	-0.01 (0.003)		

V^{θ}	**Const (1)**	**AdPos (2)**	**Organic_Comp (3)**	**OrganicPos (4)**
(1)	1.28 (0.31)***	-0.03 (0.08)	-0.02 (0.06)	-0.04 (0.06)

(2)	0.36 (0.07)***	0.006 (0.03)	-0.01 (0.03)
(3)		0.19 (0.03)***	-0.02 (0.02)
(4)			0.15 (0.04)***

*,**,*** Statistically significant at 10%, 5%, and 1% respectively

Table 3: Estimates for the CONV

	Intercept	Brand	Specificity	
Const	-3.99 (0.35)***	0.41 (1.18)	3.37 (0.97)***	
AdPos	0.88 (0.09)***	-0.04 (0.25)	0.23 (0.25)	
Organic_Comp	-0.1 (0.07)	0.0 (0.09)	-0.58 (0.19)***	
OrganicPos	0.1 (0.09)	-0.01 (0.22)	0.06 (0.27)	
Time	0.001 (0.004)			
V^{β}	**Const (1)**	**AdPos (2)**	**Organic_Comp (3)**	**OrganicPos (4)**
(1)	1.21 (0.32)***	-0.01 (0.08)	-0.04 (0.06)	-0.03 (0.09)
(2)		0.39 (0.06)***	-0.06 (0.03)**	0.005 (0.04)
(3)			0.24 (0.04)***	-0.03 (0.03)
(4)				0.29 (0.07)***

*,**,*** Statistically significant at 10%, 5%, and 1% respectively

Table 4: Estimates for the Ad Position

Variables	Intercept	Brand	Specificity
Const	1.33 (0.18)***	-0.03 (0.26)	0.62 (0.34)*
Bid	-0.56 (0.08)***	0.03 (0.19)	-0.12 (0.24)
LQScore	-0.06 (0.01)***		
Time	0.001 (0.001)		
V^{γ}	**Const**	**bid**	
Const	0.42 (0.1)***	-0.004 (0.05)	
Bid		0.19 (0.05)***	

*,**,*** Statistically significant at 10%, 5%, and 1% respectively

Table 5: Estimates for the Organic Competition

Variables	Intercept	Brand	Specificity
Const	1.95 (0.41)***	-4.92 (0.99)***	-2.71 (1.24)*
IV	0.67 (0.09)***	0.54 (0.2)***	0.34 (0.27)
Time	0.01(0.003)*		
V^{α}	**Const**	**IV**	
Const	1.71 (0.83)***	-0.18 (0.14)	
IV		0.18 (0.05)***	

*,**,*** Statistically significant at 10%, 5%, and 1% respectively

Table 6: Estimates for the Covariance Matrix Ω

.	CONV	CTR	Ad Position	Organic_Comp
CONV	0.795 (0.022)***	-0.197 (0.002)***	-0.01 (0.004)**	-0.106 (0.042)**
CTR		0.253 (0.019)***	0.009 (0.004)**	0.015 (0.025)
Ad Position			0.083 (0.003)***	0.016 (0.01)
Organic_Comp				1.356 (0.054)***

Table 7: Prediction Accuracy for Estimation & Holdout Samples

Models	CTR Fit (MAPE)		CONV Fit (MAPE)	
	Aggregate	Keyword	Aggregate	Keyword
Estimation Sample	0.40	0.39	0.30	0.30
Holdout Sample	0.42	0.42	0.33	0.32

Aggregate MAPE is the average MAPE across all datapoints. Keyword MAPE is the average of the average MAPE for different keywords

Table 8: Parameter estimates for CTR for Different Models

	Model with lagged competition as instrument (M2)	**Model with latent instrumental variable (M3)**	**Model with Keyword Fixed Effects (M4)**	**Model with no normalization of Organic positions**	**Model with Top Organic Listing as Competition**
Const	-5.34 (0.93)***	-5.55 (1.08)***	-3.71 (3.44)	-3.77 (0.49)***	-5.4 (0.92)***
AdPos	-1.28 (0.19)***	-1.38 (0.19)***	-1.38 (0.08)***	-1.57 (0.1)***	-1.59 (0.15)***
Organic_Comp	-0.01 (0.07)	0.08 (0.09)	0.18(0.09)**	0.0 (0.07)	0.15 (0.1)
Specificity	0.47 (0.9)	0.44 (0.78)	-1.06 (3.4)	2.59 (1.05)**	-0.93 (1.22)
Brand	1.37 (0.77)*	0.08 (0.69)	-0.69 (2.08)	1.09 (1.11)	1.16 (1.32)
Organic_Comp x Specificity	0.0 (0.2)	0.07 (0.09)	0.02 (0.07)	0.05 (0.2)	0.07 (0.23)
Organic_Comp x Brand	0.001 (0.05)	-0.05 (0.05)	0.001 (0.05)	0.23 (0.16)	0.0 (0.19)
OrganicPos	0.01 (0.07)	0.0 (0.06)	-0.04 (0.02)**	-0.01 (0.07)	-0.02 (0.07)
Quality Score	0.3 (0.06)***	0.31 (0.06)***	0.3 (0.06)***	0.18 (0.04)***	0.31 (0.07)***

*,**,*** Statistically significant at 10%, 5%, and 1% respectively

Table 9: Parameter estimates for CONV for Different Models

Variables	Model with lagged competition as instrument (M2)	Model with latent instrumental variable (M3)	Model with Keyword Fixed Effects (M4)	Model with no normalization of Organic positions	Model with Top Organic Listing as Competition
Const	-3.41 (0.39)***	-1.69 (0.53)***	-4.19 (3.43)	-3.75 (0.36)***	-4.07 (0.49)***
AdPos	1.54 (0.16)***	0.65 (0.16)***	0.67 (0.18)***	0.92 (0.09)***	1.59 (0.18)***
Organic_Comp	0.04 (0.07)	0.04 (0.08)	0.28 (0.1)**	-0.14 (0.07)**	0.21 (0.1)**
Specificity	-0.45 (0.86)	0.24 (1.05)	2.28 (3.34)	3.31 (0.98)***	6.53 (1.39)***
Brand	-0.17 (0.68)	0.11 (0.7)	0.29 (2.08)	-0.35 (1.06)	7.01 (1.36)***
Organic_Comp x Specificity	-0.4 (0.2)**	-0.43 (0.2)**	-0.4 (0.11)***	-0.52 (0.19)**	-0.62 (0.23)***
Organic_Comp x Brand	-0.18 (0.16)	-0.12 (0.16)	-0.03 (0.05)	0.24 (0.15)	-0.2 (0.19)
OrganicPos	-0.03 (0.06)	-0.08 (0.07)	0.02 (0.02)	0.09 (0.09)	-0.04 (0.07)

*,**,*** Statistically significant at 10%, 5%, and 1% respectively

Table 10: **Fit For Different Models**

Models	**Marginal Density**
Main Model	-8441
M2	-8387
M3	-8370
M4	-8577

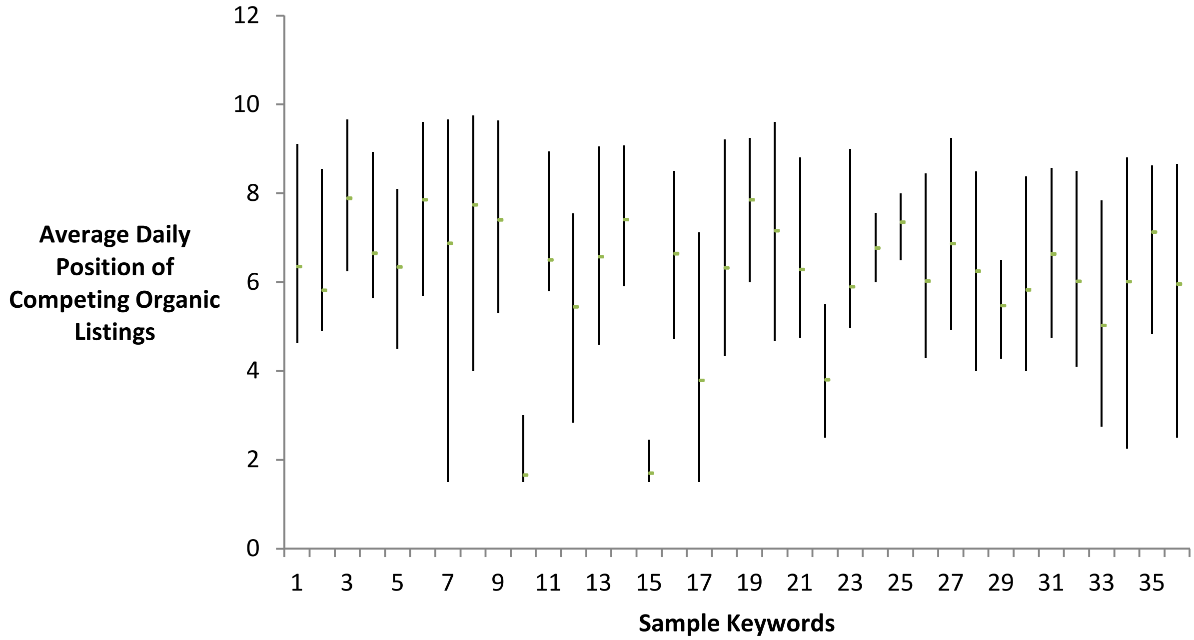

Figure 1: Variation in Average Daily Position of Competing Organic Listings