How Do Advertisers Compete in Sponsored Search Auctions? - Evidence from the Digital Camera Industry

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Abstract

This paper examines how advertisers react to the complex competitive environment in sponsored search auctions considering two salient competitive features: rank externality where the payoff of a rank position to an advertiser depends on which specific advertisers are located in other ranks, and competitor heterogeneity where diverse advertisers of different types may be competing for the same search keyword. We examine advertisers' behaviors from the lens of the strategic group theory. We first develop an approach to cluster participating advertisers into strategic groups and then empirically examine whether these groups manifest themselves in sponsored search auctions. Further, we examine whether advertisers in the same strategic group choose to appear closer to (or farther away from) each other, as opposed to advertisers from other strategic groups participating in the same auction. Our empirical analysis, based on data collected at Google, lends support to the existence of strategic groups in sponsored search auctions. We find that advertisers tend to obtain ranks in the sponsored search listings that are similar to competing advertisers from the same strategic group, regardless of whether they participate in all the auctions for the same keyword or not. Our findings contribute to the sponsored search literature by theorizing and empirically verifying advertisers' competitive behavior from the strategic group perspective.

1. Introduction

Sponsored search marketing, as the fastest growing advertising channel, has become one of the main venues for firms to compete for customers. It represents 46% of the $26 billion online advertising market in 2010 (IAB 2011). The rapid growth of the sponsored search industry has spawned growing interests in the economics, marketing, and information systems literature. Early research in this area focused on issues such as designing auction mechanisms (Edelman et al. 2007, Lahaie 2006) and ranking mechanisms (Feng et al. 2007, Lahaie and Pennock 2007, Weber and Zheng 2007, Liu et al. 2010), examining payoffs to the various parties involved (e.g., advertisers and the search engine). Several researchers have examined advertisers’ optimal bidding strategies in an attempt to characterize their equilibrium behaviors (Varian 2007, Edelman and Ostrovsky 2005, Xu et al. 2011). Based on the observation that advertisers typically received higher click-through rates when they appeared higher in the search listings, these studies have modeled the net click-through rate of an advertisement as a function of its position and quality (e.g., the quality of its advertisement or, analogously, the quality of its products and services). These models implicitly rely on an assumption that, while the click-through rate of an advertisement depends on its quality and its position, it does not depend on the competing advertisements appearing in other positions of the same auction.

Recently, a few researchers have considered more nuanced notions of competition, recognizing the externality effect imposed by other firms on the click-through rate of a focal firm’s advertisement. For example, Jeziorski and Sega (2009) note that the click-through rate on a given advertisement in a given position depends on which advertisements are shown above or below it, suggesting that the focal advertiser needs to know with which advertisements it is competing. Jerath et al. (2011) highlight the possibility of a position paradox in a market with vertically differentiated firms, where a superior firm is able to obtain more clicks than an inferior firm while its advertisement appears below the inferior one. Animesh et al. (2010) investigate differentiation strategies adopted by sellers in sponsored search auctions, focusing on two attributes for differentiation: price and quality. They find that the effect of a firm’s strategy (price- versus quality-differentiation) and the obtained rank on its advertisement’s click-through rate is moderated by the firm’s ability to differentiate itself from its adjacent rivals in the ranked listing.

While these works have provided additional insights regarding the externality effects of competitors (i.e., rank externality) on a firms advertising strategy, they are restricted to considering differences on the two dimensions - quality and price - in a generic manner. Further, they consider only a small set of competitors. Jerath et al. (2011) model two advertisers in their analysis, while Animesh et al. (2010) base much of...
their findings on a “window-of-three” approach where advertisers that appear immediately above and below a focal advertisement are considered to be the competitors. An interesting phenomenon in sponsored search auctions is that for many keywords there are a large number of advertisers bidding for slots. Additionally, as there is virtually no entry barrier to prevent any advertiser to bid on a keyword, the ending result of an auction can appear perplexing, with heterogeneous advertisers appearing at different ranks. The competitive strategy that applies to one type of a rival may not be equally relevant to another. This motivates us to examine how advertisers react to the complex competitive environment in sponsored search auctions, given rank externality and competitor heterogeneity.

The questions we examine lie at the very heart of a firm’s strategic management decisions: who competes with whom and how do competitors react to each other's actions (Desearbo et al. 2006)? In the context of sponsored search, we seek to examine firms’ bidding strategies when dealing with such heterogeneous competitors. Given the possibility of up to hundreds of competitors for a keyword, a natural question is whether a firm should consider the specific structure of the competitive market and if so, how?

The sponsored search literature has yet to provide a systematic approach to prescribe the structure of the competitive environment. Toward this end, we draw on the theory of strategic groups, first proposed in the management literature (e.g., Caves and Porter 1977, Fiegenbaum and Thomas 1995). Caves and Porter (1977) define a strategic group as a set of firms that closely compete against each other within an industry, where firms that fall into the same group are similar to one another along certain structural dimensions, e.g., degree of vertical integration and revenue. They suggest that firms within a strategic group recognize their mutual dependence more sensitively than dependence on firms outside the group. Fiegenbaum and Thomas (1995) note that a strategic group establishes a reference point for group members in the process of making strategic decisions. This body of literature theorizes the behavior of firms in a competitive market, and it provides a new lens to delineate the structure of otherwise seemingly unstructured markets such as sponsored search.

Building on strategic group theory, we investigate whether the membership in such groups plays a role in a firm’s strategic behavior in sponsored search auctions. If indeed it does, then how do firms behave? Should a firm try to position its advertisements to appear close to the advertisements of its main competitors (perhaps to signal their quality), or should it position its advertisements at a distance from such competitors (to better differentiate itself from its rivals)?

Prior research on competition and advertising provides arguments supporting both kinds of outcomes, and it is not easily apparent what may be a firm’s dominant strategy.

We examine the above questions empirically. To accomplish this, we collected auction data from Google during a 5-month span from May 2009 to October 2009. To identify strategic groups of firms competing for each of the keywords considered, we first use third-party data (from the Hoover’s and LexisNexis databases) to identify important competitors for firms that participated in these keyword auctions during our data collection period, and then use a clustering approach to determine the number and composition of strategic groups for each keyword. We find that the positions obtained by a firm do reflect the firm’s strategic group membership. Specifically, when advertisers from the same group appear in an auction listing, these advertisers appear closer to each other in terms of their positions than advertisers from other groups. Even when they do not always appear in the same auction listing, the advertisers from the same group are more likely to obtain similar positions on average, as opposed to advertisers from different groups. To the best of our knowledge, this research represents the first attempt to theorize and prescribe the competitive behavior of multiple heterogeneous advertisers in sponsored search auctions. Further, it provides empirical evidence of the existence of strategic groups in the sponsored search market, thereby addressing the call of Barney (1990) and to answer the fundamental question "does strategic group even exist?"

2. Theory Development and Hypotheses

Deciding which rank (position) to obtain in a sponsored search auction is an important decision to make for advertisers. In addition to the decay rate in click-throughs associated with lower positions, there are also externality effects imposed on the click-through rate of a focal advertiser by the positions of competitors...

Although the rank of an advertisement is ultimately determined by a search engine's complex, confidential ranking algorithm, key components of which include past CTR and the bid amount of the advertiser, strategic advertisers can still exercise considerable influence on their positions. For instance, based on their quality, firms can increase or decrease their bids to obtain higher or lower positions. Additionally, Google provides a Position Preference feature that allows an advertiser to choose to display its ads only when it is ranked higher or lower than a specific position, or it is in a range between two specific positions. Therefore, a firm’s decision on which rank to obtain can be largely considered as an endogenous marketing decision of the firm.
advertisements obtained by its competitors (Jeziorski and Sega 2009, Animesh et al. 2010, Jerath et al. 2011). A strategic advertiser’s rank choice decision should therefore factor in competing advertisers’ choices.2 Another complication in sponsored search auctions is the heterogeneity of advertisers in an auction, as advertisers from various industries with different sizes, focus, and business models often appear in the same auction. Consequently, an important decision for an advertiser is whether to try and obtain ranks close to that of their core competitors (i.e., those within the same strategic group) on the search engine’s ranked sponsored links, or to stay away from them.

The strategic group theory suggests that firms within the same group follow similar strategies and behave similarly in response to market opportunities or threats (Thomas and Venkatraman 1988). Porter (1979) asserts that mutual dependency is recognized more readily for firms within a strategic group than between firms in different groups, and thus leads to similar behavior among the firms within the same group. Ebbes et al. (2010) also argue that firms within a strategic group follow the same strategic recipes and compete more intensely with each other than with firms across strategic groups. Several analytical studies on sponsored search auctions suggest that firms with similar strategies and profitability tend to make similar bids (Edelman et al. 2007, Varian 2007), and as a result one may infer that their advertisements will appear within close proximity in an auction.

A similar outcome is also indicated by the literature on institutional theory and the herding behavior of firms. Chen and Hambrick (1995) attribute the similar behavior of firms within a strategic group to institutional theory, which holds that firms that deviate from the norm achieve lower performance and firms conform to the norm to justify resource allocation — the latter can enable advertisers to justify their advertising budgets (and thereby allocations to sponsored search).

The theoretical studies on the herding behavior of firms assert that firms’ strategic decision are influenced by the decisions of their competitors: individual firms often follow the action of the group (a herd) and so the whole herd’s behaviors converge (e.g. Bikhchandani et al. 1992). This also suggests that advertisers from the same strategic group would behave similarly by bidding for similar ranks in a sponsored search auction. Another argument for advertisers in the same strategic group to appear close to each other in an auction is provided by the contrast-assimilation theory proposed in the social communication and advertising literature (Hovland et al. 1957, Shin 2009). According to this theory, when consumers see two brands simultaneously they perceive brands that differ substantially in quality to be more different than they actually are, and perceive similar brands to be more similar than they actually are. Thus, two advertisers from two different strategic groups (with different quality perceptions associated with the groups) may not benefit from appearing very close in the same sponsored search page; it can be especially harmful for the low-brand firm. Conversely, similar firms (e.g., those within the same group) would have a higher incentive to appear close to its core competitors.

In sum, the theories on strategic group, herding, institutional behavior, and contrast-assimilation all suggest that firms within the same group may make similar decisions as to what rank to obtain. On the other hand, findings from recent studies on consumer behavior and sponsored search auction suggest the opposite — indeed, it may be preferable for advertisers in the same strategic group to not appear together in the sponsored lists. We summarize the key arguments supporting this hypothesis next.

Das et al. (2008) find that high quality, directly competitive ads placed side by side in response to a query (e.g., ads by both Honda and Toyota in response to a search for “Japanese cars”) will reduce the effectiveness of each ad, and each diminishes the appeal of the other. This phenomenon is well-known in traditional advertising channels. For example, in television advertising, television networks go to great efforts to satisfy their advertisers by ensuring an allocation of ads to commercial breaks so that competing advertisements do not appear in the same commercial break. This suggests that it may not be beneficial to advertisers when more competitors within the same group appear close to each other, and thus strategic advertisers could try to prevent this by separating themselves from each other in auction outcomes. In the context of sponsored search auctions also, Animesh et al. (2010) find that an advertiser’s inability to differentiate itself on quality from other advertiser’s appearing in immediately adjacent positions negatively impacts its click-through rate when it appears in the top ranks; surprisingly, the impact is positive when it appears in the bottom ranks. In a related vein, Ghose et al. (2011) show in an empirical study that more alternatives presented to consumers by a hotel search engine led to lower conversions for all hotels.

Identifying conditions for a dynamic equilibrium in sponsored search auctions, Zhang and Feng (2011) suggest that the cyclical equilibrium is similar to a

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2 In a sponsored search auction, all competing advertisers may be viewed as making their decisions simultaneously. During the course of the auction, the rank a competing advertiser is going to obtain is unknown to the focal advertiser, but an expectation of the rank can be formed through examining past auction outcomes.

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traditional mixed-strategy equilibrium. Considering a duopoly, they liken the scenario to the 'matching pennies' game. In a simultaneous move setting, advertisers in such a game play a mixed-strategy equilibrium in which both of them randomize, even in a repeated game setting; this suggests that advertisers from within a strategic group may not always prefer to appear side by side. When the market allows firms to move sequentially and observe each other’s actions, both advertisers alternatively choose one extreme action (e.g., one at a high rank and the other at low rank). This explanation of competitors differentiating themselves is similar to the one described by Campbell et al. (2005) where they argue that firms may collude when consumers' search cost is low, even with imperfect or no monitoring by sellers of each other's prices. Further, since the same technology that eases consumer search also allows firms to monitor each other's prices more easily, the firms can more easily detect deviations from a collusive price arrangement, allowing an even greater room for collusion. In the sponsored search context, it is relatively easy for advertisers to monitor each other's ranks. Thus, advertisers may collude by taking turns to bid for higher ranks, resulting in them keeping some distance from each other in each auction.

The literature on price dispersion provides another argument for firms to bid differently from their main competitors and thereby have their advertisements appear away from each other in these auctions. Interestingly, this literature finds a high level of price dispersion when there is intense competition among firms, contrary to the prediction of a Bertrand competition. For instance, Borenstein and Rose (1994) document significant price dispersion in the U.S Airline industry when competition is high, and attribute it to the stickiness of consumers’ unwillingness to switch. This is later verified for online travel agents by Clemons et al. (2002). In a study of the long-distance call market, Ennis (2006) shows that higher level of competition can lead to more price dispersion. Similarly, Lewis (2008) finds significant price dispersion among retail gasoline sellers in a competitive local environment even after controlling for differences in station characteristics. Cachon et al. (2008) describe a case when reduced search cost online can lead to higher price dispersion in a competition-intensive market. Baye et al. (2004) posit that the high price dispersion observed for electronic goods can be explained by the strategic pricing of firms to preclude rivals from being able to systematically exploit and undercut a fixed price. Finally, the debate on whether rivalry within groups is stronger or weaker than rivalry across groups remains unsettled. Peteraf (1993) found the rivalry within groups to be weaker than that across groups in the US airline industry. Smith et al. (1997), also studying the US airline industry, find within group rivalry to be stronger for one group (called entrenched dominant by the authors) compared to the across group rivalry, but weaker within the other groups relative to the across group rivalry. We would expect that if the within group rivalry is weaker, then the firms within a group will not appear close to each other.

With the divergent arguments and conclusions from the different streams of research, this work attempt to resolve the rank separation issue by empirically examining advertisers’ rank choice behavior. We explore which set of forces dominate, if any. Therefore, as the null hypothesis, we postulate:

**H1:** In sponsored search auctions, the ranks of advertisers within the same strategic group will be closer than the ranks of advertisers from different groups.

Hypothesis 1 implicitly assumes that all the advertisers are competing in the same instances of a keyword auction. Typically, advertisers do not have the ability to specify if the display of their advertisements in an auction should be contingent on the display (or lack thereof) of their competitors’ ads. Furthermore, advertisers usually set daily or weekly budgets, which can result in intervals during which the advertiser’s budget is exhausted for the remainder of the period and its bids are no longer in consideration until the beginning of the next period. As a result, the ranks that result from the strategy a firm implements would apply equally to auction instances in which their competitors’ ads appear as to those in which their competitors’ ads do not appear. Therefore, we next relax our hypotheses to encompass the more generic scenario where competing advertisers bid for the same keyword over a period of time, but their advertisements may not appear (or, perhaps, the firms may not bid) in every instance of the auction for the keyword during that time period. Nevertheless, the arguments to support or contradict Hypothesis 1 still hold. Therefore, we examine another hypothesis as stated below:

**H2:** Even when advertisers from the same strategic group do not appear in some auctions for a given keyword, the average ranks obtained by firms within the same group will be closer than those of firms from different groups for those auctions.

### 3. Data Collection and Strategic Group Identification

We first describe the auction data used for our empirical analysis and how we obtained them. We then describe how strategic groups are identified for the advertisers competing for a keyword.
3.1 Obtaining Sponsored Auctions Data

We consider keyword 'digital camera' that has also been examined by Animesh et al. (2010) During our data collection period, Google typically displayed the three highest ranked sponsored links on top of the organic links, and the next eight along the side of the organic ones. Therefore, for each auction, we obtained the ranks of advertising firms starting from the sponsored links above the organic list followed by those on the side, with rank increasing as we go down a list. Google requires a minimum bid for an advertiser to appear in the three positions on top. When no bid exceeds the threshold, no sponsored links are displayed on the top; in those cases we ranked the ones on the side starting from one.

To collect the data, we ran Perl scripts to automatically extract the ranking results of sponsored links on Google.com for each of the keywords. This was done roughly once an hour every day during the 5-month data collection time window. The data was collected every hour because an advertiser’s rank can vary a lot within a day. For example, we observed that the daily rank can range from 1 to as high as 11 for many advertisers. In total keyword 'digital camera' attracted 177 distinct advertisers across 2,177 auctions we extracted.

3.2 Identifying Strategic Groups

Competitor identification is a necessary precursor to the task of any competitive analysis, and the starting point for analyzing firms' competitive strategies (Smith et al. 1992, Bergen and Peteraf 2002), a key objective in strategic group theory. In sponsored search settings, advertisers bidding on a keyword may come from different industries, with different motivations and competitive strategies. Not all advertisers participating in an auction may be equally relevant to a focal advertiser. Extant research has primarily focused on identifying strategic groups in a limited manner among a relatively small number of competitors confined within the same industry (Porter 1979, Tremblay 1985, Kling and Smith 1995). Given our context, it is necessary to develop a new and objective method to identify strategic groups.

We determined strategic groups in the following manner. For a given keyword, we first identified all advertisers that bid for the same keyword. For example, 177 advertisers in total bid at least once for the keyword “digital camera,” i.e., they appeared in at least one out of a total of 2177 auctions captured in our data. The data exhibited a long tail: only 27% of the firms (48 firms) appeared more than 20 times (i.e., approximately 1% of all the auctions sampled) over the 5-month period. To ensure meaningful analysis, we included for consideration only those advertisers who appeared in at least 20 auctions. Thus 129 advertisers were dropped from our sample because it is hard to envision these low-frequency advertisers acted strategically in tandem with their competitors.

We then used a two-step process to identify the strategic groups among these advertisers. In the first step, we obtained a set of main competitors for each advertiser from the Hoover’s database, an authoritative source for determining competitors of a firm. Hoover’s uses industry experts to identify the relevant competitors of a firm based on a number of key attributes that include a company’s main business lines, its geographic rivalries, and the specific market segments it belongs to (Hoovers.com), and is recognized as a reliable source for competitor identification (Ma et al. 2009, and Ghani et al. 2000). We resorted to other databases (e.g., the Global Markets Direct database) in the LexisNexis repository as a secondary source to identify additional competitors that are not captured by the Hoover’s database. For each firm, we identified the top three competitors as indicated in Hoover’s or LexisNexis databases. For example, Amazon.com, eBay, Best Buy, and Target are frequent advertisers for the keyword “digital camera.” The Hoover’s database lists eBay, Best Buy, and Target among the main competitors for Amazon. Therefore, we identified these three firms as the top competitors for Amazon. For some advertisers, neither Hoover’s nor LexisNexis listed competitors, and furthermore, they were not identified as a competitor to other firms in the list of advertisers. For example, for the keyword “digital camera,” 26 from among the 48 advertisers that appeared more than 20 times yielded no competitors. These are mostly very small businesses, with several having ceased to exist. These 26 firms are of little strategic significance to the other firms and thus were dropped from consideration. We ended up with a list of 22 unique firms such that each of them was identified as a competitor of at least one other firm (see Table 1) from the reference databases.

The competitor lists in Table 1 cannot be directly used as strategic groups because a firm may be listed as a key competitor to many other firms by virtue of its market power, but all the other firms may not be important competitors of this firm (e.g., Wal-Mart may be an important competitor to a local grocery store, but not the other way round). Therefore, in the second step, we used a hierarchical clustering technique to identify strategic groups from the sets of competitors shown in Table 1. In hierarchical clustering, existing clusters (that may consist of one or more firms) are combined to form a single cluster in an iterative manner (see, e.g., Everitt et al. 2001). We derive a distance matrix across firms in the competitor list by first assigning a
(competitive) similarity score to each pair of firms, and then normalizing this score into a distance measure in the range $[0,1]$ (a distance matrix is required by many hierarchical clustering packages such as SAS). The similarity score for the pair $(i, j)$ is defined as the number of times firm $i$ appears in the same competitor set along with firm $j$. For example, Amazon and Best Buy have a similarity score of 4 as they appear together in four competitor sets (the sets for Amazon, Best Buy, and two other firms, Buy and Hhgregg). Intuitively, if firms $i$ and $j$ co-occur more often in the same competitor sets, the similarity score for cell $(i, j)$ is higher and the two firms are more likely to belong to the same strategic group. To convert the similarity matrix into a distance matrix, the distance between two firms $i$ and $j$ is calculated as $d_{ij} = 1 - s_{ij}/S$ where $S$ is the maximum similarity score possible. Our approach clusters firms in a manner such that each firm in a cluster can be viewed as a key competitor to every other firm in that cluster.

### Table 1: Firms and their Competitors for the Keyword “digital camera”

<table>
<thead>
<tr>
<th>Firm</th>
<th>Set of Competitors Identified by Hoover’s/LexisNexis</th>
</tr>
</thead>
<tbody>
<tr>
<td>1 Amazon</td>
<td>eBay, BestBuy, Target</td>
</tr>
<tr>
<td>2 Best Buy</td>
<td>Amazon, Sony, Target</td>
</tr>
<tr>
<td>3 Bing</td>
<td>Google, Amazon, Sony</td>
</tr>
<tr>
<td>4 Bonton</td>
<td>Target</td>
</tr>
<tr>
<td>5 Buy</td>
<td>Amazon, BestBuy, eBay</td>
</tr>
<tr>
<td>6 Circuit City</td>
<td>BestBuy</td>
</tr>
<tr>
<td>7 eBay</td>
<td>Amazon, Google, Yahoo!</td>
</tr>
<tr>
<td>8 Google</td>
<td>Bing, Yahoo!</td>
</tr>
<tr>
<td>9 Hhgregg</td>
<td>BestBuy, Amazon, Target</td>
</tr>
<tr>
<td>10 Hsn</td>
<td>Amazon, eBay</td>
</tr>
<tr>
<td>11 Kodak</td>
<td>Sony, Philips Electronics</td>
</tr>
<tr>
<td>12 Nextag</td>
<td>Amazon, Buy, Google</td>
</tr>
<tr>
<td>13 Officemax</td>
<td>BestBuy, Tigerdirect</td>
</tr>
<tr>
<td>14 Olympus</td>
<td>Kodak, Philips Electronics</td>
</tr>
<tr>
<td>15 Philips Electronics</td>
<td>Sony, Samsung</td>
</tr>
<tr>
<td>16 Rewilley</td>
<td>BestBuy</td>
</tr>
<tr>
<td>17 Ritzcamera</td>
<td>BestBuy, Target</td>
</tr>
<tr>
<td>18 Samsung</td>
<td>Sony, Philips Electronics</td>
</tr>
<tr>
<td>19 Sony</td>
<td>Philips Electronics, Kodak</td>
</tr>
<tr>
<td>20 Target</td>
<td>BestBuy, eBay</td>
</tr>
<tr>
<td>21 Tigerdirect</td>
<td>BestBuy</td>
</tr>
<tr>
<td>22 Yahoo!</td>
<td>Google, Bing, Amazon</td>
</tr>
</tbody>
</table>

### Table 2: Clustering Results

<table>
<thead>
<tr>
<th>Cluster</th>
<th>Firms</th>
<th>Group Label</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>Kodak, Philips Electronics, Samsung, Sony</td>
<td>Manufacturers</td>
</tr>
<tr>
<td>2</td>
<td>Bing, Google, Yahoo!</td>
<td>Information Portals</td>
</tr>
<tr>
<td>3</td>
<td>Amazon, Best Buy, eBay, Target</td>
<td>Major Retailers</td>
</tr>
<tr>
<td>4</td>
<td>Bonton, Buy, Circuit City, Hhgregg, Hsn, Nextag, Officemax, Olympus, Rewilley, Ritzcamera, Tiger Direct</td>
<td>Other Retailers</td>
</tr>
</tbody>
</table>

We used Ward’s clustering method as it has been found to often outperform other hierarchical clustering methods (Jain and Dubes 1988). To determine the number of clusters (i.e., the number of strategic groups), we use the pseudo $F$ statistic which measures the level of separation among all the clusters at the current level in the hierarchy, and the pseudo $r^2$ statistic which measures the separation level between the two clusters most recently joined. Both criteria have been tested and shown to perform well in identifying
clusters (Milligan and Cooper 1985). The guideline for the number of clusters is to look for consensus between the two statistics – local peaks for pseudo $F$ statistic, combined with a small value of the pseudo $r^2$ statistic for the most recently formed cluster and a larger pseudo $r^2$ for the next cluster fusion. We followed this guideline to determine the number of clusters and identified the clusters appropriately. Table 2 displays the final clustering result of the 22 competing firms. Based on the nature of firms included in each cluster, we provided descriptive labels to the clusters.

On average, 11 firms (out of total 177 firms) appear in each of the 2177 auctions we examined. To check how frequently a pair of firms tend to co-appear in an auction, we calculate the pair-wise correlation for each possible pair of firms (both within and across competing groups). A positive correlation indicates that the two firms prefer to appear in the same auction while a negative correlation suggests the opposite. Note that Cluster 4 ("Other Retailers") consists of very diverse types of firms, and the competition among those firms is considered to be weak by Hoovers. Therefore, in our experiments, we focus on the Manufacturers, Information Portals, and Major Retailers groups.

### Table 3: Firms' Co-appearance statistics

<table>
<thead>
<tr>
<th>Average Correlation</th>
<th>Positively Dependent Pairs</th>
<th>Independent Pairs</th>
<th>Negatively Dependent pairs</th>
</tr>
</thead>
<tbody>
<tr>
<td>-0.0935</td>
<td>17.5% (7/40)</td>
<td>20% (8/40)</td>
<td>62.5% (25/40)</td>
</tr>
<tr>
<td>0.0523</td>
<td>33.3% (5/15)</td>
<td>26.7% (4/15)</td>
<td>40% (6/15)</td>
</tr>
</tbody>
</table>

These three groups yield 15 within-group pairs of firms and 40 across-group pairs. For a pair of firms, when the correlation is positive and significant, the two firms are considered to be a positively dependent pair and they prefer to appear together with each other; when the correlation is negative and significant, the two firms are considered to be a negatively dependent pair and they prefer to avoid each other. We report in Table 3 the percentage of positively dependent, independent and negatively dependent pairs for within and across groups. Based on these results, we have two observations: 1) on average, the correlation between two firms from different groups is -0.0935 while that between two firms from the same group is 0.0523; 2) comparing pairs across groups to within groups, the percentage of positively dependent pairs increases from 17.5% to 33.3% while the percentage of negatively dependent pairs decreases from 62.5% to 40%.

Therefore, the firms’ appearances are more positively associated with each other if they are from the same competing groups than if they are from different groups, and our findings support the first hypothesis.

### 4. Models and Results

#### 4.1 Models to Test our Hypotheses

We test hypothesis H1 using a simple fixed-effects model (Model 1). This model directly compares the rank differences between pairs of firms from the same strategic group and rank differences between pairs of firms from different groups in each auction. We use \( \text{DiffRank}_{ijt} \) to denote the absolute value of the difference between the ranks of one firm from group \( i \) and another firm from group \( j \) in auction \( t \). We use a dummy variable \( \text{WithinGroup}_t \) to indicate whether two firms are from the same group: it has the value 1 if they are \( (i = j) \) and 0 otherwise \((i \neq j)\). Auction, denotes the \( t^{th} \) auction, an independent variable that we use to control for the auction-specific fixed effects, and \( \epsilon_{ijt} \) is the error term that is assumed to follow a normal distribution \( N(0, \sigma^2) \). If coefficient \( \beta_i \) is found to be negative and significant, it means that firms within the same strategic group are in closer proximity compared to firms from different groups when they appear in the same auction.

**Model 1:** \( \text{DiffRank}_{ijt} = \beta_0 + \beta_1 \times \text{WithinGroup}_t + \beta_2 \times \text{Auction}_t + \epsilon_{ijt} \)

To test H2, for a keyword, we pair all the \( n \) competing firms into \( \binom{n}{2} \) unique pairs and then separate all the firm pairs into two samples: Within-group-pairs and Across-group-pairs. For each pair of firms, we use the respective daily average rank of these two advertisers, excluding the auctions in which they co-appear. Thus, now the dependent variable \( \text{DiffRank}_{ijt} \) represents the absolute value of the difference between the daily averaged ranks of firms from strategic groups \( i \) and \( j \) on day \( t \). In this model we use \( \text{Day}_t \), that denotes the \( t^{th} \) day, to control for fixed effects. If the coefficient \( \beta_1 \) in Model 2 is found to be negative and significant, it means that firms within the same strategic group tend to obtain ranks more similar to each other as compared to firms from different groups, even if they do not appear in the same auctions.

**Model 2:** \( \text{DiffRank}_{ijt} = \beta_0 + \beta_1 \times \text{WithinGroup}_t + \beta_2 \times \text{Day}_t + \epsilon_{ijt} \)

#### 4.2 Results

We focus on the estimates of coefficient \( \beta_1 \) of Model 1. The coefficient \(-1.5206 \) (P<0.001) for the keyword
The result holds no matter whether advertisers appear in the same auction or not. Model 2 returns the same qualitative results: the coefficients are all negative and significant. This implies that on average, two firms obtain closer ranks when they are from the same strategic group, compared to when they are from different ones, even if they are not participating in the same auctions for a given keyword. For example, the coefficient -1.2926 (P<0.001) for the keyword “digital camera” means that on average, on a random day, any two firms can be found to be about 1.3 ranks closer to each other if they are from the same group than if they are from different ones. Thus, the findings support Hypothesis 2 as well.

5. Conclusions
This paper examines how advertisers react to the complex competitive environment in sponsored search considering two salient competitive features: rank externality and competitor heterogeneity. Extant literature has not provided a means to prescribe such an environment comprising of firms from different industries with differing size, focus and business models. Towards this end, we build on the strategic group approach to identify whether membership in such a group plays a role in a firm’s behavior in such auctions. We examine whether advertisers in the same group obtain ranks closer to each other or farther away (as opposed to firms across groups). We use authoritative third party data from Hoover’s and LexisNexis to identify direct competitors among the frequent advertisers, and develop a hierarchical clustering approach to identify strategic groups. Our empirical results show that membership in a strategic group does influence the ranks obtained by a firm, and thereby provide evidence to the existence of strategic groups in such auctions. We find that advertisers stay within close proximity of their direct competitors when appearing in sponsored search lists. Thus, while it may appear that the order in which advertisers show up on sponsored search lists are quite random and fluctuate significantly (Katona and Sarvary, 2010), our findings suggest there is an underlying systematic order to their appearance.

6. Reference


