ARTICLE IN PRESS

Journal of Business Research xxx (xxxx) xxx–xxx

Contents lists available at ScienceDirect

Journal of Business Research

journal homepage: www.elsevier.com/locate/jbusres

How should retail advertisers manage multiple keywords in paid search advertising?

Alex Jiyoung Kim[a,1], Sungha Jang[b,2,*], Hyun S. Shin[c,3]

[a] Sungkyunkwan University, South Korea
[b] San Francisco State University, United States
[c] Hanyang University, South Korea

ARTICLE INFO

Keywords:
Search advertising
Multiple keywords
Digital advertising
Consumer purchase stage
Bidding strategy
Click behavior

ABSTRACT

Consumers' online searches usually involve multiple keywords about their purchases, which vary depending on the purchase stage. Similarly, retail advertisers use a set of related keywords for competing brands. Thus, understanding how consumers search using keywords for competing brands at different purchase stages is important for retailers seeking to use multiple keywords more effectively. We examine consumers' click behavior and retailers' bids across multiple keywords. We empirically show that, while consumers search in a manner generally consistent with the purchase funnel, their behavior differs between market leader and follower brands. We also find that retailers consider the different keywords to be strategic complements, but this does not hold when consumers are close to making a purchase decision. Interestingly, retailers' bid allocation across keywords may be inconsistent with consumers' click behavior, revealing a potential opportunity to improve the performance of search advertising campaigns.

1. Introduction

Paid advertising on social media and search engines based on consumers' revealed interests, such as their past browsing history and keyword searches, is a prominent form of online advertising (eMarketer, 2017). Paid advertising has been adopted by a vast number of advertisers–from large to small and from online-only to multichannel–due to its advantages, such as targetability and measurability. Search advertising is the largest form of paid advertising in terms of spending. According to eMarketer.com (2017),[4] the value of the US search advertising market reached USD 32 billion in 2016 and is expected to exceed 45 billion by 2019. Accordingly, both academics and practitioners are paying increasing attention to search advertising. Using search advertising effectively in the digital advertising mix is a critical factor in a successful digital marketing strategy (e.g., Hoban & Bucklin, 2015; Interactive Advertising Bureau, 2016).

A unique feature of search advertising is that advertisers employ multiple search terms (i.e., keywords) in campaigns for product assortments because consumer searches frequently involve combinations of keywords driven by the consumers' needs and intentions. This multiple keyword management presents advertisers with several challenges, including the questions of which keywords to choose and how much to bid for each keyword to maximize the effectiveness of their advertising campaign (Maillé, Markakis, Naldi, Stamoulis, & Tuffin, 2012). However, the digital marketing research has paid little attention to this critical issue. Therefore, this study examines how consumers search for products using multiple keywords and how advertisers bid for such keywords, offering new insights useful to both academics and practitioners about how multiple keywords can be effectively managed in search advertising campaigns.

Search advertising becomes effective as soon as consumers begin their keyword search; thus, consumers play an active role in this process (Kim and Balachander, 2018; Rutz, Bucklin, & Sonnier, 2012). Consumers frequently search a series of related keywords, ranging from general to specific, to obtain product information and evaluate the product alternatives at various stages of their purchase decision (Court, Elzinga, Mulder, & Vetvik, 2009). For example, a consumer interested in purchasing running shoes might search a general keyword (e.g.,

* Corresponding author.
E-mail addresses: alex.kim@skku.edu (A.J. Kim), shjang@sfsu.edu (S. Jang), hyunshin70@hanyang.ac.kr (H.S. Shin).
[1] Address: SKK Business School, Sungkyunkwan University, #408 Business Hall, 25-2 Sungkyunkwan-ro, Jongno-gu, Seoul 03063, South Korea.
[2] Address: College of Business, San Francisco State University, United States.
[3] Address: School of Business, Hanyang University, Seoul, South Korea.
[4] http://searchengineland.com/google-search-ad-revenues-271188.

https://doi.org/10.1016/j.jbusres.2019.09.049
Received 25 November 2018; Received in revised form 10 September 2019; Accepted 21 September 2019
0148-2963/ Published by Elsevier Inc.

"running shoes") without any specific brand names in the early stage of the search process. On the other hand, a consumer might use a more specific keyword that includes a specific brand and model name (e.g., "Nike Lunar") when making a final purchase decision. Furthermore, consumers may exhibit different keyword search behaviors based on their prior knowledge of and preference for brands (Jerath, Ma, & Park, 2014). For instance, consumers who are loyal to Nike may start by using "Nike" in their keywords, while those who have sufficient information on their preferred Nike shoes may directly search for a specific model name (e.g., Nike Lunar) without searching for any general keywords. This implies that advertisers must thoroughly understand how consumers search and click through a set of related but different keywords in a product category if they want to improve their advertising campaigns.

Many advertisers who use search advertising are retailers who sell a wide range of products from competing manufacturers (Interactive Advertising Bureau, 2016). For example, Finish Line, a popular sporting goods retailer, carries running shoes of both Nike and Adidas, two major competitors, in its product assortments. A retailer's search advertising campaign must correspond to their product assortments by using a variety of keywords ranging from general to specific across all the brands they carry. Moreover, because advertisers pay for every click made on their ads and as the price per click is determined through a generalized second price auction (Edelman, Ostrovsky, & Schwarz, 2007),[5] the amount retailers bid per click for each keyword is a critical factor determining the cost and effectiveness of a search advertising campaign. In particular, the number of clicks each search ad receives depends on its position, and each position has different prices based on the rank that is strongly influenced by retailers' bids. Thus, to maximize the overall performance of search advertising campaigns, retailers must carefully decide how much to bid for each keyword and coordinate their bids across the multiple keywords for the competing brands they offer.

This study empirically investigates these issues concerning consumer clicks and retailer bids in search advertising in a multiple keyword context.[6] First, we examine how consumers click on search ads for a set of related keywords used at different purchase stages. We also examine how consumer clicks can change depending on the market position of the manufacturer brand used in the consumer search (e.g., whether it is a market leader or a follower brand). Second, we examine how retailers bid for keywords at different purchase stages, considering the relationships among retailers' bids across keywords, and investigate whether their bidding strategy is consistent with consumers' click behavior. The marketing and advertising literature has paid little attention to these research questions thus far. We fill this gap using a unique dataset of multiple keywords pertaining to the two running shoe brands most frequently searched by consumers, Nike and Adidas.

Our main findings are as follows. First, we find positive spillover effects from general category-level keywords to more specific brand- and model-level keywords: Consumers start searching using general category-level keywords and then narrow down their keyword choices to more specific brand- and model-level keywords as they accumulate information. This finding is consistent with the notion of the consumer purchase funnel, which describes the customer's journey toward a purchase (for details regarding the consumer purchase funnel, see Jansen and Schuster [2011] and Wiesel, Pauwels, and Arts [2011]). We also find that the spillover effects are asymmetric between leader and follower brands at the model level and that negative spillover effects may occur from model- to category-level keywords. Interestingly, our findings suggest that, while consumers' click patterns in search advertising are similar to those suggested by the purchase funnel framework, the click pattern for the brand leader may not necessarily follow the pattern identified above. Specifically, we find that brand-level keywords for the leading brand attract the most consumer clicks, indicating that brand-level keywords play a terminal role, possibly because of its high brand awareness.

Second, we find that retailers in the focal category bid on multiple keywords simultaneously, implying that retailers consider the keyword groups at different purchase stages strategic complements. Specifically, we find that retailers bid on competing brands' keywords at the brand level, which corresponds to the intermediate stage of the consumer purchase decision, but not on both brands at the model level, which corresponds to the final stage of the purchase decision. Although retailers generally treat competing brands as strategic complements, they seem to focus on a particular brand in the final stage of the consumer purchase decision: Consumers who are close to making a purchase decision may be difficult to convert. Moreover, we find a positive spillover from bids on followers' keywords to bids on brand leaders' keywords, suggesting possible keyword poaching from retail advertisers. Overall, our findings suggest that retailers' bidding strategies are not necessarily consistent with consumers' search and click behavior, pointing to the need for a better budget allocation strategy in search advertising.

Our study contributes to the digital marketing literature in several ways. First, we extend the literature by providing new insights into consumers' online search and click behavior in paid advertising media. Positive spillovers in consumer clicks from general category-level to specific brand-level keywords have already been observed (Rutz & Bucklin, 2011). We offer new insights into the relationships among consumer clicks within brand keywords. By decomposing brand keywords into brand-level and more specific model-level keywords, we show that consumers exhibit different click behaviors for market leader and follower brands. This is an important extension because brands frequently include several models (e.g., Nike Lunar, Freedom, and Air Max), and consumers' ultimate purchase decisions are made at the model level rather than at the brand level.

Second, we contribute to the literature by shedding new light on advertisers' bidding strategies. We focus on retailers' bidding strategies for multiple keywords of competing brands used at different purchase stages. Our findings reveal that retailers bid simultaneously on various keywords across purchase decision stages for both brands. Our comparison of consumers' click behavior with advertisers' bidding patterns suggests that retailers may need to be more selective when choosing keywords to be able to allocate budgets to multiple keywords more efficiently.

Third, we offer supporting evidence of advertisers' keyword poaching behavior reported in the literature (e.g., Sayedi, Jerath, & Srinivasan, 2014) based on the positive spillover effects identified from both consumer clicks and advertiser bids. Moreover, unlike the extant empirical literature, we consider retailers who carry competing manufacturers' brands in their product assortments. Whereas most prior empirical studies deal with a single brand or a single retailer without considering brand competition, we examine the bidding strategy of many retailers for competing manufacturers' brands. This enables us to examine how retailers use the keywords associated with competing manufacturer brands in their search advertising campaigns. Thus, our findings can help managers fine-tune their search advertising campaigns by providing more comprehensive and detailed insights into consumers' keyword search behavior and offering guidance on how to formulate an effective corresponding bidding strategy for keywords.

2. Literature review and research questions

2.1. Related literature

Early work on search advertising focused on issues related to search

[5] See Edelman et al. (2007) and Varian (2007) for details on the generalized second price auction.

[6] Because we focus on retail advertisers, we use "retailers" and "retail advertisers" interchangeably.

engines (Edelman et al., 2007; Edelman & Schwarz, 2010; Varian, 2007). For example, Edelman et al. (2007) characterized the equilibrium of the generalized second price auction, called "Envy-Free Nash equilibrium," and show that truthful bidding may not be an optimal strategy. In a similar vein, Varian (2007) characterized the symmetric Nash equilibrium of a search advertising auction. Researchers have also investigated the design of the search advertising auction. For example, Edelman and Schwarz (2010) investigated the effect of the minimum bid required to participate in the search advertising auction. Others have studied the financial implications of auction design from the viewpoint of a search engine. Feng, Bhargava, and Pennock (2007) and Balachander, Kannan, and Schwarz (2009) examined the implications of various auction mechanisms for the search engine's revenue, while Amaldoss, Desai, and Shin (2015) showed that the choice of auction mechanism can affect the profitability of the search engine. Kim, Balachander, and Kannan (2012) analyzed the effects of the number of advertising slots on the search engine's revenue.

The abovementioned papers focus on search engine decisions. The literature has also considered advertisers' decisions, such as optimal bids (Jerath, Ma, Park, & Srinivasan, 2011), keyword choices (Desai, Shin, & Staelin, 2014; Sayedi et al., 2014), search engine optimization (Baye, De los Santos, & Wildenbeest, 2016), and the cross-media strategy of search advertising with traditional media (Joo, Wilbur, Cowgill, & Zhu, 2014; Kim and Balachander, 2018). In search advertising, finding an optimal rank (i.e., position) based on the bid and the advertisement's qualities is critical for advertisers because both the number of clicks they receive and the amount they pay the search engine per click depend on the rank. In general, advertisers can obtain a higher rank by increasing their bid in the advertising auction to obtain more consumer clicks. However, obtaining a higher rank by increasing a bid might not be an optimal strategy for some advertisers because having a higher rank usually requires a higher cost per click (CPC), which can substantially increase the total costs of search advertising (Ghose & Yang, 2009) and can be problematic under tight budget constraints (Sayedi et al., 2014). Therefore, researchers have examined various issues related to advertisers' rank (Narayanan & Kalyanam, 2015).

While advertisers use multiple keywords in their search advertising campaigns, many studies have focused on a single keyword framework or have paid little attention to the relationships among keywords. Furthermore, although some empirical papers have considered multiple keywords (Jansen & Schuster, 2011; Rutz & Bucklin, 2011; Rutz, Trusov, & Bucklin, 2011), they have focused on multiple keywords of a single brand or retailer. Deciding how much to bid for each keyword in a multiple keyword context can be challenging because a bid and ad performance on a keyword are affected not only by the bids and performance of other keywords but also by the bids and performance of competing advertisers and brands (e.g., competing brands, such as Nike and Adidas in the running shoes category; Maillé et al., 2012). In addition, limited data availability in this context has prevented researchers from analyzing the multiple keyword management of competing advertisers (Park & Agarwal, 2018).

Several recent studies have focused on competing advertisers' keyword management, such as competition among advertisers for search ad positions and the subsequent search behavior of consumers. For example, Chan and Park (2015) modeled consumers' strategic search behavior and advertisers' competition for search ad positions using individual-level data from an anonymous search engine. Similarly, Park and Agarwal (2018) used individual consumer-level data and examine consumers' search behavior for different orders of advertising. However, these studies did not examine advertisers' bidding strategy over multiple competing keywords at various purchase stages, which is known to have a significant effect on consumers' search and click behavior (Court et al., 2009).

The literature has established that consumers engage in a series of searches (Stigler, 1961) and that their search motives vary depending on their purchase decision stage (Enquiro Search Solutions Inc, 2004; Jerath et al., 2014). Jansen and Schuster (2011) showed that the keywords used by consumers in a search engine can be classified into groups that match their consumer purchase funnel stage. For example, consumers at an early purchase stage (e.g., need recognition and information search) may use generic keywords that lack specific information like a brand name and that contain a problem to be solved. On the other hand, consumers close to the final stage of the purchase process (e.g., evaluation of alternatives and purchase) may use specific keywords that include a brand or specific product model name. Rutz and Bucklin (2011) examined the relationship between generic and brand keywords and found a positive spillover effect in consumer clicks from generic to branded keywords. Similarly, a number of studies have shown that consumers tend to use different media depending on their purchase stage (Wiesel, Pauwels, & Arts, 2011; Woodside & Bernal Mir, 2019) and that the keywords used have different effects at different purchase stages (Lu & Zhao, 2014). Thus, building on the research showing that keywords are used differently and play distinct roles across consumers' buying stages, we consider the different types of keywords used at various consumer purchase stages. Specifically, we study consumer search patterns for keywords of competing manufacturing brands at different purchase decision stages. We examine how consumers' searches of different keywords are related to each other, and how retailers bid for different keywords. Du, Su, Zhang, and Zheng (2017) considered retailers' multiple keyword management at various consumer decision stages; however, they focused on a single retailer and did not consider the interrelationships between keyword types, which might be significant for managing the multiple keywords used in search advertising campaigns.

Finally, this study considers the role of brands' market position (i.e., market leader vs. follower) in search advertising. Previous researchers have examined the strategic implications of market position in terms of whether a brand is the market leader or the follower. The findings show that firms use their marketing and R&D capabilities in different ways depending on their market position. For instance, the role of market position in patent races has been extensively studied in the economics literature (for a review, see Tirole (1988)). The studies have showed that market leaders and followers use R&D spending in different ways (e.g., Fudenberg, Gilbert, Stiglitz, & Tirole, 1983; Grossman & Shapiro, 1987; Khanna, 1995; Sundaram, John, & John, 1996). The business literature argues that a market leader can use marketing to create an entry barrier, while a follower can use marketing to increase market access (e.g., Srivastava, Shervani, & Fahey, 1998). Ofek and Savary (2003) showed that the leader and follower in a technology-intensive market have different incentive structures regarding marketing and R&D investment strategies.

To the best of our knowledge, however, no study has empirically examined how market position differences between competing brands affect the brands' search advertising keyword strategies; we address this question. Theoretical studies have suggested the possibility of poaching (i.e., keyword hijacking) between competing differentiated brands (Desai et al., 2014; Sayedi et al., 2014), whereby firms with different brand images bid on competing brands' keywords to poach (or hijack) potential customers. We empirically examine whether this phenomenon occurs in our research context.

Moreover, a brand's market position can affect customer behavior. The research shows that a market leader's brand can benefit from preemptive positioning among customers, higher perceived switching costs, and favorable preferences for the market leader (Carpenter & Nakamoto, 1989). For example, Shin, Hanssens, and Kim (2016) found that the effect of online buzz can be moderated by a brand's market position. In the search advertising context, studies have also examined the effect of brand image on consumer searches and competition between brands (Jeziorski & Moorthy, 2017; Park & Agarwal, 2018; Sayedi et al., 2014). One of the main findings in the theoretical literature is that a brand with a higher brand image tends to receive more consumers clicks in search advertising (Jerath et al., 2011). By contrast, several recent empirical papers suggest that search advertising is less valuable to advertisers with high brand prominence (Jeziorski & Moorthy, 2017) and that search advertising on market leaders' brand keywords does not work (Blake, Nosko, & Tadelis, 2015). While studies have examined the role of the brand in attracting consumer clicks, we extend the literature by focusing on two prominent brands with different market positions (i.e., Nike and Adidas) and examine how consumer clicks at different purchase decision stages are interrelated between the two.

2.2. Research questions

Considering the current state of the literature, we aim to fill several research gaps by answering the following questions:

(1) How do consumers click search ads for different keywords used at various consumer purchase stages, and how is their click behavior at each stage related to the others?

(2) How are advertisers' bids for different keywords at various stages related to each other?

(3) Are the interrelationships between consumers' click behavior and advertisers' bidding strategies consistent? Are there any differences between leader and follower brands in terms of advertisers' bidding strategies and consumers' click behavior?

We examine and compare the interrelationships among the keywords used for competing brands at different purchase stages identified by both consumers and advertisers. We further investigate keyword poaching or hijacking between competing brands, such as the brand leader and followers. We examine whether advertisers' bidding patterns show any evidence of keyword poaching. If they do, we seek to determine the stage at which they engage in poaching. Similarly, we examine whether consumers show click behavior consistent with advertisers' poaching efforts.

We address the issues raised above by classifying keywords into groups based on the consumer purchase funnel framework (Court et al., 2009; Howard & Sheth, 1969; Jansen & Schuster, 2011).[7] According to the literature on the purchase funnel, consumers pass through a staged process that starts with being aware of a need and proceeds all the way to making a final purchase decision (Court et al., 2009; Howard & Sheth, 1969). Consumers who are uncertain about which brand or model would best satisfy their needs are usually in the early stage of the search process (i.e., at the top of the purchase funnel; Jansen & Schuster, 2011).[8] Thus, their search tends to be broad and general, using general category-level keywords. On the other hand, as they accumulate information and gain a clearer idea about the product that will best fit their needs, their search becomes more specific and uses more detailed and narrow keywords, such as brand and model names (i.e., they are at the bottom of the purchase funnel). Following this framework, we classify keywords used by consumers into three levels (i.e., category, brand, and model) and examine how consumer searches for keywords at different stages are related.

Our approach is an extension of research (e.g., Rutz & Bucklin, 2011; Du et al., 2017) that has classified keywords into two groups: general and branded. We further decompose branded keywords into brand-level keywords, which merely include brand names (e.g., Nike), and model-level keywords, which include specific model names (e.g., Nike's Lunar). This enables us to separate and examine how consumer clicks from one type of keyword (e.g., general category-level keywords) affect other types of keywords (e.g., brand- and model-level keywords), and vice versa.

3. Data

We obtain our data from one of the largest websites offering search advertising in South Korea (which wishes to remain anonymous). Our data include keywords in the running shoes category, in which consumers frequently make online purchases. Nike and Adidas are dominant among the many running shoe brands in South Korea (Statistica, 2018). Nike is the leading brand, capturing approximately 40% of the market and is the representative brand in the running shoes category in South Korea. Adidas is the second-largest brand, with a market share of approximately 18%. The rest of the market is divided among many small brands with similar market shares (Fashion Insight, 2014). Moreover, most consumer searches and clicks in the running shoes category are on keywords related to those two brands; in our data, the keywords that include their brand keywords receive more than 80% of all consumer clicks in paid search advertising in the running shoes category. Although our data do not contain other keywords, Skiera, Eckert, and Hinz (2010) suggested that "long tail" keywords are not as important as thought. Therefore, we focus on the 14 keywords associated with Nike and Adidas.[9] Our dataset comprises 242 online retailers that sell running shoes produced by Nike and Adidas. Our data contain daily information from those retailers on search advertising metrics, such as payments per click, bids, quality scores, ranks, and the number of clicks from September 1, 2012 to November 30, 2012 for 14 keywords. As mentioned, these keywords receive the most clicks in the running shoes category.

We classify the keywords into three levels—category, brand, and model—in accordance with the consumer purchase funnel to understand consumers' search behavior at different purchase stages. Consumer searches tend to start at the top (or upper stages) of the purchase funnel and are usually broad and general, as explained earlier. Accordingly, the category-level keywords include general keywords without any brand or model information, such as "running shoes" and "running shoes recommendation." Consumers' searches become more specific as they gain information and move down through the purchase funnel. Our second keyword group (at the brand level) represents the middle or intermediate stage of the purchase funnel and includes brand names. Finally, the third keyword group (at the model level) represents the final stage of the consumer purchase decision, when consumers possess the greatest amount of information, and this keyword group includes keywords with specific model information, such as "(Nike) Lunar" and "(Adidas) Firebird." Because we consider two brands in our analysis, Nike and Adidas, we consider two groups—one for each brand—at the brand and model levels. Fig. 1 shows the keyword classification into five groups at the three levels of the purchase funnel.

Our bid-per-click data are for each of the keywords. If a retailer does not bid at all on a specific keyword, we have a missing value on that bid. In this case, we simply set the bid amount to zero and replace the quality score with the average quality score for that keyword during the observation period. The rank data are assigned to an advertiser for each keyword. In general, rank can be decided by the payment formula, $p_r = \frac{b_{r+1} * QS_{r+1}}{QS_r}$, where p_r and QS_r indicate the payment per click and quality score of the retailer ranked at r, respectively, and b_{r+1} and QS_{r+1} indicate the bid and quality score, respectively, of the retailer ranked at $r + 1$.[10]

[7] Note that the purchase funnel framework is consistent with the consumer decision journey (CDJ), in that consumers go through different stages when making a purchase decision and their information needs vary depending on their stage. The CDJ is an updated version of the purchase funnel framework. See Court et al. (2009) for more information. Because we do not assume a sequential consumer search, the purchase funnel and CDJ are both consistent with our framework.

[8] Even when consumers are aware of several brands, they might not be aware of the brands that would maximize their utility or satisfaction.

[9] Nevertheless, we note this below as a limitation and an avenue for future research.

[10] Although the details of ranking rules might differ slightly across search engines, this is the basic idea behind the rules used by most search engines,

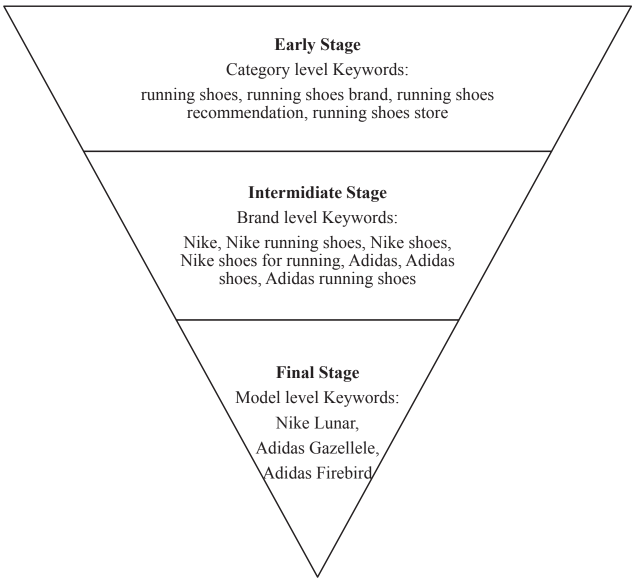

Fig. 1. Types of keywords used in consumer purchase decision stages.

Quality scores, which are computed based on the quality of each individual ad, are assigned to retailers by a search engine. Quality scores can be affected by various factors, such as the quality of the landing webpage and the number of clicks the ad has received in the past. A retailer with a higher quality score, a higher bid, or both is expected to generate higher revenue for a search engine by potentially paying it a higher advertising fee. From the search engine's viewpoint, this makes the retailer's ad more attractive; thus, the search engine has an incentive to assign a higher (better) rank to the retailer to maximize its profit. Because the search engine displays, at most, 15 ads per keyword, the ranks range from 1 at the top of the listings to 15 at the bottom. When its ad is forced out of the list (e.g., when the bid or quality score is too low), a retailer has a missing rank; we thus replace it with 16. Our click data comprise the total number of clicks each ad receives daily for a keyword. The number of clicks can be zero if a retailer does not bid on a keyword or if its ad is forced out of the listings. Finally, because we classify keywords into five groups, we combine the keyword measures into those groups. Specifically, we sum the bids and number of clicks and use the average quality scores and ranks.

Table 1 presents descriptive statistics for the major variables. It shows that Nike brand-level keywords receive a much larger average number of clicks (0.38) than the other keyword groups. The second-largest group is Adidas brand-level keywords (0.19), followed by Adidas model-level keywords (0.10), with category- and Nike model-level keywords receiving fewer clicks (0.05 and 0.02, respectively). This suggests that many consumers are already aware of Nike and Adidas as running shoe brands before they begin a keyword search.

Table 1 also shows that, on average, retailers' bids are highest for Nike brand-level keywords ($0.12), followed by the category-level keywords ($0.065). In other words, retailer competition in the advertising auction for category-level and Nike brand-level keywords is more intense than for the rest of the keywords. This finding is consistent with the general finding in the literature that competition is more intense for general keywords than for specific keywords (e.g., Rutz & Bucklin, 2011). Furthermore, because Nike is the most well-known brand with the highest market share, it would be expected to have the highest awareness among consumers prior to their search. Thus, not only is competition among retailers intense, but many consumers search and click ads associated with Nike brand-level keywords.

(*footnote continued*)
including Google and Bing.

Table 1
Descriptive statistics.

Variable	Level	Mean	S.D	Min	Max
Bids ($)	Category	0.065	0.190	0	1.735
	Nike Brand	0.126	0.343	0	2.567
	Adidas Brand	0.042	0.125	0	0.989
	Nike Model	0.032	0.099	0	0.697
	Adidas Model	0.039	0.114	0	1.303
Number of Clicks	Category	0.051	0.314	0	5.960
	Nike Brand	0.389	2.018	0	26.990
	Adidas Brand	0.197	1.506	0	32.790
	Nike Model	0.026	0.161	0	2.940
	Adidas Model	0.105	0.475	0	8.200
Quality Scores	Category	0.187	0.410	0	1.611
	Nike Brand	0.181	0.406	0	1.677
	Adidas Brand	0.156	0.391	0	1.678
	Nike Model	0.117	0.344	0	1.525
	Adidas Model	0.172	0.429	0	1.754
Ranks	Category	14.912	2.919	1	16
	Nike Brand	15.041	2.711	1	16
	Adidas Brand	15.077	2.768	1	16
	Nike Model	15.336	2.409	1	16
	Adidas Model	15.034	2.876	1	16

The number of e-retailers is 242, and the number of observations from September 1, 2012 to November 30, 2012 (91 days) is 22,022. The statistics are based on the number of observations.

In sum, Table 1 shows differences in the characteristics of consumer clicks and retailer bids across different keyword groups. For example, retailers consider category keywords to be especially important, as shown by their willingness to make the second-highest average bids on that keyword group; on average, however, consumers give much less consideration to category-level keywords than retailers do.

Table 2 presents the correlation coefficients of the major variables across the keyword groups, all of which are significant at the 0.05 level. The positive correlation coefficients of bids between the keyword groups imply that advertisers bid on multiple keywords. Similarly, the positive correlation coefficients of the number of clicks between the keyword groups indicate that consumers click on multiple keywords as well. Overall, the correlation coefficients of the same variable type (e.g., bids, number of clicks, quality score) across the keyword groups are positive. The negative correlation coefficients between the ranks and other variables indicate that the better ranks (lower ranks) are related to higher bids, more clicks, and higher-quality scores. Subsequently, we use the differencing model and check the correlations of the differenced variables, which are much lower than those of the major variables reported in Table 2. These low correlation coefficients indicate that multicollinearity is not a concern in our data.

4. Model and method

4.1. Modeling individual equations for clicks and bids

Our main objective was to examine the relationships between consumer clicks and between retailer bids across the keyword groups for competing brands (i.e., Nike and Adidas) at different purchase decision stages. Therefore, we focused on consumer click behaviors as reflected in the number of clicks per keyword group and on retailers' simultaneous decisions on how much to bid for those keywords.

In our model, retailer i bids on G keyword groups at time t (a day in our daily-level dataset) based on its policy. For equations regarding consumer clicks, we assumed that, for example, clicks on the first keyword ($click_{1it}$) are affected by clicks on other keywords ($click_{2it}, \cdots, click_{Git}$), the lagged clicks on the first keyword (e.g., $click_{1i,t-1}$, $l = 1, \cdots, L$), and other control variables, such as rank (x_{1it}). Thus, the equation for clicks on the focal keyword (e.g., the first keyword notated as $click_1$) is as follows:

Table 2
Correlation Coefficients Table.

Variable	Keyword Group		(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)	(16)	(17)	(18)	(19)	(20)
Bids ($)	Category	(1)	1																			
	Nike Brand	(2)	0.405	1																		
	Adidas Brand	(3)	0.404	0.427	1																	
	Nike Model	(4)	0.271	0.713	0.286	1																
	Adidas Model	(5)	0.166	0.195	0.548	0.169	1															
Number of Clicks	Category	(6)	0.574	0.403	0.283	0.292	0.063	1														
	Nike Brand	(7)	0.288	0.629	0.217	0.415	0.061	0.609	1													
	Adidas Brand	(8)	0.221	0.122	0.552	0.082	0.428	0.170	0.158	1												
	Nike Model	(9)	0.263	0.463	0.257	0.572	0.061	0.468	0.607	0.206	1											
	Adidas Model	(10)	0.118	0.095	0.374	0.108	0.585	0.084	0.132	0.624	0.203	1										
Quality Scores	Category	(11)	0.714	0.296	0.302	0.180	0.069	0.417	0.244	0.139	0.215	0.038	1									
	Nike Brand	(12)	0.285	0.816	0.376	0.572	0.129	0.336	0.499	0.087	0.388	0.062	0.266	1								
	Adidas Brand	(13)	0.285	0.349	0.817	0.231	0.364	0.336	0.243	0.374	0.209	0.238	0.249	0.407	1							
	Nike Model	(14)	0.261	0.659	0.278	0.934	0.140	0.338	0.415	0.079	0.562	0.096	0.195	0.588	0.259	1						
	Adidas Model	(15)	0.124	0.141	0.383	0.152	0.793	0.105	0.108	0.229	0.161	0.577	0.093	0.129	0.300	0.147	1					
Ranks	Category	(16)	−0.817	−0.393	−0.368	−0.260	−0.108	−0.565	−0.343	−0.218	−0.307	−0.099	−0.815	−0.291	−0.276	−0.263	−0.104	1				
	Nike Brand	(17)	−0.316	−0.870	−0.312	−0.642	−0.144	−0.437	−0.698	−0.114	−0.528	−0.106	−0.254	−0.801	−0.296	−0.598	−0.133	0.337	1			
	Adidas Brand	(18)	−0.310	−0.360	−0.848	−0.238	−0.451	−0.247	−0.206	−0.535	−0.221	−0.352	−0.234	−0.338	−0.831	−0.237	−0.335	0.310	0.290	1		
	Nike Model	(19)	−0.277	−0.705	−0.256	−0.897	−0.131	−0.397	−0.547	−0.108	−0.740	−0.128	−0.188	−0.557	−0.212	−0.828	−0.143	0.284	0.715	0.214	1	
	Adidas Model	(20)	−0.137	−0.164	−0.425	−0.149	−0.832	−0.076	−0.097	−0.378	−0.141	−0.733	−0.034	−0.092	−0.269	−0.117	−0.821	0.098	0.137	0.373	0.150	1

All the correlation coefficients are significant at the 0.05 level. The number of e-retailers is 242, and the number of observations is 22,022. The statistics are based on the number of observations.

$$click_{1it} = a_{i1} + \gamma_{12} click_{2it} + \cdots + \gamma_{1G} click_{Git} + \sum_{l=1}^{L} b_{1l} click_{1i,t-L} + c_1 x_{1it} + \varepsilon_{1it} \quad (1)$$

The equations for clicks on other keywords can be set up in the same way, by replacing the keywords' subscript (e.g., *2* through *G*).

We built the equations for retailer bids in a similar way. For example, we assumed that the bids on the first keyword (bid_{1it}) are affected by bids on other keywords ($bid_{2it}, \cdots, bid_{Git}$), the lagged bids on the first keyword (e.g., $bid_{1i,t-1}$, $l = 1, \cdots, L$), and other control variables, such as previous quality score and rank (w_{1it} and w_{2it}). Thus, the equation for bids on the first keyword is as follows:

$$bid_{1it} = a_{i1} + \gamma_{12} bid_{2it} + \cdots + \gamma_{1G} bid_{Git} + \sum_{l=1}^{L} b_{1l} bid_{1i,t-L} + c_1 w_{1it} + c_2 w_{2it} + u_{1it} \quad (2)$$

We can set up the other equations similarly by replacing the keywords' subscript (e.g., *2* through *G*).

After building the individual equations for each keyword, we stack them into a system of equations based on the endogenous variables: clicks and bids. The fundamental format of the equations is the same: An endogenous variable is affected by other endogenous variables, its own lagged variables, and other control variables. We explain the method and estimation procedure used for both endogenous variable types using general terms in the sub-sections below.

4.2. Method

We constructed a dynamic model to examine behavioral relationships over time in our panel dataset. For example, yesterday's bids will influence retailers' bids today, while the number of clicks made by customers today will influence the number of clicks tomorrow. Such "inertia" or "state dependence" can be incorporated into the model by adding a lagged dependent variable. However, this violates the strict exogeneity assumption because the lagged dependent variable is correlated with the disturbance term (Hsiao, 2014). Accordingly, a conventional estimator, such as least squares dummy variable or maximum likelihood estimator, is no longer consistent in finite samples (i.e., when the data are collected over a short time period). Using Monte Carlo simulation, Judson and Owen (1999) showed that the bias could be sizable even when the number of observations over time (T) reaches 30.

To address this issue, we adopted a dynamic panel GMM estimation method developed by Arellano and Bond (1991). Specifically, they proposed taking the first difference to remove individual effects and then using deeper lags of the dependent variable as instruments for differenced lags of the dependent variable. Arellano and Bond's GMM estimator ("AB-GMM" hereafter) is particularly appealing in that it addresses the potential endogeneity issue arising from omitted variables, measurement error, and/or simultaneity (Arellano, 2003). Moreover, AB-GMM relies on minimal assumptions, which offers several advantages. First, it does not require the normality of disturbance terms. Second, it does not require the formulation of initial conditions, which often raises concerns in conventional estimation approaches. Third, the use of panel data allowed us to specify retailer-specific effects, which account for any unobservable characteristics that vary across retailers. The retailer-specific effects can be either fixed or random; however, AB-GMM allowed us to estimate the model without restricting the retailer-specific effects to being either fixed or random (Bailliu & Fujii, 2004; Moral-Benito, Allison, & Williams, 2019).

In theory, AB-GMM provides consistent estimates when T is fixed (i.e., small T) and N is large (Arellano & Bond, 1991). However, both T and N are quite large in our dataset ($T = 90$, $N = 200$). In such a case, Alvarez and Arellano (2003) showed that AB-GMM might yield downward biased estimates, which raises concerns in our case. Using Monte Carlo simulation, Hsiao and Zhang (2015) showed that a simple IV (instrument variable) estimator (hereafter, IV) could be better than AB-GMM since IV produces negligible bias for a large T and large N case. Yet, they also pointed out that IV is much less efficient than AB-GMM, meaning that there is a trade-off between IV and AB-GMM. Indeed, their simulation results show that as N and T get larger (e.g., $N = T = 100$ in their setting), the size of biases from IV and that from AB-GMM become comparable. Accordingly, we chose AB-GMM over IV for our analysis.

In theory, AB-GMM is asymptotically as efficient as the maximum likelihood estimator under certain conditions (Carrasco & Florens, 2014). Moreover, we can improve the asymptotic efficiency of AB-GMM by adding more moment conditions (Ahn & Schmidt, 1995). However, this strategy does not come without costs. The number of instruments produced will be quadratic in T (i.e., the length of the time series in the dataset). If T is fairly large, an unrestricted set of lags would result in a large number of instruments. Prior research indicates that AB-GMM can be sensitive to outliers when higher moment conditions are used (Hsiao, 2014). Therefore, it is recommended that the number of moment conditions be restricted even when one has a longer time series dataset. Thus, we set the maximum number of moment conditions to four.

4.3. Estimation procedure

We set up the following model for the system of equations of both click and bids:

$$\Gamma y_{it} = \alpha_i + By_{i,t-l} + CX_{it} + \varepsilon_{it},\ i = 1,\ \cdots, N,\ t = 1,\ \cdots, T,\ l = 1,\ \cdots, L \tag{3}$$

where $y_{it} = (y_{1it}, y_{2it}, \cdots, y_{Git})'$ is the vector of contemporaneous endogenous variables, such as the number of clicks and bids, at time t, and $y_{i,t-l} = (y_{i,t-1}, y_{i,t-2}, \cdots, y_{i,t-L})'$ is the vector of lagged endogenous variables up to L lags of the focal variables. In addition, $X_{it} = (X_{1it}, X_{2it}, \cdots, X_{Git})'$ is the matrix of exogenous variables, and $\varepsilon_{it} = (\varepsilon_{1it}, \varepsilon_{2it}, \cdots, \varepsilon_{Git})'$ is the vector of error terms, which follow a multivariable normal distribution, $N(0, \Omega)$.

The parameter matrix Γ represents the relationships between the number of clicks on the keywords and between the bids on those keywords, respectively. The vector α_i captures retailer-specific effects for retailer i. In matrix B, the diagonal elements represent the dynamic effects of the corresponding endogenous variables at t-l, and the off-diagonal elements are set to zero. Matrix C represents the effects of exogenous variables. In Eq. (3), (1) some regressors are endogenous (i.e., interdependency between the dependent variables); (2) the process is dynamic in that current realizations of the dependent variables are influenced by past ones; 3) the idiosyncratic distribution may have individual specific patterns of heteroskedasticity and serial correlation. A difference GMM estimation can be used to resolve these estimation problems (Roodman, 2009).

We assumed that retailer-specific effects α_i are fixed effects and took the first difference to eliminate them. Therefore, Eq. (3) was transformed into Eq. (4) as follows:

$$\Gamma \Delta y_{it} = B\Delta y_{i,t-l} + C\Delta X_{it} + \Delta\varepsilon_{it} \tag{4}$$

where $\Delta y_{it} = y_{it} - y_{i,t-1}$, and the other differenced variables were calculated in a similar way.

Note that Eq. (4) has endogeneity issues that need to be addressed because of simultaneity and dynamic effects. First, endogeneity occurs due to the simultaneity between the endogenous variables. For example, in the first equation, y_{1it} is affected by $(y_{2it},\ \cdots, y_{Git})$. Because the error terms are correlated, $(y_{2it},\ \cdots, y_{Git})$ are correlated with ε_{1it}, causing endogeneity. Another type of endogeneity occurs due to the dynamic effects of the lagged endogenous variables. For example, in the first equation, the two terms $\Delta y_{1i,t-1} (= y_{1i,t-1} - y_{1i,t-2})$ and $\Delta\varepsilon_{1it} (= \varepsilon_{1it} - \varepsilon_{1i,t-1})$ are correlated because $y_{1i,t-1}$ depends on $\varepsilon_{1i,t-1}$. In the other equations, $\Delta y_{gi,t-1}$ and $\Delta\varepsilon_{git}$, $g = 1, \ldots, G$, are correlated in a similar way.

We used AB-GMM to resolve the endogeneity problems due to the simultaneity and dynamic effects. According to Hsiao (2014), the moment conditions below allow AB-GMM to yield consistent estimators:

$$E\left[\begin{pmatrix} y_{i,t-2} \\ \Delta X_{it} \end{pmatrix}\Delta\varepsilon_{Git}\right] = 0 \text{ or } E\left[\begin{pmatrix} \Delta y_{i,t-2} \\ \Delta X_{it} \end{pmatrix}\Delta\varepsilon_{Git}\right] = 0. \tag{5}$$

Thus, the lagged endogenous variables at *t-2* or the lagged differenced endogenous variables at *t-2* along with the differenced exogenous variables at t (ΔX_{it}) can be instrumented. In addition to the lagged (differenced) endogenous variables at *t-2*, $y_{i,t-2-j}$ or $\Delta y_{i,t-2-j}$, $j = 0, 1, \ldots, t$-3, are also legitimate instruments. To account for heteroskedasticity across retailers, we used the WC-robust standard error estimator (Windmeijer, 2005).

For the estimation, we built two separate systems of equations. First, we developed a system of consumer click equations for the number of clicks. For each equation, we included the number of clicks on the other keywords (excluding the number of clicks on the focal keyword) as the independent variables. For the control variables and exclusion restrictions, we included the rank at t, the lagged variables (one-period through seven-period) of the number of clicks of the focal keyword and day dummy variables. For the instrument variables, we used the rank and lagged variables of the focal endogenous variable along with the lagged variables of the number of clicks on all the keywords up to four lags that satisfy the model fit and the assumptions of no autocorrelation and identification restriction.

Second, we developed a system of retailer bid equations in a similar manner. In addition to the other endogenous variables used as the independent variables, we included the quality score at *t-1*, rank at *t-1*, the lagged variables (one-period through seven-period) of the bids of the focal keyword, and day dummy variables as the control variables and exclusion restrictions. For the instrument variables, we used the quality score, the rank, and the lagged variables of the focal endogenous variable along with the lagged variables of the bids on all the keywords up to four lags for the best estimation results in terms of the model fit and assumptions.

5. Results

Tables 3 and 4 present the estimation results for the number of clicks and bids, respectively. To check for no autocorrelation between error terms, we conducted Arellano-Bond tests up to seven lagged periods (e.g., AR[1] through AR[7]). No systematic autocorrelation was found between the error terms at the 0.05 level, with only a few exceptions of significant autocorrelation at random. Thus, we concluded that the no-autocorrelation assumption was not a concern. Note that the Arellano-bond test for AR (1) in the first difference equation is supposed to be correlated because of the shared one-period lagged term at the level model (i.e., $\Delta\varepsilon_{it} = \varepsilon_{it} - \varepsilon_{i,t-1}$ and $\Delta\varepsilon_{i,t-1} = \varepsilon_{i,t-1} - \varepsilon_{i,t-2}$ share the same term of $\varepsilon_{i,t-1}$).

For the over-identification test, we used the Hansen test, which assumes heteroskedasticity across retailers instead of the Sargan test, which assumes that the errors are independently and identically distributed. The null hypotheses of no over-identification were not rejected, as the p-values for all the equations were almost 1 (expressed as 1.000). Thus, we concluded that no problem was caused by over-identification. Figs. 2 and 3 depict the estimated interrelationships of consumer clicks and advertiser bids by keyword level, respectively.

5.1. Consumer clicks

We found that, once consumers click ads listed in category-level keywords, they are likely to click ads on brand-level keywords for both Nike and Adidas ($\hat{\gamma} = 1.194$ for Nike and 0.362 for Adidas). However, the reverse is not true: Consumer clicks on brand-level keywords have no significant effects on clicks on category-level keywords. Thus, if consumers start searching category-level keywords, looking for broad

Table 3
Number of clicks estimation results.

RHS	LHS									
	Category		Nike Brand		Adidas Brand		Nike Model		Adidas Model	
	Coeff.	S.E	Coeff.	S.E	Coeff.	S.E	Coeff.	S.E	Coeff.	S.E
Category			1.194**	(0.434)	0.362*	(0.167)	0.022	(0.022)	−0.062	(0.051)
Nike Brand	0.021	(0.012)			−0.004	(0.011)	0.011	(0.006)	0.003	(0.006)
Adidas Brand	0.021	(0.013)	0.077	(0.087)			0.005	(0.008)	0.133**	(0.017)
Nike Model	0.158	(0.097)	1.439**	(0.439)	−0.031	(0.094)			0.148*	(0.074)
Adidas Model	−0.031*	(0.014)	−0.042	(0.077)	0.396*	(0.183)	0.006	(0.005)		
Rank	−0.013**	(0.002)	−0.103**	(0.023)	−0.048**	(0.006)	−0.013**	(0.002)	−0.075**	(0.011)
Lagged Y at t-1	0.668**	(0.092)	0.695**	(0.058)	0.643**	(0.026)	0.487**	(0.017)	0.583**	(0.046)
Lagged Y at t-2	−0.182**	(0.05)	−0.322**	(0.043)	−0.247**	(0.031)	−0.005	(0.029)	−0.14*	(0.057)
Lagged Y at t-3	0.058	(0.047)	0.103**	(0.034)	0.099**	(0.02)	−0.029	(0.034)	0.035	(0.033)
Lagged Y at t-4	−0.096	(0.06)	−0.072**	(0.011)	−0.154**	(0.022)	−0.08*	(0.032)	−0.072	(0.048)
Lagged Y at t-5	0.087**	(0.029)	−0.016	(0.029)	0.136**	(0.031)	0.115**	(0.016)	−0.09	(0.052)
Lagged Y at t-6	0.044*	(0.022)	0.067**	(0.026)	0.016	(0.048)	0.124**	(0.02)	0.071	(0.071)
Lagged Y at t-7	0.13**	(0.044)	0.007	(0.049)	0.261**	(0.011)	0.234**	(0.028)	0.072	(0.051)
Wald$\chi^2_{(18)}$	6751.02		4244.70		49056.06		10905.36		2764.08	
Arellano-Bond test										
AR (1)										
AR (2)										
AR (3)	z = −2.68**		z = −2.76**		z = −1.93		z = −2.68**		z = −3.5**	
AR (4)	z = 0.64		z = 0.51		z = −0.11		z = −0.12		z = 0.77	
AR (5)	z = −0.82		z = −0.95		z = −1.45		z = −0.27		z = −1.93	
AR (6)	z = 1.90		z = −0.15		z = 1.42		z = 1.10		z = 0.62	
AR (7)	z = −0.88		z = 0.99		z = −0.1		z = 0.74		z = 0.15	
	z = −0.66		z = −1.78		z = −0.69		z = −0.78		z = −0.41	
	z = 0.81		z = 1.77		z = −0.52		z = 0.03		z = 0.89	
Hansen test	$\chi^2_{(570)}$ = 241.71 (*p*-value = 1.000)		$\chi^2_{(570)}$ = 241.78 (*p*-value = 1.000)		$\chi^2_{(570)}$ = 241.96 (*p*-value = 1.000)		$\chi^2_{(570)}$ = 241.99 (*p*-value = 1.000)		$\chi^2_{(570)}$ = 241.96 (*p*-value = 1.000)	

* = p-value < 0.05; ** = p-value < 0.01. The number of e-retailers is 242, and the number of observations is 20,086 after first-differencing. Day dummy variables are omitted for simplicity.

Table 4
Bid Estimation Results.

RHS	LHS									
	Category		Nike Brand		Adidas Brand		Nike Model		Adidas Model	
	Coeff.	S.E	Coeff.	S.E	Coeff.	S.E	Coeff.	S.E	Coeff.	S.E
Category			0.267**	(0.097)	0.115**	(0.042)	−0.01	(0.034)	−0.02	(0.025)
Nike Brand	0.096**	(0.028)			0.095**	(0.017)	0.182**	(0.026)	0.022	(0.021)
Adidas Brand	0.182**	(0.062)	0.435**	(0.117)			0.015	(0.049)	0.168**	(0.057)
Nike Model	0.033	(0.065)	1.362**	(0.275)	−0.011	(0.06)			0.059	(0.05)
Adidas Model	−0.126	(0.076)	0.425*	(0.185)	0.136*	(0.058)	−0.059	(0.057)		
Quality Score at t-1	−0.117**	(0.024)	−0.145**	(0.035)	−0.083**	(0.017)	−0.118**	(0.019)	−0.085**	(0.014)
Rank at t-1	0.013**	(0.004)	0.017**	(0.004)	0.006*	(0.003)	0.006*	(0.005)	0.005*	(0.002)
Lagged Y at t-1	0.628**	(0.194)	0.327**	(0.098)	0.434**	(0.123)	0.344	(0.179)	0.413**	(0.103)
Lagged Y at t-2	−0.079	(0.046)	−0.107**	(0.031)	−0.151**	(0.041)	−0.165**	(0.037)	−0.168**	(0.04)
Lagged Y at t-3	−0.123**	(0.047)	−0.069	(0.036)	−0.084*	(0.039)	−0.222**	(0.042)	−0.081*	(0.037)
Lagged Y at t-4	−0.214**	(0.051)	−0.194**	(0.031)	−0.216**	(0.043)	−0.314**	(0.049)	−0.195**	(0.055)
Lagged Y at t-5	−0.193**	(0.055)	−0.091*	(0.042)	−0.102	(0.054)	−0.095*	(0.043)	−0.194**	(0.047)
Lagged Y at t-6	0.009	(0.056)	−0.106**	(0.034)	−0.024	(0.041)	−0.041	(0.045)	−0.055	(0.048)
Lagged Y at t-7	0.074	(0.05)	0.022	(0.044)	0.008	(0.063)	0.051	(0.052)	0.125	(0.079)
Wald$\chi^2_{(19)}$	757.00		1017.87		315.05		442.46		471.01	
Arellano-Bond test										
AR (1)	z = -3.07**		z = -4.62**		z = -3.7**		z = -2.31*		z = -3.32**	
AR (2)	z = 0.27		z = -0.26		z = 0.68		z = 0.19		z = 0.12	
AR (3)	z = -1.12		z = -1.58		z = -0.88		z = -0.71		z = -0.48	
AR (4)	z = 0.61		z = 2.44**		z = 1.7		z = 2.66**		z = 1.26	
AR (5)	z = 1.99*		z = -0.88		z = -0.99		z = -1.79		z = 0.97	
AR (6)	z = -1.3		z = 0.72		z = -0.57		z = -0.54		z = -0.96	
AR (7)	z = 0.75		z = 0.1		z = 1.31		z = 0.22		z = 0.31	
Hansen test	$\chi^2_{(570)}$ = 238.77 (*p*-value = 1.000)		$\chi^2_{(570)}$ = 236.27 (*p*-value = 1.000)		$\chi^2_{(570)}$ = 234.50 (*p*-value = 1.000)		$\chi^2_{(570)}$ = 241.15 (*p*-value = 1.000)		$\chi^2_{(570)}$ = 240.78 (*p*-value = 1.000)	

* = p-value < 0.05; ** = p-value < 0.01. The number of e-retailers is 242, and the number of observations is 20,086 after first-differencing. Day dummy variables are omitted for simplicity.

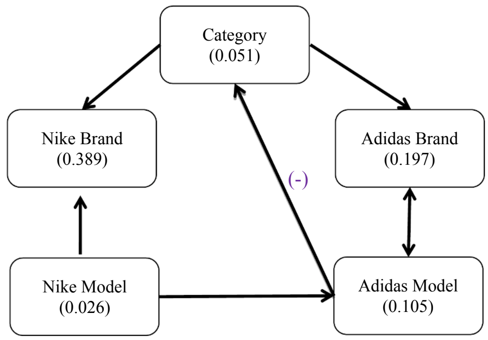

Fig. 2. Interrelationships of consumer click by keyword level. The numbers in parentheses are the averages of the number of clicks. The lines show the significant relationships between keywords at the 0.05 level. All the relationships are positive unless a minus sign is used.

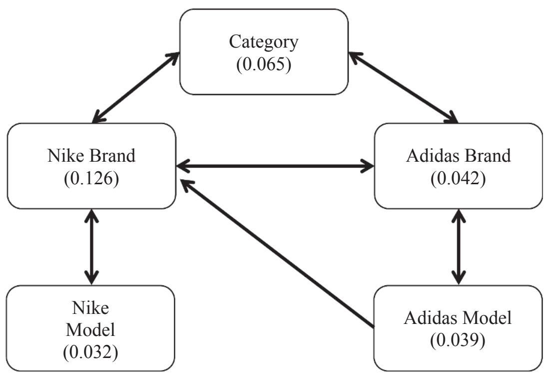

Fig. 3. Interrelationships of advertiser bids by keyword level. The numbers in parentheses are the averages of bidding amounts (unit: $). All the relationships are positive.

and general information, they then move down to brand-level keywords. By contrast, consumers who are already aware of a brand and thus start searching with brand-level keywords are not interested in category-level keywords, which might be too general for them. In other words, they may already have sufficient information and have no need to search general category-level keywords. This relationship between category- and brand-level keywords is consistent with the purchase funnel framework.

Our results for brand-level keywords were somewhat different from those for category-level keywords. We found that, at the brand level, consumers who search brand-level keywords about Nike do not move on to a search for model-level keywords about Nike or anything else. However, consumers who started their search with either category-level or Nike model-level keywords are likely to search and click Nike brand-level keywords. In other words, while no significant relationship starting from Nike brand-level keywords was observed, Nike brand-level keywords seem to play a terminal role in consumer searches. Our data show that the average number of clicks that Nike brand-level keywords receive (0.389) is significantly higher than that received by other keywords, which range from 0.026 to 0.197 (thus, it is greater than the sum of all the others).

We interpret this finding as follows. The literature on the leader–follower relationship suggests that a market leader has a higher level of consumer awareness (Shin et al., 2016) and is thus more likely to be searched for by consumers. Because Nike is the leading brand in the Korean market with strong brand awareness, we argue that Nike brand-level keywords may be the first keywords many consumers recall when considering running shoes. Statistics show that over 40% of Korean consumers responded that Nike was their favorite sports brand (Statistica, 2018). In other words, Nike brand-level keywords may be the initial point of keyword search in many consumers' keyword searches. Since Nike is the leader and thus the representative brand in the running shoes category, a significant number of consumers may start searching using Nike brand-level keywords and may find sufficient information to fill their needs without requiring further searches for other keywords. Moreover, the large average number of clicks on Nike brand-level keywords could include consumers who terminate their search process after searching those keywords (e.g., some consumers might decide they do not need the product after the initial search, or some might search without any intention to buy).

We found a different pattern for Adidas. Once consumers search Adidas brand-level keywords, they move down to model-level keywords ($\hat{\gamma}$ = 0.133). Combined with the relationship between category- and brand-level keywords, our finding indicates that consumers' click behavior for Adidas is consistent with the purchase funnel framework: We observed positive relationships from the category-level all the way down to model-level keywords. The situation is less clear for Nike, however, as mentioned, although a positive relationship was observed between category- and brand-level keywords.

Overall, our findings suggest that, although consumers' click patterns are generally consistent with the purchase funnel framework, the leading brand can exhibit different patterns. This finding is also consistent with the theoretical research on poaching behavior. Sayedi et al. (2014) showed that a brand follower has an incentive to poach the brand keyword of the market leader. Our finding lends empirical support to the finding that poaching a market leader's brand keywords could be effective, given that we show a large number of consumer clicks on leading-brand keywords without significant spillover effects on other keywords.

Another interesting finding at the brand level is the lack of any relationship between the brand-level keywords of the two brands. Consumers who search for Nike (Adidas) brand-level keywords do not also search for Adidas (Nike) brand-level keywords. One possible explanation for this result is that consumers of running shoes have strong brand preferences and therefore show little interest in other brands. It could also suggest that their brand preference is strong enough to prevent them from searching for keywords related to other brands.

At the model level, we found an asymmetric relationship wherein clicks on Nike model-level keywords have a positive effect on Adidas model-level keywords ($\hat{\gamma}$ = 0.148), but the reverse is not true. This finding provides evidence that the market follower's poaching of the market leader's keywords can be effective as consumers who click on the model-level keywords of the leader brand could click on the keywords of the follower. In addition, Nike model-level keywords have a significantly positive effect on Nike brand-level keywords ($\hat{\gamma}$ = 1.439). As mentioned, the brand leader might have a higher likelihood of being searched by consumers (e.g., Shin et al., 2016). Thus, some consumers who do not necessarily have a brand preference for the leading brand might search the leader brand's keywords first, including its model-level keywords, and then move on to search other keywords, such as the competitors' model-level keywords. In a similar vein, consumers might start by searching for the model-level keywords of the leading brand because they are already well aware of it, including its model-level information. On the other hand, consumers who search for Adidas models first might have already decided what to search for (e.g., they might be loyal to the follower brand); otherwise, they would have started by searching for the leading brand.

Another interesting finding is that clicks on Adidas model-level keywords have a significantly negative effect on category-level keywords ($\hat{\gamma}$ = −0.031), which is also consistent with the purchase funnel framework. One potential explanation for this result is that consumers who search model-level keywords might have already obtained sufficient information and are unlikely to search using broader category-level keywords, which would be associated with more general category-level information. Moreover, based on the leader–follower argument, consumers who are interested in the follower's specific model (e.g., Adidas Gazelle), although they might not be many, might already possess detailed category knowledge and a specific preference for the brand. These would be less likely to use category-level keywords in their search. However, consumers who are interested in the follower's models might still be interested in the brand itself, which explains the positive relationship between Adidas model-level and Adidas brand-level keywords ($\hat{\gamma} = 0.396$).

The effects of the control variables are as expected. First, rank has a negative effect on clicks for all keyword groups. Thus, consumers are more (less) likely to click on the ads featured in the upper (lower) positions. This result is consistent with the general findings in the search advertising literature on the relationship between advertising position and number of clicks (Ghose & Yang, 2009). The coefficients on the lagged number of clicks (past clicks) show that the number of clicks received in the past has a positive effect on the number of clicks consumers make in the current period. For example, the lagged number of clicks at *t-1* has a positive effect, and its coefficient is far greater than the other lagged numbers of clicks. The coefficients of the one-period lagged variables range between 0.487 (Nike model) and 0.695 (Nike brand), showing persistent click behavior. This finding is also consistent with the search advertising research, which has found that a significant number of consumer clicks on an ad in the past indicates its usefulness (i.e., consumers find the ad helpful and effective). Finally, serial correlation tests confirm that the assumption of no serial correlation of error terms is satisfied.

5.2. Retailers' bidding strategy

We now discuss the estimation results for the retailers' bids as well as the implications of their bidding strategies. First, we found positive relationships between keyword groups at different levels. For example, we found positive two-way relationships between category- and brand-level keywords (for Nike$\hat{\gamma} = 0.096$ and 0.267 and for Adidas$\hat{\gamma} = 0.182$ and 0.115, respectively) and between brand- and model-level keywords of the same brand (for Nike$\hat{\gamma} = 1.362$ and 0.182; for Adidas$\hat{\gamma} = 0.136$ and 0.168, respectively). These positive two-way relationships indicate that retailers bid on multiple keywords at different levels simultaneously because they understand that consumers use different keywords depending on their place in the consumer purchase funnel. These two-way relationships occur for both Nike and Adidas. Therefore, our findings suggest that retailers attempt to allocate their search advertising budget across the keywords at different levels.

Second, we find positive two-way relationships between Nike and Adidas at the brand level ($\hat{\gamma} = 0.435$ for Nike and 0.095 for Adidas, respectively), meaning that retailers who bid on Nike brand keywords also bid on Adidas brand keywords. These results are consistent with the practice because most retailers in our dataset sell both brands. Interestingly, unlike the positive relationships between the keywords at the brand level, we found no relationship between the keywords at the model level, meaning that retailers do not bid on Nike and Adidas model-level keywords simultaneously.

This result could suggest that, while retailers bid on multiple keywords, they may focus on a single brand at the model level rather than multiple brands (or some of all brands). For example, if a retailer has a strength in a particular brand, such as in price or assortment, it naturally focuses on that brand's keywords, especially at the model level. Consumers who search the most specific model-level keywords might be very close to making a purchase decision (i.e., at the bottom of the purchase funnel; Court et al., 2009). Accordingly, retailers do not need to bid for model-level keywords unless they have a good chance of winning customers. On the other hand, consumers who are still in the intermediate stage of their purchase process (searching brand-level keywords in our study) might still be swayable, leading advertisers to bid on multiple brand-level keywords.

Third, interestingly, Adidas model-level keywords have a positive effect on Nike brand-level keywords ($\hat{\gamma} = 0.425$), but the reverse is not true. For example, retailers who bid on Adidas Gazelle tend to bid on Nike running shoes. Since Nike is the leading brand in the market, retailers strong in Adidas products may still want to advertise with Nike brand keywords. As shown above, the largest number of consumer searches use Nike brand-level keywords and retailers would acknowledge that the leading brand has the highest brand awareness. Thus, the follower brand's optimal strategy would be to poach the brand leader's brand keywords (Sayedi et al., 2014). Moreover, we have already observed that Nike model-level keywords have a positive effect on Nike brand-level keywords. Therefore, we conclude that retailers realize that many consumers are aware of the leading brand (Nike) and that consumers search using keywords related to the leader, regardless of their purchase decision stage.

The effects of the control variables are as expected. First, the quality score at *t-1* has a negative effect on bids at *t* across all keyword groups. In other words, if an ad's quality was high in the last period, retailers could reduce their bids in the current period. Because rank is determined according to both bid and quality score, this result indicates that retailers might attempt to optimize their bids by adjusting them depending on their ads' qualities. Second, the rank at *t-1* has a positive effect on bids at *t*. Thus, retailers increase the bid if their ad had a lower rank in the last period to improve their rank in the current period. Third, although the effects of lagged bids vary, one common finding is that the effects of lagged bids at *t-1* are positive and have higher magnitudes than the lagged bidding amounts at other times. This means that retailers' bids are influenced most heavily by their own bids in the most recent period. The coefficients of the one-period lagged variables range between 0.327 (Nike brand) and 0.628 (Category), implying that retailers persistently bid on keywords. Serial correlation tests confirm that the assumption of no serial correlation of error terms is satisfied.

6. Discussion and conclusions

6.1. Summary and discussion

Our main purpose was to empirically examine how consumers search a variety of related keywords depending on their purchase stage and how retailers bid on multiple keywords in their search advertising campaigns. Understanding consumers' keyword search behavior is important because they usually perform a series of searches using related yet different keywords depending on their purchase decision stage. Understanding consumer search behavior can enable retailers to maximize the effectiveness and efficiency of their search advertising campaigns. This managerial task is particularly important for online retailers, who usually operate advertising campaigns on limited budgets. The research thus far has failed to use a consumer purchase stage framework to examine the multiple keyword management of retail advertisers who carry competing manufacturers' brands. Therefore, using a unique dataset composed of the most frequently searched keywords in the running shoes category, we generated empirical findings that offer interesting insights into consumer clicks and retailer bids on multiple keywords as well as managerial implications that can help retailers improve their decisions regarding advertising keyword choice and bids.

Our findings suggest that consumer click behavior for multiple keywords is consistent with the purchase funnel framework. Consumers who search for general and category-level information tend to search for mode-specific information afterwards. Our findings also suggest that, while the click behavior generally reflects the purchase funnel framework, click behavior for competing brands may exhibit different patterns. Specifically, the behavior of consumers who look for the follower brand, Adidas, seems to be consistent with the purchase funnel framework, but this does not seem to be true for the leading brand, Nike. For the leading brand, the brand-level keywords seem to play a terminal role as clicks on both category- and model-level keywords lead to clicks on brand-level keywords. Thus, we observed an asymmetric effect of market position between brands in consumer searches and click behavior (e.g., Shin et al., 2016). Moreover, our findings lend empirical support to the view that a keyword poaching or hijacking strategy is optimal when differentiated brands compete for search ads (Desai et al., 2014; Sayedi et al., 2014).

Regarding retail advertisers' bidding strategy, we found that retailers may consider keywords at different levels to be strategic complements. Specifically, they bid on all keywords at the category, brand, and model levels, which reflect different stages in the consumer purchase decision process. Retailers also consider Nike and Adidas keywords at the brand level strategic complements because they bid on both brand-level keywords simultaneously. This result is intuitive because most of the retailers in our dataset sell both brands. On the other hand, because consumers searching with model-level keywords might already be close to making a final purchase decision, retailers might think that bidding for the model-level keywords of both brands is not as effective as focusing on keywords about a brand in which they have an advantage. Finally, retailers seem to implement a poaching strategy between market leader and follower brands, as we find positive relationships between the follower's model-level keywords and the leader's brand-level keywords.

6.2. Theoretical and practical contributions

We make several important contributions to the literature. First, we advance the digital advertising research by enhancing our understanding of consumers' online search and click behavior in paid advertising. We showed a positive relationship in consumer clicks from category-level keywords to more specific brand-level keywords but not vice versa, consistent with previous findings in marketing studies (Du et al., 2017; Rutz & Bucklin, 2011). Unlike those studies, however, we identified additional relationships within the brand keywords by decomposing them into brand-level and specific model-level keywords. Our results show positive two-way relationships between brand-level and model-level keywords for market follower Adidas and a one-way relationship for market leader Nike. Thus, although consumers would not move up to category-level keywords, they would move between brand- and model-level keywords. This finding is in line with the current trend in digital advertising wherein consumer searches are less likely to be sequential, and consumers are more likely to add and subtract alternatives from their consideration set while searching than before (Court et al., 2009). Moreover, our finding that consumers' click patterns differ between the market leader's and follower's brands suggests that the asymmetric effect of the competing brands' market positions (e.g., Carpenter & Nakamoto, 1989; Shin et al., 2016) can be extended to consumers' search behavior.

Second, our findings offer new insights into advertisers' bidding strategies for various keywords used at different purchase stages (Du et al., 2017). We showed that the relationships among retailers' bids for different keywords are mostly positive. This indicates that retailers exhibit simultaneous bidding behavior on various keywords across consumer purchase stages for both brands. This also suggests that retailers may be bidding on as many keywords as possible, thus spending more than necessary, because retailers might lack an understanding of their target consumers—particularly of their key search and click patterns. Retailers who use their information correctly to predict consumer behavior and brand loyalty for different brands might be capable of more selective, and thus more efficient, keyword choice and bidding strategies. Our results offer useful insights into advertisers' optimal bids on multiple keywords by comparing consumers' click behavior and advertisers' bidding patterns. For example, consumer clicks on Nike model-level keywords have positive spillover effects on Adidas model-level keywords. However, advertisers who bid on Nike model-level keywords do not seem to take this fact into account, as no positive relationship was observed between bids for Nike and Adidas model-level keywords. Our findings also suggest that retailers could make better use of category-level keywords in this product category. Category-level keywords are not the most expensive kind, yet positive spillover is possible from them to brand-level keywords. Overall, our findings suggest that retailers need to allocate their advertising budgets across keywords more efficiently.

Third, our results suggest that retail advertisers' bidding strategies may exhibit keyword poaching (hijacking), which has proven to be optimal by the theoretical literature. Theoretical studies have suggested that a brand with a lower-quality image in the market has an incentive to poach from a higher-quality brand (Desai et al., 2014; Sayedi et al., 2014). Our results regarding retailers' bids show that advertisers who bid on a follower brand's keywords are more likely to bid on the leader's brand keywords but not vice versa. Further, our results regarding consumer clicks support the view that keyword poaching is a valid marketing strategy, as we found a positive relationship from the brand leader's keywords to the follower's keywords.

6.3. Limitations and future research direction

Our study has several limitations, which call for further research. First, our data were drawn from the running shoes category and were collected over three months. It would be worthwhile to examine other product categories with different characteristics, including durable products and non-durable products, luxury and functional brands, and utilitarian and hedonic products, to further validate our findings (Bridges, 2018; Chu, Kamal, & Kim, 2013; Liang & Liu, 2019; Taylor & Costello, 2017). Second, our dataset contains retailers' search advertising that sells competing brands. Including more data on manufacturers' own search advertising might reveal different patterns in their bids across multiple keywords, providing more insightful implications for managing multiple keywords. Third, our data contain only a limited number of keywords used for search advertising in the running shoes category. Although the keywords in our data receive the most consumer clicks in the running shoes category, it would be worthwhile to include more keywords, including long-tail keywords. Similarly, it would be interesting to examine mobile versus non-mobile environments, as the device used to search keywords may imply different consumer intentions (Kim, Kang, & Taylor, 2018). Fourth, though AB-GMM seems appropriate for our context, there is room for efficiency improvement (e.g., Ahn & Schmidt, 1995) and weak instrument solution (e.g., Moral-Benito et al., 2019), which can be considered by future researchers. Fifth, while a joint estimation of clicking behavior and bidding strategy was not attempted in our study, future researchers can jointly estimate advertisers' bidding strategy, a search engine's ranking system, and consumers' clicking behavior. Finally, optimal strategies for multiple keyword management could be examined. For example, analytical modeling could be used to derive optimal keyword choices and bidding strategies. If appropriate datasets are used for product prices, costs, and conversion rates, one could perform simulations to identify optimal bid levels for managing multiple keywords. We leave this task to future researchers. In spite of these limitations, our findings provide new insights into multiple keyword management, which we hope will generate more interest in search advertising and digital marketing research.

Funding sources

This work was supported by the National Research Foundation of Korea (NRF-2018S1A5A8030699). The third author appreciates the support of the research fund of Hanyang University (HY-2016).

Declaration of Competing Interest

None.

Appendix A. Supplementary material

Supplementary data to this article can be found online at https://doi.org/10.1016/j.jbusres.2019.09.049.

References

Ahn, S. C., & Schmidt, P. (1995). Efficient estimation of models of dynamic panel data. *Journal of Econometrics, 68*, 5–27.

Alvarez, J., & Arellano, M. (2003). The time series and cross-section asymptotics of dynamic panel data estimators. *Econometrica, 71*(4), 1121–1159.

Amaldoss, W., Desai, P. S., & Shin, W. (2015). Keyword search advertising and first-page bid estimates: A strategic analysis. *Management Science, 61*(3), 507–519.

Arellano, M., & Bond, S. (1991). Some tests of specification for panel data: Monte Carlo evidence and an application to employment equations. *Review of Economic Studies, 58*, 277–297.

Arellano, M. (2003). *Panel data econometrics* (2nd ed.). Oxford: Oxford University Press.

Bailliu, J., & Fujii, E. (2004). *Exchange rate pass-through and the inflation environment in industrialized countries: An empirical investigation.* Canada: Bank of Working Paper2004–2021.

Balachander, S., Kannan, K., & Schwarz, M. (2009). A theoretical and empirical analysis of alternative auction policies for search advertisements. *Review of Marketing Science, 7*, 1–51.

Baye, M. R., De los Santos, B., & Wildenbeest, M. R. (2016). Search engine optimization: What drives organic traffic to retail sites? *Journal of Economics & Management Strategy, 25*(1), 6–31.

Blake, T., Nosko, C., & Tadelis, S. (2015). Consumer heterogeneity and paid search effectiveness: A large-scale field experiment. *Econometrica, 83*(1), 155–174.

Bridges, E. (2018). Hedonic and utilitarian shopping goals: A decade later. *Journal of Global Scholars of Marketing Science, 28*(3), 282–290.

Carpenter, G., & Nakamoto, K. (1989). Consumer preference formation and pioneering advantage. *Journal of Marketing Research, 26*(3), 285–298.

Carrasco, M., & Florens, J.-P. (2014). On the asymptotic efficiency of GMM. *Econometric Theory, 30*(2), 372–406.

Chan, T. Y., & Park, Y. H. (2015). Consumer search activities and the value of ad positions in sponsored search advertising. *Marketing Science, 34*(4), 606–623.

Chu, S. C., Kamal, S., & Kim, Y. (2013). Understanding consumers' responses toward social media advertising and purchase intention toward luxury products. *Journal of Global Fashion Marketing, 4*(3), 158–174.

Court, D., Elzinga, D., Mulder, S., & Vetvik, O. J. (2009). The consumer decision journey. *McKinsey Quarterly, June*.

Desai, P., Shin, W., & Staelin, R. (2014). The company that you keep: When to buy a competitor's keyword. *Marketing Science, 33*(4), 485–508.

Du, X., Su, M., Zhang, X., & Zheng, X. (2017). Bidding for multiple keywords in sponsored search advertising: Keyword categories and match types. *Information Systems Research, 28*(4), 711–722.

Edelman, B., Ostrovsky, M., & Schwarz, M. (2007). Internet advertising and the generalized second price auction: Selling billions of dollars worth of keywords. *American Economic Review, 97*(1), 242–259.

Edelman, B., & Schwarz, M. (2010). Optimal auction design and equilibrium selection in sponsored search auctions. *American Economic Review, 100*(2), 597–602.

eMarketer. Net US Search Ad Revenues by Company 2016-2019. (2017). https://www.emarketer.com/chart/211332/net-us-digital-ad-revenues-by-company-2016-2019-billions.

Insight, Fashion (2014). The absolute power in running shoes. *Nike.*.

Feng, J., Bhargava, K., & Pennock, D. (2007). Implementing sponsored search in web search engines: Computational evaluation of alternative mechanisms. *INFORMS Journal of Computing, 19*, 137–148.

Fudenberg, D., Gilbert, R., Stiglitz, J., & Tirole, J. (1983). Preemption, leapfrogging, and competition in patent races. *European Economic Review, 22*, 3–31.

Ghose, A., & Yang, S. (2009). An empirical analysis of search engine advertising: Sponsored search in electronic markets. *Management Science, 55*(10), 1605–1622.

Grossman, G., & Shapiro, C. (1987). Dynamic R&D competition. *Economic Journal, 97*, 372–387.

Hoban, P., & Bucklin, R. E. (2015). Effects of Internet display advertising in the purchase funnel: Model-based insights from a randomized field experiment. *Journal of Marketing Research, 52*(3), 375–393.

Enquiro Search Solutions Inc. Inside the mind of the searcher. (2004). https://www.manningmarketing.com/dvi/wp-content/uploads/2019/07/Inside-the-Mind-of-the-Searcher-2004.pdf.

Howard, J. A., & Sheth, J. N. (1969). *The theory of buyer behavior*, *14*. New York: Wiley.

Hsiao, C. (2014). *Analysis of panel data* (3rd ed.). New York, NY: Cambridge University Press.

Hsiao, C., & Zhang, J. (2015). IV, GMM or likelihood approach to estimate dynamic panel models when either N or T or both are large. *Journal of Econometrics, 187*(1), 312–322.

Interactive Advertising Bureau. IAB Internet advertising revenue report. (2016). https://www.iab.com/wp-content/uploads/2016/04/IAB-Internet-Advertising-Revenue-Report-FY-2015.pdf.

Jansen, B. J., & Schuster, S. (2011). Bidding on the buying funnel for sponsored search and keyword advertising. *Journal of Electronic Commerce Research, 12*(1), 1–18.

Jerath, K., Ma, L., & Park, Y. (2014). Consumer click behavior at a search engine: The role of keyword popularity. *Journal of Marketing Research, 51*(4), 480–486.

Jerath, K., Ma, L., Park, Y., & Srinivasan, K. (2011). A "position paradox" in sponsored search auctions. *Marketing Science, 30*(4), 612–627.

Jeziorski, P., & Moorthy, S. (2017). Advertiser prominence effects in search advertising. *Management Science, 64*(3), 1365–1383.

Joo, M., Wilbur, K., Cowgill, B., & Zhu, Y. (2014). Television advertising and online search. *Management Science, 60*(1), 56–73.

Judson, R. A., & Owen, A. L. (1999). Estimating dynamic panel data models: A practical guide for macroeconomists. *Economics Letters, 65*(1), 9–15.

Khanna, T. (1995). Racing behavior: Technological evolution in the high-end computer industry. *Research Policy, 24*, 933–958.

Kim, A., & Balachander, S. (2018). Coordinating traditional media advertising and search advertising in brand marketing. Working Paper. Sungkyunkwan University.

Kim, A., Balachander, S., & Kannan, K. (2012). On the optimal number of advertising slots in a generalized second price auction. *Marketing Letters, 23*(3), 851–868.

Kim, J., Kang, S., & Taylor, C. R. (2018). Technology driven experiences from mobile direct to virtual reality. *Journal of Global Scholars of Marketing Science, 28*(1), 96–102.

Liang, Y., & Liu, C. (2019). Comparison of consumers' acceptance of online apparel mass customization across web and mobile channels. *Journal of Global Fashion Marketing, 10*(3), 228–245.

Lu, X., & Zhao, X. (2014). Differential effects of keyword selection in search engine advertising on direct and indirect sales. *Journal of Management Information Systems, 30*(4), 299–326.

Maillé, P., Markakis, E., Naldi, M., Stamoulis, G. D., & Tuffin, B. (2012). Sponsored search auctions: An overview of research with emphasis on game theoretic aspects. *Electronic Commerce Research, 12*(3), 265–300.

Moral-Benito, E., Allison, P. D., & Williams, R. (2019). Dynamic panel data modeling using maximum likelihood: An alternative to Arellano-Bond. *Applied Economics, 51*(20), 2221–2232.

Narayanan, S., & Kalyanam, K. (2015). Position effects in search advertising and their moderators: A regression discontinuity approach. *Marketing Science, 34*(3), 388–407.

Ofek, E., & Savary, M. (2003). R&D, marketing, and the success of next-generation products. *Marketing Science, 22*(3), 355–370.

Park, C. H., & Agarwal, M. K. (2018). The order effect of advertisers on consumer search behavior in sponsored search markets. *Journal of Business Research, 84*, 24–33.

Roodman, D. (2009). How to do xtabond2: An introduction to difference and system GMM in Stata. *The Stata Journal, 9*(1), 86–136.

Rutz, O. J., & Bucklin, R. E. (2011). From generic to branded: A model of spillover in paid search advertising. *Journal of Marketing Research, 48*(1), 87–102.

Rutz, O. J., Bucklin, R. E., & Sonnier, G. P. (2012). A latent instrumental variables approach to modeling keyword conversion in paid search advertising. *Journal of Marketing Research, 49*(3), 306–319.

Rutz, O. J., Trusov, M., & Bucklin, R. E. (2011). Modeling indirect effects of paid search advertising: Which keywords lead to more future visits? *Marketing Science, 30*(4), 646–665.

Sayedi, A., Jerath, K., & Srinivasan, K. (2014). Competitive poaching in sponsored search advertising and its strategic impact on traditional advertising. *Marketing Science, 33*(4), 586–608.

Shin, H., Hanssens, D. M., & Kim, K. (2016). The role of online buzz for leader vs. challenger brands: The case of the MP3 player market. *Electronic Commerce Research, 16*(4), 503–528.

Skiera, B., Eckert, J., & Hinz, O. (2010). An analysis of the importance of the long tail in search engine marketing. *Electronic Commerce Research and Applications, 9*(6), 488–494.

Srivastava, R. K., Shervani, T. A., & Fahey, L. (1998). Market-based assets and shareholder value: A framework for analysis. *Journal of Marketing, 62*(1), 2–18.

Statistica. Favorite sportswear brands in South Korea as of March 2018. (2018). https://www.statista.com/statistics/783101/south-korea-favorite-sportswear-brands.

Stigler, G. J. (1961). The economics of information. *Journal of Political Economy, 69*(3), 213–225.

Sundaram, A., John, T., & John, K. (1996). An empirical analysis of strategic competition and firm values: The case of R&D competition. *Journal of Financial Economics, 40*, 459–486.

Taylor, C. R., & Costello, J. P. (2017). What do we know about fashion advertising? A review of the literature and suggested research directions. *Journal of Global Fashion Marketing, 8*(1), 1–20.

Tirole, J. (1988). *The theory of industrial organization.* Cambridge: MIT Press.

Varian, H. (2007). Position auction. *International Journal of Industrial Organization, 25*, 1163–1178.

Wiesel, T., Pauwels, K., & Arts, J. (2011). Practice prize paper—Marketing's profit impact: Quantifying online and off-line funnel progression. *Marketing Science, 30*(4), 604–611.

Windmeijer, F. (2005). A finite sample correction for the variance of linear efficient two-step GMM estimators. *Journal of Econometrics, 126*, 25–51.

Woodside, A. G., & Bernal Mir, P. (2019). Clicks and purchase effects of an embedded, social-media, platform endorsement in internet advertising. *Journal of Global Scholars of Marketing Science, 29*(3), 343–357.

Alex Jiyoung Kim is Assistant Professor of Marketing at the SKK Business school, Sungkyunkwan University (Seoul, South Korea). His research has appeared in premier journals such as *Journal of Marketing, Marketing Letters, and International Journal of Advertising.* He received his B.S. and M.A. degrees from the University of Illinois at Chicago (Illinois, USA), and Ph.D. in Management (Major: Marketing) from Purdue University (Indiana, USA).

Sungha Jang is Associate Professor of Marketing at San Francisco State University. His research interests include consumer search behaviors, choice decisions, and firms'

targeting strategies. His research has appeared in premier journals such as *Journal of Business Ethics*, *Journal of Interactive Marketing*, *International Journal of Research in Marketing*, and *Marketing Letters*. He received his B.S. in Statistics and M.B.A. degrees from Korea University and Ph.D. in Management from the University of Texas at Dallas.

Hyun Shin is Associate Professor of Marketing at the School of Business, Hanyang University (Seoul, South Korea). He serves as Ashoka U Change Leader and the Editor of *Stanford Social Innovation Review (SSIR) Korean Edition*. His research has appeared in premier journals such as *Management Science* and *Sustainable Development*. He received his B.B.A. and M.B.A. degrees from Seoul National University (Seoul, South Korea), M.S. in Economics from the University of Illinois at Urbana-Champaign (Illinois, USA), and Ph.D. in Management (Major: Marketing) from UCLA (California, USA).