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The Effects of Price Rank on Clicks and Conversions in Product List Advertising on Online Retail Platforms

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Abstract. In light of the critical role of price information in consumers' decision making, this study investigates the effect of price rank on consumers' responses to product list advertising (PLA) throughout the purchase funnel, as well as the moderating effects of two keyword attributes. A hierarchical Bayesian model, using a unique data set from a leading electronic shopping platform and a simulated experiment, reveals that in the early phases of the purchase funnel, consumers are more likely to click on extremely priced options (i.e., the highest or lowest), which consumers use as anchors to evaluate the broad range of options. Later in the purchase funnel, when clicks tend to convert to purchases, consumers instead are more likely to click on moderately priced options, which usually offer a compromise between price and quality. The effects of price rank diminish among advertisements that sponsor more specific keywords and increase among those that sponsor more popular keywords. These findings provide new insights into the role of price information in the PLA context, as well as managerial implications for devising effective PLA strategies.

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Keywords: product list advertising • price rank • keyword specificity • keyword popularity • click-through rate • conversion rate • consumer purchase funnel

Sponsored search advertising is an increasingly important tool for both sellers promoting their products and buyers searching for products, and it also has become an important source of revenue for platforms such as Google, Amazon, and Facebook. Extensive studies in the information systems literature (summarized in Table A1 in Online Appendix A) have explored the performance determinants and bidding strategies of search advertising. Researchers have highlighted the influences of rank positions (e.g., Animesh et al. 2011 and Agarwal and Mukhopadhyay 2016) and keyword features in a competitive online environment (e.g., Lu and Zhao 2014, Im et al. 2016, and Gong et al. 2018). Other studies have examined optimal bidding strategies for search advertising with a focus on the bidding price (usually operationalized as the cost per click; e.g., Liu et al. 2010, Zhang and Feng 2011, and Amaldoss et al. 2015), the choice of keyword categories and match types (e.g., Du et al. 2017), and budget allocations (e.g., Sayedi et al. 2014 and Zhang et al. 2014).

In this paper, we focus on one particular type of sponsored search advertising: product list advertising (PLA). In PLA, unlike sponsored links or banners, products from the same category are selected based on the consumer's specific search keywords and listed side by side for comparison. In addition, sellers bid a cost per click (CPC) for product category keywords, which can range in scope from specific (e.g., white running shoes) to general (e.g., shoes). As an example, Google PLA involves four steps: First, a seller chooses a product to enter in PLA, writes its description, and decides on a price to display in the search results. Second, the seller chooses a product category and CPC for the bid. Third, Google determines which products will actually appear in PLA using real-time auctions, the CPCs, and other factors such as Google's seller-quality score. Finally, for each consumer, the displayed product list is determined by the match between the consumer's search keywords and the product category (Figure B1 in Online Appendix B). As a platform for search advertising, PLA offers three distinct features: (1) detailed product and price information, (2) side-by-side comparisons of competing products in the same category, and (3) product listings based on the consumer's search keywords.

Given that PLA offers more product information than sponsored search results, one may expect that the provided product information affects consumer behaviors (namely, clicks and conversions). More specifically, because PLA displays competing products in the same category, the advertising performance of a particular product should depend on its attributes *relative* to the attributes of other products in the list. In this paper, we focus on price because, of all the information available, price is the easiest to compare across products in a choice set and is critical for consumers' assessments of product value (Rajendran and Tellis 1994). Unfortunately, the search advertising literature lacks insight into pricing strategies that account for the prices of competing products (i.e., price rank), even though firms often benchmark against competitors' prices (Oh and Lucas 2006). In this paper, we attempt to answer three questions: (1) How does a product's price rank in a product list affect its clicks and conversions? (2) How do attributes of search keywords affect the relationship between price rank and clicks/conversions? (3) What underlying psychological mechanisms drive these effects?

Accordingly, we develop two studies. In study 1, we investigate how PLA responses (clicks and conversions) vary with the price rank of the search results. Using detailed information about 200,000 PLAs from a leading electronic shopping platform, we introduce *price rank* as an important managerial variable in the search advertising context. We find that consumers anchor on the price rank to develop expectations, assess alternatives, and find a compromise between price and quality. After controlling for the product price, display rank, and other relevant factors, we find that price rank has contrasting effects on the click-through rate (a U-shaped effect) and conversion rate (an inverted U-shaped effect). In addition, two keyword attributes (specificity and popularity) moderate the effects of price rank; keyword popularity increases both effects (i.e., makes the U-shape and inverted U-shape steeper), whereas keyword specificity weakens both effects (i.e., makes the U-shape and inverted U-shape flatter).

In study 2, we conduct an experiment to verify between- and within-consumer variations in keyword-search behaviors. Between-consumer variations are revealed by the contrast between *search-only* participants, who merely seek information, and *search-and-buy* participants, who search and then make purchase decisions. Clickstream data from 235 consumers revealed that the focus of search-and-buy consumers shifts along the purchase funnel. Specifically, search-and-buy consumers use early stage clicks to establish anchors based on the extremely priced options, whereas late-stage clicks (i.e., those that are more likely to convert to purchases) are driven by the need to find a compromise between product price and quality and, thus, favor moderately priced options. By contrast, search-only consumers click on extremely priced options throughout the search process. Clickstream data also indicate higher conversion rates for moderately priced products than for extremely priced products.

The findings of this paper provide four major contributions to the online advertising literature. First, this paper is among the first to focus on PLA, a relatively new form of online advertising. Second, this paper introduces price rank as a novel driver of advertising effectiveness, thus providing new insight into a dynamic optimal bidding strategy in which the seller adjusts the product's price or choice of product to achieve a particular price rank that is tailored to the seller's advertising objective (either to attract searches or maximize purchases). By contrast, prior research on bidding decisions has focused on keyword categories, match type, bidding price, and budget (e.g., Zhang and Feng 2011, Amaldoss et al. 2015, and Du et al. 2017). Third, this paper differentiates between two outcomes of online advertising effectiveness—the click-through rate and conversion rate—and demonstrates that sellers face a tradeoff between them because clicks and conversions occur in different stages of the purchase funnel and, thus, involve different behavioral mechanisms. Finally, the specificity and popularity of keywords are known to influence consumers' click and conversion decisions (Jerath et al. 2014, Narayanan and Kalyanam 2015), but this paper goes further by showing that these attributes also function as boundary conditions of the effects of price rank in the PLA context.

Related Literature

This paper relates to two streams of online advertising literature: sponsored search advertising and online display advertising. First, with regard to the sponsored search advertising literature, this paper focuses on how keyword attributes and rank positions affect consumer click and conversion behaviors. Keyword attributes such as specificity and popularity are known to influence these behaviors. For example, Jerath et al. (2014) find that click behavior varies significantly across different keywords because the composition of consumers varies across keywords. In addition, keyword attributes reflect consumers' choices and purchase stages. For example, keyword specificity moderates the relationship between display position and consumer choice because a consumer's involvement and likely segment affect the specificity of their search queries (Agarwal et al. 2011). Lu and Zhao (2014) show that the use of specific (versus general) keywords leads to a higher marginal contribution to indirect sales. Gong et al. (2018) find that consumer click behavior varies significantly across keywords, and such variation can be partially explained by keyword specificity; higher keyword specificity is associated with both a higher click-through rate and faster decay on top-positioned advertisements. Therefore, the overall effect of keyword specificity on the click-through rate varies across positions.

Keyword popularity also functions as a moderator, though it has received somewhat less attention. Jerath et al. (2014) show that the search volume of a keyword decreases consumers' likelihood of clicking on a sponsored search result over an organic search result. Prior studies have also examined the effects of rank positions. For example, Animesh et al. (2011) demonstrate that although a decrease in the rank position decreases the click-through rate, the magnitude of this negative effect depends on whether consumers are focused on quality versus driven by price. Agarwal and Mukhopadhyay (2016) highlight the rank position as a moderator of the effect of advertisement quality. A top rank attracts the highest click-through and conversion rates (Xu et al. 2011, Rutz et al. 2012, Narayanan and Kalyanam 2015), though the economic benefits may not always compensate for the high cost of reaching this position (Ghose and Yang 2009).

Although PLA resembles other types of sponsored search advertising in that it is based on the consumer's keyword search, it differs in two important ways: PLA provides detailed product and price information, and it enables side-by-side comparisons of competing products in the same category. We know little about the effects of price rank on advertising performance, even though price information is a pronounced feature of PLA, and consumers compare prices carefully when making purchase decisions (Lynch and Ariely 2000). More specifically, we predict that the effects of price rank on a consumer's behavior might be influenced by the keywords used by that consumer. We investigate price rank as a display attribute and consider its interaction with two keyword attributes: popularity and specificity. Our consideration of both between-consumer variations and within-consumer variations extends the literature, most of which investigates behavioral variations among consumer segments (i.e., between consumers) exclusively (Animesh et al. 2011, Jerath et al. 2014, Chan and Park 2015, Im et al. 2016).

Second, with regard to the online display-advertising literature (for a review, see Choi et al. 2020), the present research makes contributions in two domains: advertising design and bidding strategy. With regard to advertising design, Goldfarb and Tucker (2011) identify two factors that independently increase purchase intent: matching the advertisement to the website content and decreasing the advertisement's obtrusiveness. In combination, however, these two strategies are ineffective. Braun and Moe (2013) highlight the importance of advertising design in an advertising campaign and demonstrate how online advertisers can increase the number of website visits and conversions by varying the creative content. Bruce et al. (2017) use a dynamic model to test the effects of various sizes of static and animated display-ad formats and consider how the effectiveness of an ad design varies with the ad format and consumer segment. Trendel et al. (2018) compare the abilities of imagery and text to improve explicit and implicit attitudes, and they find that imagery-based information can affect both explicit and implicit attitudes, whereas text affects only explicit attitudes.

With regard to bidding strategy, online display advertising typically uses real-time bidding, and prior research has examined facets of bidding strategies, including the choice of categories, match type, and bidding price (Zhang and Feng 2011, Zhang et al. 2014, Amaldoss et al. 2015, Du et al. 2017). For example, Du et al. (2017) show that generic versus branded keywords and exact versus broad matches have differential effects on search advertising performance. Others have examined the possibility of using more dynamic bidding strategies in keyword auctions. Zhang and Feng (2011) recommend a cyclical pattern of equilibrium bidding prices, and Zhang et al. (2014) show that the optimal search advertising strategy involves frequent adjustments to both the bid price and daily budget. Balseiro and Gur (2019) demonstrate the performance of adaptive pricing strategies in different competitive bidding settings. Balseiro et al. (2015) identify a complex optimal bidding strategy for advertisers with tight budgets. In sum, there is an ongoing need to develop adaptive, optimized, real-time bidding algorithms (e.g., Tunuguntla and Hoban 2021).

Like online display advertising, PLA uses real-time bidding that is affected by both the platform's algorithms and the advertiser's bidding strategy, and PLA also embeds product messages in the advertising design. However, PLA differs from online display advertising in two important ways. First, the outputs of online display advertising depend on the consumer's browsing behavior, while PLA uses the consumer's keyword search. Second, PLA offers side-by-side comparisons of competing products in the same category, whereas online display advertising does not. Therefore, PLA requires a nuanced bidding strategy that incorporates (1) the product's display information (namely, price), (2) competitors' display information,

(3) keyword category, and (4) interactions between the first three variables.

Furthermore, prior studies in keyword and display advertising have evaluated advertising performance with either the click-through or conversion rate (Choi et al. 2020) without considering a possible tradeoff between the two. A tradeoff would be quite impactful, given that advertising effectiveness is driven by both clicks and conversions. Our research represents a response to the question by Choi et al. (2020, p. 89) about "which metrics should be evaluated and optimized in display advertising" and call for research to "explore the relationship among advertisers' display ad objectives, optimization processes, and various KPIs evaluated in practice."

In sum, our study contributes to the online advertising literature by (1) examining PLA as a recent development in online advertising, (2) introducing price rank as a novel driver of advertising performance, (3) differentiating between clicks and conversions as the two outcomes of online advertising effectiveness, and (4) considering two keyword attributes as moderators of the effects of price rank on the click-through and conversion rates.

Theoretical Background and Hypotheses Development

Consumer Choice and Price Comparison

Consumers develop and modify their preferences within a choice set, as might be represented by a list of sponsored advertisements that result from a search (Bettman et al. 1998). But choice sets can be daunting in size, especially in the online setting (Mazumdar et al. 2005). Therefore, consumers rely on criteria—especially price—to cull the options and create a manageable choice set (Wu and Rangaswamy 2003, Mazumdar et al. 2005). In particular, if consumers experience an uncertainty about a purchase decision, but do not want to expend effort to eliminate it, they might adopt the product price as a straightforward indicator of other attributes (e.g., quality, function, and brand equity) that are easily compared between alternatives (Degeratu et al. 2000). Consumers may be especially likely to use product price as a shortcut for evaluating sponsored listings, which tend to evoke less consumer engagement than organic listings (Jerath et al. 2014).

Building on these insights from the price-comparison literature (Table A2 in Online Appendix A), we consider two behavioral patterns and corresponding mechanisms for search and purchase decisions that may affect consumers' responses to PLA. Specifically, we propose that consumers may use the price rank as an anchor or compromise tool. Consumers may adopt extreme prices as anchors that inform reservation prices for other products (Krishna et al. 2006) and willingness to pay (Adaval and Wyer 2011). Moderate prices, usually attached to options that represent compromises between price and quality, instead affect brand choice (Kivetz et al. 2004a,b). The prevalence of each mechanism should vary with the phase of the purchase funnel and consumers' level of involvement.

Behavioral Mechanisms

Anchoring Effect for Information Searches. An anchoring effect is most likely to occur in the early stages of the purchase funnel. Consumers experience the most ambiguity when they start forming a choice set (Hauser and Wernerfelt 1989), so they rely more heavily on anchoring-and-adjustment processes (Carpenter and Nakamoto 1989, Hoch and Deighton 1989), meaning that they judge the stimulus along an attribute dimension with some uncertainty (Tversky and Kahneman 1974). Instead of carefully reviewing every alternative, consumers can minimize their search effort by selecting extreme values along a dimension (e.g., price) and adjusting their expectations to arrive efficiently at a plausible value. The most extreme values (i.e., the highest and lowest prices) provide easy anchors for consumers' price perceptions (Kalwani et al. 1990), so prices are attractive reference points for searches made under uncertainty (Epley and Gilovich 2006). Krishna et al. (2006) further show that extremely priced products within a set of moderately priced options affect the reservation price for a moderately priced product in the same category, particularly if the products are closely related and presented contiguously. An explicit comparison of products against the price anchor activates a consideration of product features available for the same price, which then influences consumers' willingness to pay (Adaval and Wyer 2011). After reviewing the extreme options, consumers identify key product features they want to compare and develop expectations about those features before making purchase decisions or pursuing additional searches.

Compromise Effect for Purchases. Another relevant behavioral pattern is extreme aversion, which is driven by the compromise effect. The compromise effect denotes the phenomenon that the product is more appealing when it is an intermediate (versus extreme) option in a choice set (e.g., Simonson 1989 and Simonson and Tversky 1992). Thus, "compromise" implies a context effect, whereby the attractiveness of an option is greater in the context of the choice set in which it is an intermediate (compromise) option than in a choice set in which it is an extreme option. When consumers approach a purchase decision, they likely pay more attention to moderately priced products as viable compromises that balance the tradeoffs between options (Dhar et al. 2000, Chernev 2004). Therefore, the compromise effect should occur in the later stages of the purchase funnel, when consumers are narrowing down their consideration set to a few plausible alternatives. It is important to note that anchoring and compromise effects are not opposites or mutually exclusive. Rather, they function at different decision stages: the anchoring effect in the information-search stage and the compromise effect in the purchase stage.

Consumer Responses: Clicks and Conversions

Consumers can engage with products in PLA by clicking or converting. "Clicking" enables consumers to retrieve product information with which they can develop expectations and evaluate alternatives. "Converting" involves an active purchase.

Clicks. When consumers search for information about a topic (in this case, via keyword searches in the early stages of the purchase funnel), they tend to develop anchors for evaluating the product options in the search results. Clicking a sponsored display involves minimal engagement, and consumers gain basic information that informs their expectations about products of interest. As consumers screen product options and form choice sets during these early stages, they pay more attention to extreme prices because they are more informative as points of reference. Then, consumers can anchor on these points of reference to identify desired qualities and/or prices and efficiently compare products according to those features (Epley and Gilovich 2006, Krishna et al. 2006). For instance, a high price can signal high quality, whereas a low price may reflect low quality. After viewing some extreme options, consumers may either evaluate moderate alternatives or continue their search with a new keyword. In later stages of the purchase funnel, however, consumers are more likely to click on serious purchase considerations. At this point in the search, the choice set usually includes moderate options that represent a compromise between product price and quality.

The net effect of clicks—that is, whether consumers use clicks primarily to develop anchors or identify compromises—usually varies along the purchase funnel: More time and clicks are expended for exploratory searches in earlier stages than for purchase decisions in later stages. Previous findings establish that conversion rates are much lower than click-through rates (Yang and Ghose 2010, Agarwal et al. 2011, Rutz et al. 2012). We anticipate that click behaviors, operationalized as the click-through rate, are driven primarily by consumers' need for exploration to build anchors, not by their need to identify compromises for the final purchase decision. Thus, we hypothesize that consumers are more likely to click on extremely priced displays, which provide the most useful information for anchoring, than on moderately priced ones. Formally:

Hypothesis 1. *Price rank has a U-shaped effect on the click-through rate of a product displayed in PLA such that the click-through rate is higher for extremely priced products than for moderately priced ones.*

Conversions. When consumers browse keyword-search results, they are considering products from the same category, but with different features. A conversion (i.e., a click that leads to a sale) requires engagements that are deeper than the average exploratory search because the consumer must determine whether the product option meets their specific needs. According to compromise effect theory (Dhar et al. 2000, Chernev 2004, Kivetz et al. 2004a), consumers seek tradeoffs among product features when making purchase decisions, and the two primary features of interest are price and quality (Mehta et al. 2003). However, product quality is difficult to evaluate in sponsored search advertising, so consumers might try to infer quality from price, with the belief that a higher price indicates higher quality (Feng and Xie 2012). Thus, conversions (relative to exploratory searches) are more likely to involve compromises, so conversions should occur more often in response to moderately priced options than to extremely priced ones.

Hypothesis 2. *Price rank has an inverted U-shaped effect on the conversion rate of a product displayed in PLA such that the conversion rate is higher for moderately priced products than for extremely priced ones.*

Moderating Effects of Search Keyword Attributes

Search keywords reflect the breadth of the market (niche versus mass) and the consumer's shopping stage and goal (Jeziorski and Segal 2015). In this regard, keyword attributes—particularly specificity and popularity—reflect the characteristics of consumer segments. Keyword specificity (i.e., level of detail) indicates a consumer's stage in the decision-making process (Rutz et al. 2012, Narayanan and Kalyanam 2015), whereas keyword popularity (i.e., the frequency with which a keyword is searched) indicates the size of the market segment and the consumer's level of product involvement (Jerath et al. 2014).

Keyword Specificity. The relationship between the price rank and a consumer's click behavior should depend on the specificity of their search keywords. Consumers are more likely to minimize their search effort by anchoring on prices when they experience a high level of ambiguity (Hauser and Wernerfelt 1989), so the influence of price rank should diminish during more in-depth (specific) searches for two reasons: The choice set should be smaller, and consumers likely have already developed specific preferences (Agarwal and Mukhopadhyay 2016). Meanwhile, consumers who use general keywords have more ambiguous preferences and are primarily searching for information to develop their preferences (Rutz et al. 2011, Jerath et al. 2014). The anchor function of extremely priced products should be more critical for general keyword searches (Biswas and Blair 1991) and should diminish (that is, the U-shaped effect of price rank on the click-through rate should flatten) for specific keyword searches.

As discussed previously, consumers who are nearing a conversion tend to pay more attention to moderately priced products, which represent viable compromises between price and quality (Dhar et al. 2000, Chernev 2004, Kivetz et al. 2004b). However, consumers with specific preferences (reflected in more specific keywords) have less need to seek a compromise among the product features; they tend to choose the product that best meets their predetermined preferences (Dhar et al. 2000). That is, the inverted U-shaped effect of price rank on the conversion rate should flatten for specific (versus general) keyword searches.

In sum, specific keywords reflect predetermined preferences and, thus, indicate that the consumer will rely less on both anchoring and compromise. The effects of price rank should diminish.

Hypothesis 3. *Keyword specificity weakens the U-shaped effect of price rank on the click-through rate, making the curve flatter.*

Hypothesis 4. *Keyword specificity weakens the inverted U-shaped effect of price rank on the conversion rate, making the curve flatter.*

Keyword Popularity. Keyword popularity reflects the size and scope of the market—less popular keywords are associated with niche (i.e., long-tail) markets, whereas more popular keywords are associated with mass (i.e., popular) markets. Agarwal and Mukhopadhyay (2016) suggest that sponsored listings that correspond to less popular keywords represent a distinguishable, niche choice set; Dewan and Ramaprasad (2012) note that a less popular product for a niche "long-tail" market involves greater uncertainty in the mind of the consumers compared with that for a mass market because popular products have more sources for product information, such as online review and word of mouth. Such uncertainty makes consumers more likely to use anchoring for product evaluation, as all product listings may provide relevant information. In addition, to the extent that preferences for niche ("long-tail market") are more heterogeneous (Dewan and Ramaprasad 2012), the product-listing results for niche keywords may provide idiosyncratic information, so consumers should have less need to use price as an indicator when evaluating a choice set with a variety of distinguishable qualities (Dalgic and Leeuw 1994). Meanwhile, in popular markets, the intense competition drives marketers to make the products and advertisements as competitive as possible—every option may appear equally attractive in design, function, and quality. Without an efficient way to narrow down the choice set, consumers rely more heavily on anchoring (Bagwell and Riordan 1991).

For the conversion rate, consumers who search for less popular keywords can retain a more independent judgment of the product, tend to have higher product involvement, and may hold more product knowledge (Jerath et al. 2014). For example, the keyword "Ciele running shoe" is less popular than "Nike running shoe," so consumers who search for the former likely are more involved in the running-shoe market, whereas consumers who search for the latter may simply be relying on the familiarity of a popular brand name. The elaboration likelihood model of persuasion (Haugtvedt and Petty 1992) argues that consumers with low involvement tend to use peripheral information processing, base their purchase decisions on peripheral cues that are easy to process (e.g., product price information), and make compromise decisions based on these peripheral cues. Meanwhile, consumers with high involvement tend to use central information processing, base their purchase decisions on more careful evaluations of product attributes, and are less likely to compromise (Petty and Cacioppo 1986). Therefore, consumers who search for popular keywords are more likely to use price rank to identify a compromise, strengthening the effect of price rank on the conversion rate.

Hypothesis 5. *Keyword popularity increases the U-shaped effect of price rank on the click-through rate, making the effect steeper.*

Hypothesis 6. *Keyword popularity increases the inverted U-shaped effect of price rank on the conversion rate, making the effect steeper.*

Study 1, The Seller's Perspective: Evidence from a Retail Search Engine

Research Context

The data set comes from one of the world's largest electronic shopping platforms, which features online-only stores with products in categories ranging from raw materials to finished goods. It serves more than 18 million buyers and sellers from more than 240 countries and regions. The platform offers PLA, and the bidding procedure occurred daily during the time of data collection. First, sellers select certain products to bid on and decide on the product description, price, product category keyword (i.e., the product category under which the product will be listed), and the CPC. Then, the platform determines the display list and rank using factors that are intended to ensure the relevance of the listed products; common considerations include the CPC, product relevance, and seller quality. Finally, the listed sellers pay the advertising platform based on the CPC and number of click-throughs.

After searching for a certain keyword, consumers encounter the search-results page, which features both organic and sponsored listings (Figure B1 in Online Appendix B). The sponsored advertisements appear in a separate vertical column alongside the column of organic listings; each page features up to eight sponsored advertisements, and each provides detailed product information: name, picture, unit price, and past sales. Consumers can click on the sponsored advertisement to view the product page, which features more detailed information (e.g., multiple pictures, consumer reviews, and original and current prices). Consumers may customize the sequence of the organic listings by applying filters, but the sponsored listings are unaffected.

For one month (June 2017), we collected advertising activities and consumer responses for the most active 969 keywords across 91 subcategories in four industries: home decoration and design (100 keywords; e.g., "decorative design"), healthcare (602 keywords; e.g., "foot massager"), DIY tools (212 keywords; e.g., "ultrasonic cleaner"), and gym equipment (55 keywords; e.g., "yoga mat"). Our data set contained 207,407 observations of sponsored advertisements that featured 6,534 products and 189 sellers. The average keyword received 7,692 searches, 2,775 clicks, and 201 conversions per day.

Key Measures

Searches, Clicks, and Conversions. We measured three key response variables daily. Following prior literature (e.g., Yang and Ghose 2010 and Rutz and Bucklin 2011), we define *search* as the daily number of searches for the focal keyword, *click* as the number of clicks that the focal ad received, and *conversion* as the number of purchases generated through clicks for the focal ad.

Price Rank and Display Rank. The price rank reflects how the price of the focal product compares to the prices of all sponsored advertisements. This variable is operationalized as a rank from one (the lowest price) to eight (the highest price). For convenience, we divide the ranking of price by the number of sponsored advertisements on the page, so the normalized variable *PriceRank* ranges from 1/8 to 1. The display rank is the position of the focal advertisement on the page; the topmost position is considered the most advantageous (Agarwal et al. 2011, Jerath et al. 2011). Again, we divide by the total number of sponsored advertisements, so *DisplayRank* ranges from 1/8 to one, with smaller values representing more advantageous positions.

Keyword Specificity and Popularity. Following the prior literature on keyword specificity (Agarwal et al. 2011, Yang et al. 2013), we count the number of modifiers, which might describe a feature, version, brand name, or function. We adapt the measure of keyword popularity from Jerath et al. (2014), which avoids the risk of multicollinearity (i.e., popular keywords tend to be less specific) by controlling for specificity using the rank of the search volume. That is, $Popularity_i = SearchRank_{ik}/N_k$, where N_k is the number of keywords with specificity k, and $SearchRank_{ik}$ is the rank of the search volume of keyword i among all keywords with the same specificity k. The descriptive statistics and details about the variables appear in Tables A3 and A4 in Online Appendix A.

Model Specification

We cast our simultaneous model in a hierarchical Bayesian framework. For keyword i at time t, the advertisement j receives n_{ijt} clicks and m_{ijt} conversions out of N_{ijt} searches, where $0 \le m_{ijt} \le n_{ijt} \le N_{ijt}$. We define the probability of a click as p_{ijt} and the probability of conversion as q_{ijt}. In our model, the two consumers' decisions—whether to click and whether to convert—yield three possible outcomes: a click followed by conversion ($p_{ijt}q_{ijt}$), a click with no conversion ($p_{ijt}(1 - q_{ijt})$), and no click ($1 - p_{ijt}$). The probability of observing (n_{ijt}, m_{ijt}) is given by

$$f(m_{ijt}, n_{ijt}, p_{ijt}, q_{ijt}) = \frac{N_{ijt}!}{(N_{ijt} - n_{ijt})!(n_{ijt} - m_{ijt})!m_{ijt}!} \quad (1)$$
$$(1 - p_{ijk})^{N_{ijt}-n_{ijt}}[p_{ijk}(1 - q_{ijk})]^{n_{ijt}-m_{ijt}}(p_{ijk}q_{ijk})^{m_{ijt}}.$$

The Consumer's Decision to Click. Following prior literature (Ghose and Yang 2009, Jerath et al. 2014), we model the click-through rate as a function of the observed heterogeneities *Specificity*, *Popularity*, *PriceRank*, *Price*, and *DisplayRank*, as well as the observed and unobserved keyword- and time-level heterogeneities. When consumers encounter sponsored advertisements, they compare the products and decide whether to click on one or more. The probability of click p_{ijt} by the latent consumer utility function U_{ijk}^{click} can be modeled as a multinomial choice model, with

$$p_{ijt} = \frac{\exp(U_{ijt}^{click})}{1 + \sum_{k \in K_{it}} \exp(U_{ikt}^{click})}, \quad (2)$$

and

$$U^{click}_{ijt} = \alpha_{0i} + \alpha_{1i}PriceRank_{ijt} + \alpha_{2i}PriceRank^2{}_{ijt} + \alpha_3 Specificity_i + \alpha_4 Popularity_i + \alpha_5 DisplayRank_{ijt} + \alpha_6 Price_{ijt} + \alpha_{7-13}\boldsymbol{X_{ijt}} + \delta^{click}_t + \theta^{click}_j + \eta_{ijt}. \quad (3)$$

In these equations, δ^{click}_t is the random effect of time t, θ^{click}_j is the random effect of the seller, and K_{it} is the set of ads that appears in the search results. $\boldsymbol{X_{ijt}}$ is a vector of observed covariates: the average organic price, average sponsored price, keyword length, cumulative past sales, length of the advertisement title, and two dummy variables indicating whether keyword i contains certain brand names and promotions. To capture keyword-level heterogeneity, we use random coefficients for the intercept and *PriceRank*.

$$\begin{bmatrix}\alpha_{0i}\\ \alpha_{1i}\\ \alpha_{2i}\end{bmatrix} = \begin{bmatrix}\bar{\alpha}_0\\ \bar{\alpha}_1\\ \bar{\alpha}_2\end{bmatrix} + \begin{bmatrix}0 & 0\\ \alpha_{11} & \alpha_{12}\\ \alpha_{21} & \alpha_{22}\end{bmatrix} \times \begin{bmatrix}Specificity_i\\ Popularity_i\end{bmatrix} + \begin{bmatrix}\xi^{\alpha}_{0i}\\ \xi^{\alpha}_{1i}\\ \xi^{\alpha}_{2i}\end{bmatrix}. \quad (4)$$

$$\left(\xi^{\alpha}_{0i}, \xi^{\alpha}_{1i}, \xi^{\alpha}_{2i}\right) \sim \mathrm{MVN}(\mathbf{0}_{1\times 3}, \boldsymbol{\Sigma}^{\boldsymbol{\alpha}}_{3\times 3}). \quad (5)$$

The Consumer's Decision to Convert. The keyword advertising literature suggests that conversion rates vary across keywords (*Specificity* and *Popularity*) and display rank (Yang and Ghose 2010, Rutz et al. 2012). Consumers in our research context must click to observe the volume of online reviews, ratings, and discount rate, so these variables are exogenous to the click behavior. After clicking on a sponsored advertisement, consumers decide whether to convert. The probability of conversion, q_{ijt}, can be modeled as:

$$q_{ijt} = \frac{\exp(U^{conv}_{ijt})}{1 + \exp(U^{conv}_{ijt})}, \quad (6)$$

and

$$U^{\mathrm{conv}}_{\mathrm{ijt}} = \beta_{0i} + \beta_{1i}PriceRank_{ijt} + \beta_{2i}PriceRank^2{}_{ijt} + \beta_3 Specificity_i + \beta_4 Popularity_i + \beta_5 DisplayRank_{ijt} + \beta_6 Price_{ijt} + \beta_7 Volume_{ijt} + \beta_8 Rating_{ijt} + \beta_9 DiscountRate_{jt} + \beta_{10-16}\boldsymbol{X}_{ijt} + \delta^{\mathrm{conv}}_t + \theta^{\mathrm{conv}}_j + e_{ijt}, \quad (7)$$

where δ^{conv}_t is the random effect of time t and θ^{conv}_j is the random effect of the seller of advertisement j. We again capture unobserved keyword-level heterogeneity with a random coefficient:

$$\begin{bmatrix}\beta_{0i}\\ \beta_{1i}\\ \beta_{2i}\end{bmatrix} = \begin{bmatrix}\bar{\beta}_0\\ \bar{\beta}_1\\ \bar{\beta}_2\end{bmatrix} + \begin{bmatrix}0 & 0\\ \beta_{11} & \beta_{12}\\ \beta_{21} & \beta_{22}\end{bmatrix} \times \begin{bmatrix}Specificity_i\\ Popularity_i\end{bmatrix} + \begin{bmatrix}\xi^{\beta}_{0i}\\ \xi^{\beta}_{1i}\\ \xi^{\beta}_{2i}\end{bmatrix}, \quad (8)$$

and

$$\left(\xi^{\beta}_{0i}, \xi^{\beta}_{1i}, \xi^{\beta}_{2i}\right) \sim \mathrm{MVN}(\mathbf{0}_{1\times 3}, \boldsymbol{\Sigma}^{\boldsymbol{\beta}}_{3\times 3}). \quad (9)$$

The Seller's Decision on Price Rank. Next, we model the seller's strategic price-rank decision. Following Rutz et al. (2011), we adopt a latent instrumental variable (LIV) to capture omitted variances that might lead to endogeneity. The LIV decomposes the endogenous covariate into a systematic part (i.e., exogenous part; does not correlate with the error) and an endogenous part (possibly correlated with the error). This approach allows for unbiased estimation of the effect of an endogenous variable when the instrumental variables are unobserved, weak, or invalid (see Online Appendix D for a detailed description). We assume that λ_{ijt} follows a multinomial distribution with probability $(\pi_1, \pi_2, \ldots, \pi_n)$, where π_c is the probability that the cth ($c = 1, 2, \ldots, n$) latent category fits the observation, and $\sum_{i=1}^{n}\pi_i = 1$; ω is an n-dimensional vector containing the latent category means. The number of latent categories is determined empirically by the model fit. Thus, we model *PriceRank* as a function of the LIV and the random effects of time t and seller j.

$$PriceRank_{ijt} = \lambda_{ijt}\omega + \delta^{Pricerank}_t + \theta^{Pricerank}_j + v_{ijt}. \quad (10)$$

The Seller's Decision on Price. Sellers determine the advertised price after learning their display rank, so they can adjust the price to achieve a competitive price rank. We include the number of bid keywords and the number of advertised prices offered by seller j at time t (i.e., $KeywordNum_{jt}$ and $ProductNum_{jt}$) to capture an omitted seller strategy. Thus, we model *Price* as:

$$Price_{ijt} = \Psi_0 + \Psi_1 Specificity_i + \Psi_2 Popularity_i + \Psi_3 DisplayRank_{ijt} + \Psi_4 Volume_{ijt} + \Psi_5 Rating_{ijt} + \Psi_6 DiscountRate_{ijt} + \Psi_7 p_{ijt-1} + \Psi_8 q_{ijt-1} + \Psi_9 KeywordNum_{jt} + \Psi_{10} ProductNum_{jt} + \Psi_{11} Price_{ijt-1} + \Psi_{12} PriceRank_{ijt-1} + \Psi_{13-19}\boldsymbol{X_{ijt}} + \delta^{Price}_t + \theta^{Price}_j + \tau_{ijt}. \quad (11)$$

The Seller's Decision on Display Rank. Finally, sellers consider their advertising performance from their previous bid when pursuing the optimal advertising position in their next bid. The platform determines the final display rank based on the CPC, relevance of the product, and quality index of the seller. Thus, we model *DisplayRank* as:

$$DisplayRank_{ijt} = \varphi_0 + \varphi_1 Specificity_i + \varphi_2 Popularity_i + \varphi_3 Volume_{ijt} + \varphi_4 Rating_{jjt} + \varphi_5 p_{ijt-1} + \varphi_6 q_{ijt-1} + \varphi_7 KeywordNum_{jt} + \varphi_8 ProductNum_{jt} + \varphi_9 Price_{ijt-1} + \varphi_{10} PriceRank_{ijt-1} + \varphi_{11} DisplayRank_{ijt-1} + \varphi_{12-18}\boldsymbol{X_{ijt}} + \delta^{rank}_t + \theta^{rank}_j + u_{ijt}. \quad (12)$$

To account for unobserved covariates and endogeneity, we also allow the five error terms to correlate:

$$\left(\eta_{ijt},\ \varepsilon_{ijt},\ v_{ijt},\ \tau_{ijt},\ \mu_{ijt}\right) \sim \mathrm{MVN}(\mathbf{0}_{1\times 5},\ \mathbf{\Omega}_{5\times 5}). \quad (13)$$

Identification

Endogeneity issues might arise due to omitted variables that affect the price rank, click-through rate, and conversion rate. We consider three potential omitted variables. First, product quality might affect the seller's desired keywords and desired display rank. Second, the seller's strategy might drive the advertised product price, price rank, and/or display rank. Third, the competition's strategy might affect the focal product's display rank, price rank, and advertising outcomes. We sketch the model using the following simultaneous equations:

$$p_{ijt} = f(PriceRank_{ijt}, Price_{ijt}, DisplayRank_{ijt}, \boldsymbol{X}^{p}_{ijt}, \eta_{ijt}), \quad (14)$$

$$q_{ijt} = f(PriceRank_{ijt}, Price_{ijt}, DisplayRank_{ijt}, \boldsymbol{X}^{q}_{ijt}, \varepsilon_{ijt}), \quad (15)$$

$$PriceRank_{ijt} = f(\gamma_{ijt}\omega, v_{ijt}), \quad (16)$$

$$Price_{ijt} = f(DisplayRank_{ijt}, \boldsymbol{X}^{price}_{ijt}, \tau_{ijt}), \quad (17)$$

and

$$DisplayRank_{ijt} = f(\boldsymbol{X}^{rank}_{ijt}, \mu_{ijt}), \quad (18)$$

where X^{p}_{ijt}, X^{q}_{ijt}, X^{price}_{ijt}, and X^{rank}_{ijt} are covariates that include exogenous variables. Within this system, omitted product quality is captured by cumulative past sales (*PastSales*), as well as the review volume and ratings (observable only to consumers who click). The seller's previous observations (i.e., lagged terms) are unobserved and exogenous to the consumer's decisions, whereas the seller's strategic choices (i.e., advertised product numbers and the number of keywords) affect the price and display ranks and, conditional on product price, are exogenous to price rank. We use $\lambda_{ijt}\omega$ to represent the LIV, designed to capture the influences of omitted variables. The error terms capture omitted information observed by decision makers (consumers, sellers, and the platform), but not the researchers.

Finally, another potential endogeneity concern involves keyword popularity, which can affect how sellers design advertisements and how buyers react to them. We adopt a two-step estimation process, which requires an instrumental variable that satisfies the exclusion restriction condition. We use the predicted percentage change in the search volume, which is provided by the online shopping platform. The platform generates this prediction using information collected across all major search engines. This variable is exogenous to the click-through and conversion rates because (1) the predicted popularity changes are not observed by consumers, only by the platform and participating sellers; and (2) the predicted popularity change correlates with actual popularity because the predictions are based on statistical models that use current keyword popularity. We regress current popularity over the instrumental variable and other predetermined keyword-level covariates. First-step results suggest that the predicted search volume change significantly correlates with popularity ($\beta = 0.092$, $p < 0.01$) with a good model fit ($R^2 = 0.508$). We verify the validity of the instrumental variable with the Durbin-Wu-Hausman test through an augmented regression test (Davidson and MacKinnon 1993), and we find that the instrumental variable significantly changes the estimation results for both outcomes (click-through rate: F-statistics = 31.37, $p < 0.01$; conversion rate: F-statistics = 52.44, $p < 0.01$). As the second step, we replace the popularity measure with the predicted value from the first-stage regression in the main model.

Estimation Results

We adopt a Markov Chain Monte Carlo (MCMC) method to estimate our proposed model. We draw samples from the posterior distribution of 40,000 iterations following a burn-in of 40,000 iterations, and we save every 40th draw to avoid autocorrelations (see Online Appendix C for the MCMC algorithm). To determine the appropriate number of LIVs, we test the models with two to five latent categories; the model with two latent categories provides the best fit (Tables A5 and A6, Online Appendix A). The estimated categorical means (ω) are −7.834 and 1.082, and the categorical probabilities (π) are 0.301 and 0.699, respectively. The separate LIV categorical means and nonextreme probabilities indicate the effectiveness of the LIV, following a bimodal distribution (Ebbes et al. 2005). We find significant covariance between outcomes and endogenous covariates (price rank, price, and display rank) in the estimated variance-covariance matrix (Tables A7 and A8, Online Appendix A), indicating that the proposed model captures the endogeneity introduced by unobserved factors.

Table 1 presents the estimation results of the proposed model (model 4) along with the results of a few benchmark models. The LIV-only model has the best model fit, suggesting that the LIV can account for the endogeneity issue of price rank. Price rank has a negative first-order term ($\bar{\alpha}_1 = -2.117$, $p < 0.01$) and positive second-order term on the click-through rate ($\bar{\alpha}_2 = 1.786$, $p < 0.01$), indicating a U-shaped effect—that is, products with more extreme prices (i.e., higher or lower than most alternatives) receive more clicks from keyword searches, in support of Hypothesis 1. By contrast, price rank has a positive first-order effect

Table 1. Estimation Results

	Model 1 w/o endogeneity correction		Model 2 simultaneous equations		Model 3 simultaneous equations and LIV		Model 4 LIV-only	
Dependent variable	Click-through rate	Conversion rate	Click-through rate	Conversion rate	Click-through rate	Conversion rate	Click-through rate	Conversion rate
Main effects								
Price Rank	**−1.970 (0.095)**	**1.793 (0.100)**	**−2.398 (0.088)**	**1.519 (0.101)**	**−2.023 (0.185)**	**1.793 (0.124)**	**−2.117 (0.082)**	**1.534 (0.100)**
Price Rank^2	**1.537 (0.086)**	**−1.531 (0.089)**	**1.837 (0.082)**	**−1.297 (0.091)**	**1.524 (0.089)**	**−1.359 (0.095)**	**1.786 (0.079)**	**−1.297 (0.089)**
Moderating effects								
Price Rank × *Specificity*	**1.069 (0.074)**	**−0.877 (0.075)**	**1.201 (0.066)**	**−0.777 (0.092)**	**1.009 (0.059)**	**−0.808 (0.080)**	**1.136 (0.072)**	**−0.763 (0.093)**
Price Rank^2 × *Specificity*	**−0.824 (0.072)**	**0.853 (0.068)**	**−1.178 (0.065)**	**0.751 (0.084)**	**−0.872 (0.057)**	**0.782 (0.074)**	**−1.106 (0.070)**	**0.739 (0.085)**
Price Rank × *Popularity*	**−0.847 (0.102)**	**0.445 (0.090)**	**−0.797 (0.085)**	**0.418 (0.089)**	**−0.524 (0.081)**	**0.409 (0.097)**	**−0.718 (0.076)**	**0.396 (0.099)**
Price Rank^2 × *Popularity*	**0.834 (0.098)**	**−0.461 (0.082)**	**0.526 (0.081)**	**−0.447 (0.080)**	**0.545 (0.077)**	**−0.436 (0.090)**	**0.642 (0.073)**	**−0.440 (0.088)**
Control variables								
Specificity	**−0.614 (0.114)**	**0.479 (0.048)**	**−0.668 (0.056)**	**0.438 (0.059)**	**−0.546 (0.066)**	**0.453 (0.052)**	**−0.632 (0.106)**	**0.434 (0.063)**
Popularity	**0.148 (0.058)**	**−0.121 (0.052)**	**0.470 (0.048)**	**−0.104 (0.051)**	**0.243 (0.040)**	**−0.109 (0.054)**	**0.406 (0.041)**	**−0.193 (0.057)**
Price	**−0.622 (0.010)**	**−0.430 (0.013)**	**−1.064 (0.009)**	**−0.513 (0.014)**	**−1.187 (0.047)**	**−0.840 (0.077)**	**−1.091 (0.009)**	**−0.513 (0.014)**
Display Rank	**0.231 (0.015)**	**−0.152 (0.016)**	**0.268 (0.017)**	**−0.124 (0.015)**	**0.298 (0.068)**	**−0.172 (0.019)**	0.005 (0.014)	**−0.137 (0.014)**
Keyword Length	−0.244 (0.125)	**0.115 (0.030)**	**0.397 (0.046)**	**−.122 (0.034)**	**0.424 (0.058)**	**0.118 (0.030)**	**0.227 (0.106)**	**0.120 (0.032)**
Promotion	**−0.321 (0.025)**	−0.061 (0.042)	**−0.142 (0.022)**	**−0.104 (0.037)**	−0.070 (0.042)	**−0.198 (0.047)**	**−0.281 (0.022)**	**−0.117 (0.036)**
Brand	−0.107 (0.295)	−0.032 (0.064)	**−0.466 (0.105)**	−0.026 (0.063)	**−0.498 (0.140)**	−0.029 (0.070)	**−0.446 (0.187)**	−0.031 (0.071)
Title Length	**0.076 (0.009)**	**0.070 (0.011)**	**0.030 (0.008)**	**0.070 (0.011)**	−0.020 (0.014)	**0.063 (0.011)**	**0.032 (0.008)**	**0.069 (0.011)**
Avg. Sponsor Price	**−0.150 (0.021)**	**0.095 (0.010)**	**0.052 (0.011)**	**0.074 (0.010)**	**1.251 (0.038)**	**0.101 (0.012)**	**−0.169 (0.016)**	**0.071 (0.010)**
Avg. Organic Price	**0.523 (0.022)**	**0.027 (0.008)**	**0.197 (0.011)**	**0.028 (0.008)**	**0.539 (0.011)**	**0.027 (0.008)**	**0.770 (0.020)**	**0.027 (0.008)**
Past Sales	**0.108 (0.015)**	**0.105 (0.025)**	**0.093 (0.032)**	**0.105 (0.025)**	**0.123 (0.023)**	**0.099 (0.024)**	**0.070 (0.012)**	**0.108 (0.025)**
Review Number		0.039 (0.022)		**0.045 (0.022)**		**0.039 (0.021)**		0.040 (0.023)
Discount Rate		**−0.065 (0.012)**		**−0.060 (0.011)**		**−0.085 (0.013)**		**−0.061 (0.011)**
Consistent Rating		**0.035 (0.016)**		**0.030 (0.015)**		0.026 (0.015)		**0.031 (0.015)**
DIC	99,302,185.646		97,017,769.434		106,205,630.177		96,230,936.741	

Notes. (1) To avoid the influence of the first-page bias (Agarwal et al. 2011) and incomparability of sponsored advertisements on later pages, we use only the samples displayed on the first page of the search results (i.e., the top eight positions). (2) Both specificity and popularity are standardized. (3) The model description indicates how the endogeneity of price rank was handled. (4) This table includes the posterior means and posterior standard deviations (in parentheses). (5) Estimates significant at 95% are bolded. (6) Two latent instrumental categories were adopted in models 3 and 4.

($\bar{\beta}_1 = 1.534$, $p < 0.01$) and a negative second-order effect on the conversion rate ($\bar{\beta}_2 = -1.297$, $p < 0.01$), indicating an inverse U-shaped effect—that is, products with moderate prices (relative to the alternatives) receive more conversions, in support of Hypothesis 2. When the price rank moves from extreme to moderate, the click-through rate decreases by 27.59% (from 4.54% to 3.29%), and the conversion rate increases by 26.71% (from 2.17% to 2.77%).

Table 1 also reveals the moderating effects of (standardized) keyword specificity and popularity. The U-shaped effect of price rank on the click-through rate is weakened by greater specificity ($\alpha_{11} = 1.136$, $p < 0.01$, first-order; $\alpha_{21} = -1.106$, $p < 0.01$, second-order) and enhanced by greater popularity ($\alpha_{12} = -0.718$, $p < 0.01$, first-order; $\alpha_{22} = 0.642$, $p < 0.01$, second-order), in support of Hypothesis 3 and Hypothesis 5, respectively. The inverted U-shaped effect of price rank on the conversion rate is enhanced by greater popularity ($\beta_{12} = 0.396$, $p < 0.01$, first-order; $\beta_{22} = -0.440$, $p < 0.01$, second-order) and weakened by greater specificity ($\beta_{11} = -0.763$, $p < 0.01$, first-order; $\beta_{21} = 0.739$, $p < 0.01$, second-order), in support of Hypothesis 4 and Hypothesis 6, respectively.

Figure 1 illustrates the evidence for Hypotheses 3–6. In panel (a), keyword specificity weakens consumers' tendency to click on extremely priced displays and, thus, minimizes the change in the click-through rate as the price rank moves from extreme to moderate: For low-specificity keywords, the click-through rate decreases by 39.54% (from 9.16% to 5.53%), but for high-specificity keywords, it decreases by only 12.10% (from 2.20% to 1.93%). In panel (b), keyword popularity augments the change in the click-through rate as the price rank moves from extreme to moderate: For low-popularity keywords, the click-through rate decreases by only 18.94% (from 2.88% to 2.33%), but for high-popularity keywords, it decreases by 34.93% (from 7.10% to 4.62%). In panel (c), keyword specificity weakens the change in the conversion rate: As the price rank changes from extreme to moderate, the conversion rate increases by 10.40% (from 3.59% to 3.96%) when keyword specificity is high and by 45.60% (from 1.31% to 1.91%) when keyword specificity is low. In panel (d), keyword popularity augments the change in the conversion rate: As the price rank moves from extreme to moderate, the conversion rate increases by 37.58% (from 1.71% to 2.36%) when keyword popularity is high and by only 16.57% (from 2.76% to 3.22%) when keyword popularity is low.

Robustness Checks

To test the robustness of the results, we conduct additional robustness checks regarding (1) alternative predictors, (2) lagged differences, and (3) the price rank among sponsored and organic listings combined. The details of the robustness checks and results are reported in Online Appendix E.

Post Hoc Analysis: Price vs. Price Rank

To further investigate the effects of price rank and actual price, we extend the proposed model by adding log(price), its quadratic term, and their interactions with the two keyword attributes (see Online Appendix F for details). We use the estimation results to simulate the outcomes for four categories of keywords: niche-general (low popularity, low specificity), niche-specific (low popularity, high specificity), popular-general (high popularity, low specificity), and popular-specific (high popularity, high specificity).

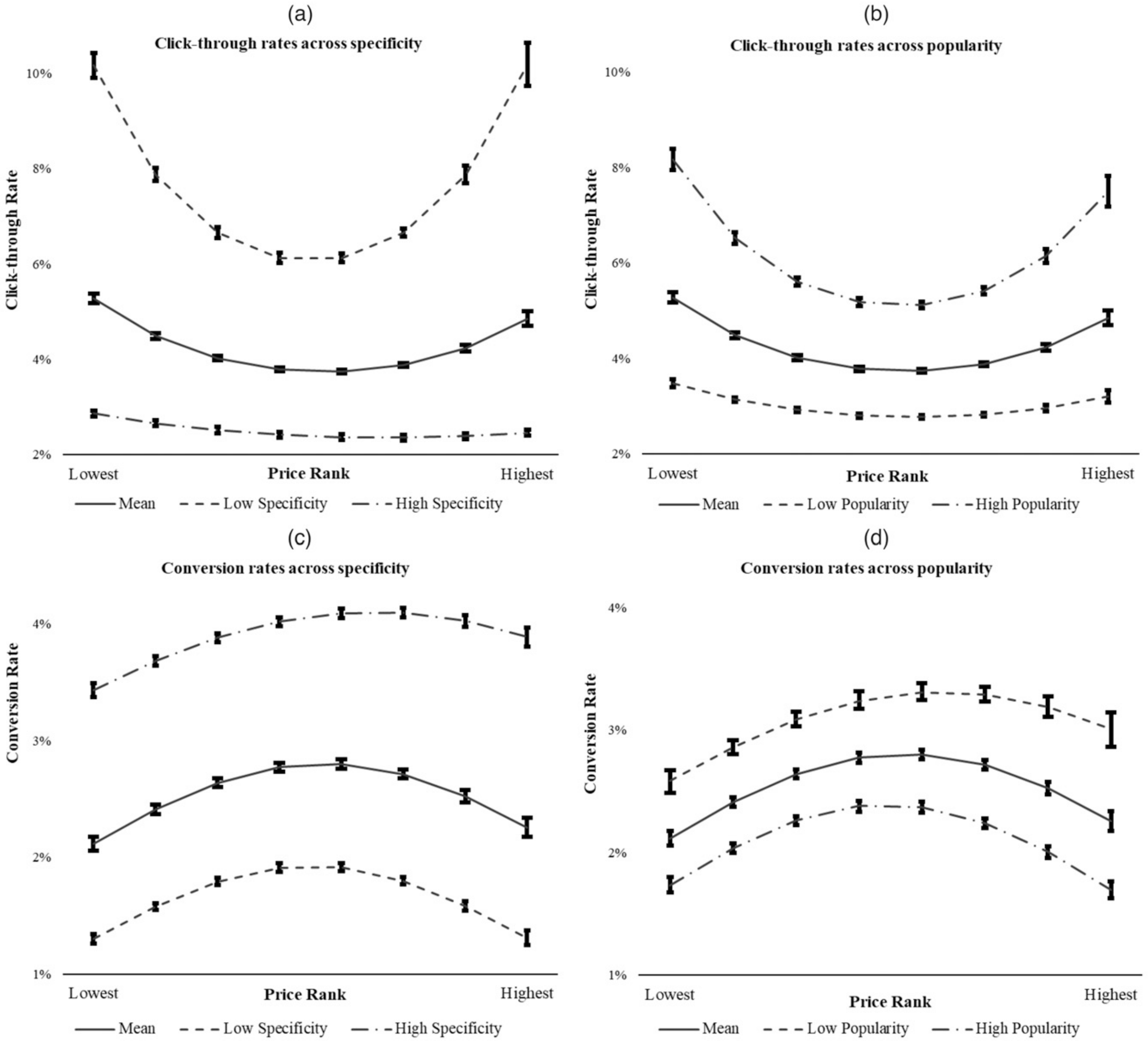
Table 2 presents the simulation results. A comparison of the coefficients of the click-through and conversion rates reveals that the price rank is more influential than the actual price. Holding price rank constant, both the click-through rate (columns (1) and (3)) and conversion rate (columns (2) and (4)) are optimized by low prices across all four keyword categories and price ranks, but the influence is trivial (a 10% price change leads to a less than 0.15% change in the click-through and conversion rates). In addition, although low prices are appealing in all four keyword categories, a lower price rank is not always preferable. Overall, the post hoc analysis suggests that differences in click-through and conversion rates are driven primarily by price rank rather than by actual price.

We interpret this finding in relation to prior studies on two reference price effects: past experience and context (Rajendran and Tellis 1994, Mazumdar et al. 2005). A change in the product price may affect the attractiveness of a product via comparisons with the product's historical prices—which are salient only to consumers who have past experience with the product. A change in the price rank instead may affect consumers' perceptions of the context and relevant comparisons. In the PLA context, consumers likely have little information about historical prices, so we anticipate a greater influence of reference price effects due to the context (in this case, the price rank).

Summary and Discussion

We reveal asymmetric effects of price rank on the click-through and conversion rates such that consumers generally are more likely to click on extremely priced options, but more likely to purchase moderately priced options. For the click-through rate, the advantage of an extreme price rank is smaller for more specific keywords and greater for more popular keywords. For the conversion rate, the disadvantage of an extreme price rank is especially notable for more popular keywords and weaker for more specific keywords. The post hoc analysis suggests that in the

Figure 1. The Effects of Price Rank



Notes. (1) The images were drawn based on the estimation results in Table 1. (2) High/low specificity and popularity are defined as one standard deviation above/below the mean. (3) The error bars indicate the range of 95% confidence intervals in posterior values.

context of PLA, the price rank has a stronger impact on advertising performances than the actual price.

Study 2, the Consumer's Perspective: Evidence from an Experiment

The objectives of study 2 are twofold. First, we seek to add confidence to the findings of study 1 by addressing potential endogeneity concerns due to selection bias and omitted variables. Second, we use simulated clickstream data to investigate the underlying mechanisms of the effects of price rank. With this experiment, we exogenously determine three key endogenous variables (price rank, advertised price, and display rank) from study 1, and we also track consumer clickstreams to monitor both search and purchase behaviors.

Method

Participants and Design. A total of 310 respondents (34.84% women) were recruited from Amazon's Mechanical Turk and randomly assigned to one of two experimental conditions: *search-only* and *search-and-buy*. In the search-only condition, participants evaluated seven search advertisements and predicted the price of a new product. In the search-and-buy condition, participants evaluated seven search advertisements and chose

Table 2. Post Hoc Analysis

Panel A: Niche-general keywords and popular-general keywords

		(1) CTR	(2) CR	(3) CTR	(4) CR
Price rank	Price adjustment, %	Niche-general keywords, %		Popular-general keywords, %	
Low	−10	1.869	1.869	3.213	2.322
	0	1.844	1.850	3.202	2.299
	+10	1.818	1.831	3.192	2.275
Medium	−10	1.545	2.125	2.333	2.737
	0	1.524	2.103	2.324	2.710
	+10	1.503	2.082	2.317	2.683
High	−10	1.690	1.994	2.532	2.350
	0	1.667	1.974	2.522	2.326
	+10	1.644	1.954	2.515	2.302

Panel B: Niche-specific keywords and popular-specific keywords

		(1) CTR	(2) CR	(3) CTR	(4) CR
Price rank	Price adjustment, %	Niche-specific keywords, %		Popular-specific keywords, %	
Low	−10	4.373	2.303	7.384	2.859
	0	4.260	2.300	7.266	2.855
	+10	4.148	2.296	7.155	2.850
Medium	−10	4.292	2.426	6.389	3.123
	0	4.182	2.423	6.286	3.118
	+10	4.071	2.419	6.189	3.113
High	−10	4.350	2.564	6.431	3.019
	0	4.238	2.560	6.327	3.014
	+10	4.126	2.556	6.229	3.009

Notes. (1) Niche/popular and specific/general represent high/low values of specificity and popularity, respectively, set as one standard deviation above/below the mean. (2) Low, medium, and high levels represent the 25th, 50th, and 75th percentiles of the price rank. (3) The values −10%, 0%, and 10% represent the percentage change in the product price, given the price rank. (4) Coefficients that are insignificant at a 90% level are equal to zero.

one product to purchase. To ensure that participants would take the hypothetical scenario seriously, we informed participants that their payment would be based on their task performance.[1] We excluded 11 participants who failed to make decisions and 64 participants who bought a product without conducting a search, leaving 235 valid observations.

Procedure. The experimental web page featured seven search advertisements, ostensibly elicited by a search for the keyword "cat stand." All seven advertisements mimicked actual sponsored keyword advertisements on Amazon.com (Figures B2 and B3, Online Appendix B). The product prices ranged from $25.80 to $94.98, and the advertisements provided basic information such as a picture, review volume, and average rating. To avoid position effects, the sequence of the seven advertisements was randomized between participants. We ruled out potential review influences by holding the average rating constant and making the review volumes approximately the same (around 450 reviews) to mimic a more realistic situation. To account for the influence of other unrandomized product-specific information, we used a variable $Design_{ik}$ to measure consumer interest.

Participants could click on any of the seven advertisements to view a detailed product page. Platform-level labels (e.g., a tag that indicates "Amazon's choice") on the product pages were the same across the seven alternatives. From each product page, participants could choose to "return to the main page"; in the search-and-buy condition, participants also could choose to "buy this product." Participants who clicked "return to the main page" could review as many of the seven search advertisements as they wanted. In the search-and-buy condition, participants who clicked "buy this product" left the website as they had made their final decision. Finally, participants completed items to measure the covariates and some demographic questions.

Measurement and Model

Measures. The dependent variables are participants' clickstreams and purchase decisions. The clickstream comprises all clicks, with the exception of the final click (i.e., the conversion) in the search-and-buy condition. The sequence of clicks, $Stream_{ij}$, ranges from zero to one and is defined as the click sequence j divided by consumer i's total number of clicks N_i ($Stream_{ij} = \frac{j-1}{N_i-1}$, $j = 1, \ldots, N_i$); $Stream_{ij} = 0$ for the first click and $Stream_{ij} = 1$ for the last click (excluding the conversion). The summary statistics are reported in Table A9, Online Appendix A.

Model. We use a multinomial choice model to estimate clicks and conversions. Participants presumably decided among the seven alternatives with consideration for their search orientation, search phase, and other covariates: $Design_{ik}$, consumer i's interest in product k (without disclosure of the price), measured on a seven-point scale from "not interested" to "extremely interested"; $PreClick_{ijk}$, whether product k was clicked by consumer i prior to the jth click; and $Volume_{ijk}$, the review volume of product k on consumer i's jth click. The probability that consumer i's jth click was on a product with price rank k (P_{ijk}), according to the latent consumer utility function U_{ijk}, is:

$$P_{ijk} = \frac{\exp(U_{ijk})}{\sum_q \exp(U_{ijq})}, \quad (19)$$

where $q = 1, \ldots, 7$, and

$$U_{ijk} = \rho_{0k} + \rho_{1k} Stream_{ij} + \rho_2 Design_{ik} + \rho_3 PreClick_{ijk} + \rho_4 Volume_{ijk}. \quad (20)$$

The conversion model uses a similar framework:

$$U_{ik} = \varphi_{0k} + \varphi_1 Design_{ik} + \varphi_2 PreClick_{ik} + \varphi_3 Volume_{ijk}, \quad (21)$$

where $Stream_{ij}$ represents the sequence of the jth click, ranging from zero to one, within consumer i's clickstream; ρ_{0k} captures variations in the probability that product of price rank k appears in the first click; $\rho_{0k} + \rho_{1k}$ captures variations in the probability that product of price rank k appears in the last click; φ_{0k} captures variations in the probability that product k ultimately is purchased, all relative to the baseline; ρ_2 and φ_1 account for product heterogeneity other than price; ρ_3 and φ_2 capture the potential influence of repeated clicks to ensure that each click is independent of previous clicks; and ρ_4 and φ_3 capture the potential influence of the review volume.

Results

The multinomial choice model with the maximum-likelihood estimation produces the results in Table 3. Extremely priced products were more likely to be clicked at the beginning of the search process. Across conditions, products with extreme prices received more clicks than products with moderate prices in both the search-and-buy condition (extreme: $\rho_{01} = 1.188$, $p < 0.01$; $\rho_{07} = 1.183$, $p < 0.01$; moderate: $\rho_{03} = -0.766$, $p < 0.05$; $\rho_{04} = -1.532$, $p < 0.01$; $\rho_{05} = -1.092$, $p < 0.01$) and the search-only condition (extreme: ρ_{01}

Table 3. Estimated Results for Study 2

	Clicks				Conversions
	Search-and-buy		Search-only		
Variables	(1) Main	(2) Full	(3) Main	(4) Full	(5)
Rank1 (ρ_{01})	0.821 (0.173)***	1.188 (0.262)***	0.549 (0.180)***	0.953 (0.301)***	−1.184 (0.512)***
Rank3 (ρ_{03})	−0.442 (0.185)***	−0.766 (0.352)**	−0.721 (0.213)***	−0.950 (0.438)**	1.288 (0.311)***
Rank4 (ρ_{04})	−0.478 (0.194)***	−1.532 (0.441)***	−0.844 (0.217)***	−0.919 (0.437)**	1.304 (0.275)***
Rank5 (ρ_{05})	−0.170 (0.177)	−1.092 (0.370)***	−0.586 (0.205)***	−0.504 (0.390)	1.012 (0.297)***
Rank6 (ρ_{06})	0.147 (0.169)	−0.164 (0.300)	0.117 (0.188)	0.325 (0.328)	−0.316 (0.404)
Rank7 (ρ_{07})	0.776 (0.172)***	1.183(.261)***	0.398 (0.184)***	0.804 (0.306)***	−0.899 (0.449)***
Stream (ρ_{11})		−0.840 (0.451)*		−0.853 (.471)*	
Stream (ρ_{13})		0.501 (0.536)		0.360 (0.605)	
Stream (ρ_{14})		1.515 (.609)***		0.119 (0.609)	
Stream (ρ_{15})		1.564 (0.533)***		−0.130 (0.565)	
Stream (ρ_{16})		0.650 (0.470)		−0.392 (0.496)	
Stream (ρ_{17})		−0.990 (.458)**		−0.869 (0.483)*	
Design (ρ_2)	−0.001 (0.081)	−0.005 (0.083)	0.204 (0.093)**	0.200 (0.093)**	−0.026 (0.046)
PreClick (ρ_3)	−1.857 (0.162)***	−1.743 (0.161)***	−1.733 (0.180)***	−1.607 (0.182)***	−0.555 (0.233)**
Volume (ρ_4)	−0.005 (0.002)***	−0.006 (0.002)***	0.002 (0.002)	0.002 (0.002)	0.013 (0.003)***
R^2	0.085	0.118	0.076	0.082	0.036

Notes. Rank 2 is the baseline. Stage = 0 for the first click, and stage = 1 for the last click. The last click indicates a purchase for participants in the search-and-buy condition.
*$p < 0.10$; **$p < 0.05$; ***$p < 0.01$.

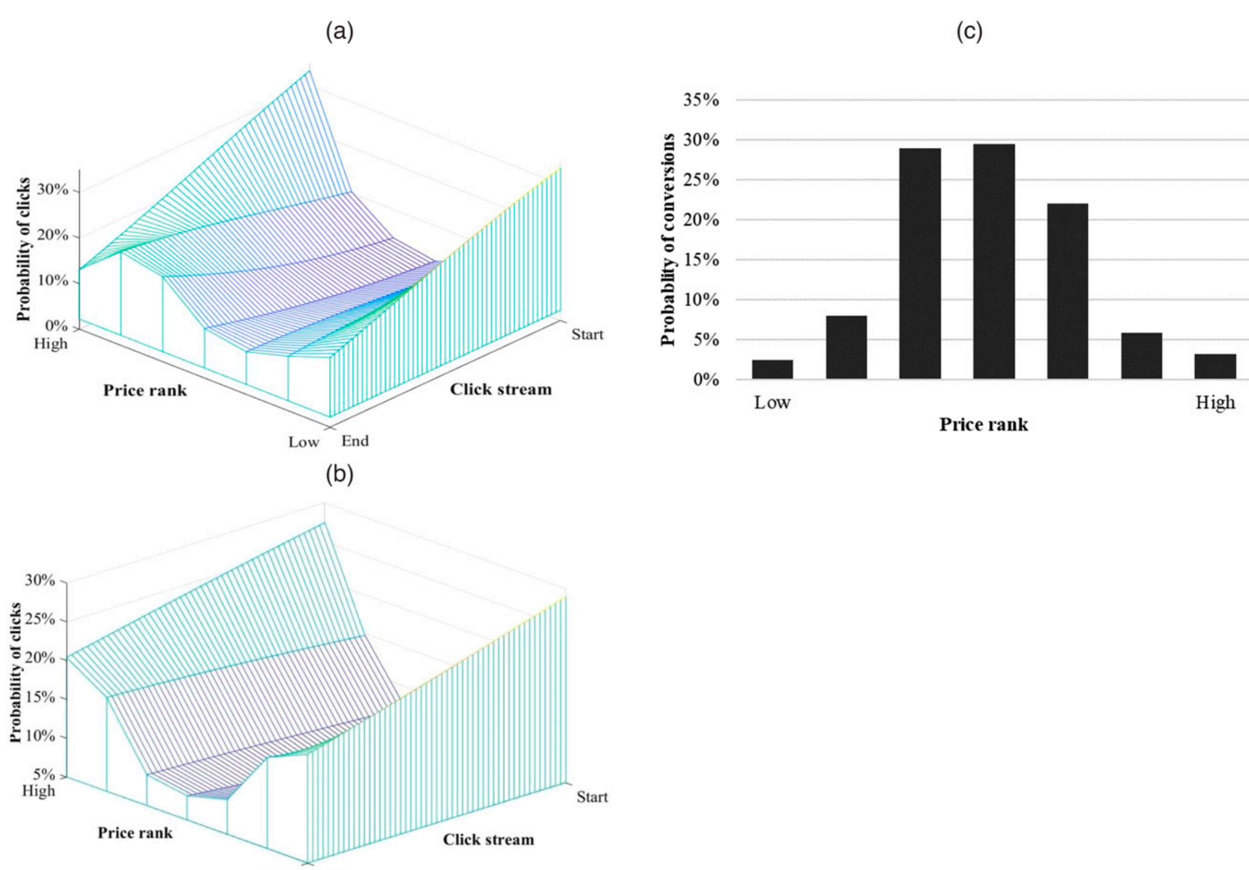
$= 0.953$, $p < 0.01$; $\rho_{07} = 0.804$, $p < 0.01$; moderate: $\rho_{03} = -0.950$, $p < 0.05$; $\rho_{04} = -0.919$, $p < 0.05$; $\rho_{05} = -0.504$, $p > 0.10$). Near the end of their clickstreams, however, participants in the search-and-buy condition displayed a preference reversal such that *Stream* positively affected the click probability of moderately priced products ($\rho_{14} = 1.515$, $p < 0.01$; $\rho_{15} = 1.564$, $p < 0.01$); this effect did not occur in the search-only condition ($\rho_{13} = 0.360$, $p > 0.10$; $\rho_{14} = 0.119$, $p > 0.10$; $\rho_{15} = -0.130$, $p > 0.10$). In addition, *Stream* negatively affected the click probability for extremely priced products in both conditions (search-and-buy: $\rho_{11} = -0.840$, $p < 0.10$; $\rho_{17} = -0.990$, $p < 0.05$; search-only: $\rho_{11} = -0.853$, $p < 0.10$; $\rho_{17} = -0.869$, $p < 0.10$). The estimation results for the conversion model (column (5), Table 3) suggest that participants preferred moderately priced products (φ_{03}=1.288, $p < 0.01$; $\varphi_{04} = 1.304$, $p < 0.01$; $\varphi_{05} = 1.012$, $p < 0.01$) over extremely priced alternatives ($\varphi_{01} = -1.184$, $p < 0.01$; $\varphi_{06} = -0.316$, $p > 0.10$; $\varphi_{07} = -0.899$, $p < 0.01$) when making their final purchase decisions.

Panels (a) and (b) of Figure 2 depict the dynamic nature of participants' click behaviors. At the beginning of the clickstream, participants in both conditions favored extremely priced options. As they progressed, however, participants in the search-and-buy condition (panel (a)) shifted toward moderately priced options, whereas participants in the search-only condition (panel (b)) continued to favor extremely priced products, though to a lesser extent. Panel (c) of Figure 2 illustrates the estimation results for the conversion model, in which participants showed a strong preference for moderately priced products. Moreover, participants' clicks prior to conversion tended to favor alternatives with moderate to high prices rather than moderate to low prices.

Summary and Discussion

The results of study 2 add confidence to our empirical findings from study 1 by verifying the mechanisms that underlie within-consumer variations in click behaviors across different consumer groups. The *search-only* participants, who represent consumers in the early stages of their search, tended to click on

Figure 2. (Color online) Estimated Results of Consumer Choices



Notes. (a) Decision funnel for participants in search-and-buy. (b) Decision funnel for participants in search-only conditions. (c) Estimated results for conversions.

extremely priced options throughout their search (but especially in the beginning). This pattern is consistent with our premise that anchoring is most relevant in the early stages, when consumers lack sufficient information and need reference points to develop preferences (Carpenter and Nakamoto 1989, Hoch and Deighton 1989). The *search-and-buy* participants, who represent consumers across the entire purchase funnel, had similarly ambiguous preferences in the early stages, so—like their search-only peers—they clicked on extremely priced products. After gaining reference points, search-and-buy consumers moved toward a decision and focused on the most viable compromises (i.e., moderately priced options). In sum, study 2 supports our theory that variations across decision phases cause consumers to display different price-rank preferences in their clicks and conversions.

Discussion

Search advertising is an important source of revenue for search engines and a vast advertising platform for online sellers. In this paper, we introduce PLA as a relatively new form of search advertising and show that firms can benefit from manipulating their products' price ranks and sponsored keywords according to their strategic goals.

Theoretical Implications

First, this paper contributes to the keyword-search advertising literature by investigating PLA as a recent advance. Prior research has examined aspects of keyword advertising, including the choice of keywords and optimal position to attract consumers and increase sales in a competitive online environment (Animesh et al. 2011, Agarwal and Mukhopadhyay 2016, Im et al. 2016, Gong et al. 2018). However, the existing literature does not necessarily generalize to PLA, in which search results provide more information (e.g., product type and price information) than is typical in other online sales environments. Second, we introduce price rank as a novel driver of advertising performance. Prior studies on price as a key driver of online buyers' behaviors (Oh and Lucas 2006, Hinz et al. 2011) are particularly relevant to PLA, as buyers can easily compare prices among advertised products in the same category. We find that price rank has a U-shaped effect on the click-through rate and an inverted U-shaped effect on the conversion rate. Both effects are weakened by keyword specificity and strengthened by keyword popularity. The analysis of clickstream data in study 2 confirmed the click and conversion patterns revealed in study 1. Our findings suggest that price rank is a unique determinant of clicks and conversions in PLA.

Third, we differentiate between clicks and conversions as the two outcomes that determine the effectiveness of online advertising. Specifically, we demonstrate a tradeoff between clicks and conversions that varies across the purchase funnel. Both studies show that clicks—from consumers in search of generic information—tend to favor the extremely priced options, particularly in the early stages of the purchase funnel. Consumers click on extremely priced options to develop anchors that inform their preferences and assessments of other alternatives. By contrast, conversions—a form of deeper engagement that comes at the end of the purchase funnel—favor moderately priced options, which represent feasible tradeoffs (i.e., compromises) between price and quality.

Finally, although keyword specificity and popularity are known to influence consumers' click and purchase decisions (Jerath et al. 2014, Lu and Zhao 2014, Agarwal and Mukhopadhyay 2016), we show that these keyword attributes are boundary conditions of the effects of price rank on consumers' responses to PLA. Furthermore, these keyword attributes can differentiate market segments based on the consumers' needs for anchoring and compromise. Consumers who use specific keywords are more likely to have well-developed preferences and background knowledge; consumers who use popular keywords are likely part of a larger segment, such as a mass market. The moderating effects of keyword specificity and popularity highlight how these two attributes can differentiate consumers' responses (i.e., clicks and conversions) to price rank in sponsored advertisement lists. These different consumer segments differ in their need for anchoring versus compromise options. Advertisements prompted by more specific keywords are less likely to be affected by price comparisons, so the anchoring and compromise effects of price rank diminish. By contrast, consumers who use popular keywords encounter a wider array of alternative options, so the anchoring and compromise effects of price rank increase. The empirical results highlight the distinct natures of the two moderators: Specific keywords are deployed by consumers who are more engaged and averse to extremes, whereas popular keywords reflect competition in the choice set and are used by consumers who rely more heavily on market signals such as product prices.

Managerial Implications

Firms that regularly and repeatedly participate in PLA may need to adjust their advertising offers to improve their results. Given that PLA provides detailed product and price information and allows side-by-side comparisons of competing products in the same category, managers should acknowledge that the displayed price and, by extension, the price rank have nuanced effects on consumer behaviors. We provide three managerial implications for firms that participate in PLA.

First, firms constantly adjust product prices to improve their sales performance; our results reveal that the price rank, too, should be considered and optimized in that the price rank drives the click-through and conversion rates. Thus, firms should closely monitor their products' rankings within the search results. In practice, sellers can use a variety of commercial ad scanners (e.g., Prisync and PriceZag) to monitor their competitors' advertisements. Furthermore, advertising platforms such as Amazon.com offer an automatic pricing system that helps sellers optimize their prices relative to their competitors'. To assess the prevalence of price-adjustment strategies, we conducted an online survey of 244 sellers that participate in PLA on one of the largest e-commerce platforms. These sellers represent a variety of industries (e.g., clothing, home electronics, computers and peripherals, food and grocery, and beauty and health), and a large majority (87%) indeed monitor the price ranks of their products.

Second, we highlight a tradeoff embedded in price-rank decisions: A price rank that drives more clicks does not necessarily lead to more conversions (i.e., sales). Thus, managers should develop differentiated strategies that target one of the two broad objectives: either driving traffic or maximizing revenue. To drive traffic, managers should strive for an extreme (i.e., either high or low) price rank to elicit more clicks to the firm's web store; the firm can then follow up with online consumer-engagement tools such as cross-selling, product recommendations, and promotions. To maximize direct revenue from PLA, managers instead should strive for a moderate rank to satisfy consumers' desire for a compromise between price and quality that offers the highest overall value. The survey of 244 sellers also asked about the primary purpose of a recent product that had participated in PLA. We found that 70% of the products were intended to drive revenue, whereas 30% were intended to drive traffic. Of the revenue-driving products, a majority were intended to have a moderate price rank (moderate: 54%, high: 30%, low: 16%); of the traffic-driving products, a majority tend to have an extreme price rank (low: 60%, high: 25%, moderate: 15%).

Third, further analysis of our data set suggests two specific avenues for achieving the desired price rank: Change the product price if the required change is within a certain range or change the advertised product if the required price change is beyond a certain range. We caution that this paper does not explicitly address how a firm can "strategically" adjust price rank to achieve its objectives, but our model-free evidence and online survey offer some implications. Of the surveyed sellers that monitor price rank, 82% reported adjusting their bidding strategy for better outcomes. In about 30% of the observations, sellers continued to advertise the same product, but changed the price within 10% to achieve a different price rank; the correlation between the change in price (i.e., $Price_t - Price_{t-1}$) and change in price rank (i.e., $PriceRank_t - PriceRank_{t-1}$) is 0.208. For instance, a seller of electric massagers initially had the second-to-lowest price rank at 96 CNY ($14.76) and then reduced the price to 95 CNY ($14.62) to achieve the lowest rank. Alternatively, 32% of the sellers changed the advertised product (e.g., premium versus basic version, with a price difference ranging from −90% to +900%) to achieve the desired price rank; the correlation between the change in price (i.e., $Price_t - Price_{t-1}$) and change in price rank (i.e., $PriceRank_t - PriceRank_{t-1}$) is 0.314. For example, a seller of ultrasound cleaners initially listed a basic version, among eight alternatives, ranked second-lowest (somewhat extreme) at 1,015 CNY ($156.15), and then switched to a premium version, ranked third-highest (relatively moderate) at 2,508 CNY ($385.85).

The results of our survey also provide some anecdotal evidence. Many of the sellers reported using these strategies—of the 82% of sellers that often adjust the bidding strategy to achieve a different price rank, 31% usually adjust the product price, 40% usually bid a different product for the same keyword or same product for a different keyword, and 29% use a combination of the two strategies. These results provide anecdotal evidence that sellers adjust their PLA bidding strategies to manipulate price rank and achieve better outcomes.

Managers can also leverage keyword specificity and popularity as segmentation tools and then strategically adjust the product price or choose a product in a different price range to compete effectively in PLA. The results of our post hoc analysis across four combinations of keyword specificity and popularity Table 2 offers specific suggestions. For example, if firms target a consumer segment using popular, general keywords, they can increase the absolute number of clicks and conversions with an extreme (ideally, low) price rank. It also is possible to improve the efficiency of search advertising with a moderate price rank, but price rank matters less for consumer segments that use niche, specific keywords.

Limitations and Further Research

This study offers essential insights into the effects of price rank and the moderating roles of two keyword attributes, and its limitations suggest opportunities for future research. Although we focus on price rank, PLA contains many additional types of information, such as review comments and temporary promotions, that are critical inputs for online consumers' purchase decisions. Research that incorporates these diverse aspects of online environments could deepen the understanding of consumers' responses to PLA. Further, although this paper focuses on a static PLA context (i.e., for a given keyword, the same product list was generated for all consumers), future research can examine a more dynamic PLA context that supports behavioral targeting (i.e., the product list varies with the consumer's past online behaviors).

Second, we identify ideal price ranks for clicks and conversions that may be difficult to implement under real-world constraints. Continued research should investigate how firms might do so. For example, game-theory approaches might model dynamic interactions between competitors to determine how a focal firm should update its price based on the competitors' prices in a previous round. Third, further research could include additional keyword attributes (i.e., beyond specificity and popularity) to determine their segmentation potential and ability to reflect consumers' knowledge, interests, and search goals. Such an investigation could lead to a greater understanding of consumers and their behaviors in online advertising environments. In study 2, we included only one keyword to focus on the key theoretical mechanisms, but research with multiple keywords might reveal additional moderating effects of keyword attributes.

Endnote

[1] The task performance was not measured, and participants were not given any metric of their performance. All participants received the same basic reward ($0.5) and performance reward ($0.5) regardless of their choices.

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