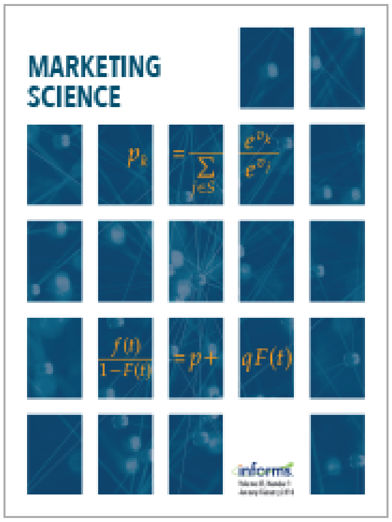

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Attribution Strategies and Return on Keyword Investment in Paid Search Advertising

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Firms use different attribution strategies such as last-click or first-click attribution to assign conversion credits to search keywords that appear in their consumers' paths to purchase. These attributed credits impact a firm's future bidding and budget allocations among keywords and, in turn, determine the overall return-on-investment of search campaigns. In this paper, we model the relationship among the advertiser's bidding decision for keywords, the search engine's ranking decision for these keywords, and the consumer's click-through rate and conversion rate on each keyword, and analyze the impact of the attribution strategy on the overall return-on-investment of paid search advertising.

We estimate our simultaneous equations model using a six-month panel data of several hundred keywords from an online jewelry retailer. The data comprises a quasi-experiment as the firm changed attribution strategy from last-click to first-click attribution halfway through the data window. Our results show that returns for keyword investments vary significantly under the different attribution strategies. For the focal firm, first-click attribution leads to lower revenue returns and a more pronounced decrease for more specific keywords. Our policy simulation exercise shows how the firm can increase its overall returns by better attributing the real contribution of keywords. We discuss how an appropriate attribution strategy can help firms to better target customers and lower acquisition costs in the context of paid search advertising.

Data, as supplemental material, are available at https://doi.org/10.1287/mksc.2016.0987.

Keywords: attribution strategies; paid search advertising; ROI; keyword specificity; budget allocation; first-click attribution; last-click attribution; multi-touch attribution

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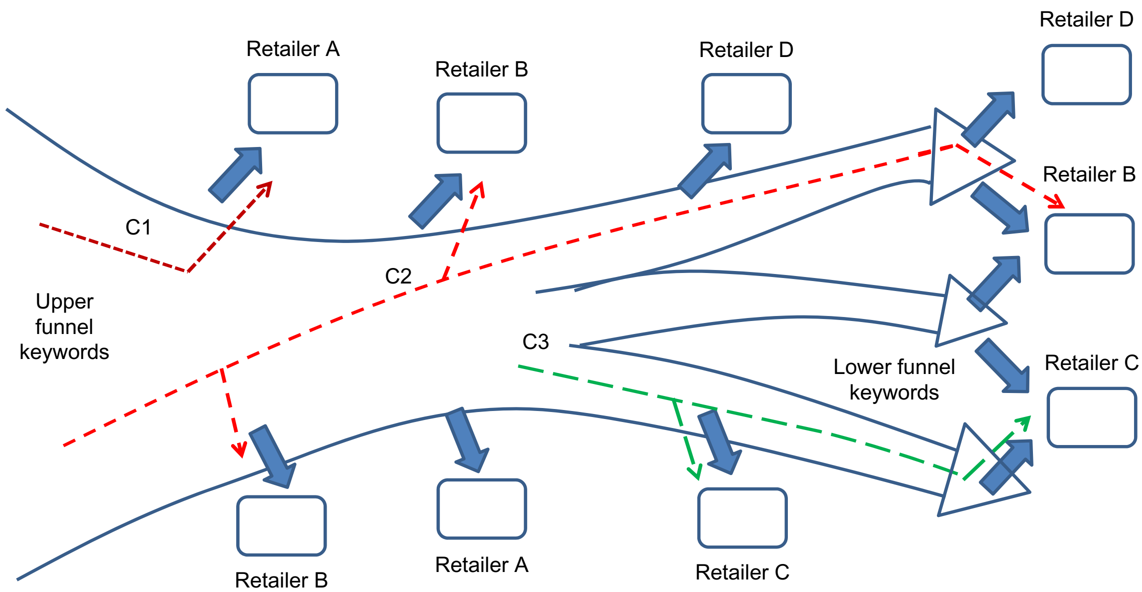
1. Introduction

Search engine marketing is predicted to comprise 44% of online marketing budgets for many companies by 2019. Total U.S. spending on paid search engine marketing is forecast to be more than $45 billion by 2019 with an annual growth rate of 10% (VanBoskirk et al. 2014). Much of this spending is on paid or "sponsored" search results for which the firm pays the search engine. In this paper, we focus on such paid search ads and examine how the firm's attribution strategies impact the return on investment (ROI) of a paid search campaign.

Search engines assist potential customers in finding useful information online by using customer specified search keywords, irrespective of where the customers are in their consumer decision journey (Court et al. 2009). Consider, for example, consumers shopping online for jewelry, with the possible paths they may take as they move through their decision journeys or purchase funnels as shown in Figure 1. Customers who are early in their purchase funnel (identified as C1 and C2 in Figure 1) could use more general search keywords such as "jewelry" to identify more information about products and retailers as they may not have a specific jewelry item in mind or be aware of any specific online jewelers. We call such keywords "upper funnel keywords" in Figure 1. Other customers, such as C3, may have a specific item and/or online retailer already identified and may use more specific keywords such as "diamond necklace" or "BlueNile engagement ring" (i.e., lower funnel keywords in Figure 1).

The search keywords and the sequence in which customers use the specific keywords as they progress

Figure 1 (Color online) Generating Visits Using Keywords in the Purchase Funnel



in their purchase funnel could significantly differ across the population of potential customers. Similarly, retailers can differ in the mix of keywords they bid for and the amount they bid for each keyword (i.e., bid level). For example, in Figure 1, customer C1 uses an upper funnel keyword, comes across Retailer A and visits that website and never comes back (i.e., he purchases there or offline or decides not to buy in that category). Customer C2 uses an upper funnel keyword and visits Retailer B, preferring them as their ads are ranked higher than the other retailers that bid for the same keyword, but does not buy during that visit. Subsequently, C2 uses other keywords and re-visits Retailer B culminating in a purchase when visiting with a lower funnel keyword. On the other hand, customer C3 uses only lower funnel keywords and visits Retailer C twice before making a purchase at that retailer on the second visit.

Customers C1, C2, and C3 are heterogeneous in the type of keywords they use possibly driven by the stage of the purchase funnel they are in, their level of category knowledge, their specific need, and so on. On the other hand, Retailers A through D are also heterogeneous in the mix of keywords they bid for and their bid levels (which determine their rank in paid search ads and visibility). Retailer A, by bidding only for upper funnel keywords, has no chance of attracting C3 who mainly uses lower funnel keywords, while Retailer C, by bidding only for lower funnel keywords, has no chance of attracting a customer such as C1, who starts her search by using upper funnel keywords. Retailer D loses customer C2 to Retailer B as it has bid lower for the keyword and has a lower ranked ad than Retailer B. Thus, the mix of keywords for which a retailer bids and their bid levels have important implications for the potential customer segments it could acquire through the keywords. A wrong or unbalanced mix and/or wrong bid levels may cause the retailer to lose large segments of potential customers.

We argue that the attribution strategy a firm uses directly impacts the mix of keywords it bids on and their bid levels under budget constraints and, therefore, impacts the efficiency of customer acquisition. Consider, for example, customer C2 in Figure 1 who visits Retailer B multiple times using different keywords. If Retailer B credits C2's conversion at its website to the last used keyword, it does not give any credit to the upper funnel keyword that C2 used to arrive at the retailer's website for the first time. Retailer B, therefore, is more likely to bid higher and allocate a higher budget for the lower funnel keywords, while bidding lower for the upper funnel keywords and allocating an insufficient budget to the upper funnel keywords as it considers those keywords to be less effective under the attribution strategy being used. This lowers the rank of Retailer B's ad of upper funnel keywords among all of the competitive ads (or its ad may not even appear in the first few pages of search results) when consumers (such as C1 and C2) use these keywords in the future. If the upper funnel keywords were, in reality, effective, this misattribution may lead Retailer B to miss the opportunity to acquire visits from a segment of potential customers. Similarly, if the upper funnel keywords were only marginally effective and if the retailer misattributes them as having a high impact, then the retailer may bid higher and allocate a higher budget for them at the expense of the more effective lower funnel keywords. In both cases, the retailer ends up investing in an inappropriate mix of keywords and bid levels that lead to an inefficient use of investment and lower ROIs.

In this paper, we present the first empirical study that examines the influence of attribution strategies on the realized ROI of paid search investments and provide insights into the impact of attribution strategies on the effectiveness of the upper funnel and lower funnel keywords in the customers' purchase journeys. We show that the use of single touch attribution strategies such as first-click attribution (assigning all of the conversion credit to the first clicked keyword) or last-click attribution (assigning all of the conversion credit to the last clicked keyword) is likely to lead to inefficient keyword investments and lower ROIs. The policy simulation based on our model identifies better attribution strategies that can lead to significantly higher revenues. The methodology we propose would allow firms to determine the effectiveness of their current attribution strategy and whether and how they can improve it. To our knowledge, this is the first study that examines the impact of attribution strategies on the ROI of paid search campaigns.

The significance of our study lies in the fact that attribution is an important problem for all paid search advertisers as it drives resource (budget) allocation. When a firm has a finite budget and when the maximum amount the firm can spend on all keywords is greater than the available budget, the attribution strategy becomes relevant and important: It affects the mix of keywords for which the firm bids and, more important, the amount invested in each keyword, and thus, the efficiency of customer acquisition. When there is a budget constraint, the firm does not have enough resources to bid high to get the top position for all keywords of interest; hence, for a large number of keywords the firm ends up bidding low. The attribution strategy in place determines which set of keywords are bid high and which set are bid low and thus impacts the efficiency of customer acquisition. This issue is the same for all firms whether it is a large firm like Amazon or a smaller firm as long as they are bidding for multiple keywords.

Additionally, paid search campaigns are generally automated and run on a daily basis by algorithms that determine campaign specifics. In such a context, misattributions of credit for keywords can lead to a significant drop in campaign ROIs that compounds over time as historical results form the basis for future investments in many algorithms. Such inefficiencies are likely to be more significant as the purchase journey becomes longer with multiple uses of search keywords before a conversion occurs, and the potential for misattribution is much higher compared to a case with one or two touches in the purchase journey. First, with paid search budgets exceeding $20 million annually in many large organizations, understanding the impact of attribution strategy on ROIs can avoid significant waste in investments. Second, determining the real and correct impact of upper funnel and lower funnel keywords in effecting conversions allows a firm to understand its internal website effectiveness and optimize the design of its website and internal search functions to increase conversions. Again, this is a not a trivial issue: Improving conversions at the website even by a margin can have a significant impact on revenues. Our research provides insights into this and a methodology to test the efficacy of the attribution strategy in place and improve it.

2. Background

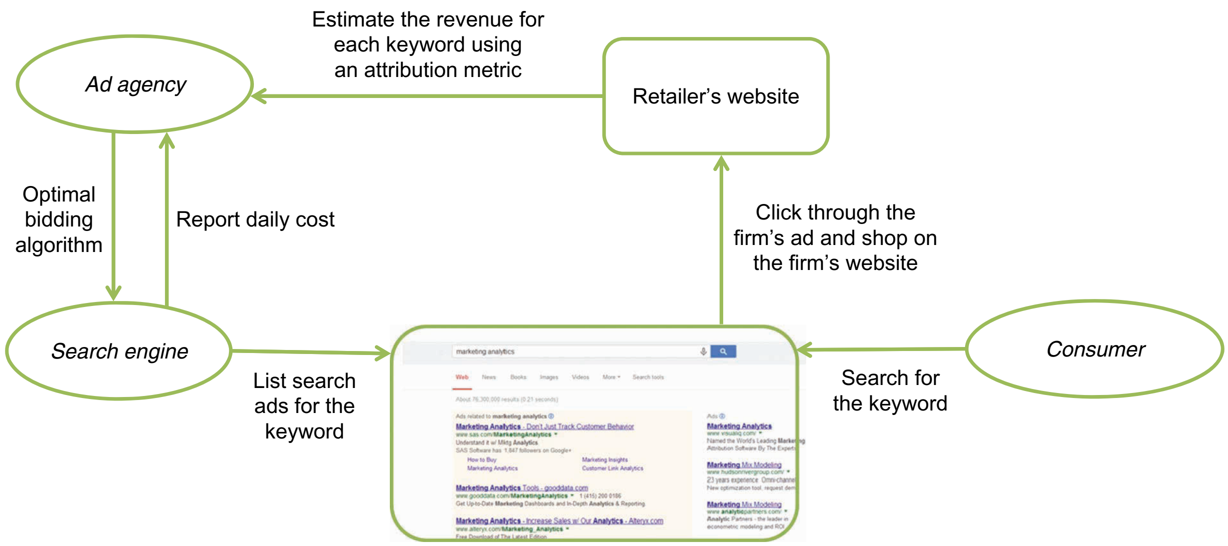
We first consider the players in the paid search market, i.e., the advertiser,[1] the search engines, and the customers, and the roles they play (see Figure 2).

To reach potential customers through paid search advertising, the advertiser needs to pick the right "keywords," write effective ad copy and text, and choose the relevant landing page. A keyword is usually a phrase with multiple words; the advertiser can specify the match type of each keyword to avoid missing any potential customers (Web Appendix A (available as supplemental material at https://doi.org/10.1287/mksc.2016.0987) provides the definitions and examples for different match types). After specifying the keyword and the match type, the advertiser decides how much to bid on each keyword and submits the bid for the auction at the search engine. The search engine operates a generalized second-price auction to assign the "positions" (i.e., where the ad appears) for the paid search ads. At most search engines, such as Google, Bing, and Yahoo, the ad position of a keyword is ranked according to the bid as well as the quality score (as a measure of the relevance) of an advertiser with respect to a keyword.

When the advertiser's bid and quality score is high enough to appear among the paid search results in response to a consumer's query, it is counted as an "impression." Upon viewing the search results, the customer may click on the result that is most relevant to her needs, and then land on a website through the link embedded in the ad, which is counted as a "click-through." The search engine charges the advertiser according to the number of click-throughs on its ads times the cost-per-click (CPC) (determined in a generalized second-price auction). When an advertiser's ad appears in the search results but the customer

[1] We use the term advertiser to refer to the online firm implementing the search campaign or the ad agency if it implements the search campaign on the firm's behalf. In our institutional context, the ad agency implements the campaign as shown in Figure 2.

Figure 2 (Color online) Institutional Context



chooses not to click on the ad, it will hurt the advertiser's click-through rate (CTR) and the future quality scores of this keyword. On a daily basis, search engines provide performance reports at the keyword level to the advertisers. Web Appendix B shows an example of such statistics provided by Google to our focal firm, including the number of impressions, the number of clicks, average CPC, average position, and quality scores at the keyword level.

Once the customer lands on the advertiser's website, the advertiser can track the keyword click-throughs and conversions at the website at the cookie ID level and measure the ROI[2] of each keyword against the incurred cost. When the customer clicks on only one keyword used by the advertiser to visit the website and makes a purchase, measuring the ROI of that keyword is straightforward. However, when the consumer clicks on multiple keywords from the advertiser and makes multiple visits to the website before making a single conversion, the advertiser must assign the conversion credit back to multiple keywords using a specific attribution strategy.

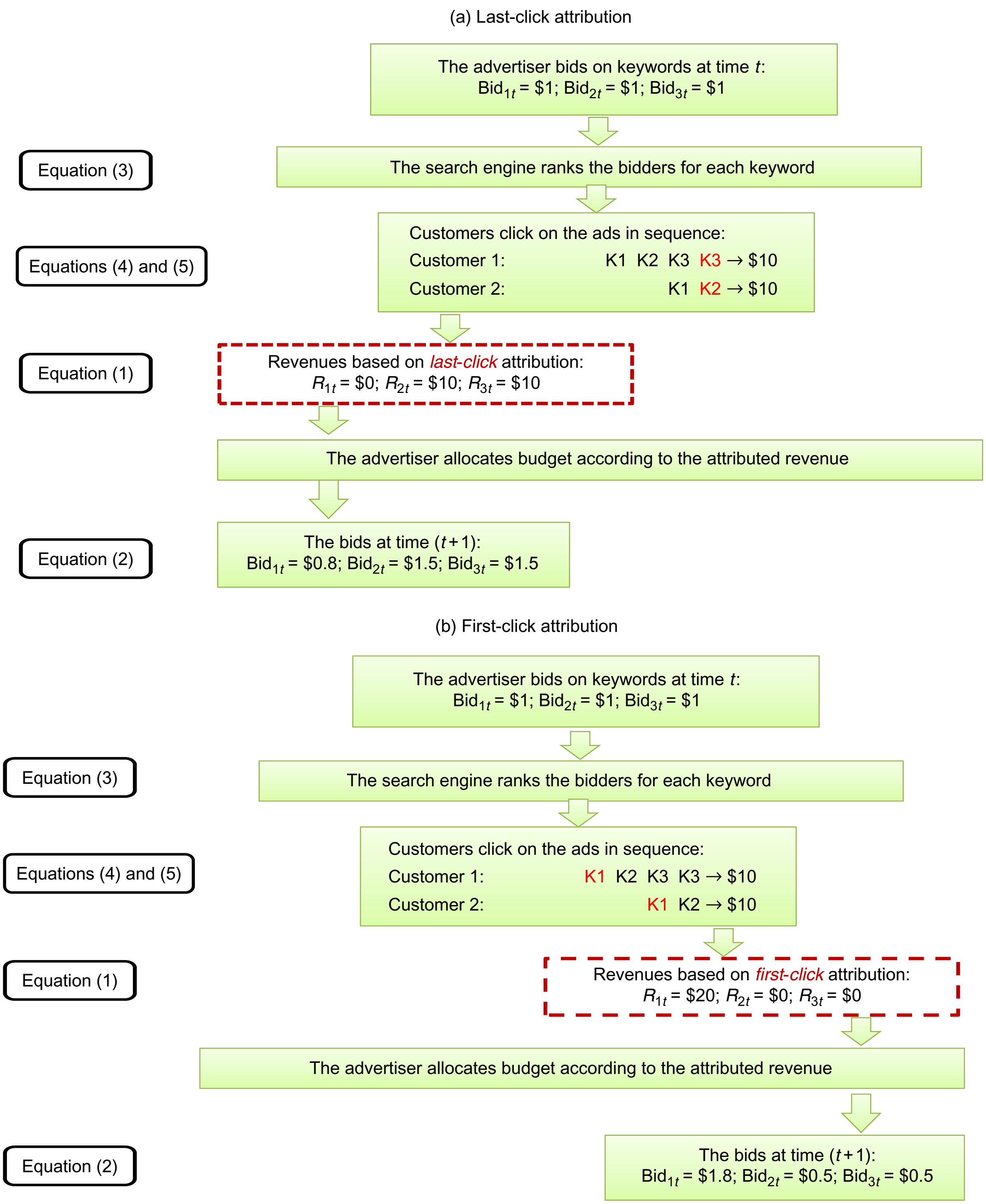
2.1. Attribution, Bidding, and ROI

In practice, a variety of attribution strategies are used. Assume a customer visits a jewelry retailer's website three times through the advertiser's paid search ads of keywords "jewelry," "silver necklace," and "silver necklace with ruby" (in that order), and makes a purchase on the last visit. The last-click attribution strategy gives all of the conversion credit to the last clicked keyword, i.e., "silver necklace with ruby." Alternatively, the advertiser can use the first-click attribution and assign the entire conversion credit to the first clicked keyword, i.e., "jewelry." Others may believe that these three keywords assist the customer in completing the purchase, and thus each deserves a portion of the conversion credit (i.e., fractional attribution).

Using two scenarios, Figure 3 illustrates how attribution strategies influence the realized keyword ROI and thus affect the advertiser's bidding decision for the next period. In Figure 3(a), we assume the advertiser bids on three keywords: K1, K2, and K3. Assume that at time t, the advertiser bids \$1 on each keyword and submits these bids to the search engine and earns commensurate positions for their keywords. Assume that there are two hypothetical customers' purchase journeys: Customer 1 clicks on K1 with no conversion, K2 with no conversion, and K3 twice (in that sequence), and then makes a purchase of \$10 at time t, while Customer 2, as part of her purchase journey, clicks on K1 and K2 in sequence before making a \$10 conversion at time t. Using the last-click attribution strategy, the advertiser would assign the conversion credit for Customer 1's purchase to K3 and Customer 2's conversion credit to K2. Accordingly, the overall imputed revenue is \$0 for K1, \$10 for K2, and \$10 for K3. Based on these keyword-level ROIs, the advertiser increases the bid on K2 and K3 from \$1 to \$1.5, as these keywords have performed well, and lowers the bid on K1 to \$0.8 due to its unsatisfactory performance at time t. These new bid values are somewhat arbitrary in this example and only illustrate an expected increase or decrease in subsequent bid values based on the bidding algorithm, which essentially orders the keywords based on their ROI, i.e., expected revenue over expected cost, and bids

[2] We use revenue as the measure of return rather than profits as we do not have information on the cost of goods sold. However, the percentage margins of the items sold at the website are somewhat similar. Additionally, since the revenue provided to us by the firm is disguised, we are focusing on the percentage of revenue increase rather than absolute values.

Figure 3 (Color online) The Role of the Attribution Strategy



high on those keywords with higher returns and low on those keywords with lower returns.

Figure 3(b) shows the scenario resulting from using a first-click attribution strategy. Assume the advertiser still bids on the same keywords at the search engine and that the customers click on the same sequences of keywords and each makes a \$10 conversion. That is, everything else is equal, but the advertiser uses the first-click attribution instead of the last-click attribution to impute conversion credit for the keywords. Then the imputed revenue is \$20 for K1 and \$0 for both K2 and K3. Conditional on these keyword ROIs, the advertiser would submit a higher bid on K1 and lower bids on K2 and K3 in the next period.

The illustration shows how the attribution strategies can influence the keyword ROIs, and how the keyword ROIs in turn influence the bid level on each keyword going forward and the mix of keywords bid for. Although the initial bids by the advertiser at time t are the same, as are the customers' click-throughs and conversions, different attribution strategies lead to completely different bidding decisions for the advertiser in time $t+1$. If the true optimal attribution for the focal advertiser in Figure 3 is the first-click strategy, then when the advertiser uses last-click attribution as in Figure 3(a), it would underestimate the revenue contribution made by K1 and thus underbid on K1 at time $t+1$. Consequently, the lower bid on K1 leads to a less advantageous ad position that could be ineffective in targeting certain valuable customer segments and lose the conversions to which K1 could have led. Over time, this targeting inefficiency is compounded as future bids increasingly depend on the past data of click-throughs on the inefficient mix of keywords and bids.

The conventional wisdom of the path to purchase is that consumers originate their search with broad upper funnel keywords and narrow them down to more specific keywords in the lower purchase funnel (Ghose and Yang 2009, Agarwal et al. 2011). From this perspective, since all of the keywords compete for a fixed budget, the lower conversion credits of broad upper funnel keywords when using the last-click attribution lead to a lower investment on broad keywords in the next period. This results in lower ad positions and fewer click-throughs and conversions from broad keywords (Ghose and Yang 2009, Rutz et al. 2012). Consequently, the ROI potential of the broad keywords is not fully realized. Similarly, the first-click attribution limits the more specific and narrow keywords in reaching their full potential in generating revenue. To our knowledge, no research has shed light on the impact of attribution strategies on the ROI of search campaigns.

2.2. Our Research Focus and Positioning

Focusing on the above question, we empirically analyze the ROI of the paid search campaigns at the individual keyword level, using a six-month panel data of several hundred keywords from an online jewelry retailer. The relationship among the advertiser's bidding decision, the search engine's ranking decision, and the consumers' responses are jointly modeled in a simultaneous equations system. At the beginning of the data window, the advertiser used the last-click attribution strategy and switched to the first-click attribution halfway through the data window, thereby rendering a quasi-experiment. (We will discuss this in more detail in Section 3.) Given the data, we analyze the keyword ROI of the advertiser's search campaigns under each of these two extremes of attribution strategies. Based on these analyses, we develop, in the context of the application, a new attribution strategy that accounts for the contributions of a keyword under both last-click and first-click strategies, and inform the advertiser how much it can improve its ROI by appropriately changing the attribution strategy. Note that the purpose of this research is not to find *the optimal* attribution strategy. Instead, we highlight the importance of accounting for the attribution in paid search advertising (which, to our knowledge, has not yet been examined in the literature). We provide a modeling framework for advertisers to better understand the ROI of their search campaigns, identify better attribution strategies, more efficiently allocate their keyword marketing budget, and improve their ROI on search investments.

In developing our model, we follow the norm in extant research of simultaneously modeling the advertiser's bidding decision, the search engine's position decision, and the customer's CTR and conversion rate (Ghose and Yang 2009, Agarwal et al. 2011, and Rutz et al. 2012). Similar to this extant research, we explicitly capture the endogenous relationship between the ad position and the consumer's responses. Additionally, we consider the supply side, i.e., the advertiser's bidding decision and the resulting revenue outcomes, by modeling the focal firm's decision process (Kumar et al. 2011), in which the current bid is determined based on the most recent revenue outcomes. Our research is also related to the growing body of literature that has shed light on the optimal bid (Skiera and Abou Nabout 2013, Yao and Mela 2011), the impact of ad agency compensation, ranking mechanism, customer reviews, etc., on search campaign profits (Abou Nabout et al. 2012, Ghose et al. 2014), the synergy between paid searches and organic searches (Yang and Ghose 2010), and the synergy between paid search marketing and offline marketing (Joo et al. 2013). However, we do not explore these factors in our research: The bidding algorithm that the advertiser uses remains the same across different attribution strategies, the ad agency's compensation is a fixed fee structure that does not impact the bidding process, and the focal advertiser's organic ranking is also low enough to ignore the possibility of spillovers across organic and paid searches.

Our research is also related to recent work in attribution models, which has examined the influence of attribution on marketing effectiveness (Berman 2015, Li and Kannan 2014). Li and Kannan (2014) find significant differences in realized ROI resulting from different attribution methods in the multichannel context. Unlike our research wherein we have data only at the aggregate keyword level, their approach takes into account spillovers across channels based on the entire purchase funnel data at the individual touch point level. Similarly, while Rutz and Bucklin (2011) examine spillovers across keywords, i.e., from generic to branded, our research does not focus on that issue due to the aggregate nature of our data. However, to our knowledge, no research has examined the impact of attribution methods on the realized keyword effectiveness in paid search campaigns. Our study fills this gap by analyzing the impact of attribution strategies on realized effectiveness in terms of ROI at the keyword level, and how this impact varies across heterogeneous keywords.

3. Institutional Context, Data, and Model Free Evidence

The focal firm in our study is an online jewelry retailer with no physical store. This jewelry retailer sells its own brand of jewelry on its website and acquires customers purely through advertising at two search engines, i.e., Google and Bing. The firm does no offline advertising; it works with only one ad agency for its paid search campaign on a fixed monthly fee basis. The ad agency implements the paid search campaign on the firm's behalf under a specific fixed daily budget set by the firm (as in Figure 2). The ad agency uses a proprietary bidding algorithm (Kamath 2011) for daily bidding on keywords based on the daily budget (we will provide more details about this bidding algorithm in Section 4.2). Given the fixed fee arrangement, an ad agency's incentives do not play a role in the bidding (Abou Nabout et al. 2012).

The firm was using last-click attribution for assigning credit to keywords until May 2012. Around this time Google espoused the idea that customers search for generic and broad keywords first, gather information over time, and then search for narrower and more specific keywords in the later part of their respective purchase funnel. The firm felt that using last-click attribution resulted in the narrower and branded terms getting more credit than they deserved. Because the ad agency was solving a bid optimization problem under a budget constraint for a given time period, this could result in the agency allocating less spending to the broad upper funnel keywords. If the agency did not aggressively bid for broad upper funnel keywords, it would result in fewer potential customers being part of their upper purchase funnel, and subsequently result in fewer people clicking on the branded and narrower search keywords. The firm believed that switching to a first-click attribution strategy would correct for this bias and instructed the ad agency to experiment with a change in the attribution strategy to observe the impact on overall revenues. Therefore, we consider the changeover an exogenous shock. Thus, if a customer clicked on multiple keywords in her purchase journey before a conversion, the ad agency used last-click attribution to assign conversion credits before May 2, 2012, and used first-click attribution from May 2, 2012, and onwards. The change in attribution strategy gives rise to a quasi-experiment that offers a unique opportunity to examine how the attribution strategies influence the imputed ROI of each keyword in leading to conversions.

The advertiser bids on about 200,000 keywords[3] at Google and Bing; 505 keywords get at least one click during the data collection period from January 21 to July 18, 2012. The data contain daily information at the keyword level, including the number of impressions, the number of clicks, average CPC, average position, quality score,[4] and the *disguised* revenue of the keyword for each day. Table 1 reports the summary statistics of these keyword characteristics across the entire data period (columns 1 and 2). We do not have access to the click-through data at the cookie ID level, which are used internally by the ad agency and the firm to attribute conversion credit. The focal firm spent around $4 million in paid search advertising annually during the time of this study. Based on the spending, it was at the 75th percentile among the 151 clients the ad agency had at that time, and placed at the 33rd percentile in terms of the number of keywords that had at least one click in six months. Thus, the focal firm is fairly representative of the firms spending on paid search advertising.[5]

Figure 4 shows the daily budget, cost, and attributed revenue for all keywords. The budget and cost figures are fairly constant from the beginning to mid-May, and then increase from late May to the end of the data window. The ad agency is given a fixed daily budget by the firm and decides the bid level for each keyword on a daily basis. Although the daily budget is a binding constraint in the search engine bidding algorithm, it is not a strict binding constraint in the agency's implementation.[6] The total costs of

[3] The firm bids on a large pool of keywords, which does not lead to extra costs as the firm only pays when keywords are clicked. The number of keywords clicked remained fairly the same over time (see Web Appendix C for the number of unique keywords clicked each month and across attribution strategies). Thus, we can fairly conclude that there is no selection bias in our analysis and that the data generating process remains the same across strategies.

[4] Google and Bing use quality score and bid to determine the position of search results. Quality score is on a scale from 1 to 10 at both search engines, where 10 is the best score.

[5] Chevrolet annually spent $15.5 million in paid search advertising, Comcast $19 million, Microsoft $16.3 million, Marriott $20.9 million, DirectTV $18.4 million, Best Buy $23.7 million, and AT&T $40.8 million around the same time (Wordstream Research, http://www.wordstream.com/articles/google-earnings).

[6] The search engines allow the advertiser to set a "budget" and when the advertiser's spending reaches this "budget" limit, their search ads will no longer be shown in response to the customer's search queries. In our context, the ad agency sets the "budget" for the search engines at a level much higher than the budget given by the firm to avoid potentially censoring impressions and click-throughs.

Table 1 **Summary Statistics**

	Total	Daily average across the entire data window	Daily average under last-click condition	Daily average under first-click condition
Impression	84,788,062	471,045	432,771	521,096
Clicks	1,033,982	5,744	5,326	6,291
Checkout	1,727	10	9	10
Checkout revenue[a]	1,571,923	8,733	8,661	8,826
Cost	1,714,715	9,526	8,020	11,496
ROI (= Checkout rev/cost) (%)	92	92	108	77
Average CPC		1.48	1.34	1.65
Average position		2.26	2.43	2.06
Average quality score		5.43	5.46	5.39
Average click-through rate (%)		1.22	1.23	1.21
Average conversion rate (%)		0.17	0.18	0.16

[a]The revenue is disguised, and so the ROI metric is used for comparison across conditions.

all of the search campaigns may exceed the daily budget specified by the firm as shown in Figure 4. There are a few revenue spikes around Valentine's Day and Mother's Day, both of which are explicitly captured in the model and discussed in Section 4. Table 1 provides the daily average of the various metrics under the last-click strategy (column 3) and the first-click strategy (column 4). The average impressions are higher under first-click, as are the average clicks, checkouts, and checkout revenues (which are disguised figures). However, the costs (and budget allocated) are much higher under the first-click strategy. Note that the budget endogenously reflects the seasonality and promotions at the firm's website. The ratio of average revenues over average costs is 1.08 under the last-click strategy, but only 0.77 under the first-click strategy, indicating much lower ROI for the first-click strategy. Although, the average position of the keywords under the first-click condition is smaller (and better), all of the other measures such as average CPC, average quality score, average CTR, and average conversion rate are worse than those under the last-click strategy. The model free evidence seems to indicate that first-click leads to less efficient spending of acquisition dollars, but the complex relationships between these metrics makes it difficult to unravel and parcel out the individual effects. This is where our proposed model plays a critical role.

4. Model

In this section, we model the supply and demand sides of paid search ads using a simultaneous equations system. On the demand side, we model the advertiser's revenue outcome for each keyword, which depends on customer responses and the attribution strategy used. Customer responses are modeled through aggregate CTR and conversion rates. On the supply side, we model the advertiser's daily bidding decision for each keyword based on the previously attributed revenue for each keyword and the daily budget. We then close the loop as in Figure 2 by modeling the search engine's ad position decision for each keyword. In discussing each equation, we also justify the variables selected based on theory and extant research.

4.1. The Advertiser's Revenue Model

The advertiser's total attributed revenue[7] from keyword i on day t, R_{it}, can be factored as follows:

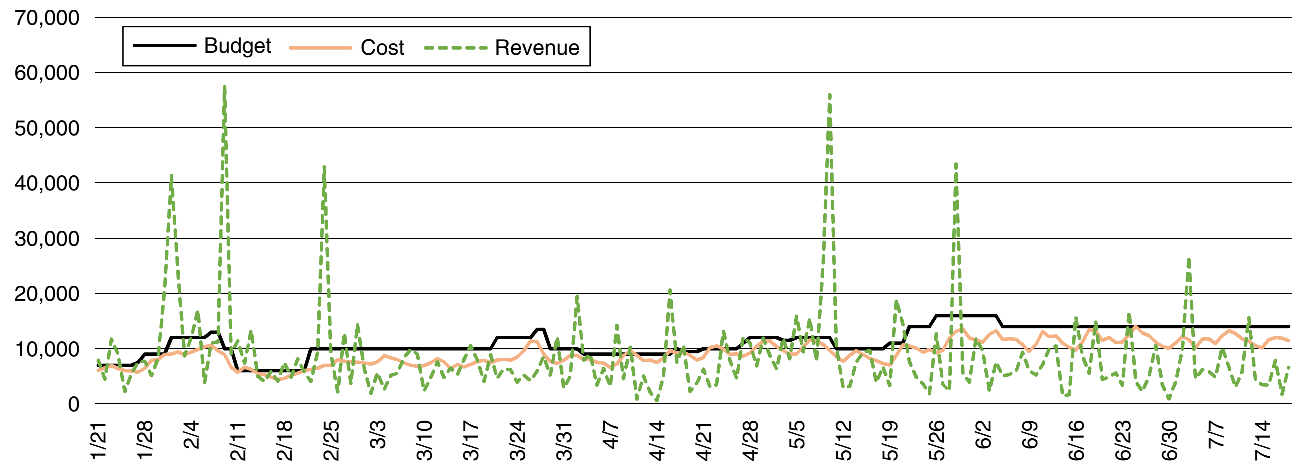
$$R_{it} = Impression_{it} \times CTR_{it} \times CONV_{it} \times AR_{it}, \qquad (1')$$

where $Impression_{it}$ is the number of impressions of keyword i on day t; CTR_{it} is the CTR (the number of clicks on the ad divided by the number of impressions of the ad); $CONV_{it}$ is the conversion rate (the number of conversions resulting from the clicks on the ad divided by the number of clicks on the ad); and AR_{it} is the average revenue per conversion for keyword i at time t. The first three variables ($Impression_{it}$, CTR_{it}, and $CONV_{it}$) are directly represented in Equation (1), whereas AR_{it}, the average revenue imputed for keyword i on day t, can be influenced by the keyword characteristics (e.g., Agarwal et al. 2011), the advertiser's attribution strategy, and overall spending on the products based on promotions at the website, seasonal effects, etc. We therefore capture AR_{it} as a function of these variables as shown in Equation (1)

$$\begin{aligned}\ln(R_{it}) = {} & \alpha_0 + \alpha_1 \ln(Impression_{it}) + \alpha_2 CTR_{it} + \alpha_3 CONV_{it} \\ & + \alpha_4 Specificity_i + \alpha_5 Specificity_i^2 + \alpha_6 FC_t \\ & + \alpha_7 FC_t \times Specificity_i + \alpha_8 \ln(Budget_t) + \varepsilon_{it}. \quad (1)\end{aligned}$$

[7] The calculation of R_{it} is straightforward when the last-click strategy is used. However, when the first-click strategy is used, although the impressions and clicks might occur at time t, the conversion could materialize at a later point in time, say at time $t+10$. The data for R_{it} under the first-click strategy in Equation (1) has all of the conversions that occurred after time t, such as the conversion at $t+10$ in our above example. The data may have a censoring problem in the sense that some keywords might deserve credit for the conversions that could have materialized after we stopped the data collection. We provide a robustness check in Web Appendix D to examine this issue.

Figure 4 (Color online) Daily Budget, Cost, and Revenue



The main keyword characteristic we relate to the average revenue is how broad or specific a keyword is.[8] Extant literature finds that the *specificity* of a keyword (i.e., measure of how broad or specific a keyword is within a product category, e.g., "jewelry" versus "gold ring with sapphire") influences the realized effectiveness of search campaigns (Agarwal et al. 2011, Ghose and Yang 2009, Rutz et al. 2012). We capture this characteristic of keyword i with $Specificity_i$ in Equation (1). A larger value for $Specificity_i$ indicates that keyword i is more specific, or less broad. To obtain these specificity scores for our research, each keyword in our application was rated by two independent judges on the specificity dimension.[9] (Two alternative measures of *Specificity* were also examined and are reported in Web Appendix E.) To account for the nonlinear effects of keyword specificity, we include the quadratic term $Specificity_i^2$.

The changeover in the attribution strategy is captured by FC_t in Equation (1), where FC_t is 1 when first-click attribution was used (on or after May 2) and 0 when last-click attribution was used (before May 2). All else being equal, a positive coefficient of FC_t implies that the first-click attribution leads to a higher R_{it} summed over all keywords i and all times t. In addition, we capture the possible interaction effects between keyword specificity and the attribution strategies. The amount spent at the website varies over time as a function of seasonality and/or promotions at the website. Although these factors are unobserved, we know that the firm determines and varies its daily budget, $Budget_t$, for search advertising based on these factors (that is, an increase in acquisition cost is justified by the expected increase in average customer spend at the website). Thus, we use $Budget_t$ as a proxy in Equation (1) to capture the above effects. Finally, the error term ε_{it} follows Normal distribution.

4.2. The Advertiser's Bidding Model

The bidding algorithm the advertiser uses solves an optimization problem to pick the keywords and their associated bid-levels to maximize the expected revenue subject to the budget constraint. While the bidding algorithm used is proprietary, it is very representative of the general approach used in the industry (Web Appendix F provides more details of the algorithm used by the focal firm and the types of algorithms used in the industry). The algorithm orders each keyword-bid level combination in terms of expected ROI from highest to lowest. It starts picking from the top such that each keyword is picked only once until the total expected costs are just under or equal the available budget constraint. This bin-packing optimization algorithm maximizes the expected revenue. The generation of bids is as follows:

The Bidding Procedure (*identical under both attribution strategies*):

1. Apply the attribution strategy in effect in the past (last-click or first-click that was used) to historically observed path-to-conversion data.

2. Based on the past attributed (last-click or first-click) revenue data, build a time-series model that predicts the expected revenue for a given keyword for the following day as a function of the bid levels.

[8] We also included branded or nonbranded characteristics of a keyword in Equation (1) but it was not significant.

[9] Two independent judges were hired to evaluate the specificity of all of the keywords. They were not told the research objectives. Each judge independently rated each keyword an integer specificity score in the range [1, 5], where more specific keywords received higher scores. The mean of judge ratings was 2.383 and the median is 2. The interjudge reliability according to Perreault and Leigh's (1989) index of reliability is 0.82, well above the 0.7 threshold recommended for exploratory research (Rust and Cooil 1994).

3. Again, based on past daily cost data, for each keyword, build a time-series model that predicts the expected spending for the following day as a function of the bid levels. (There is no relevance of attribution to the cost model.)

4. Solve the bin-packing optimization problem for the keywords that were modeled in steps 2 and 3: Maximize the expected revenue across all of the keywords such that the expected spending across all of the keywords is less than the budget constraint. Because revenue and cost for a given keyword are a function of bid, the argmax for the optimization problem will be the optimal bid level for the next day.

The above procedure computes the bid level for a keyword for each search engine and adjusts bids using heuristics based on quality score changes (although these changes are rare), search engine effects, and specific branded keywords. Given large decay rates, the time-series also heavily weights the most recent revenue (the day before) over revenue earned in the more distant past.

Given the above variables used in the generation of the bid, we model the advertiser's bidding decision on keyword i on day t, bid_{it}, conditional on the budget on day t, and the expected revenue of keyword i. Specifically, we use the lagged-revenue-per-click (RPC) $rpc_{i,t-1}$ as a proxy of the expected revenue of keyword i in the current period.[10] Thus bid_{it} is proportional to $rpc_{i,t-1}$ and $Budget_t$, and further heuristically adjusted based on quality score, QS_{it}, search engine, and branded characteristics of keyword, which leads to Equation (2′). That is

$$\begin{aligned} bid_{it} \times QS_{it} \propto rpc_{i,t-1} \times Budget_t & \\ & \times (\text{adj. factor for search engine}) \\ & \times (\text{adj. factor for branded keyword}). \end{aligned}$$

Taking the log transformation of this relationship and rearranging, we have

$$\begin{aligned} &\ln(bid_{it}) \\ &\quad = \beta_0 + \beta_1 \ln(rpc_{i,t-1}) + \beta_2 \ln(Budget_t) \\ &\qquad + \beta_3 \ln(QS_{it}) + \beta_4 Google_i + \beta_5 Brand_i + \xi_{it}. \qquad (2') \end{aligned}$$

Since the observations of bid_{it} are not available, we instead use the average CPC, CPC_{it}, as a proxy for bid_{it} (Ghose and Yang 2009, Abou Nabout et al. 2014) in Equation (2). The advertiser bids for keywords at Google and Bing, thus the dummy variable $Google_i$ captures the different competitive environment at the two search engines. Similarly, the variable $Brand_i$ captures the different competitive levels between the branded keywords and other keywords. The error term ξ_{it} follows Normal distribution

$$\begin{aligned} &\ln(CPC_{it}) \\ &\quad = \beta_0 + \beta_1 \ln(rpc_{i,t-1}) + \beta_2 \ln(Budget_t) \\ &\qquad + \beta_3 \ln(QS_{it}) + \beta_4 Google_i + \beta_5 Brand_i + \xi_{it}. \qquad (2) \end{aligned}$$

4.3. The Search Engine's Ad Position Decision

The search engine uses the bid multiplied by the quality score to determine the positions of paid search ads associated with the same keyword. That is, the ad position, $Position_{it}$, is influenced by CPC_{it} (as a proxy for bid_{it}) and QS_{it}. In line with previous empirical research (Ghose and Yang 2009, Agarwal et al. 2011), we use a log–log model to capture this relationship. Note that $Position_{it}$ is the daily average position of keyword i on day t, which is a continuous variable. Again, we include the dummy variables $Google_i$ and $Brand_i$, and also control for the possible seasonality with the dummy variables for Valentine's Day (equal to 1 during the two weeks before Valentine's Day) and Mother's Day (equal to 1 during the two weeks before Mother's Day).[11] The error term ζ_{it} follows Normal distribution

$$\begin{aligned} \ln(Position_{it}) = \theta_0 + \theta_1 \ln(CPC_{it}) + \theta_2 \ln(QS_{it}) & \\ + \theta_3 Google_i + \theta_4 Brand_i & \\ + \theta_5 Valentine_t + \theta_6 Mother_t + \zeta_{it}. & \qquad (3) \end{aligned}$$

4.4. The Aggregate Customer's Click-Through Rate and Conversion Rate

On the customer's side, we model the aggregate CTR and conversion rate. The aggregate CTR of keyword i on day t is modeled in a logistic regression as follows:

$$CTR_{it} = \frac{\exp(y_{it})}{1+\exp(y_{it})}, \quad \text{and}$$

$$\begin{aligned} y_{it} = \mu_0 + \mu_1 \ln(Position_{it}) + \mu_2 \ln(QS_{it}) & \qquad (4) \\ + \mu_3 Specificity_i + \mu_4 Specificity_i^2 + \mu_5 Brand_i & \\ + \mu_6 Valentine_t + \mu_7 Mother_t + \eta_{it}. & \end{aligned}$$

Following the extant literature, we model the aggregate CTR, CTR_{it}, as a function of the ad position, $Position_{it}$ (Ghose and Yang 2009), the expected quality of the ad (we use QS_{it} as a proxy, see Agarwal et al. 2011), and the keyword specificity, i.e., $Specificity_i$ and $Specificity_i^2$ (Ghose and Yang 2009, Rutz et al. 2012). In addition, the impact of branded keywords and seasonality is controlled with the dummy variables, $Brand_i$, $Valentine_t$, and $Mother_t$. Because we

[10] We also added lags of revenues greater than one, but they were insignificant given the large decay rates in the bidding algorithm time-series models.

[11] We also tried including a dummy variable for weekends (Friday, Saturday, and Sunday), but this weekend dummy was not significant in Equations (3)–(5).

use search-engine-specific quality scores, the search engine effects are already inherent in this equation. The error term η_{it} follows extreme value distribution.

Furthermore, we model the aggregate conversion rate of keyword i on day t as follows:

$$CONV_{it} = \frac{\exp(z_{it})}{1+\exp(z_{it})},$$

$$\begin{aligned} z_{it} = {} & \phi_0 + \phi_1 \ln(Position_{it}) + \phi_2\, Specificity_i \\ & + \phi_3\, Specificity_i^2 + \phi_4\, Brand_i + \phi_5\, Valentine_t \\ & + \phi_6\, Mother_t + \delta_{it}. \end{aligned} \tag{5}$$

Several studies have shown that the conversion rate, $CONV_{it}$, is influenced by $Position_{it}$ (Agarwal et al. 2011, Ghose et al. 2014, Ghose and Yang 2009, Yang and Ghose 2010) and keyword specificity, i.e., $Specificity_i$ and $Specificity_i^2$ (Rutz et al. 2012). In addition, we control for the presence of brand name ($Brand_i$) and seasonality ($Valentine_t$ and $Mother_t$). We do not include quality score QS_{it} in the conversion decision due to its insignificance on inclusion, which is consistent with previous studies (Agarwal et al. 2011, Ghose et al. 2014) which show that once the customer arrives at the firm's website and starts shopping, the quality of the search ad is no longer relevant. The error term δ_{it} follows extreme value distribution.

We specify an unrestricted variance-covariance matrix for the error terms in Equations (1)–(5) and estimate it as part of the three-stage least squares (3SLS) estimation procedure.

The focus of our research is to explore the impact of attribution strategies on the realized ROI. Note that the attribution variable, FC_t, is explicitly captured in only Equation (1), while its impact indirectly influences Equations (2)–(5). First, the attribution strategy directly affects the imputed revenue of a keyword as shown in Equation (1). Then, in Equation (2), the RPC, $rpc_{i,t-1}$, is based on the imputed revenue in Equation (1) at time $(t-1)$ divided by the number of clicks at time $(t-1)$. That is, $rpc_{i,t-1}$ already incorporates the impact of the attribution. In the remaining equations, the impact of the attribution is not directly captured: In Equation (3), the ranking decisions at the search engine are based on the bids and the quality scores, regardless of the attribution strategy used by the advertiser; on the customer's side, the attribution is not reflected in Equations (4) or (5) because the customer is not aware of the change in the advertiser's attribution strategy.[12] However, the indirect impact of attribution exists: The attribution strategy determines $rpc_{i,t-1}$ and $rpc_{i,t-1}$ influences the bid in Equation (2), and then the bid determines the ad position in Equation (3), which in turn affects the CTRs in Equation (4) and the conversion rates in Equation (5). Going back to Equation (1), the CTR and conversion rate, together with endogenous variables $Impression_{it}$ and $Budget_t$, determine the imputed revenue of a keyword. This is how the models link through the endogenous variables (R_{it}, $rpc_{i,t-1}$, CPC_{it}, $Position_{it}$, CTR_{it}, $CONV_{it}$, $Impression_{it}$, and $Budget_t$) and how the attribution strategy plays a role in this endogenous equations system.

4.5. Exclusion Restrictions and Identification

The equations system (Equations (1)–(5)) has simultaneity bias because some dependent variables are explanatory in at least one of the other four equations. Such dependence can create endogeneity problems and bias the estimation outcome. To account for such simultaneity and endogeneity issues, we use a 3SLS method to jointly estimate all of the parameters in Equations (1)–(5).

Table 2 shows the endogenous variables included in Equations (1)–(5) as well as the excluded exogenous variables in each of these equations.[13] The justification for exclusion of the variables below along with justification for inclusion of variables in the equations as discussed in Sections 4.1 through 4.4 presents our complete arguments for exclusion restrictions. Quality score, QS_{it}, is excluded in the revenue equation (Equation (1)) in line with previous studies (Agarwal et al. 2011, Ghose et al. 2014), who argue that once the customer arrives at the firm's website and starts shopping, the quality of the search ad is no longer relevant. Our research also supports this finding: On adding QS_{it} into Equations (1) and (5), its coefficients are not significant in either equation. In addition, the included variables $Impression_{it}$, CTR_{it}, and $CONV_{it}$ are all directly and significantly influenced by $Brand_i$ and holiday dummies (Equations (4) and (5)), and QS_{it} (Equation (4)). Moreover, the variable $Budget_t$ (included in Equation (1)) picks up the variations in the daily advertising expense, seasonality, as well as any promotions at the website, all of which are considered and taken into account when the firm determines the budget.

[12] In fact, this ensures that the data generating process does not change, as customers' clicking and conversion behavior is the same regardless of the attribution strategy in place. In Web Appendix G we show empirical evidence of this by comparing the CPC, CTRs, and conversion rates of keywords that have the same positions under first-click and last-click strategies. They remain the same across the different strategies.

[13] Note that although the quality score depends on some factors (e.g., CTRs), which are endogenously determined in this simultaneous equations system, the quality score is given by the search engine based on a long period of historical data and most of the time that value remains constant. Only around 11% (57) out of the 505 keywords have one or two changes in their quality scores during the six-month data window. Thus, we treat quality score as an exogenous variable in the equations system.

Table 2 **Endogenous and Exogenous Variables**

	Endogenous variables	Excluded exogenous variables
Equation (1)	$\ln(Impression_{it})$, CTR_{it}, $CONV_{it}$, $\ln(Budget_t)$	$\ln(QS_{it})$, $Google_i$, $Brand_i$, $Valentine_t$, $Mother_t$
Equation (2)	$\ln(rpc_{i,t-1})$, $\ln(Budget_t)$	$Specificity_i$, FC_t, $Valentine_t$, $Mother_t$
Equation (3)	$\ln(CPC_{it})$	$Specificity_i$, FC_t
Equation (4)	$\ln(Position_{it})$	FC_t, $Google_i$
Equation (5)	$\ln(Position_{it})$	FC_t, $\ln(QS_{it})$, $Google_i$

For Equation (2), we include only those variables used in the generation of the bid by the advertiser such as $rpc_{i,t-1}$, $Budget_t$, QS_{it}, $Brand_i$, and Search engine indicator $Google_i$ (see bidding algorithm in Section 4.2). As in Equation (1), $Budget_t$ already captures the variation in advertising expenditure, seasonality effects, and promotions at the website. We have thus excluded keyword specificity measures and holiday dummies from this equation as they are not explicitly considered in the bid generation as are the other included variables.

Likewise, in Equation (3), a decision made by the search engines, we exclude keyword specificity measures and instead include $Brand_i$ and $Google_i$. Since $Budget_t$ is not observed by the search engine, we include the holiday dummies instead. The quality score QS_{it} and bid (CPC) are also included as they are considered critical for the position obtained by a keyword per extant research. Equations (4) and (5), modeling consumers' CTR and conversion rate, include holiday dummies, whether the keyword is branded, the position of the keyword, etc. The variable of daily budget, $Budget_t$, is excluded as it is not observed by consumers and is, in any case, immaterial to consumers' decision-making. Search engine dummy is excluded in the click-through Equation (4) because the QS_{it} captures the variations across search engine; inclusion of $Google_i$ is also insignificant. For Equation (5), conversion happens at the website and search engine is not relevant at that point. The quality score QS_{it} is excluded in Equation (5), again based on Agarwal et al. (2011) and Ghose et al. (2014); its insignificance on inclusion in the equation shows the conditional independence.

Finally, the number of endogenous variables is strictly less than the number of excluded exogenous variables in each equation; thus, it satisfies the order conditions. The system also satisfies the rank conditions and thus we can identify all of the parameters in this simultaneous equations system.

5. Empirical Analysis

5.1. Results

Tables 3 through 7 present the estimation results of Equations (1)–(5) with the 3SLS method. The according variance-covariance matrix among these equations is provided in Table 8.

Table 3 provides the coefficient estimates of Equation (1). The positive and significant coefficients for $\ln(Impression_{it})$, CTR_{it}, and $CONV_{it}$ indicate that a higher volume of impression and higher CTR and conversion rate are associated with higher revenue. In addition, the coefficient of $\ln(Budget_t)$ is also positive and significant, indicating that more marketing dollars can lead to more revenue.

The specificity of a keyword, $Specificity_i$, is measured by judges' ratings of a keyword in the range $[1, 5]$. The coefficient of $Specificity_i$ is positive and significant, while the coefficient of $Specificity_i^2$ is not significant, demonstrating a monotonic increasing curve

Table 3 **Coefficient Estimates from Revenue Model**

		Estimates	Std. error
α_0	Intercept	−6.615	1.460***
α_1	$\ln(\text{Impression}_{it})$	0.342	0.040***
α_2	CTR_{it}	0.095	0.012***
α_3	CONV_{it}	0.983	0.242***
α_4	Specificity_i	0.035	0.013**
α_5	$\text{Sq}(\text{Specificity}_i)$	0.003	0.010
α_6	FC_t	−0.158	0.036***
α_7	$\text{FC}_t \times \text{Specificity}_i$	−0.070	0.012***
α_8	$\ln(\text{Budget}_t)$	0.597	0.132***

**Significant at 0.01; ***significant at 0.001; otherwise not significant at 0.1.

Table 4 **Coefficient Estimates from Cost-per-Click Model**

		Estimates	Std. error
β_0	Intercept	−4.857	0.476***
β_1	$\ln(\text{rpc}_{i,t-1})$	3.256	0.227***
β_2	$\ln(\text{Budget}_t)$	0.538	0.048***
β_3	$\ln(\text{QS}_{it})$	−0.814	0.040***
β_4	Google_i	−0.026	0.033
β_5	Brand_i	−2.991	0.261***

***Significant at 0.001; otherwise not significant at 0.1.

Table 5 **Coefficient Estimates from Position Model**

		Estimates	Std. error
θ_0	Intercept	1.845	0.024***
θ_1	$\ln(\text{CPC}_{it})$	−0.587	0.011***
θ_2	$\ln(\text{QS}_{it})$	−0.385	0.010***
θ_3	Google_i	−0.445	0.008***
θ_4	Brand_i	−1.960	0.028***
θ_5	Valentine_t	0.100	0.007***
θ_6	Mother_t	0.024	0.007***

***Significant at 0.001.

Table 6 **Coefficient Estimates from Click-Through Rate Model**

		Estimates	Std. error
μ_0	Intercept	−4.961	0.043***
μ_1	$\ln(\text{Position}_{it})$	−2.594	0.068***
μ_2	$\ln(\text{QS}_{it})$	1.685	0.021***
μ_3	Specificity_i	−0.202	0.008***
μ_4	$\text{Sq}(\text{Specificity}_i)$	−0.044	0.005***
μ_5	Brand_i	−0.006	0.084
μ_6	Valentine_t	0.651	0.025***
μ_7	Mother_t	−0.021	0.021

***Significant at 0.001; otherwise not significant at 0.1.

Table 7 **Coefficient Estimates from Conversion Rate Model**

		Estimates	Std. error
ϕ_0	Intercept	−4.578	0.010***
ϕ_1	$\ln(\text{Position}_{it})$	0.003	0.014
ϕ_2	Specificity_i	−0.003	0.002†
ϕ_3	$\text{Sq}(\text{Specificity}_i)$	0.000	0.001
ϕ_4	Brand_i	0.315	0.017***
ϕ_5	Valentine_t	0.019	0.005***
ϕ_6	Mother_t	0.020	0.004***

†Significant at 0.1; ***significant at 0.001; otherwise not significant at 0.1.

for the relationship between keyword specificity and revenue. That is, everything else being equal, the realized revenue is higher for more specific keywords when the firm is using the last-click attribution. Next, we examine the impact of attribution dummy and its interaction with keyword specificity. The coefficients of FC_t and $FC_t \times Specificity_i$ are negative and significant, indicating that switching from the last-click attribution to the first-click attribution will hurt the advertiser's revenue, and that this negative impact is more prominent for specific keywords. In other words, when the firm is using the first-click attribution, the coefficient for $Specificity_i$ is $(0.035 - 0.070 =)$ -0.035, which implies a negative relationship between keyword specificity and revenue. Note that this overall impact of attribution strategy (α_6) is determined by the relative effectiveness of advertiser's keywords in its portfolio. If the advertiser's keyword portfolio contains more effective upper funnel keywords, α_6 is more likely to be positive, i.e., such a keyword portfolio would generate more overall revenue with first-click strategy. On the other hand, if the advertiser's keywords portfolio contains more lower funnel keywords, then α_6 is more likely to be negative (as in the focal study). The implication is that such a keyword portfolio leads to higher overall revenue when using the last-click attribution strategy. In Section 5.2, we revisit the results in Table 3 and interpret them at the keyword level.

The coefficient estimates of Equation (2) are presented in Table 4. The results reveal a positive and significant relationship between the current bid on a keyword (CPC acting as a proxy) and its lagged RPC. Meanwhile, the coefficient of $\ln(Budget_t)$ is positive and significant, indicating that the advertiser bids more when a higher level of budget is available. Furthermore, when the quality score of a keyword is higher, the advertiser tends to lower the bid on the keyword as it stands a better chance of getting a good position even with a lower bid. Although we include a dummy variable, $Google_i$, to control for the possibly different competition environment at Google versus Bing, it turns out to be insignificant. However, $Brand_i$, is significant and negative. It implies that the advertiser bids significantly less on branded keywords due to the lower competition level. In sum, all of the signs of the coefficient estimates in Table 4 are as expected.

In Table 5, the dependent variable is $\ln(Position_{it})$, a higher value of which means that the ad is placed in a lower, less advantageous position. The negative coefficient of $\ln(CPC_{it})$ indicates that when the advertiser bids more on a keyword, the value of $\ln(Position_{it})$ is smaller; thus, the ad is placed in a better position. Similarly, the negative coefficient of $\ln(QS_{it})$ indicates that when the expected quality (quality score as a proxy) of this keyword is higher, the ad position is better. Again, we have controlled for the different search engines, the coefficients of which are negative and significant, implying that the chance of getting a better ad position is greater at Google than at Bing. Furthermore, the presence of the brand name in the keyword can improve the ad position. As for seasonality, during the two weeks before Valentine's Day as well as the two weeks before Mother's Day, the position is less advantageous (positive and significant coefficients) at the same CPC compared with other times, reflecting a more competitive jewelry market before these two holidays.

Table 6 provides the coefficient estimates of Equation (4), which is the logistic regression of CTR.

Table 8 **Variance-Covariance Matrix**

	Equation (1)	Equation (2)	Equation (3)	Equation (4)	Equation (5)
Equation (1)	7.437	0.383	0.015	0.026	−0.797
Equation (2)	0.383	5.265	0.094	−0.415	−0.016
Equation (3)	0.015	0.094	0.224	0.305	0.000
Equation (4)	0.026	−0.415	0.305	2.184	−0.004
Equation (5)	−0.797	−0.016	0.000	−0.004	0.122

The coefficient of $\ln(Position_{it})$ is negative and significant, indicating that when the paid search ad moves to a less advantageous position (i.e., the value of $\ln(Position_{it})$ becomes larger), the CTR would decrease; this is consistent with previous findings (Agarwal et al. 2011, Ghose et al. 2014, Ghose and Yang 2009, Rutz et al. 2012). In addition, the coefficient of $\ln(QS_{it})$ is 1.685, positive and significant, implying that a higher quality score can increase the CTR. The coefficient of $Specificity_i$ and $Specificity_i^2$ shows an inverted U-shaped curve with respect to the CTR, with the inflection point at −2.295, smaller than the minimum value of $Specificity_i$. Thus, the relationship between the CTR and keyword specificity is negative. That is, the CTR for specific keywords is lower compared with broad keywords, everything else being equal. Furthermore, the presence of the brand name in the keyword is not significant. Although the CTR during the two weeks before Valentine's Day is higher, we do not find a positive and significant impact before Mother's Day, which may imply that customers were more actively searching for Valentine's Day gifts than for Mother's Day gifts or jewelry for other occasions.

Table 7 shows the coefficient estimates of Equation (5). The coefficient of $\ln(Position_{it})$ is not significant, indicating that the conversion rates do not change significantly as the position of the ad moves up or down in the result list. This echoes the finding by Agarwal et al. (2011). The implication here is important: When the advertisers spend more to win a better ranking in the result list, i.e., a smaller value for $\ln(Position_{it})$, the CTR increases as shown in Table 6, but the change in conversion rate is marginal and not significant according to the results in Table 7. Moreover, neither the linear term nor the quadratic term of the keyword specificity is significant at the 5% level. Thus, we are unable to draw conclusions on conversion probability based on whether a customer is searching a broad keyword or a specific keyword. As for the control variables, the presence of the brand name in the keyword and Valentine's Day and Mother's Day have a positive and significant impact on the conversion rate.

Finally, robustness checks with alternative models with different data windows and with fixed effects (see Web Appendix D) show that our above results are quite stable. Additionally, comparing the predictions of our proposed model with alternative models, such as Ghose and Yang's model (2009) and the model without supply side (see Web Appendix H), our model performs better.

5.2. Interpretation at the Keyword Level

Next, we interpret the results in Tables 3–7 at the keyword level.

We consider two keywords, i.e., "onyx ring" and "black onyx sterling silver ring," as examples. According to the information provided by the firm (based on a random sample of 20% of their Web visitors from September 2012 to February 2013), the keyword "onyx ring" appeared 60 times as the first clicked keyword in customers' purchase journeys, and 41 times as the last clicked keywords. As for the keyword "black onyx sterling silver ring," it appeared three times as the first clicked keyword and eight times as the last clicked keyword in customers' purchase journeys. This is consistent with our hypothesis that the broad keywords are more likely to be used in the upper purchase funnel, whereas specific keywords are more likely to be used in the lower purchase funnel.

We decompose the impact of keyword specificity and attribution on the revenue of two example keywords. The keyword specificity, $Specificity_i$, is 2 according to judges' ratings for keyword "onyx ring," and the value of $\alpha_4 Specificity_i + \alpha_5 Specificity_i^2$ is 0.082. For a more specific keyword such as "black onyx sterling silver ring," $Specificity_i$ is 4, and the value of $\alpha_4 Specificity_i + \alpha_5 Specificity_i^2$ is 0.188. When the advertiser uses the first-click attribution, $\alpha_6 FC_t + \alpha_7 FC_t \times Specificity_i$ is −0.298 for keyword "onyx ring" and −0.438 for keyword "black onyx sterling silver ring." All else being equal, the impact of keyword specificity, the attribution dummy, and the interaction of both on log-revenue under first-click strategy is −0.216 for keyword "onyx ring" and −0.250 for keyword "black onyx sterling silver ring." These changes render a more negative impact on the revenue of more specific keywords.

The changes in revenue will also lead to a cascading effect on the CPC, ad position, CTR, and conversion rate. Table 9 shows the changes in the average predicted revenue, CPC, ad position, CTR, and conversion rate for a sample of keywords. For example, in Table 9 we find that after the firm switches to first-click attribution the daily revenue of "onyx ring" increases by 8.615 and its CPC increases by 1.796, while the position moves up by 1.321. The CTR has increased by 2.433%; the change in conversion is negative but fairly marginal. Overall, using the first-click strategy promotes the broad keywords, such as "onyx ring" by increasing their bid level to get a higher position, which could then lead to a higher CTR. Compared with the corresponding values under the last-click strategy, the higher CTR and the same level of conversion rate as before implies higher attributed revenue, which then leads to a higher bid on broad keywords. The changes on the specific keyword, "black onyx sterling silver ring," are very different: Under the first-click strategy, the average daily revenue decreases by 5.344. Although its CPC is higher by 0.454, the ad position moves down and the resulting CTR is lower while

Table 9 Changes for Example Keywords When Switching from the Last-Click to the First-Click

		Predicted value				
Keyword	Specificity	Δ daily revenue	Δ CPC	Δ position	Δ CTR (%)	Δ conv. rate (%)
Men's rings	1	2.639	0.027	−0.313	0.116	0.000
Ruby jewelry	1	4.457	0.321	−0.367	0.745	0.000
Sapphire jewelry	1	3.692	0.539	−0.358	0.431	−0.001
Mother's ring	2	1.214	0.371	−0.295	0.224	−0.002
Onyx ring	2	8.615	1.796	−1.321	2.433	−0.002
Promise rings for him	2	2.381	−0.291	0.447	0.470	0.001
Black onyx rings	3	−2.633	−0.177	−0.305	1.794	0.000
Mother's stackable rings	3	−1.688	0.133	−0.185	1.045	−0.001
Ruby engagement rings	3	−1.379	0.009	−0.106	−3.212	0.001
Black diamond engagement rings	4	−4.596	0.230	−0.140	0.308	0.002
Black onyx sterling silver ring	4	−5.344	0.454	0.266	−0.611	0.001
Engagement rings blue sapphire	4	−7.271	1.466	0.312	−0.298	0.001
Princess cut black diamond engagement rings	5	−0.453	−0.617	−0.113	0.957	0.000

the conversion rate is higher but negligible. Overall, the first-click strategy decreases the daily revenue of this specific keyword.

Note that the above discussion focuses on the general directions of changes. For example, the broad keyword "promise rings for him" is bid lower under the first-click condition and its average ad position is slightly lower as well. Although the lower ad position implies a lower CTR (Agarwal et al. 2011, Ghose and Yang 2009, Rutz et al. 2012), this could be compensated for by other factors in Equation (4) such as the quality score, and eventually lead to a positive change in the CTR of 0.470%.

5.3. Policy Simulation: A Better Attribution Strategy

The focal firm has experimented with last-click attribution strategy and first-click attribution strategy. Either strategy assigns the conversion credit only to a single click on the paid search ads. Next, we simulate a scenario where the advertiser uses a combined (weighted) attribution strategy, which considers the potential contribution of a keyword under the last-click and the first-click attribution strategies and then allocate the budget accordingly. Note this is not the *optimal* attribution strategy. Rather, we intend to show that with an *improved* attribution scheme, which considers the potential contribution of a keyword in the upper and lower funnels of a purchase journey and assigns appropriate conversion credit to the keyword, the advertiser can increase revenue with the same budget.

For each keyword, we calculate the average lagged RPC under the first-click attribution (rpc_i^{FC}) and the last-click attribution (rpc_i^{LC}). Then we calculate a weighted sum of both sets of average lagged RPC as

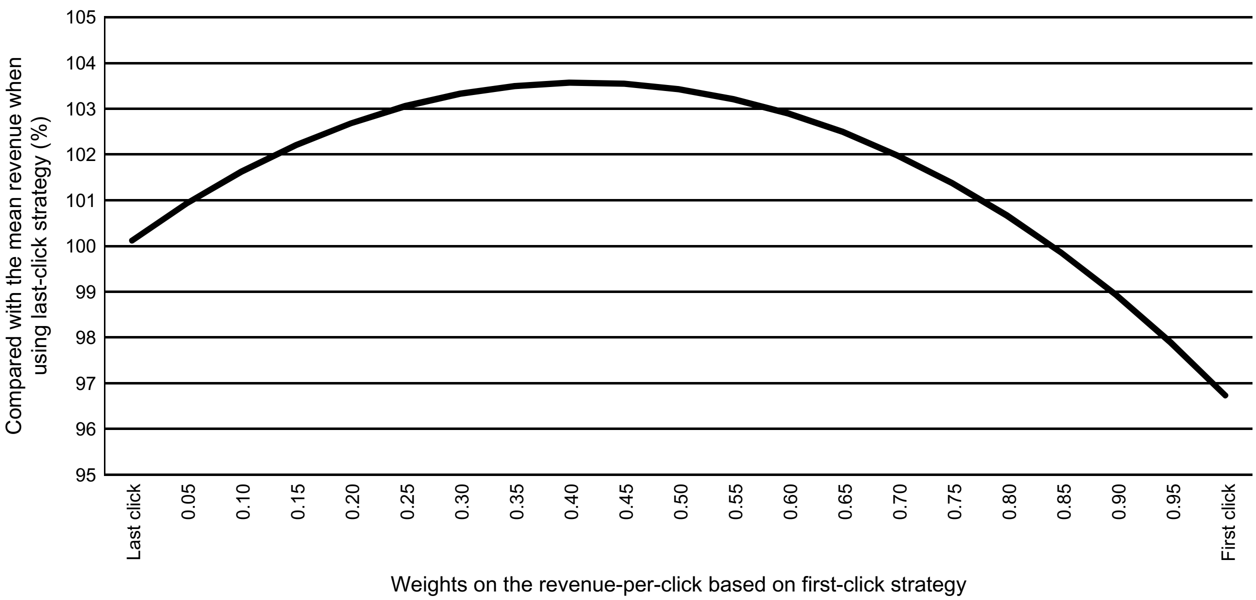
$$rpc_i^{New} = \alpha \times rpc_i^{FC} + (1-\alpha) \times rpc_i^{LC}, \qquad (6)$$

where α is between 0% (i.e., last-click strategy) to 100% (i.e., first-click strategy), to account for the potential contribution of a keyword in upper and lower funnels of a purchase journey. Using the rpc_i^{New} and the coefficient estimates of Equation (2) in Table 4, we can predict the bid on each keyword and then plug the predicted bid into Equation (3) to generate predicted ad position. Next, the predicted ad position can help us predict the CTR and conversion rate with Equations (4) and (5), respectively. The changes in CTR and conversion rate will eventually influence the revenue outcome in Equation (1). In Web Appendix I we show that a convex combination of revenue under first-click and last-click can provide an attribution strategy with revenue more than or equal to the revenue under last-click or first-click strategy and be a lower bound of the optimal revenue.

We calculate the expected costs with predicted CPC in Equation (2), predicted CTR in Equation (4), and the average impression level observed in the data. Then we rank all of the keywords according to their expected ROI, i.e., expected RPC divided by CPC, and pick keywords from the highest ROI to the lowest such that the total expected costs with the selected keywords are no larger than the budget (this is the underlying logic of the bidding algorithm and thus accounts for the budget constraint). Figure 5 presents the relationship between α and the simulated revenue. The maximum revenue is achieved when α is 41.3%; the revenue is 3.6% higher than the average revenue under the last-click strategy.

In addition, we have investigated a different scenario wherein the RPC in the simulation, rpc_i^{New}, is the larger one between rpc_i^{LC} and rpc_i^{FC}, instead of in Equation (6). Note that we use the actual RPC under each strategy rather than predict it using Equation (6). Using this strategy with the same budget constraint, the simulated revenue is 1.7% higher than

Figure 5 **Revenue of Using Simulated Strategies—Compared with the Revenue of Using Last-Click Strategy**



the mean revenue under the last-click strategy, still a better strategy than both last-click and first-click.

Based on the information provided by the advertiser, 85% of the visitors (defined by unique cookie IDs) only click through their paid search ads once, while most of the remaining 15% of visitors have two or three clicks. Yet the difference in attribution strategy shifts the position of the keywords for which it bids. The positions of the keywords in the firm's portfolio under the first-click strategy underperform the portfolio mix under the last-click strategy. By making the attribution strategy weighted, as suggested by the policy simulation, the new mix of keywords and their positions can improve revenue by as much as 3.6%. This has a significant impact on reducing customer acquisition costs using search campaigns.

6. Contributions, Implications, and Limitations

The overarching contribution of our paper is to make search campaigns more efficient and effective. To that end, we examine the complex relationships among the players in the paid search market, i.e., the ad agency, the client firm, the search engine, and the consumer, the decisions and outcomes characterizing each player, and the interrelationships among these decisions and outcomes. Using a six-month panel data of 505 keywords from the ad agency of an online jewelry retailer, we jointly model relationships among the firm's revenue outcome and (ad agency's) bidding decisions, the search engine's ranking decision, and the consumer's CTR and conversion rate, cope with the potential simultaneity bias with simultaneous equations model, and address the endogeneity with a 3SLS estimation procedure. While extant research has modeled the demand side of such relationships (e.g., Ghose and Yang 2009), we also model the supply side and provide a complete picture of the search ecosystem.

We focus on the impact of attribution strategy on the realized ROI of keywords in search campaigns, an issue that, to our knowledge, has not been examined in prior research. Attribution is an important problem for all advertisers because it drives resource allocation. When a firm has a finite budget (which is true for all advertisers regardless of size) and when the maximum amount the firm can spend on all keywords is greater than the available budget, the attribution strategy becomes a very relevant and important problem. It affects the amount invested in each keyword, which set of keywords are bid high and which set are bid low, and thereby, the efficiency of customer acquisition. This issue is the same for all firms whether large, such as Amazon or a small firm, as long as they are bidding for multiple keywords, except that the budget size and the number of keywords considered could be different depending on the size of the firm.

A useful analogy for attribution is the cost accounting that every firm does in its various functions. Even if a firm has just two keywords that are being bid on, depending on the attribution method chosen, the budget allocation on the keywords will differ and hence, the bid decision will change. This analogy of cost accounting is valid for most organizations. As we show, with appropriate corrections to often used heuristics such as last-click and first-click strategies, there can be a significant improvement in ROI. The suggestions we provide based on our policy simulation, such as using a combined weighted strategy, remain easy to implement but have a significant upside potential in improving ROI. As firms increase their spending in search campaigns, especially for large firms, which spend more than \$20–\$30 million annually, a 3.6% increase in ROI can be substantial.

Another important contribution of our research is that we provide a methodology that can easily be used to test the efficacies of different attribution strategies. Because search campaigns tend to be very different across industry and product categories in terms of their impact on customers' decision processes, customers' knowledge, purchase cycles, and purchase funnels, etc., it is difficult to generalize which attribution strategy is the correct one to use in all situations. Advertisers can experiment with one strategy for a short time, then change the strategy and use our model to tease apart the impact of the attribution scheme on the revenue outcome and even develop better strategies as we did in our simulation exercise. Research such as this is also easy to conduct as it only requires the change of attribution scheme that leads to different bidding.

Our results also provide insights into the efficiency of the search campaign at the keyword level under different attribution strategies. As we illustrate in Section 5.2, some keywords' performance is shown to be better under the first-click strategy while other keywords' performance is better under the last-click strategy. This allows an advertiser to identify important keywords that act as originators of purchase funnel and those that act as convertors in the funnel. Generally, we would expect the broad keywords to perform better under the first-click strategy and the narrow keywords to perform better under the last-click strategy. However, if we find that a broad keyword also performs well under the last-click scheme, then this may suggest that the firm's internal website is well designed (with its own search functionality in the website) to convert a customer who visits by using a broad keyword. On the other hand, a narrow keyword lagging expectation under the last-click scenario may indicate that the website is not optimally designed to convert potential customers with very specific needs in mind. Finally, our model can be used to predict and quantify the impact of such design factors on revenue, CPC, CTR, conversion rate, and the position of a paid search ad.

Our research is not without limitations. Given that the data we use are at the aggregate keyword level and not at the customer purchase funnel level (where we would also know the position of the keywords in the purchase funnel), we lose some relevant information that could be useful to optimize the attribution strategy or incorporate spillovers across keywords (e.g., Rutz and Bucklin 2011). First, while in our application the purchase funnels mainly consist of a few touches, this can be a significant limitation in other applications with longer purchase funnels. Second, we do not have access to all data such as promotions at the firm's website and other firm-level actions but use daily budget as an endogenous variable to reflect new product introduction, seasonal items, and website promotions. Having all firm-level data can help build more accurate models. Third, we represent search engine position decision as a function of a firm's bidding and quality score and abstract away any competitive effects. Thus, strategic aspects at the search engine level are not considered in our model although these could play an important role (e.g., Amaldoss et al. 2015, Desai et al. 2014). On the other hand, the simplicity of our model formulation allows us to understand the impact of attribution strategies on other similar marketing instruments such as the ROI of real-time bidding display advertising.

Supplemental Material

Supplemental material to this paper is available at https://doi.org/10.1287/mksc.2016.0987.

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