ABSTRACT

Title of Document: **ATTRIBUTION MODELING AND MARKETING RESOURCE ALLOCATION IN AN ONLINE ENVIRONMENT**

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This dissertation contains one conceptual framework and two essays on the attribution modeling and marketing resource allocation in digital marketing. Chapter II presents the conceptual framework for attribution modeling and hypotheses related to the carryover effects and spillover effects of the information collected during the customer's prior visits through different marketing channels to a firm's website on subsequent visits and purchases.

In Chapter III, I propose a method to measure the incremental value of individual marketing channels in an online multi-channel environment. The method includes a three-level measurement model of customers' consideration of online channels, their visits through these channels and subsequent purchase at the firm's website. Based on the analysis of customers' visits and purchases at a hospitality firm's website, I find significant carryover and spillover effects across different marketing channels. According to the estimation results, the relative contributions of each channel are significantly different as compared to the estimates from the widely-

used “last-click” metric. A field study was conducted where the firm turned off paid search for a week to validate the ability of the proposed approach in estimating the incremental impact of a channel on conversions. This method can also be applied in targeting customers with different patterns of touches and identifying cases where e-mail retargeting may actually decrease conversion probabilities.

Chapter IV analyzes the impact of attribution metric on the overall effectiveness of keyword investments in search campaigns. Different attribution metrics assign different conversion credits to search keywords clicked through the consumers’ purchase journey, and the attribution-based credits affect the advertiser’s future bidding and budget allocation for keywords, and in turn affect the overall return-on-investment (ROI) of future search campaigns. Using a six-month panel data of 476 keywords from an online jewelry retailer, I empirically model the relationship among the advertiser’s bidding decision, the search engine’s ranking decision, and the click-through rate and conversion rate, and analyze the impact of the attribution metric on the overall ROI of search campaigns. The focal advertiser changed the attribution metric from last-click to first-click half-way through the data window. This allows me to estimate the impact of the two attribution metrics on budget allocation, which in turn influences the realized ROI under different attribution regimes. Given the mix of the keywords bid by the advertiser, the results show that first-click leads to lower overall revenues and this impact is stronger for the more specific keywords. The policy simulation shows that the advertiser would be able to improve their overall revenue by more than 5% by appropriately changing the attribution metric for individual keywords to account for their actual contribution.

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Dissertation submitted to the Faculty of the Graduate School of the
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Dedication

To my Mom

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Chapter 1 : Introduction

According to a recent forecast, the total U.S. spending on search marketing is slated to increase from $15 billion in 2011 to $24 billion by 2016. The 2016 estimates for display ads and e-mail marketing are $25 billion and $0.24 billion, respectively (eMarketer 2012). These figures indicate the overall popularity of online marketing interventions to draw traffic to firms' websites. Customers may directly visit the firm’s website on their own initiative, visit through different sources such as search engines and referral sites, or visit by interacting with some marketing interventions such as display ads and emails. Upon the customer’s response (such as clicking on display ads, e-mail links, firm’s paid search ads, or choosing any other source on their own), these interventions become the touch points or “channels” through which they visit and convert at the firm’s website (Martin 2009; Mulpuru et al. 2011).

Online marketers invest significant resources in driving traffic to their websites through multiple marketing interventions and channels. With increased availability of customer-level data in online multi-channel environments, it is now possible to track all the touch points of customers in their purchase funnel before they convert at a firm’s website. This dissertation presents a conceptual framework and two essays to examine how the data of customers’ online purchase funnel in a multi-channel context can help firms attribute appropriate conversion credit to marketing interventions and make appropriate marketing investments.

The marketing channels can be further categorized into outbound marketing channels and inbound marketing channels. In outbound marketing channels, such as e-mail channel and display channel, the firm determines when to communicate with customers, while in inbound marketing channels, such as paid search channel and referral channel, the customers reach out to the firm on their own initiative. Some marketing managers believe customers appearing in inbound marketing channels have higher conversion potential and leaving the choice to customers makes the marketing interaction less intrusive. On the other hand, the outbound marketing can be used to reach and push ads to customers who would not visit the firm's site otherwise, which follows the "more reach more sales" logic in traditional mass marketing.

In many product and service categories, customers visit a firm's websites several times through multiple channels before a conversion occurs. A visit to the firm's website through a specific channel, say a search or a referral site, exposes the customer to additional information regarding the attractiveness of the product and service vis-à-vis competing and complementary offers and has an impact on subsequent visits to the website.

In practice, the multiple touches a customer makes in a purchase funnel prior to a conversion are rarely considered in measuring the effectiveness of campaigns across various touch points or channels. Traditionally, a conversion at the website is credited to these different channels on the basis of "last-clicked" or "last-touched" channel, entirely ignoring the multiple channels a customer might have touched in the purchase funnel preceding the last click. Such aggregate measurements are, in turn, used to determine the level of investment (e.g., bids for search keywords) in future marketing campaigns. Consequently, such aggregate measures do not take into account the timing and sequence of earlier interventions and the resulting interactions across marketing channels, nor reflect their relative incremental impact in leading to website visits and conversions. That said, what the aggregate measures suggest with regard to the effectiveness of these channels could be biased and misleading which could then contribute to sub-optimal allocation of marketing budget across channels and campaigns (Martin 2009). In addition, these channels are usually managed and measured using separate systems and often by different teams within an organization – display and paid search by one, e-mail campaigns by another, etc., producing incompatible data across different sample frames (Atlas 2008; Green 2008). The incompatible measurements across multiple channels results in double counting and disproportional attribution of conversion credit to each channel. It is necessary to understand the nature of the interactions across the multiple marketing channels touched by the same customer and develop an integrated model on the bases of this understanding. Then the firm is able to correctly measure the incremental contribution of every single marketing channel and decide on an optimized marketing budget.

In Chapter II, I develop a conceptual framework and propose hypotheses related to the nature of the interactions across marketing channels. I define the impact of a visit on subsequent visits and purchases in the same channel as carryover effects. For example, a click on a display ad could lead to more clicks on other display ads and possibly purchases at the firm’s website following these clicks. Similarly, I define the impact of a visit on subsequent visits and purchases in other channels as spillover effects, such as a search visit leading to a subsequent click-through on a display ad and possibly a conversion later. These effects can vary across customers in how they choose to use different channels and respond to the various online marketing interventions (Mulpuru et al. 2011).

Measuring the effectiveness of the investment across multiple marketing channels is critical for marketing managers, especially for products with a long purchase funnel or with touch points across multiple marketing channels. For durable goods and high involvement products and services such as travel, customers may visit a firm's website many times through multiple channels before committing a conversion.

Chapter III proposes a method to tease out the incremental value of each marketing channel in leading to conversions in a multi-channel environment. I develop a three-level measurement model of customers' consideration of online channels, their visits through these channels over time and subsequent purchase at the website, according to the conceptual framework demonstrated in Chapter II. Using the customers' path data of visits and purchases at a hospitality firm's website, I measure the carryover and spillover effects through the customers' purchase funnel. Based on the estimation results, I am able to attribute the relative contributions of each individual channel and compare it with the estimates from the "last-click" metric. In addition, I validate the model with a field experiment and discuss the implication for re-targeting certain customers with certain patterns of touches in their purchase funnels.

The past few years has witnessed a rapid growth in search engine marketing. The marketing opportunities are gathered and auctioned at the search engines very efficiently. Many companies outsource their operation of search engine marketing to intermediary ad agency where millions of marketing allocation decisions are made automatically on a daily basis. The high conversion propensity and high marketing operation efficiency gives rise to the exponential increase of paid search marketing. The spending on paid search marketing is predicted to account for 48% of the overall spending on digital marketing from 2011-2016 (VanBoskir 2011).

Chapter IV particularly focuses on the paid search marketing channel and examines the role of attribution in search campaigns. I use the keyword-level data of search campaigns from an online jewelry retailer who has changed their attribution metric half-way through the data window. This unique dataset provides a natural experiment for attribution metrics and allows me to analyze the simultaneous and endogenous changes trigged by the change of attribution metric to the advertiser, the customer, and the search engine. The analyses in Chapter IV shed light on the impact of attribution metric on the overall effectiveness of keyword investments in search campaigns

Chapter V summarizes the contribution and the implication of this dissertation and concludes with future research opportunities.

Chapter 2 : Conceptual Framework

2.1 An Illustration of the Multi-touch Phenomenon

Let us consider a hypothetical online purchase funnel scenario of a sample of customers as shown in Table 2-1. For each customer, the current visited channel is indicated in column 3, whether she converts on that current visit or not in column 4, and the prior visited channels in column 2. The channel alternatives through which a customer reaches the firm's website include Direct clicking-through "firm.com" (D), Search (S), Referral sites (R), E-mails (E), and Display banner ads (B). In addition, customers may encounter Display Impression (I) but choose to click through it or not. Applying the commonly used metric – the last-click metric – to the data, the firm would attribute 50% (2 out of 4) of the conversions to Direct channel, 25% each to Display and Search. However, this last-click metric totally ignores the influence of prior channel touches. For example, both of the current Direct visits that ended up with conversions were preceded by visits from a Referral channel (customer 1 and 3), while the two current Direct visits that did not convert were preceded by Search visits (customer 7 and 8). Thus, unless these prior visits have no impact on current visits, ignoring such spillovers could lead to biased estimates of attribution.

<Insert Table 2-1 about here>

Realizing this limitation of last-click metric, some practitioners have proposed other metrics – such as "first-click" metric which assigns the credit to the first touch, or "uniform", "weighted" or "exponential" metric which considers all the touch points leading up to a conversion and allocates the credit of the conversion accordingly. Some database researchers have developed data driven methods (Dalessandro et al. 2012, Shao and Li 2011), but they still only consider the paths that have ended in conversions and disregard the path of touches that do not lead to conversions (Petersen et al. 2009). The pitfalls of these metrics can be illustrated by the cases of customer 4 and 5 in Table 2-1. They have the same paths, one ending in conversion while the other not, yet the existing metrics in practice do not make use of the useful information contained in the path of no conversion. In addition, none of the data driven metrics incorporate the underlying consumer behaviors, such as the different stages in information processing a consumer might go through along the purchase funnel (Bettman et al. 1998) and the changes in customers' cognitive costs incurred from visit to visit (Johnson, Bellman, and Lohse 2003; Zauberman 2003) .

It is clear that a more sophisticated metric should account for the many factors that characterize customer purchase funnels as in Table 2-1. First, customers differ significantly in terms of the channels they use in arriving at a firm's website. Some use Search and Direct, others use Referral and Direct. Some customers are targeted by e-mail and display ads, while others are not. This indicates that customers' consideration of channels to visit the firm's website could be heterogeneous. Additionally, some have a longer purchase funnel than others, and the impact of the channels touched could decay over time at different rates. The carryovers of prior touches could affect future visits and conversions in different manner. For example, for customer 1, the carryover of Search visits lead to more Search visits, but for customer 2, the repeat Display impressions may spill over to a Search visit and affect the conversion during that visit. For customer 7, while the carryover of Search visits leads to more Search visits, it may not ultimately contribute to a conversion. Understanding the nature of such carryovers and spillovers is important for marketing budget allocation. Managers would like to know whether e-mail visits lead to more direct visits to the firm's website which then lead to conversions, over and above the conversions that occur through the e-mail channel right away. They would also be interested in knowing whether repeated display impressions play a role in leading to more click-trough's in the search channel, or leading to website visits and conversions elsewhere.

2.2 A Conceptual Framework

In the next, I propose a conceptual framework which focuses on the purchase funnel in the context of online shopping of high involvement goods or services (see Figure 2-1). The purchase funnel captures a series of stages that a customer moves through in making a purchase – (1) the consideration stage, where the customer recognizes her needs and considers different channels for information search, (2) the visit stage, where the customer visits the website through a specific channel for information search and evaluation of alternatives, and finally (3) the purchase stage, where the customer makes a purchase (e.g., Wiesel, Pauwels, and Arts 2011).

<Insert Figure 2-1 about here>

Given individuals' diverse habits for gathering information in the online shopping context, customers vary in their consideration of channels to use in visiting a firm's website. Some may be loyal to the website and consider going directly, while some may consider search channel for better prices and options. Some may consider both. While firms reach out to customers with e-mail and display ads, consumers also seize the control of their purchase decision by seeking for the helpful information themselves (Court et al. 2009). I make a distinction between *customer-initiated channels*, which consumers seek out on their own initiative, and *firm-initiated channels*, where firms initiate marketing interventions (Bowman and Narayandas 2001; Wiesel, Pauwels, and Arts 2011). The propensity to consider a customer-initiated channel might evolve over a long time horizon (Valentini, Montaguti, and Neslin 2011). Based on their awareness, experience, and expectations about these channels, they may make these channel consideration decisions in advance and store them in memory for use when the appropriate occasion arises. That is, consumers evaluate each channel they are aware of with regard to the benefit it provides versus the incurred search cost and arrive at a smaller set of channels they would consider for future information search when a purchase need arises (Hauser and Wernerfelt 1990; Mehta, Rajiv, and Srinivasan 2003). The channels in the consideration set act as "pre-decisional constraints" (Punj and Brookes 2002) to simplify the customer initiated search process when a purchase has to be made. On the other hand, the firm initiates marketing interventions targeting customers through e-mails and display ads. Extant research focusing on display banner ads (Goldfarb and Tucker 2011) indicate that online display ads tend to have small behavioral impact and play insignificant role in ad recall, suggesting customers consider it only when encountered. Thus, the firm initiated channel options enter into customers' consideration sets only when customers encounter them as a result of firm's targeting.

2.3 The Carryover and Spillover Effects

Conditional on their consideration sets, customers make visits to the firm's website through these channels and make a decision on purchase. Note that the impact of a visit on subsequent visits and purchases in the same channel is defined as carryover effects, while the impact of a visit on subsequent visits and purchases in other channels as spillover effects. I will look into the carryover and spillover effects both at the visit stage and purchase stage. *That is, I define carryover and spillover effects at the visit stage as the impact on the probability of a visit through a channel, while at the purchase stage I define them as the impact on the probability of making a purchase through a channel.*

A customer's decision to visit the firm's website through a specific channel depends on the marginal benefits derived vis-à-vis marginal costs incurred in the visit. The benefit is the perceived mean attractiveness of making a purchase decision through the channel. The costs include the effort required to find the needed information (Shugan 1980) which can be viewed as an opportunity cost (Kim, Albuquerque, and Bronnenberg 2010) and the cognitive costs in processing the information (Johnson, Bellman, and Lohse 2003) which are, in turn, moderated by other factors (explained below). As customers make multiple visits to the firm's website through various channels over time, the carryover and spillover of prior visits increase or reduce the costs of current visit. As customers gain familiarity with a channel and its informational content, I expect the carryover of previous visits through that channel to reduce the costs in the same channel due to cognitive lock-in effects (Johnson, Bellman, and Lohse 2003; Bucklin and Sismeiro 2003), risk reduction over multiple visits, and self-reinforcement effects (Song and Zahedi 2005). The spillover across channels could reduce costs to the extent the channels are similar in nature and similar reinforcing information is sought by customers. If the channels are very different or if different types of information are sought by customers, then spillover could increase costs as customers may incur switching costs in breaking cognitive lock-in and adjusting to different types of channels. Thus, at the visit stage I model carryover and spillover through their impact on the costs of visiting a channel, with the costs reflecting not only the search cost, opportunity cost, and cognitive costs but also the mere exposure effects, reinforcement learning, and risk reduction as customer gather information across visits.

At the purchase stage, as customers make visits through different channels over time, the contextual information derived from the channels, such as information on other alternatives from a search engine or complementary goods from a referral site including their price and promotion, is compared and contrasted with the website's offering. This cumulative informational stock accrued over the past visits manifests itself as a utility of all prior visits through the channel, and gets added to the utility of the website's offering. Thus, the cumulative informational stock works to increase or decrease the overall utility of making a purchase at the website. The value of the information gathered at a specific visit could decay over time depending on the channel and market dynamics, and thus the cumulative informational stock of prior visits would weigh the later visits more than the earlier ones (Ansari, Mela, and Neslin 2008; Terui, Ban, and Allenby 2011).

2.2.1 Impact of Carryover on Visiting

For customer-initiated channels, as customers make repeat visits through a channel, the cognitive costs of visiting should decrease due to cognitive lock-in effects (Johnson, Bellman, and Lohse 2003). So the cumulative experience (visits and time spent) in visiting through this type of channel should reduce the costs of visiting. On the other hand, since the firm-initiated channels – display ads and e-mails – may differ in content and specifics across different encounters, the impact of prior cumulative experience and exposure on a specific visit could be insignificant. For example, Chatterjee, Hoffman, and Novak (2003) find that customers who are inclined to respond to display ad interventions would do so at their first exposure than later exposures. Thus, the carryover impact of firm-initiated contacts could hurt the future visits through the same channel. Also, DoubleClick (2004) reported a declining click-through on each additional display banner exposure. Ansari, Mela, and Neslin (2008) suggest optimizing the content and timing of e-mail to maximize its impact by showing that e-mail, though costless to the firm, could generate negative influence on visits to the firm in the long run. Thus, I posit:

Proposition 1: *The carryover of prior visits through customer-initiated channels will reduce the costs of visiting through the same channel, while the carryover of impressions/ visits of firm-initiated channels will either have no impact or increase the costs of visiting in the same channels.*

2.2.2 Impact of Spillover on Visiting

Regardless of which channel a customer has experienced in the prior visit, when he/she encounters a targeted e-mail or display ad that provides very specific information on product/service features, price and promotion, it is likely to reduce the cost of clicking on the interventions and visiting the website. This is because content in these marketing interventions could be similar to the information that customer is seeking. Similarly, if a customer's prior visit to the website was through display ad or e-mail click-through, then the subsequent visit through any channel (especially a customer-initiated channel) is likely to be one where those specific product, price and promotion information are compared with other offers and information. Since the goal of such channel visits are clear with specific information requirement in mind, the spillover effect on the costs of visiting is also likely to be one towards reducing the costs of visiting. Also, Sherman and Deighton (2001) and Ilfeld and Winer (2002) report that banner exposure can increase ad awareness, brand awareness, and lead to more site visits. I expect that similar "billboard" effects could exist for e-mail interventions too. Information contained in e-mail newsletters can help customers refine their needs and narrow down their search domain. Also, firms can use e-mail campaign to steer customers to referral channels or direct channels that might be more lucrative to the firm (Myers, Pickersgill, and Metre 2004; Neslin and Shankar 2009). In addition, the product information and ongoing campaigns covered by search keywords and e-mail newsletters are very likely to overlap. Therefore, I can expect spillover from customer-initiated channels to reduce the cost of visiting through firm-initiated channels and vice-versa.

With regard to spillover among search, referral and direct channels, when customers switch across these channels they are likely to search for complementary as well as comparative information on the product in the current channel vis-à-vis their prior channels. This could lead to increased costs as there could be switching costs due to different informational content and layout and the need to break cognitive lock-ins (Johnson, Bellman, and Lohse 2003). However, within search channels (organic versus paid search) I expect the spillover effects to reduce the costs of visiting as the informational content, layout, and experience effects could be reinforcing.

Proposition 2a: *The spillover of customer-initiated channel visits on the costs of visiting in firm-initiated channels is negative (reducing the costs of visiting) and the spillover of firm-initiated channel visits on the costs of visiting in customer-initiated channels is also negative.*

Proposition 2b: *While spillovers between organic and paid search channels will reduce the costs of visiting through the other, the spillover across search, referral, and direct channels are likely to increase the costs of visiting through the other two channels.*

2.2.3 Impact of Carryover on Purchase

Extant research suggests that display ad exposures seem to be processed at a pre-attentive level and may benefit ultimate purchase (Drèze and Hussherr 2003; Manchanda et al. 2006). Manchanda et al. (2006), using a hazard modeling approach find display ads can accelerate the purchase timing. In addition they find the number of display impression as well as the number of sites and pages containing the display ads all have a positive impact on the repeat purchase probability. Abhishek, Fader, and Hosanagar (2012) find display ads, although do not have an immediate impact on conversion, can affect customers at an early stage of their purchase funnel. Once customers start to click on the ads, it implies they are much more likely to convert than not interacting with the ads. A recent ComScore report also finds the banner ad impression could be more influential in leading to conversions than the click-throughs (Lipsman 2012). Thus, I would expect the carryover impact of display ads to be positive on purchases. A similar argument can be made with regard to e-mails. Repeat direct visits, which are customer initiated, could imply that a customer has a higher preference for the firm's offering (Bowman and Narayandas 2001) and thus does not shop around in other channels. This carryover could lead to a positive impact on purchase probabilities. With regard to the carryover of search and referral channels, one can expect that customers' visiting through these channels could focus on finding better deals. Yet, if a customer has made repeat visits to the websites through search and referral channels, it might indicate he/she finds the website's offering to be more attractive as compared to the other ones they encountered in prior visits in search or referral channel, and hence is more likely to make a purchase (positive carryover). Chan, Wu, and Xie (2011), for example, show that the customers acquired through paid search channel make more purchases and generate higher customer lifetime value than customers acquired from other channels. Wiesel, Pauwels, and Arts (2011) also find compared with e-mail the profit impact of paid search is more enduring, i.e. it wears in faster and wears out more slowly. Overall, the expectation for positive carryover is strong.

Proposition 3: *The carryover effects are positive on purchase probabilities.*

2.2.4 Impact of Spillover on Purchase

Yang and Ghose (2010) examine the spillover between organic search and paid search and report a positive yet asymmetric pattern, i.e. the impact of organic search on paid search is over three-times stronger than the impact of paid search on organic search. They also conducted field experiment to show that the total click-through rates, conversion rates, and revenue are lower in the absence of paid search than in the presence of it, highlighting the spillover from paid search. I could therefore expect positive spillover effects across search channels. With regard to firm-initiated channels, I should expect carryover of e-mail and display ads to have positive impact on purchase probabilities in any of the customer-initiated channels. Such repeat response to firm-initiated channels may indicate higher preference level for the firm's offering, which, in turn, could lead to positive spillover and increase in overall purchase probabilities regardless of which channel they make a visit through (cf., Manchanda et al. 2006).

Proposition 4: *The spillover effects between organic and paid search channels on purchase probabilities are positive, and the spillover effects of firm-initiated channels on purchases through customer-initiated channels are also positive.*

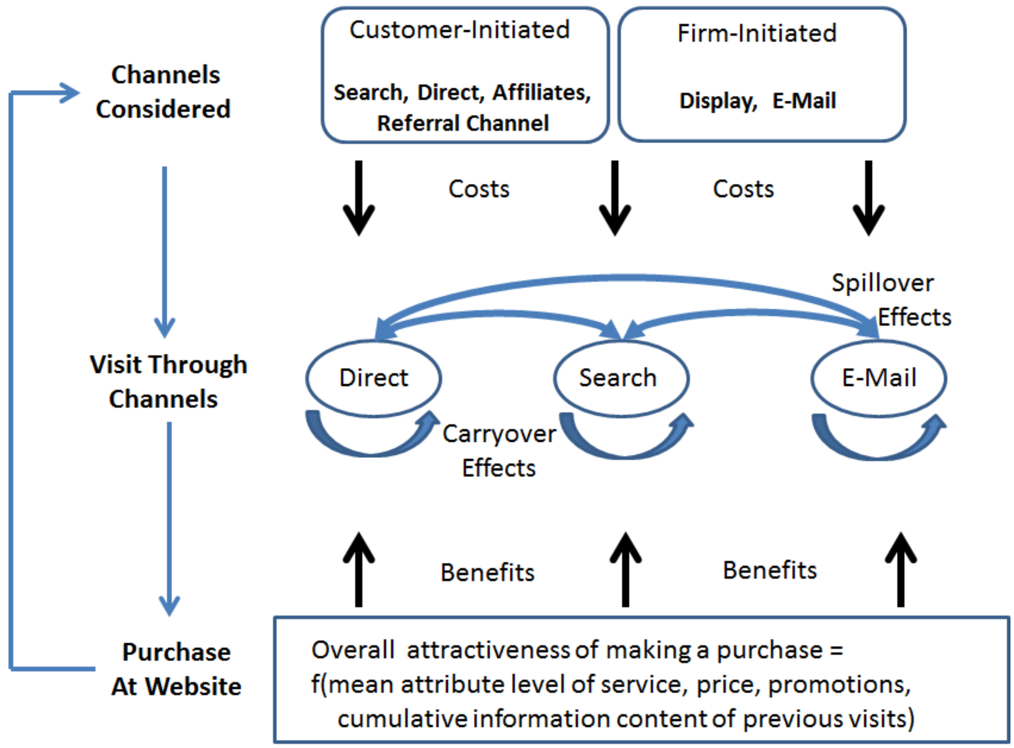
I do not have a priori expectations with regard to the spillover effects across search, direct and referral channels, or the spillover from these customer-initiated channels on purchases through firm-initiated channels. I expect these effects to depend on the preference intensities and price sensitivities of customers visiting through these channels, and let the data provide us context dependent insights.

Table 2-1 Consumer Touch Points Illustration

Customer	Prior Channel Touches	Current Visit through Channel	Conversion Status
1	S S S R	D	Yes
2	B I I I	S	Yes
3	E E R	D	Yes
4	R E I B	B	Yes
5	R E I B	B	No
6	R R R E	E	No
7	S S S S	D	No
8	S D S	D	No

Note: D = Direct, S = Search, R = Referral, E = E-Mail, I = Display Impression, and B = Display.

Figure 2-1 Conceptual Framework



Chapter 3 : Attributing Conversions in Online Multi-Channel Environment in the Presence of Carryovers and Spillovers

3.1 Introduction

Marketers invest a lot in online marketing dollars to attract traffic to their websites through various channels, such as search engines, referral websites, and social media, etc. The objective of this essay is to analyze the nature of carryover and spillover effects of prior visits to a firm's website across a number of commonly used online touch points or channels, both at the stage of visiting the website and at the stage of purchasing at the website.

Based on the conceptual framework proposed in Chapter II, I develop a three-level choice model to estimate the carryover and spillover effects using individual level data of customer touches in their purchase funnel. This measurement model accounts for (1) the heterogeneity across customers' consideration of channels through which to visit the website (not all customers may consider all channels in visiting a website. For example, some may consider search channels but are unaware of referral channels; some may be targeted by e-mails but others are not), and (2) the carryover, spillover and the sequence effects of prior channel interventions that contribute to the website visits, and (3) the subsequent purchase conversions. The model provides the basis for measuring the incremental impact of a channel on conversions at a firm's website in an online multi-channel context.

This research falls within the realm of multi-channel marketing. Extant studies in multi-channels have focused attention on customer lifetime value, total spending across channels and cross-selling, dynamics among media, both in the offline and online contexts (Venkatesan and Kumar 2004; Kumar and Venkatesan 2005; Li, Sun, and Montgomery 2011; Stephen and Galak 2012; Kushwaha and Shankar 2013). However, none have examined the issue from the viewpoint of understanding the impact of marketing interventions and touches at different stages of the online purchase funnel and attributing conversion credit to the multiple channels. This research is also related to studies that analyze the impact of individual channels *outside* the website such as display ads, e-mails and search engines in enabling conversions at the website (Chatterjee, Hoffman, and Novak 2003; Manchanda et al. 2006; Ghose and Yang 2009; Rutz and Bucklin 2011). Instead of focusing only on a specific marketing intervention as in the preceding work, this research integrates the effects of a variety of marketing interventions/channels, such as search, display ads, e-mails, affiliate websites, referral engines, etc. on website visits and conversion (cf. Ansari, Mela, and Neslin 2008; Naik and Raman 2003). Finally, there are studies that examine customers' conversions *within* websites – focusing on the existence of lock-in effects within websites (Johnson, Bellman, and Lohse 2003; Zauberman 2003), learning effects impacting cognitive costs of using a website (Bucklin and Sismeiro 2003; Moe and Fader 2004) and the impact of demographic, site and visit characteristics (Danaher, Mullarkey, and Essegaier 2006). In contrast, I account for the influence of a preceding channel visit or marketing intervention a visitor might have had before reaching the website that could affect the subsequent purchasing behavior. Overall, this study fills a unique niche by being the first one to examine the nature of carryover and spillover effects in a multi-channel context using a conceptual framework, and to propose a methodology to apportion and allocate the credit for conversions that occur at firm's website to marketing channels by estimating these carryovers and spillovers.

The customer path data in this research are from an online firm in the hospitality industry. The empirical analysis shows that there are significant carryover and spillover effects both at visit stage and purchase stage, the nature of which varies significantly across channels as conceptualized. For example, e-mails and display ads trigger visits through other channels, while e-mail leads to purchases through search channels. The empirical analysis also shows that the attribution based on the proposed measurement model paints a much different scenario of relative contributions of these channels as compared to the widely-used last-click attribution metric. For example, e-mail, display and referral channels are significantly undervalued by last-click metric, while the contribution of search channels is significantly inflated compared to their real contribution. A field study conducted at the firm's website by turning off paid search for a week provides a strong validation for the proposed model's ability to estimate the incremental effect of a channel on conversions. I highlight the implications of the results for budgeting marketing investment across these channels. I also highlight the usefulness of the results through an illustration of whether or not the firm should retarget their customers with repeated e-mails based on customers' prior visit path.

In the remainder of this Chapter, I provide the overview and details of the measurement model set in a choice modeling framework, followed by the information of the data and empirical results, the field study results, and the path analysis for targeting. In the end, I highlight the managerial implications and contributions, and conclude with a discussion of limitations and future research.

3.2 Model Overview

The conversion decision of a customer at an online site, according to the conceptual framework proposed in Chapter 2 (Figure 2-1), consists of three stages: the consideration of alternative customer-initiated channels and the encountered marketing interventions, the visit decision and the purchase decision. I develop an individual-level probabilistic model explicitly accounting for these stages (see an illustration in Figure 3-1).

<Insert Figure 3-1 about here>

3.2.1 Consideration of Channels

Given the diverse individual habits in gathering information in the online shopping context, I expect to see a significant variation in customers' consideration of channels to use in visiting a firm's website. In order to control for individual heterogeneity in the consideration of channels, I allow individuals in this model to have different consideration sets of channels, which could include both customer-initiated channels and firm-initiated channels. I assume that an individual's consideration of customer-initiated channels in visiting the firm's website is the same across all visits and purchase occasions, while the firm-initiated channels (display ad and e-mail) which enter into consideration when a customer has encountered them, to vary across visit occasions. Since the data are collected in a short time window during which the firm's marketing strategies and tactics remained constant, this assumption is justified. Also, recent research findings in the context of web browsing and purchasing support the notion that consumers have fixed consideration sets, with size and elements being heterogeneous across customers (De Los Santos, Hortaçsu, and Wildenbeest 2012).

Assume there are Q channels available for a customer to reach the firm's website on their own initiative, and meanwhile, the firm operates *(J-Q)* firm-initiated channels. Thus, a customer's consideration set could include up to J channels, with the customer-initiated channels remaining constant across visit occasions and the firm-initiated channels varying across occasions.

To study the consideration of customer-initiated channels, I assume, following the model proposed by van Nierop et al. (2010), that individual i ($i=1,\dots,I$) has a Q-dimension vector of latent utility, $\tilde{C}_i^*$, for considering each customer-initiated channel q (q=$1,\dots,Q$) in the visit decision. The Q-dimension vector $\tilde{C}_i^*$ is jointly drawn from a multivariate Normal distribution as in Equation (1). Further, each element of latent utility c_{iq}^* is determined by a set of customer-specific characteristics R_i shown in Equation (2). The latent utility c_{iq}^* is associated with a binary value c_{iq}, where $P(c_{iq}=1)=P(c_{iq}^*>0)$ implies that channel q is included in individual i's consideration set. I normalize all the diagonal elements in Σ to be 1 for identification, so that the off-diagonal elements are, therefore, the correlations of considering two channels.

$$\tilde{C}_i^* = (c_{i1}^* \ldots c_{iq}^* \ldots c_{iQ}^*)^T \sim N_Q(\varphi, \Sigma) \qquad q = 1, \ldots, Q \tag{1}$$

$$c_{iq}^* = R_i \alpha_{iq} + \varepsilon_{iq} \tag{2}$$

For the firm-initiated marketing interventions, I use $\{c_{i(Q+1)}, \ldots, c_{iJ}\}$ to indicate whether customer *i* encounters any marketing intervention in channel *(Q+1)* to channel *J* in each of their visit decision.

I exclude the empty consideration set from this model (van Nierop et al. 2010), since I can observe a customer in the data only if she has made at least one visit to the focal firm's website through one of the *J* channels. Define H_k as one combination of any positive number of channels out of J channels, where $k = 1, \ldots, (2^J - 1)$. The multivariate probit variable $C_i = (c_{i1} \ldots c_{iJ})^T$ is the same as H_k with a probability $P(C_i = H_k \mid \alpha, \Sigma)$.

Given the consideration of channels, I model the visit decision and subsequent purchase decision in a two-level nested logit framework. That is, the realization of the consideration set determines the structure of the nested logit model. At any online visit occasion *n* (n=1*,…,*N_i) , individual *i* can choose to visit the firm's website through channel *j*, (V_{in} =*j*, $j \in \{c_{ij} = 1\}$), gathering new information to possibly make a purchase, or not make any visit at all (V_{in} =0) (outside option). Notice that channel *j* can be either a customer initiated channel ($j \in \{c_{ij} = 1,\ 1 \le j \le Q\}$) or a marketing intervention encountered on that visit occasion ($j \in \{c_{ij} = 1,\ \ (Q+1) \le j \le J\}$). Given the visit through channel *j*, individual *i* may decide to make the purchase in the same visit (B_{ijn} = 1) or not (B_{ijn} = 0). I assume that some search at the firm's website precedes the purchase stage in every occasion *n*, because the consumer has to at least search for the availability of a specific service (e.g., airline seat availability on a specific date) before purchasing. Given the specific set of considered channels, C_i, the probability of purchase by individual *i* via channel *j* at occasion *n* is:

$$P(B_{ijn}=1, V_{in}=j \mid C_i) = \Pr(B_{ijn}=1 \mid C_i, V_{in}=j) P(V_{in}=j \mid C_i) \quad (3)$$

In the following, I first introduce the purchase decision and then discuss the visit decision, where the option value of a purchase is accounted for through the inclusive values.

3.2.2 Purchase Decision

Conditional on the consideration of and the visit through a certain channel, consumer *i*'s perceived utility of purchasing in channel *j* at occasion *n* is W_{ijn} (Equation 4). The conditional purchase probability is determined based on a logit form (Equation 5), where τ is the scale parameter for the visit decision associated with the purchase decision. The error term ζ_{ijn} follows logistic distribution. The utility of no purchase is $W_{i0n}=0$.

$$W_{ijn} = \bar{W}_{ijn} + \zeta_{ijn}, \qquad j = 1,\ldots,\mathrm{J}, \quad (4)$$

$$\Pr(B_{ijn}=1 \mid C_i, V_{in}=j) = \frac{\exp(\bar{W}_{ijn}/\tau)}{1+\exp(\bar{W}_{ijn}/\tau)}, \qquad j = 1,\ldots,\mathrm{J} \quad (5)$$

In Equation (6), I assume that the overall perceived attractiveness of purchasing a product/service can vary along some mean attribute level of the offering

(Erdem and Keane 1996). In this context, since the hospitality service in every purchase is unique and distinct, and thus could be a new experience to the consumer, I construct a model where consumers are imperfectly informed about these attribute levels of the service. At the outset, consumer i perceives the mean attribute level of her target service to be purchased in channel j as γ_{ij} in Equation (6).

$$\bar{W}_{ijn} = \gamma_{ij} + \sum_{k=1}^{J} \gamma_{ij,k} G_{ikn} . \tag{6}$$

The intercept γ_{ij} is set by prior experiences and expectations of the attractiveness of purchasing through a channel. For example, a customer going to the firm's website through a click on display ad or an e-mail or through a coupon/referral site may have some mean expectation of the attractiveness of the purchases she might make. The overall attractiveness of making a purchase is then updated by the information she collects through channel visits, e.g., search engines (Google, Yahoo, etc.), referral engines (TripAdvisor.com, etc.) or the focal company's website and by the information conveyed in marketing interventions such as display ads and e-mails the customer may encounter. For each of the J channels, including Q customer-initiated channels (such as search, direct, and referral), and *(J-Q)* channels of firm-initiated marketing interventions (display ad, e-mail), the perceived overall attractiveness at occasion n is in Equation (6). The term G_{ikn} detailed in Equation (7) is the cumulative informational stock/content that contains the informational influence of all the preceding visits that individual i has been exposed to in channel k up to the $(n-1)^{th}$ visit, where n=1,…,N_i (Ansari, Mela, and Neslin 2008, Terui, Ban, and Allenby 2011). The indicator d_{ikh} equals to 1, if individual i chooses to visit channel *k* at occasion *h*. The informational effect of past channel visits decays at a channel-specific decay rate λ_k , according to the elapsed days $(t_{ikn} - t_{ikh})$. The instantaneous informational influence of any visit/intervention is normalized to 1, but the relative magnitude of this instantaneous influence of channel *k* compared with other channels can be picked up by the coefficients $\gamma_{ij,k}$ in Equation (6).

$$G_{ikn} = \sum_{h=1}^{n-1} d_{ikh} \times (1-\lambda_k)^{(t_{ikn}-t_{ikh})} \tag{7}$$

A visit to the website will incur cost S_{ijn} , which is captured only in the visit decision, but treated as sunk cost in the purchase decision discussed in this subsection. In sum, consumer i 's expected utility of purchasing in channel j at occasion *n*, W_{ijn} , is captured by Equation (8).

$$W_{ijn} = \bar{W}_{ijn} + \zeta_{ijn} = \gamma_{ij} + \sum_{k=1}^{J} \gamma_{ij,k} G_{ikn} + \zeta_{ijn} \qquad j = 1, \ldots, \mathrm{J} \tag{8}$$

3.2.3 Visit Decision

I posit that consumer *i*'s decision to visit channel *j* at visit occasion *n* depends on the perceived utility for that visit. The perceived utility U_{ijn} (Equation 9) is a function of customer *i*'s perceived benefits of visiting channel *j*, $\beta_{0,ij}$ (say, the useful information they can gather from the visit), and the attractiveness of the purchase/no purchase option through that channel on occasion *n* captured by the inclusive value term and its coefficient, τI_{ijn} , minus the disutility of the incurred cost $\beta_{ij} S_{ijn}$.

Consumer *i*'s inclusive value of purchase or no purchase option in channel *j* at occasion *n* is $I_{ijn} = \log\left\{1 + \exp(\bar{W}_{ijn} / \tau)\right\}$. The error term η_{ijn} follows a generalized extreme value distribution. The utility of not visiting, U_{i0n}, is normalized to be 0. At each visit occasion, the customer compares the perceived net utility of visiting by trading-off the potential purchase benefits against the incurred costs, and chooses to visit the channel that offers the greatest net utility or not visit at all.

$$U_{ijn} = \bar{U}_{ijn} + \eta_{ijn} = \beta_{0,ij} + \tau I_{ijn} - \beta_{ij} S_{ijn} + \eta_{ijn} \qquad j = 1, \ldots, \mathrm{J} \qquad (9)$$

The cost S_{ijn} is further parameterized in a logit form bounded between [0, 1] as

$$S_{ijn} = \frac{\exp(\mu_j T_{ijn} + \sum_{k=0}^{J} \mu_{j,k} L_{ik,n-1})}{1 + \exp(\mu_j T_{ijn} + \sum_{k=0}^{J} \mu_{j,k} L_{ik,n-1})} \qquad j = 1, \ldots, \mathrm{J}\ . \qquad (10)$$

That is, it is always costly to make a visit, but total costs level off as the customer's experience and knowledge in a channel reaches a certain amount. This specification has wide appeal. Moorthy, Ratchford, and Talukdar (1997) empirically find that unit search cost is quadratic as a function of experience, with an initial increase and then a decrease lending support to the S-shaped marginal impact of the variables on total costs. Recently, Seiler (2013) has used the same specification to parameterize search costs[1]. T_{ijn} is the cumulative time spent at website visiting through channel *j* capturing carryover of these visits. This is determined on the basis of the difference between the start time stamp and the end time stamp associated with

[1] I have estimated the model with an alternative linear specification of the costs and find that the proposed specification leads to better model fits (see Table 3).

each visit/impression. I also include a set of *(J+1)* lag visit dummies, $\{L_{ik,n-1}, k = 0,\ldots, J\}$, indicating the channel visited by consumer *i* at occasion *(n-1)*, with 0 representing no visit in previous occasion. This can be viewed as a first order Markov process to capture the short-term carryover and spillover effects[2].

The coefficients in the cost function, μ_j and $\mu_{j,k}$'s , can be either positive or negative. For example, positive μ_j or $\mu_{j,k}$'s imply the corresponding variables can increase the cost S_{ijn}, while negative μ_j or $\mu_{j,k}$'s imply reducing the cost. In addition, the coefficients μ_j capture the relative importance of total previous visits in the same channel (long-term carryover) versus $\mu_{j,k}$'s capture the latest visit through channel *k* (short-term carryover or spillover) to the total cost S_{ijn}. Meanwhile, the coefficient of cost, β_{ij}, in Equation (9) determines the relative disutility of the cost S_{ijn} compared to $\beta_{0,ij}$ and τI_{ijn} in the utility function. Thus, with this formulation, I can compare the marginal impact of the cost of visiting with β_{ij} and compare the relative importance of long-term carryover versus last visit with μ_j and $\mu_{j,k}$'s. In order to identify the coefficient β_{ij} as well as μ_j and $\mu_{j,k}$'s, I set $\mu_{j,0}$'s to be 1. In addition to the short-term and long-term impact captured in *S*, the impact of cumulative informational stock G_{ikn} influence the visit utility through the inclusive value I_{ijn}. Thus, the visit decision is a comprehensive decision, because it takes into

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[2] I use visits lagged by one period, based on previous findings by Montgomery et al. (2004) that the first order Markov performs better than zero order Markov process. This could also be viewed as behavioral reinforcement. In addition, in this empirical application when I accounted for the visits in (n-2) occasion, it did not significantly change the relative magnitude of costs across channels. Neither did it improve the goodness of fit of the model.

account not only the short-term impact of lagged visit $L_{ik,n-1}$ in S_{ijn} but also the long-term accumulated informational stock of past visits and marketing interventions in T_{ijn} as well as the inclusive value terms, I_{ijn} .

Notice that consumer *i*'s visit decision is conditional on her consideration set. That is, given C_i , the probability of individual i visiting channel j at occasion n is

$$\Pr(V_{in} = j \mid C_i) = \frac{c_{ij} \exp(\bar{U}_{ijn})}{1 + \sum_{k=1}^{J} c_{ik} \exp(\bar{U}_{ikn})}, \qquad \text{for} \qquad j = 1, \ldots, J \tag{11}$$

and $$\Pr(V_{in} = 0 \mid C_i) = \frac{1}{1 + \sum_{k=1}^{J} c_{ik} \exp(\bar{U}_{ikn})}$$

Overall, the joint likelihood function in Equation (12) takes into account the consideration, visit and purchase stages. I estimate the model using the Markov chain Monte Carlo approach, which provides a computationally tractable estimation of the large number of parameters in the model. Appendix I provides details of prior and full conditional distributions.

$$L(B \mid \theta) = \prod_{n=1}^{N_i} \prod_{i=1}^{I} \prod_{j=1}^{J} \sum_{k=1}^{2^J - 1} P(C_i = H_k \mid \alpha, \Sigma) \times \left[b_{ijn1}{}^{B_{ijn}} b_{ijn0}{}^{(1-B_{ijn})} \right] \tag{12}$$

where $$\begin{aligned} b_{ijn1} &= P(V_{in} = j \mid C_i; \beta, \mu, \tau) P(B_{ijn} = 1 \mid C_i, V_{in} = j; \gamma, \lambda) \\ b_{ijn0} &= P(V_{in} = j \mid C_i; \beta, \mu, \tau)[1 - P(B_{ijn} = 1 \mid C_i, V_{in} = j; \gamma, \lambda)] \end{aligned}$$

3.3 Empirical Analysis

3.3.1 Data

The data for this study are provided by a franchise firm in the hospitality industry. The firm uses a variety of online marketing channels, such as e-mails, search engines – both organic and paid search – display ads, referral engines and affiliates, etc. to attract customer visits to their website[3]. The average monthly visit to the firm's website in 2010 was around 26 million. The path data for each customer are developed by integrating data feeds from DoubleClick for advertisers (display ad and search engines), Omniture Site Catalyst (visits from different sources using cookies and login IDs), affiliate websites, and e-mail campaign management system. More specifically, when a web visitor is served a display ad (impression or click through) or a paid search, the DoubleClick cookie is placed on the visitor's machine. DoubleClick then provides the firm a file of all display impressions, display clicks and paid search clicks at the cookie ID level, containing the click through URLs associated with each ad campaign code and each keyword. The same campaign code/keyword embedded in the click-through URL and the timestamp can help the firm successfully match the DoubleClick cookie ID with the firm's website visitor's ID and thus the data sets are merged.

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[3] Organic Search and Paid Search represent the visits originated from a click at search engines, such as Google, Bing and Yahoo. Organic search is free traffic to the firm's website, while paid search involves a fee per click for the firm. Referral engines include referral sites such as TripAdvisor.com and Kayak.com, B2B referrals, event management tools, social media. E-Mail channel represents the visits by a visitor who received an e-mail and clicked the link embedded in the e-mail. It also includes visits from a guest who received an e-confirmation of their booking or pre-arrival e-mail and clicked through the link in that e-mail. Finally, Display channel represents those visits made to the website by clicking on a display banner advertisement.

For all e-mail campaigns, a unique tracking code is created for each campaign email sent to every recipient. These tracking codes of campaign and recipients are also embedded in the click through URL and captured by the firm at the time the visitor enters the site. For referral engines, all inbound traffic (paid and unpaid referrals) to the firm's website has tractable referral information associated with the external referrer. In addition, the firm uses Omniture Site Catalyst to capture visits through firm.com (direct), organic search and other visit.

Overall, the path data provide information on display impressions and e-mail drops each customer encountered over time and whether it was clicked or not, click through visits from search engine (organic and paid), referral sites, and direct visits[4]. It does not include visits to search engines and referral sites that did not result in a click-through to the firm's website but this is captured by the outside option in the proposed model as they do not materialize in visits to the firm's website. The firm can also use cookies and login IDs to identify their rewards program customers and their specific rewards tiers – Rewards Level-1, Rewards Level-2, Rewards Level-3 and Rewards Level-4, from the lowest level to the highest. Across tiers, there are differences in customers' purchase frequency as well as purchase funnel (Rewards Level-4 is given to individuals as honorary membership, not based on actual purchases).

The dataset is a random sample from visitors to the firm's website during a week in late August, 2011, with their visit history between late June and late August, 2011. I track each visitor's 68 days' history containing whether an online visit was

[4] A Direct visit is made by customers via typing in the URL of the firm's website.

made each day, visits through different channels to the focal firm's website, the instances of marketing interventions, and purchases if any. In the data, the average time between the first visit since the previous purchase and the current purchase was 9.2 days, indicating that a 2-month window should be sufficient to capture all relevant historical data to explain visit and conversion decisions. Among the 1997 customers, 163 made multiple purchases ranging from 2 to 11 times. I applied stratified sampling based on the number of visits through each channel to assure the overall and channel-wise conversion rates in the sample are close to the firm's average of 4.5% and to allow me reliably estimate the impact of various independent variables on conversion at the website. All contiguous visits through the same channel within 30 minutes with the same campaign code are treated as a single visit. The summary statistics in Table 3-1 are based on 1997 unique customers' data, comprising 22369 click-through visits to the firm's website. The Display channel in Table 3-1 includes the display impressions with no click-through by customers who have visited the firm's website. Overall, 815 customers made 1128 purchases over the study duration. As seen in Table 3-1, the conversion rates in each channel vary significantly with Display being the lowest and Paid Search being the highest.

<Insert Table 3-1 about here>

I have provided two more perspectives on the data: a matrix of current visit (n) versus last visit (n-1) in Table 3-2, and a matrix of current visit (n) versus all prior visits (n-1 n-2, n-3,,..) in Table 3-3. Table 3-2 shows, given the current channel of visiting, what was the preceding channel a customer visited through. The large numbers on the diagonal reflect the stickiness of customers' visiting to a certain channel. Meanwhile, the off-diagonals are not quite symmetric. For example, a Direct visit preceding a Display happens 84 times, but a Display leading to a Direct visit happens 124 times. Note that the total number of visits at occation (n-1) in each channel is all less than the numbers in column 2 of Table 3-1, and the difference is the number of visits of the very last visit made by customers. For example, the total number of visits in Organic Search channel in occasion (n-1) is 4060 in Table 3-2, and the total number of Organic Search visits presented in Table 3-1 is 4469. This implies for (4469-4060=) 409 customers, their very last visit in the data occurs in Organic Search channel. In Table 3-3, the channels in the first column are the current channel through which the customer visits the website at occasion *n*, while each row shows the number of all prior visits in occasion *(n-1)*, *(n-2)*, and so on. For example, for all the visits in Organic Search, there are 3307 visits in Organic Search channel previously and 934 visits through Paid Search happened in the past, and the prior visits in Referral, Direct, E-Mail, and Display before these Organic Search are 1445, 1621, 862, and 862, respectively. The proposed estimation techniques essentially decompose the data into components in the consideration set stage, the carryover and spillover both at the visit and purchase stage.

<Insert Table 3-2 about here>

<Insert Table 3-3 about here>

3.3.2 Model Fit

The proposed model is compared with alternative models on the dimensions of model fit (in-sample) and model predictions (out-of-sample) and outperforms all of them. Table 3-4 provides the model fit details of the proposed model and alternative models in terms of Log Marginal Likelihood values and the mean absolute percentage error (MAPE) of fit using the calibration sample. The alternative models estimated include (1) Model 1, that has all three stages but does not include the decay parameters in the informational stock variables in the purchase stage (that is, decay is assumed to be zero for all visits), (2) Model 2, which contains only the visit and purchase stages (each consumer considers all channels – exogenously specified with no variations across customers), (3) Model 3, which has all three stages but does not include the lagged visits as explanatory variables in the visit stage, and (4) Model 4, which has all three stages but specifies costs as a linear function of explanatory variables instead of in a logit form, (5) a naïve model with only channel specific constants at the visit stage and purchase stage, and (6) the proposed model. The model fit in terms of the Log Marginal Likelihood values indicates that the proposed model is superior to all alternative models. Additionally, the results indicate that the consideration sets, the lag variables in the visit stage and the decay parameters in the purchase stage do play a significant role in contributing to the explanatory power of the model, and thus are important variables to consider in explaining visits and purchases at the firm's website. It is particularly noteworthy that the lag variables as part of costs in the visit stage contribute significantly to the fit of the model.

<Insert Table 3-4 about here>

I also examined the fit across channels with posterior predictive check. I use posterior predictive check (PPC) to investigate the fit across channels. PPC uses proposed model and the parameter estimates to generate predicted data, and then compare these predicted data with the observed ones (Gelman et al. 1996, Gilbride and Lenk 2010, Rutz, Trusov, and Bucklin 2011). I simulated the predicted purchases in each channel based on 5,000 MCMC iterations after 20,000 burn-in. At each iteration, I calculate the chi-square statistics to examine the discrepancy between the predicted purchases and the observed purchases. Figure 3-2 shows the distribution of the chi-square statistic of each channel and the vertical line represents the sample mean of the chi-square statistic. The p-values vary from 0.11 in Display channel to 0.74 in Paid search channel, but all the p-values are greater than 0.1, which indicates the proposed model fits the data well.

<Insert Figure 3-2 about here>

3.3.3 Model Predictions

I check the predictive validity of the proposed model and the best alternate model (Model 2) using two validation samples. Both are random samples of the visitors to the firm's website and contain similar historical path data for each customer as in the calibration sample. The calibration model is based on consumers visiting the firm's website during the last week of August, 2011. The first validation sample is a hold-out sample from the same set of cohorts. The second validation sample is of visitors to the website in the last week of October, 2011.

Table 3-5 compares the predicted number of purchases through different channels in the hold-out sample using the estimates from the two models with the observed conversions. I observe that the proposed model predicts not only the total number of purchases in the sample fairly well, but also the aggregate number of purchases in each channel, while the alternate model (Model 2) also does reasonably well. This is not surprising as van Nierop et al. (2010) find similar results in comparing a model with consideration sets to a model without consideration sets. In addition to results reported in Table 3-5, I test the predictive power of the models using historical data for a 7-day forward forecast rather than for the next day, based on validation sample 2. That is, when I predict day 7, I still use the historical data up to day 0 and not using day 1 through day 6 actual data in the prediction. The reason for this test of predictive power is that I will be using the proposed model for prediction when paid search is turned off for a week (discussed later). It is in the 7-day forecast that the advantage of the proposed model is evident as it performs much better than Model 2. While the observed purchases in the first validation sample is 265, the proposed model predicts 259 and Model 2 predicts 287. This indicates that the rich heterogeneity incorporated at the consideration stage in the model pays-off well in out-of-sample predictions.

<Insert Table 3-5 about here>

3.3.4 Model Estimates

Table 3-6 provides the estimates of the proposed model. These estimates are posterior means based on 5,000 MCMC iterations, after 20,000 iterations used as burn-in. I investigate the iteration plots and use Geweke convergence test (Geweke 1992) where I compare the estimated parameters based on the first 1000 iterations, the 2001-3000 iterations, and 4001-5000 iterations after burn-in period to determine the convergence to stationary posterior distributions of the parameters in the proposed model. The table shows the channel specific estimates for the four customer-initiated channels – Organic Search, Paid Search, Referral and Direct – and two marketing intervention based channels – E-mail and Display – at the consideration, visit, and purchase stages. I discuss these stages separately.

<Insert Table 3-6 about here>

Consideration stage. I model a consumer's consideration of customer-initiated channels (Organic Search, Paid Search, Referral and Direct) as a function of their level of membership in the firm's loyalty program (non-member, Rewards Level-1 through Rewards Level-4). I expect the membership levels to act as a proxy for consumers' experience, affect and commitment towards the firm's brand and capture their impact on the channels they would consider in visiting the website. As shown in Table 3-6, a non-rewards-program member is more likely to consider Organic Search and Paid Search as compared to the rewards program members at any level, while they are less likely to consider Referral and Direct channels as compared to the rewards program members. Rewards Level-3 and Rewards Level-4 members are more likely to consider Direct as compared to the Rewards Level-1 and Rewards Level-2 members. The estimated correlation matrix of consideration (not reported) indicates that customers are more likely to consider Organic and Paid Search together (correlation coefficient .69) and Referral and Direct together (correlation coefficient .87). An analysis of the posterior distribution of the consideration set probabilities (not reported) indicates that non–rewards members (over 85% of them) consider all customer-initiated channels, while around 20% of Rewards Level-3 and Rewards Level-4 members consider only Direct channel with a small percentage of them (<

10%) considering all customer-initiated channels. Overall, I find a significant heterogeneity in the consideration of the customer-initiated channels.

Visit stage. The estimates of visit stage in Table 3-6 provide (1) the long-term carryover effects of prior visits on costs of visiting the channel through the inclusion of cumulative time spent visiting through each channel and (2) short-term carryover and spillover effects through the use of lag variables. The coefficients for cumulative time indicate that for all customer-initiated channels, except Organic Search, the carryover effects on the costs of visiting the channel is significantly negative (thus reducing the costs). This result could be due to cognitive lock-in effects (Johnson, Bellman, and Lohse 2003), mere exposure effects, reinforcement learning effects, and risk reduction that activate with increased experience in visiting through customer-initiated channels, thereby reducing the costs of revisiting. The long-term carryover effects of firm-initiated channels, however, are not significant. This is consistent with Chatterjee, Hoffman, and Novak (2003) and Double Click's (2004) results that customers who respond to display ad interventions do so at their first exposure rather than at later exposures and that repeated display ad exposures have no added impact.

The short-term carryover effects (Lag-Organic on Organic Search, Lag-Paid on Paid Search, and so on, ranging from -1.26 to -2.43) indicate that all these effects contribute to reducing the costs of re-visiting. That is, if a customer made a visit through a specific channel in the last occasion (within the last day or on the same day), the cost for the current visit through the same channel is reduced. The lag effects of Organic Search on both E-Mail (-.30) and Display channel (-.25), and the lag effects of Paid Search (-.49 on E-Mail and -.43 on Display) indicate a spillover effect of these customer-initiated channels in reducing costs of visiting through firm-initiated channels. However, spillover effects of firm-initiated channels on customer-initiated channels are, by and large, mixed.

For example, prior Display visits reduce the costs of visiting through Organic and Paid Search, consistent with the findings of Ilfed and Winer (2002) and Sherman and Deighton (2001), which show that display ad exposure not only increases ad awareness and brand awareness but also leads to more visits ("billboard effects"). On the other hand, the lag effect of E-mail visit increases the cost of visiting through Organic Search (.74), Direct visit (.24) and Display (.49). A possible explanation for this could be that those customers visiting the firm's website clicking through e-mails are more likely to come back through E-mail channel or shop around using Paid Search or Referral channels. As for the lag effect of Organic Search on Paid Search and vice-versa, the spillover effects reduce costs of visiting through the other channel. However, I find that the spillover effects of Paid Search on Organic Search (-.79) are much stronger than in the reverse direction (-.18). This is contrary to what Yang and Ghose (2010) find in their study that Organic Search has a much stronger effect in leading to clicks in Paid Search than the reverse effect.

The coefficients for the costs of visit vary across channels reflecting the extent to which the visit decisions in these channels are sensitive to these costs. The coefficients for Referral, Direct and E-Mail (-3.58, -3.11, and -3.58) are the highest in magnitude indicating that a unit drop in costs of visiting is likely to impact repeat visits through each of these channels much more significantly than that for the Organic Search, Paid Search and the Display channels. These results highlight that the impact of carryover or spillover could be much higher for Referral, Direct and E-Mail channels as compared to the other channels. Finally, the coefficient of the inclusive value is significant (.35, which is closer to 0 than 1) indicating that the inclusive value plays a critical role in trading off the perceived attractiveness of the purchase/no-purchase option in a channel versus the incurred costs of visiting through that channel.

Purchase stage. At the purchase stage, the informational stock captures the impact of prior visits with their respective decays over time, indicating the lingering effect of information gathered in prior visits on purchase probability of the current visit. I find that the carryover effects of firm-initiated channels are significantly contributing to increase purchase probabilities.

These results are consistent with extant research which suggests that exposures to display banner ads seem to be processed at a preattentive level and may benefit ultimate purchase likelihood (e.g., Drèze and Hussherr 2003; Manchanda et al. 2006). Specifically, Manchanda et al. (2006) find that the number of display impressions, as well as the number of sites and pages containing the display ads, has a positive impact on repeat purchase probability. A recent comScore (2012) report also indicates that the banner ads impression could be more influential than the click throughs in leading to conversions. The carryover effects of Organic Search, Paid Search and Referral are also significantly positive. This implies that for the focal firm more repeated visits to the website through these channels are indicative of the greater attractiveness of the firms' offering vis-à-vis their competitors and thus indicative of a higher likelihood of purchase. The carryover effect of Direct visits is also positive, consistent with Bowman and Narayandas's (2001) finding that customers who directly visit the firm's site more often may have a stronger preference for the firm's offering, thus leading to a positive carryover.

With regard to spillover, I find informational stock of Organic Search has a positive spillover on purchases through Paid Search channel, while the reverse effect is not significant. While informational stock of Display has a positive spillover on purchases through E-Mail channel, the reverse spillover is not significant. The spillover effects of informational stock of firm-initiated channels are, by and large, positive on purchases through customer-initiated channels, except for the effect of informational stock of Display on Referral channel which is significantly negative. This may indicate that customers who visit through Display click-through often may use the Referral channel for gathering additional information but may not consummate purchase through that channel. It is also interesting to note that the spillover of informational stock of Organic and Paid Search are all negative (when significant) on purchases through Referral, E-Mail and Display channels. Given that, at the visit stage, the spillovers of Search channels contribute to reducing the costs of visiting in Referral, E-Mail and Display channels, one can similarly surmise that the customers who visit the website through search channels often use these other channels mainly for gathering information but not for making purchases on those visits. *In short, search can help in bringing in more visits, but not necessarily more conversions*. Additionally, the spillover of other channels on Paid Search and Direct purchases are always positive indicating that the informational stock of other channel visits lead to ultimate conversions during Paid Search and Direct visits. Overall, the results are consistent with the conceptual model proposed in Chapter II. There are significant carryover and spillover effects both at visit and purchase stages.

The estimated decay rates of information gathered in a channel provide insights into how fast the informational stock accumulates in each channel. I observe that the decay rates are generally low for the Search channels and E-Mail channel (.27 for Organic Search, .38 for Paid Search, and .31 for E-Mail), while it is the highest for Display channel (.53). Thus, a search click-through or an e-mail click-through has significantly long lasting impact, while a Display impression or click-through has the least enduring impact. Viewing this from a complementary perspective, display retains only .5% of its original informational value after 7 days, while Organic Search retains 11.0%, Paid Search 3.5% and E-mail 7.4%. The corresponding values for Referral and Direct are in the 2% range. Although the relatively high informational value of an e-mail is understandable given that it can be retrieved and used again, the finding that searches also retain long-lasting informational value is notable and useful. This may indicate that search, even if it occurs earlier in the purchase funnel, has some impact on the ultimate conversion.

Next, I account for these carryovers and spillovers in estimating the contribution of the different channel visits to the overall conversion to get a better picture of the relative contributions of the channels than what a “last-click” metric can provide us.

3.3.5 Estimating Contribution to Conversions

Given the calibration data and the estimates from Table 3-6, I can estimate the impact of a specific channel, say e-mail, on predicted probabilities of conversion by excluding e-mail from the proposed model to predict the probabilities of conversion without e-mails. The difference between the predicted number of conversions with and without e-mails should provide an estimate of the incremental value of e-mails in the calibration data in affecting conversions through e-mail channel as well as other channels. However, the above estimates are incremental, given that other variables (channels) already exist in the model, and may already explain significant variance in the dependent variable. Therefore, using the idea of Shapley value in game theory (Shapley 1953), I calculate the total contribution of each channel in leading to a conversion by averaging over their incremental contributions in all possible channel combinations . (see Dalessandro et al. (2012) and Shao and Li (2011) for the application of Shapley value on multi-touch data with data driven approach). Appendix II provides an illustration using the Shapley value to calculate the marginal contribution of a channel. From this analysis, the last two columns in Table 3-7 shows the contribution of each channel to purchase conversions, which is compared against the two widely-used metrics in the industry: (1) the last-click attribution metric which gives the entire credit to the visit when conversion occurred and (2) 7-day average attribution metric which assigns the conversion credit equally to all the visits made in the past 7 days. Note that these metrics, unlike the proposed model, use touch data ended in conversions and exclude all non-conversion data.

<Insert Table 3-7 about here>

In Table 3-8, I provide the Bayesian confidence intervals for the estimated contribution of each channel. The attribution percentages provided by the proposed model are different from what the last-click metric provides. The attribution of Organic Search drops from 25% to 16% with Bayesian confidence interval [15.0%, 17.8%] (with a 36% reduction in attribution as compared to the last-click metric), while Paid Search drops to 6% ([CI 5.6%, 6.8%]), with a 40% relative reduction in attribution. Referral channel gets 24% attribution [CI 23.8%, 24.8%], which is a 33% increase in attribution from the last-click model. Direct channel which has the highest attribution at 31% in the last click model accounts for a somewhat lower 28% of the attribution as per the proposed model with confidence interval [19.2%, 36.0%]. E-Mail and Display attribution has increased significantly. E-mail attribution improves from 12% to 19% [CI 17.0% to 20.4%] with 58% increase in attribution. Display shows the greatest (75%) increase in attribution, accounting for 7% [CI 6.4% to 7.2%].

<Insert Table 3-8 about here>

While attribution percentages across channels differ between Last-Click and 7-Day Average metrics, their conversion ranks stay the same in both models. However, the proposed model leads to significantly different estimates of attribution percentages and different ranks by accounting for the carryovers and spillovers. For example, the attribution of Organic Search drops significantly from 25% to 16%, while Paid Search decreases to 6% and drops to the last rank. While Referral channel climbs to the second rank with 24%, E-Mail and Display attributions almost double their number of conversions credited in Last-Click metric. The results show that there are significant changes in attributions which would have far-reaching implications for ROI and budget allocations for marketing interventions such as paid search, display and e-mail. In Table 3-6 all other channels have positive spillovers in enabling purchases through Direct channel, which could account for the drop in its attribution, although Direct also gains from spillovers to other channel. The most dramatic drop in attribution is in Organic Search, which has positive spillover from Referral and E-Mail, both of which gain in attribution probably at the expense of Organic Search. These results clearly highlight the importance of considering the path data of converters and non-converters in estimating attributions of the channels and accounting for the carryover and spillover effects across channels on conversion. This also suggests the firm could intervene with marketing actions that could possibly play a positive role in effecting conversions at the website, which is discussed in the following subsections. Extant research finds the effectiveness of different types of marketing interventions may depend on customers' loyal tiers (Rust and Verhoef 2005), but I find the contribution of a channel in this context varies little across loyal tiers. Table 3-9 shows the contribution to conversions for loyal tier Level-1 to Level-4. From column 2 to column 6, I can see the distribution of contribution to conversions in each loyal tier. Compare the percentage in each row, I can find the contribution of a channel varies in a small neighborhood regardless of the loyal tiers.

<Insert Table 3-9 about here>

3.3.6 Field Study with Paid Search Off

The proposed model helps managers in understanding the incremental effect of each channel and predicting their impact on conversions. Even in situations when one channel (say, Paid Search) was to be turned off, the proposed model is able to predict the reallocation of channel shares in leading to conversions. To test and further validate the proposed model, I obtained a validation sample covering the period August - November in 2011, in which the firm shut down the paid search option for one week (November 3 through November 9). Using this validation sample, I made two sets of predictions of conversions for this one week period when Paid Search was off. The first set of predictions (Paid Search On) was made by assuming that all channels were available for this one week (Prediction "A" in Figure 3-3). Note that the proposed model was calibrated on a sample with all channels available. The second set of predictions (Paid Search Off) was based on the fact that Paid Search channel was not available for any customers to consider or choose. Since I have explicitly modeled the consideration set of consumers, I can constrain consideration probabilities of Paid Search channel to be zero in estimating this set of predictions (Prediction "B" in Figure 3-3).

<Insert Figure 3-3 about here>

Table 3-10 provides the two sets of predicted conversions (A and B) along with the observed conversions during this week. First, in comparing the total predictions with Paid Search On and Paid Search Off, I find that overall conversions drop from 11,893 to 11,106, a decrease of 6.6% in conversions. This drop could be due to the absence of Paid Search – that is, the incremental contribution of Paid Search for this sample, which is lost when Paid Search is turned off. This is less than the 923 conversions (7.8% of total conversions) predicted for the Paid Search channel when assuming all channels are available. It appears that some of the Paid Search conversions are being recaptured by other channels when Paid Search is turned off (see Column 4) resulting in only a 6.6% drop in conversions rather than the 7.8% or more.

<Insert Table 3-10 about here>

Second, the prediction for total conversions with Paid Search Off (11,106) is fairly close to the observed conversions in the study (11,395) with a MAPE of 2.6%. What's more, the 95% highest posterior density (HPD) of the predictions of conversions for each channel contains the observed number of conversions for all channels except Organic Search. This validates the ability of the proposed model in predicting conversions when a specific channel is not available, and illustrates how the proposed model can be used to estimate the incremental contribution of a channel. Third, comparing the predicted conversions with Paid Search Off and the observed conversions channel by channel, I find that the observed conversions through Organic Search is much higher (MAPE=30%), with Referral conversions also being higher (MAPE=21%) while Direct conversions are lower (MAPE=16%) than what the proposed model predicted. The proposed model performs much better than a model that does not take the consideration stage into account. I further investigated the prediction variance of Organic Search, by segmenting the Paid Search conversions in the validation sample with "branded" and "unbranded" keywords. Approximately 73% of the Paid Search conversions are based on "branded" keywords, while the rest (27%) are through "unbranded" keywords. Since the firm has a very strong brand, their relative rank of branded keywords in the Organic Search pages is almost always the first, while for many unbranded keywords they bid on, the firm also ranks within the first webpage of Organic Search results. Thus, when Paid Search is off, it appears that much of the conversions previously stemming from paid branded keywords are being recaptured by free Organic Search, instead of being "lost", while a good percentage of "unbranded" keyword conversions do get lost. This could possibly explain why the observed conversions through Organic Search is much higher (43%) than what the model predicted, and the observed overall conversions is somewhat higher (3%) than what the model predicted. In sum, given the firm's brand strength and 73/27 split between branded and unbranded keyword in Paid Searches, the recapture rate of Paid Search conversions when pausing Paid Search is higher than what the model predicts.

3.3.7 Purchase Funnel and Marketing Interventions

A key insight that emerges from the results is the understanding of whether and when to intervene with marketing actions given a customer's path in the purchase funnel to the firm's website. Since the model provides the estimates of the impact of previous visits (the lag estimates in Table 3-6), it is possible to predict for a customer, given his/her purchase funnel data to date, the probabilities of visit through different channels for the next visit occasion and the probability of a purchase on that visit under different intervention scenarios. I illustrate this with an example of e-mail intervention. In the calibration sample, e-mail interventions target a significant number of customers regardless of their rewards program status – specifically, 23% of the non-members and 45% of the members were targeted, with the content of the e-mail the same across customers. To stay within the confines of the calibration model for the illustration, I focus the analysis only on customers who have already been targeted with e-mail interventions in their past. Thus, the objective is to understand under what path characteristics the firm can increase the overall probability of conversion for a customer who has had a prior e-mail intervention in his/her path by targeting the customer with another e-mail intervention; and under what conditions the firm is better off not targeting them by another e-mail.

Table 3-11 provides these probability estimates for selected instances of path data that have prior e-mail interventions. In Row 1, a customer is observed for the first-time entering the website on Day (T-2) through Organic Search channel, makes another visit through E-Mail channel on Day (T-1). If there is no intervention, the total probability of purchase through any channel on Day T is .447, with a visit most likely through Organic Search. However, an E-Mail intervention on Day T increased the total probability of purchase to .474. The e-mail delivery is almost without cost to the firm after it makes an initial investment in its e-mail campaign system. Assume that the revenue of one conversion is $100. The economic value of delivering an extra e-mail in this situation is (.474 – .447) *$100 = $2.7. Considering the number of e-mails sent by the firm, identifying the right customer to target implies a significant increase in revenues.

<Insert Table 3-11 about here>

Table 3-11 provides many such scenarios. It is seen that when a visit on Day (T-1) happens through the Direct channel (Rows 3 and 6), the best option for the firm is to not intervene as E-mail intervention can only lower the likelihood of conversion. Rows 7 through 10 provide similar scenarios where the advantage of e-mail targeting is clearly contingent upon the path taken by a customer. This illustration provides the utility of the proposed approach for retargeting customers with marketing interventions. If customers' history of touches in the purchase funnel is tracked once they enter the website for the first time, the firm can use the data to customize the price and promotion for each identified customers to maximize their purchase probability (see Grewal et al. 2011 for a more detailed discussion on targeted online promotion). For a full-fledged implementation of such individualized targeting, the criterion used for targeting, especially in display channel, has to be worked into a supply side equation. Also, using a dynamic optimization procedure (Li, Sun, and Montgomery 2011) a firm can identify optimal targeting policies considering customers' current and future probabilities of purchase.

3.4 Conclusions

This essay sheds light on the nature of carryover and spillover effects across online marketing channels through which customers visit a firm's website. This is the first study, to my knowledge, which examines these effects in the online channel context at the distinctly different stages – visit and purchase. The empirical study illustrates the importance of estimating these effects so that the attribution of each channel to the overall conversions at the website can be accurately determined. This has useful managerial implications for allocating marketing budget across marketing channels and for targeting strategies. I will first examine the implications for the specific context I have studied, and then discuss the more general implications.

3.4.1 Implications for the Focal Firm

This study finds significant spillover effects of firm-initiated channels to customer-initiated channels both at the visit stage and at the purchase stage. Firm-initiated interventions also impact visits in the short-term with no long-term carryover effects. This implies that managers have to take a more inclusive and macro view of the returns on investments in firm-initiated interactions. Considering all the impact, the last click metric significantly underestimates the contribution of E-Mails, Display ads, and referrals to conversions. The finding of undervalued display ads echoes the study by Shao and Li (2011). Similarly, the role of Referral channel is also underestimated by the last-click metric. Significantly, the real impact of Organic Search on conversions is much lower than what it appears to be in the last-click metric. For the focal firm it is clear that some customers, having visited the website through other channels previously, are using Organic Search purely as a navigational tool to get to the website in completing purchases. The impact of Paid Search and Direct are also diminished. Given that the changes in attributions based on the proposed model are considerably different (ranging from -40% to +75%), it clearly implies a different allocation of marketing budget. The focal firm in this study uses the attribution estimates to charge their franchisees for the various marketing programs such as paid search, referrals, and other campaigns, so even if the attribution ranks were only marginally different it would still make a sizable difference for such appropriations. Attributions based on the proposed model would render these appropriations in line with the incremental purchases that the franchisees actually observe at their properties. This will enhance franchisees' confidence in such metrics and the fairness perception of the firm in how they pass on the marketing costs. The proposed attribution model is designed to be estimated and run for each period, say a month, so that it becomes the basis for allocating the marketing expenses and attribution for each channel for each month. This can also form the basis for determining the acquisition costs through each channel and understand the efficacies of each channel in each period.

Although the results show that E-Mail and Display ads are effective in the short-run, it is important that they are not used indiscriminately to target all visitors to the websites using the often-used strategy of "retargeting", where e-mails and displays follow visitors everywhere once they click on an e-mail, display ad or visit the website (Helft and Vega 2010). As the path analysis results show, retargeting visitors to the website with e-mails is not always the best strategy. While in some cases e-mail retargeting increases the overall purchase probability for those customers, in other cases it actually hurts the purchase probability for the same segment of customers. This is consistent with the finding by Kumar et al. (2008) that contacting customers at the time they are predicted to purchase can lead to higher profits and ROI than contacting them without any guidance on the predicted timing of conversion. In addition, recent reports (Mattioli 2012) have suggested that retailers are finding that overuse of e-mails actually annoys many customers, thus rendering them less effective. The proposed model can be used for such customized targeting using path data analysis to identify cases for which e-mail and display retargeting are likely to contribute to more conversions.

The proposed model enables me to estimate how conversions through different channels are affected when one channel is not available. I observe that a significant portion of the conversions that could have occurred through Paid Search channel is recaptured through Organic Search. Because the firm in this research has a strong brand and ranks highly in organic search results, I conjecture that Organic Search recaptures many of the branded keyword searches that could have occurred through Paid Search. Thus, the incremental contribution of Paid Search to conversions is much lower than what a last-click model would lead us to believe, and the firm can reallocate marketing investments given the estimates of the incremental contribution suggested by the proposed methodology.

Finally, I find that Search and E-mail channels have a significant longer impact than Display. This finding implies that a search, even if it occurs earlier in the purchase funnel, has some impact on ultimate conversion. Identifying the specific search keywords that have such impact early in the purchase funnel might be useful from the tactical viewpoint of increasing customer acquisition.

3.4.2 General Implications

It is evident from this study that neither the last-click attribution metric nor the 7-day average metric are good measures for understanding the real impact of firm-initiated channels as well as customer-initiated channels on conversions. These metrics consider only those visits that result in conversion immediately. Although they may provide passable results in product categories with a very short purchase funnel (with one or two touch points) and with fewer channels, they will invariably be misleading in product/service categories with a longer purchase funnel, as in high-involvement categories (e.g. consumer durables and travel services), as well as for firms with multiple channels, both customer-initiated and firm-initiated. In the latter case, I also expect that the last-click model would underestimate the effectiveness of firm-initiated efforts, and it is imperative that firms use the proposed framework to estimate the real incremental impact. The real incremental impact estimates can provide directional help in reallocating the marketing-mix spending such that the channels whose impacts are underestimated by conventional metrics would receive more budget allocation and those whose impacts are overestimated would receive less allocation.

The results suggest that the incremental impact of Paid Search channel may not be as high as what the last-click model would suggest, and if Paid Search were to be discontinued, much of its impact can be recaptured through the Organic Search channel. The generalizability of this result, however, depends on the brand strength of the firm. If the brand is not very strong, then such recaptures may not materialize as the firm may not get a high enough position in Organic Search. All else being equal, I conjecture that the stronger the brand, the lower the incremental effect of Paid Search on ultimate conversion. This framework provides a useful tool to determine this incremental contribution and to determine if the cost of effecting a conversion through Paid Search is less than the incremental revenue obtained through the channel. Since paid search makes up around 50% of the overall spending in online marketing budget for many firms in 2011 to 2016 (VanBoskirk et al. 2011), such analysis can be useful to contain marketing costs through very selective use of keywords and possible negotiations with search engine companies.

One of the useful features of the proposed model is that it incorporates customers' consideration sets of channels to use in visiting the firm's website. As there is significant heterogeneity and self-selection in customers' consideration of channels to use, by modeling consideration sets endogenously, the proposed modeling framework allows me to accurately predict the conversions through different channels when one of them (for example, paid search, as in this study) is not available.

3.4.3 Limitations and Future Research

Because I estimate the model using secondary data and not experimental data, it is possible that alternative explanations exist for the effectiveness of display and e-mail campaigns, such as selective targeting of customers with inherently higher propensity to purchase (Manchanda, Rossi, and Chintagunta 2004). This problem is somewhat mitigated in this study as e-mail is not specifically targeted – e-mail offers are not just sent to rewards program members, but also to all past purchasers and all visitors with e-mail registration irrespective of which channel they usually visit. With respect to display, targeting is an issue as the firm uses Doubleclick as a vendor. To check whether such targeting is correlated with the channels customers often use or with their rewards program membership, I estimated the incidence of display impressions and conversions across customers visits through different channels, and as well as across non-members and rewards levels. A similar exercise was conducted with e-mail incidence and conversions. Both analyses revealed that the correlations were minimal, indicating there is no systematic pattern in targeting, at least not on the observed dimensions of channels and rewards program membership. Although the results are conditional on firm's ongoing targeting strategies, I believe that the effects of strategic targeting are not likely to change the essential nature of the results. The focal firm provides a variety of substitutable products in a wide price range. Customers with different budgets can easily find their affordable choice within the target firm. To minimize selectivity bias, I can compare the results on different cohorts of visitors separated a spell of one month or more, and use the observed variations in the firm's targeting and promotional campaigns to make the results more useful (for the discussion on competition effects, see Appendix III).

I find significant and positive carryover effects in most channels at both visit and purchase stages. However, the long-term carryover effects of firm-initiated channels (i.e., E-mail and Display channels) are insignificant in the visit stage. This calls for further research using customer-level path data or even conducting field experiments to empirically evaluate the long-term carryover effects of firm-initiated channels. Moreover, to determine the spillover effects from customer-initiated channels to firm-initiated channels (and the reverse effects) in a more generalizable manner, further research should consider data across several firms in different industries. The data lack detailed demographic information and prior purchase information. In addition, at the purchase stage I did not use data on prices, promotion, or attributes of the offering that visitors could view before making their choices. Further research with such data could extend the analyses of carryover and spillover effects to different segments of customers, accounting for customers' heterogeneity in preference and price response parameters, and could thus provide managers with actionable guidance with respect to each segment.

In the current research, I modeled customer visits using a static framework. However, in the context of planned purchases, customer visits could be modeled in a dynamic setting, taking into account their forward-looking and strategic behavior. As a possible extension to this study, further research could examine long-term dynamic changes in search behavior and purchase decisions using structural models with appropriate long-term data. I did not model the supply-side decision, such as targeting customers in e-mail campaigns, selecting locations for banner ads, or choosing the keywords to bid on for paid search; yet the data of the conversion path are conditional on these decisions (which the firm has already made). Given this endogeneity, the proposed model measures the relative effectiveness of these channels, conditional on the firm's decisions. Modeling supply-side decisions would be useful to examine the impact of marketing interventions under policies different from those in this research. I leave this undertaking for further research.

Finally, the proposed model has a broader application beyond the business-to-customer context. For example, in business markets, sales conversion is often preceded by multiple vehicles of marketing efforts (e.g., trade shows, direct mailings, e-mail campaigns, salesperson visits), and the proposed framework and methodology should be well suited to analyze such contexts.

Tables and Figures

Table 3-1 Summary Statistics

Channel	**Channel Visits**	**Purchases**	**Purchase/Visit Conversion Rate**
Organic Search	4469	285	6.38%
Paid Search	1557	114	7.32%
Referral	3980	201	5.05%
Direct	7959	347	4.36%
E-Mail	2804	138	4.92%
Display	1600	43	2.69%
Total	**22369**	**1128**	**5.04%**

Table 3-2 Contiguous Visits for the same customer

	Visit at Occasion (n-1)					
Visit at Occasion n	**Organic Search**	**Paid Search**	**Referral**	**Direct**	**E-Mail**	**Display**
Organic Search	2071	557	542	463	295	186
Paid Search	440	394	125	128	91	275
Referral	577	113	2118	490	354	93
Direct	462	92	442	5579	431	124
E-Mail	329	69	360	434	1345	81
Display	181	200	87	84	60	700
Total	4060	1425	3674	7178	2576	1459

Table 3-3 nth Visits versus All Prior Visits

Current Visit Channel	**Prior Organic Search**	**Prior Paid Search**	**Prior Referral**	**Prior Direct**	**Prior E-Mail**	**Prior Display**
Organic Search	3307	934	1445	1621	862	862
Paid Search	1220	903	583	590	396	967
Referral	1777	432	3391	2211	1088	580
Direct	1694	410	1721	6532	1425	548
E-Mail	1255	320	1146	1737	2307	455
Display	738	539	366	437	315	1127

Table 3-4 Model Comparison

Channel	Model 1	Model 2	Model 3	Model 4	Model 5	Proposed Model
Organic Search	0%	10%	43%	40%	237%	30%
Paid Search	6%	19%	90%	82%	190%	3%
Referral	120%	14%	193%	103%	311%	21%
Direct	124%	30%	71%	65%	863%	14%
E-Mail	98%	23%	29%	31%	189%	15%
Display	84%	37%	71%	62%	2076%	33%
Overall	74%	20%	35%	24%	502%	1%
Log-Marginal Likelihood	-13580	-14692	-17033	-13629	-173093	-12521

Notes: All the percentage values in this table are mean absolute percentage errors (MAPE)

Table 3-5 Validation Results

Purchases in Each Channel	Observed	Prediction by Proposed Model	MAPE	Prediction by Model 2	MAPE
Organic Search	668	638	4%	684	2%
Paid Search	307	328	7%	367	20%
Referral	675	692	3%	837	24%
Direct	790	746	6%	761	4%
E-Mail	398	380	5%	399	0%
Display	67	76	13%	89	33%
Total Purchases	2905	2860	2%	3137	8%

Table 3-6 Model Estimates

Channels / *Variables*	Organic Search	Paid Search	Referral	Direct	E-Mail	Display
	(Estimates are posterior means)					
Consideration Stage:						
Intercept	**1.60**	**1.84**	**2.43**	**2.65**		
Rewards Level-1	.04	.04	**.92**	**.59**		
Rewards Level-2	-.03	**-.15**	**.74**	**.69**		
Rewards Level-3	**-.16**	**-.18**	**.46**	**1.92**		
Rewards Level-4	**-.17**	**-.19**	**1.00**	**.94**		
Visit Stage:						
Intercept	**2.27**	**1.26**	**-.92**	**.40**	**-.36**	**1.92**
Cost	**-1.37**	**-1.96**	**-3.58**	**-3.11**	**-3.58**	**-1.56**
τ (tau)	**.35**					
Cost:						
Cumulative time	-.77	**-1.15**	**-.99**	**-1.41**	-.78	-.79
Lag Organic Search	**-2.10**	**-.18**	**-.20**	.07	**-.30**	**-.25**
Lag Paid Search	**-.79**	**-1.97**	**-.19**	.11	**-.49**	**-.43**
Lag Referral	**-.38**	**-.13**	**-2.43**	.05	.12	.01
Lag Direct	**.47**	**-.29**	.03	**-1.71**	**.19**	-.01
Lag E-Mail	**.74**	**-.18**	**-.21**	**.24**	**-2.04**	**.49**
Lag Display	**-.27**	**-.27**	**.16**	-.04	.11	**-1.26**
Lag No Visit	1	1	1	1	1	1
Purchase Stage:						
Intercept	**-1.29**	**-.94**	**-1.11**	**-1.29**	**-1.38**	**-1.39**
Info Stock - Organic Search	**.68**	**.17**	**-.39**	**.21**	**-.21**	-.12
Info Stock - Paid Search	.03	**.44**	.03	**.23**	.04	**-.26**
Info Stock - Referral	**.16**	.03	**.35**	**.18**	.11	**.44**
Info Stock - Direct	-.11	**.22**	**.70**	**.73**	**.22**	**.47**
Info Stock - E-Mail	**.28**	**.61**	-.15	.08	**.83**	.06
Info Stock - Display	.07	**.16**	**-.38**	**.22**	**.28**	**.40**
λ=(1- Decay Rate)	**.73**	**.62**	**.57**	**.59**	**.69**	**.47**

Notes: Bold indicates that the 95% posterior interval excludes zero.
τ is the coefficient of the inclusive value.

Table 3-7 Contribution to Conversions

Channel	Observed	Last Click %	Last Click Ranking	7-day Average %	7-day Average Ranking	Proposed Model %	Proposed Model Ranking
Organic Search	285	25%	2	24%	2	16%	4
Paid Search	114	10%	5	8%	5	6%	6
Referral	201	18%	3	18%	3	24%	2
Direct	347	31%	1	30%	1	28%	1
E-Mail	138	12%	4	14%	4	19%	3
Display	43	4%	6	6%	6	7%	5
Total	**1128**	**100%**		**100%**		**100%**	

Table 3-8 Percentage of Contribution to Conversions

	Last Click Metric	Proposed Model	
Channel	**Percentage of Contribution**	**Percentage of Contribution**	**Confidence Interval**
Organic Search	25.3%	16.4%	[15.0% 17.8%]
Paid Search	10.1%	6.2%	[5.6% 6.8%]
Referral	17.8%	24.3%	[23.8% 24.8%]
Direct	30.8%	27.6%	[19.2% 36.0%]
E-Mail	12.2%	18.7%	[17.0% 20.4%]
Display	3.8%	6.8%	[6.4% 7.2%]
Total	**100%**	**100%**	

Table 3-9 Contribution to Conversions across Rewards Program Status

Channel	Non-Member	Level-1	Level-2	Level-3	Level-4
Organic Search	22%	20%	19%	17%	19%
Paid Search	7%	5%	5%	4%	7%
Referral	22%	23%	26%	24%	22%
Direct	25%	26%	25%	26%	30%
E-Mail	16%	20%	21%	23%	15%
Display	8%	5%	3%	6%	7%
	100%	100%	100%	100%	100%

Table 3-10 Predicted Conversions – Field Study

	Assuming Paid Search On			Paid Search Off		Observed
Channel	**Predicted**	**95% HPD region**	**Predicted**	**95% HPD region**	**MAPE**	
Organic Search	1023	[869 1192]	1711	[1553 1854]	30%	2453
Paid Search	923	[782 1071]	0			0
Referral	2775	[2231 3226]	1784	[1376 2308]	21%	2271
Direct	5785	[4204 7410]	6269	[4320 7426]	16%	5398
E-Mail	907	[782 1049]	1260	[1109 1349]	13%	1114
Display	480	[378 569]	82	[19 207]	48%	159
Total	11893		11106		2.60%	11395

Table 3-11 Path Sequence and Visit/Purchase Probabilities

	Day(T-4)	Day (T-3)	Day (T-2)	Day (T-1)	Day T				
					No intervention		E-mail intervention		
Row	**Visit thru**	**Visit thru**	**Visit thru**	**Visit thru**	**Visit Prob.**	**Purchase Prob.**	**Visit thru**	**Click Prob.**	**Purchase Prob.**
1	X	X	OS	E-Mail	0.196	0.447	OS	0.185	**0.474**
2	X	X	PS	E-Mail	0.193	0.446	OS	0.182	**0.473**
3	X	X	E-Mail	D	0.421	0.565	D	0.208	0.512
4	X	E-Mail	OS	PS	0.23	0.356	PS	0.184	**0.463**
5	X	E-Mail	OS	R	0.238	0.341	R	0.184	**0.465**
6	X	E-Mail	OS	D	0.421	0.564	D	0.208	0.51
7	E-Mail	R	X	X	0.214	0.137	OS	0.188	**0.15**
8	E-Mail	D	X	X	0.359	0.335	D	0.187	0.149
9	OS	E-Mail	X	X	0.18	0.172	OS	0.217	**0.191**
10	PS	E-Mail	X	X	0.19	0.136	PS	0.216	0.121

Notes: OS is Organic Search; PS is Paid Search; R is Referral; D is Direct; X is no visit.
Bold number in the last column indicates the purchase probability is increased with e-mail intervention.

Figure 3-1 An Illustration of the Three-Stage Model

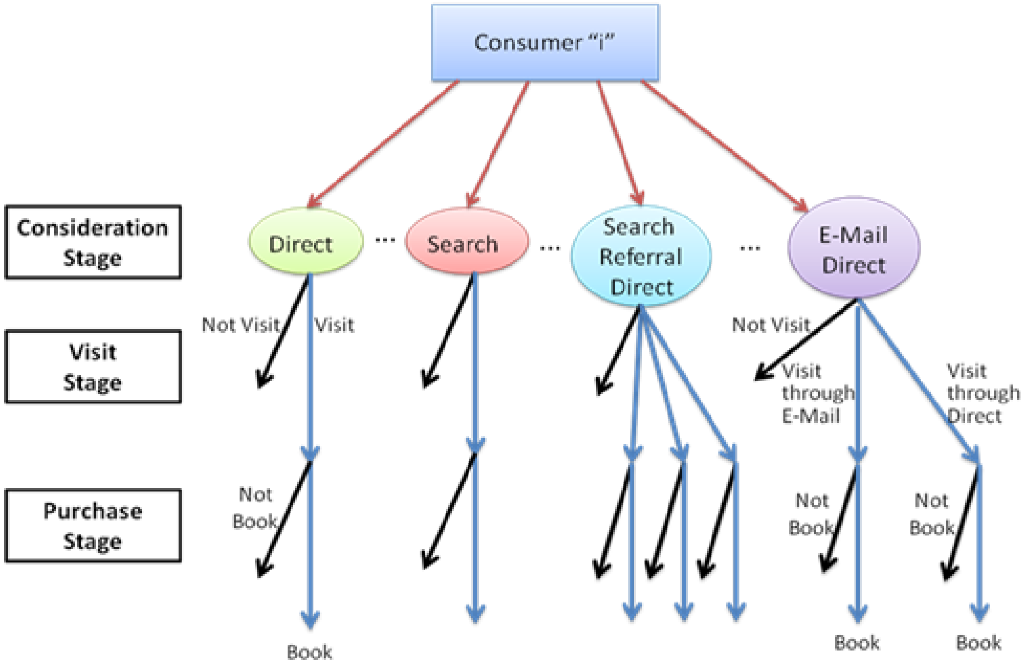


Figure 3-2 Posterior Predictive Check

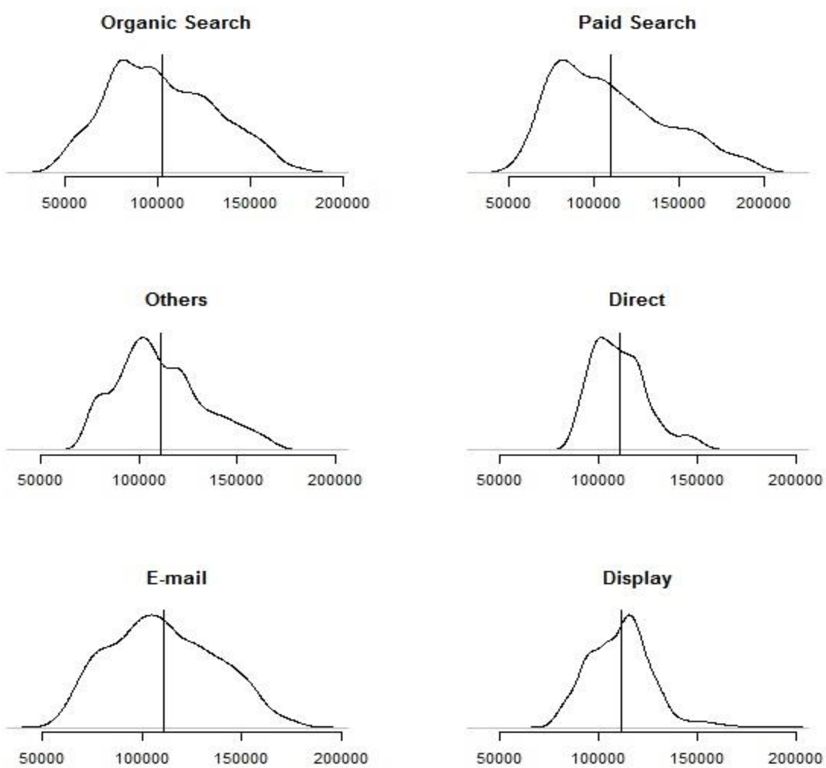
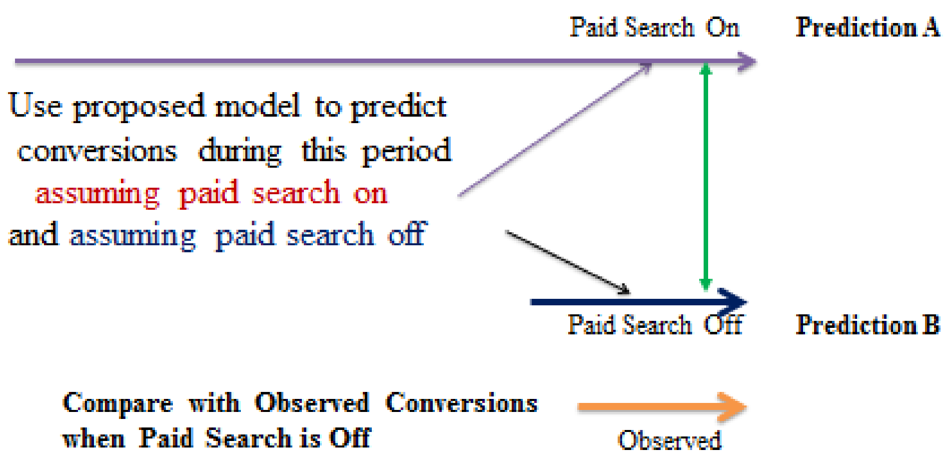


Figure 3-3 Field Study Specifics



Chapter 4 : Impact of Attribution Metrics on Return on Keyword Investment in Paid Search Advertising

4.1 Background

Since its introduction in late 1990s, search engine marketing has become the most prevalent online marketing vehicle in the past decade and is predicted to comprise 48% of online marketing budget in many companies over 2011 to 2016 (VanBoskirk et al. 2011). The US marketing spending on paid search is forecasted to be more than $33 Billion by 2016 and the annual growth rate is more than 12% (Forrester 2011, eMarketer 2014). There are several widely used U.S.-based search engines, such as Google, Yahoo, Bing, and Ask, and some international search engines such as Baidu and Yandex, among which Google is the indisputable leader and claims to cover 83% of Internet users worldwide (Google 2013).

Search engines can assist customers to find useful information. The customer starts a search by typing in a search query at the search engine. Figure 4-1 illustrates an example of the search results at Google in response to the search query “jewelry”. There are two types of search results: (1) paid search results on the top with colored background and on the right side (both marked by the boxes)[5] and (2) organic search results in the center below the paid search results. At other search engines, for example at Yahoo and Bing, paid search results are placed on the top and the bottom,

[5] Among the six paid search ads in Figure 4-1, the three ad positions in the center are considered to be more advantageous than the other three ad positions on the right side.

as well as on the right side of the page. In this Chapter, I am focusing only on the paid search ads[6], which are also called sponsored search ads.

<Insert Figure 4-1 about here>

Each paid search ad typically contains a headline, a few descriptive words, and a hyperlink to the advertiser's website. In order to reach the right customers through paid search advertising, the advertiser needs to pick the "keywords" they want their ads to show up for, write effective ad copy and text, and choose the relevant landing page. A keyword is usually a phrase that contains multiple words and the advertiser can specify the match type of each keyword to avoid missing any potential customers (Appendix IV provides the definitions and examples for different match types). After specifying the keyword and the match type, the advertiser can submit a bid accordingly to the search engine[7]. Then triggered by a search query on this particular keyword, the search engine operates a generalized second-price auction to assign the positions (where the ad shows up) for all the paid search ads. At the three leading search engines – Google, Yahoo, and Bing, for example, the ad position for a keyword is ranked according to the bid as well as the quality score (or quality index) of an advertiser with respect to a keyword. The quality score is a measure of how relevant the keywords, the paid search ads, and the landing pages are to the audience. If two advertisers submit the same bid on a keyword, the advertiser with a

[6] A firm can hire a Search Engine Optimization company to optimize its websites in order to be positioned at better locations among the free organic search results. However, Search Engine Optimization is not the focus of this research.

[7] The firm can go to any of the widely used search engines and set up the paid search ads on its own. Alternatively, the firm can hire an advertiser to make the decision on keywords and match types. This could vary case by case in practice. In this research, I focus on the case where the advertiser is paid by the firm to implement paid search advertising on the firm's behalf, under a budget constraint set exogenously by the firm. More discussion is provided in the Model section.

higher quality score will win the auction. When the advertiser’s bid and quality score is high enough to appear among the paid search results in response to the consumer’s query, it is counted as an impression. After seeing the search results, the customer may click on the result that is most relevant to his/her needs, and then lands on a website through the link embedded in this ad, which is counted as a click-through. The search engine charges the advertiser according to the number of click-throughs on their ads times the cost-per-click (determined in the generalized second-price auction). That is, the customer in front of the search results determines which result he or she will click on and this decision also determines which advertiser, if any, will pay for this click. When an advertiser’s ad appears in the search results but the customer chooses to click on other paid search ads or clicks on organic search results, it will hurt the advertiser’s click-through rate on this keyword and lower the advertiser’s quality score on this keyword in the future.

Several features make paid search advertising very attractive to marketing managers. First, the advertising cost is performance-based. Unlike the impression-based cost in many other marketing media (for example, display ads and TV ads), in paid search advertising the advertisers only pay for the clicks, i.e. for the visits to their websites. Second, in paid search advertising the customers take the initiative in reaching out to the advertisers, which means when the customers type in a search query at the search engine, they may already have some need in mind, and thus have a higher conversion propensity if the paid search ads match their need well. Moreover, research shows that customers acquired from Google can generate more lifetime value than customers acquired by offline word-of-mouth (Chan, Wu and Xie 2011).

In order to understand how the returns on search investment are realized, let us first look at the contextual background of paid search advertising and the roles of the advertiser, search engine, and customer. Figure 4-2 illustrates the relationship among the advertiser's bidding decision, the search engine's position decision, and the customer's responses to paid search ads.

<Insert Figure 4-2 about here>

First, the advertiser decides how much to bid on each keyword and submits the bid to the auction at the search engine. The search engine posts the relevant paid search ads upon the consumer's search query. The customer sees the search results and chooses to click on the advertiser's ad or not. If he/she clicks on the ad, the customer lands onto the advertiser's website, the search engine charges the advertiser for this click-through based on a generalized second price auction. Search engines provide performance reports at the keyword level to help the advertisers understand the performance of each keyword. For example, Google provides daily statistics at the keyword level, including the number of impressions, the number of clicks, average cost-per-click (CPC), average position, and quality scores. Table 4-1 shows an example of such statistics.

<Insert Table 4-1 about here>

Once the customer lands on the advertiser's website, the advertiser is able to track his/her conversions. Many advertisers/firms can track the keyword click-throughs at the cookie ID level and measure the return-on-investment (ROI) of each keyword against the incurred cost. When the customer clicks on only one keyword provided by the advertiser and then makes a purchase, it is straightforward for the advertiser to measure the ROI of that keyword. However, when the consumer clicks on multiple keywords from the advertiser before making a single conversion, the advertiser needs to assign the conversion credit with a certain attribution metric.

Figure 4-3 illustrates two scenarios where the attribution metrics influence the realized ROI and thus affect the advertiser's bidding decision for the next period. In Figure 4-3(a), I assume the advertiser bids on 3 keywords: K1, K2, and K3. At time *t*, the advertiser bids $1 on each keyword and submits these bids to the search engine. Then the search engine ranks the advertiser's paid search ads comparing their bids and quality scores to the competing bids and quality scores on the same keywords, and presents the paid search ads in response to the customer's search queries. Assume in the meanwhile that there are two hypothetical customers' paths to purchase: Customer 1 clicks on K1 once, K2 once, and then K3 twice in order before making a purchase of $10 at time *t*, while Customer 2 clicks K1 and then K2 before making a $10 conversion at time *t*. If the advertiser uses the last-click as the attribution metric, the conversion credit of Customer 1's purchase is assigned to the last clicked keyword (K3) and Customer 2's conversion credit is assigned to the last clicked keyword (K2). Accordingly, the overall imputed revenue is $0 for K1, $10 for K2, and $10 for K3. Based on these 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*. (Note these new bid values are arbitrary numbers for illustrative purpose).

<Insert Figure 4-3 about here>

Figure 4-3(b) shows a different scenario resulting from the use of a different attribution metric. Assume the advertiser still bids on the same keywords at the search engine and 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 this imputed revenue, the advertiser would submit a higher bid on K1 and lower bids on K2 and K3 in the next period.

The example in Figure 4-3 shows how the attribution metrics could influence the imputed revenue of each keyword, and the imputed revenues in turn influence the bid on each keyword going forward. Although the initial bids by the advertiser at time *t* are the same and so are the customers' click-throughs and conversions, different attribution metrics would lead to completely different bidding decisions for the advertiser in time *(t+1)*. Assume the optimal attribution metric for the focal advertiser in Figure 4-3 is the first-click attribution. If under the above scenario the advertiser uses the last-click attribution as in Figure 4-3(a), then they would underestimate the revenue contribution made by K1 and thus underbid on K1 at time *(t+1)*. As a consequence, the lower bid on K1 leads to less advantageous ad position of K1 and further hurts the chance of conversion that K1 could have led to. This results in an important yet neglected issue in the research of paid search advertising – the attribution of conversion credit to keyword click-throughs. When a consumer clicks on multiple paid search ads before making a single conversion, how should the advertiser give the conversion credit to one or more keywords? In practice, a variety of attribution metrics are used to assign the conversion credit to keywords. One of the most frequently used attribution metrics is the last-click attribution, which gives all the conversion credit to the last clicked keyword used by the customer before the conversion. For example, 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 order, and makes a single purchase at the end. The last-click attribution metric gives all the conversion credit to the last clicked keyword "silver necklace with ruby". Alternatively, the advertiser can use the first-click attribution and assign the entire conversion credit to the first clicked keyword "jewelry". Some other managers may believe that all of these three keywords assist the customer in completing the order, and thus each deserves a portion of the conversion credit.

This raises a few important questions: when the consumer clicks on multiple keywords through their purchase journey, what keywords are more likely to be clicked in the earlier stage of a purchase journey and what keywords are more likely to be clicked towards the end of a purchase journey? A widely held belief is that the consumer starts with broad keyword and narrows it down to more specific keywords. Both Agarwal, Hosanagar and Smith (2011) and Ghose and Yang (2009) find that the specificity of a keyword has some impact on its effectiveness in paid search campaigns. The broad keywords are used by the advertiser for branding and awareness campaign, but these keywords may bring in customers who are only browsing and not yet seriously considering purchase. Additionally, the broad keywords are more expensive per click due to the higher level of competition, and could be very inefficient by inevitably reaching many individuals who are not the desired audience. If the advertiser uses the first-click attribution, for example, then the broad keywords would gain more conversion credits, compared with the case where the advertiser uses the last-click attribution. Following the flow chart in Figure 4-2, different attribution metrics lead to different budget allocation. Since all the keywords compete for a fixed budget, the lower conversion credits of broad keywords when using the last-click attribution lead to lower investment on broad keywords, which results in lower ad positions for broad keywords. The lower position implies fewer click throughs and conversions from broad keyword (Ghose and Yang 2009, Ruts, Bucklin, and Sonnier 2012), and consequently the ROI potential of those broad keywords are not fully realized. Similarly, the first-click attribution would limit the specific keywords to reach their full potential in generating revenue. To my knowledge, no research has shed light on the impact of attribution metrics on the ROI of search campaigns both in terms of potential ROI as well as realized ROI. In this research, I would like to investigate this issue by examining the impact of attribution on the investment at the keyword level and how the different investment due to different attribution influences the ROI of search campaigns.

In order to answer these questions above, I 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 consumer's responses are jointly modeled in a simultaneous equations system. At the beginning of the data window, the advertiser uses the last-click attribution, and then switches to the first-click attribution half-way through the data window. In this research, I analyze the ROI of the advertiser's search campaigns while using these two extreme cases of attribution metrics, respectively. Based on these analyses, I am able to recommend a new attribution metric that combines the measures under both last-click and first-click metrics, and inform the advertiser how much they can improve their ROI by merely changing the attribution metric. Note that the purpose of this research is not to find the optimal attribution metric for each keyword which could heavily depend on the industry and the strength of the focal advertiser's brand. Instead, I intend to show the long-ignored importance of attribution in paid search advertising and provide a modeling framework to assist the advertisers to better understand the ROI of their search campaigns and better allocate their marketing budget to reach their full ROI potential.

4.2 Literature Review

Several aspects of paid search advertising have been studied with theoretical models, such as the auction mechanism (Edelman, Ostrovsky, and Schwarz 2007), the signaling effect (Chen and He 2011), and click fraud (Wilbur and Zhu 2009). Ghose and Yang (2009) conduct one of the earliest empirical researches on paid search advertising. They simultaneously model the customer's click-through rate and conversion rate, the search engine's position decision, and the advertiser's bidding decision. They show that both click-through rates and conversion rates decrease as the position moves to the bottom. However, Agarwal, Hosanagar and Smith (2011) experiment with the bids and find that among the first 7 ad positions, as the position moves down, the click-through rate drops but the conversion rate increases, and such increase in the conversion rate is greater for more specific keywords. Rutz, Bucklin and Sonnier (2012) account for the omitted observations and measurement errors and confirm Ghose and Yang's (2009) finding that higher position leads to higher click-through rates as well as higher conversion rates. All these researches mainly focus on the endogenous relationship between the ad position and the consumer's responses. In line with the extant research, I also explicitly model the advertiser's bid decision, the search engine's ad position decision, and the consumer's responses, to capture the endogenous relationship among these three players – the advertiser, the search engine, and the consumer, in paid search marketing. Moreover, I would like to advance the understanding on the supply side – the advertiser's bidding decision and the according revenue outcomes. I incorporate them into the model by following the focal advertiser's decision making process, i.e. current bid is determined based on recent revenue outcomes.

A growing body of literature has shed light on the optimized 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 search and organic search (Yang and Ghose 2010), and the synergy between paid search marketing and offline marketing (Joo et al. 2014). However, no published research has tapped into the impact of attribution methods on the realized keyword effectiveness in paid search campaigns. Li and Kannan (2014) find large discrepancies in the ROI measures resulting from different attribution methods. This study fills in this gap by analyzing the impact of attribution metrics on the realized effectiveness in terms of ROI at the keyword level, and how this impact varies across heterogeneous keywords.

4.3 Data

The data set consists of daily data of 476 unique keywords advertised at Google and Bing during January 21st to July 18st, 2012, by an online jewelry retailer. This jewelry retailer only advertises at these two search engines and sells its own brand of jewelry on its website. The data are obtained from the only advertising agency hired by this jewelry retailer, and contain the daily information at the keyword level, including the number of impressions, the number of clicks, average cost-per-click, average position, quality score[8], and disguised revenue of the keyword on that day. Table 4-2 reports the summary statistics of these keyword characteristics. I do not have access to the click-through data at the cookie ID level, which are internally used by the advertiser to attribute conversion credit.

<Insert Table 4-2 about here>

Figure 4-4 shows the daily budget, cost, and revenue for all search campaigns. The budget and cost is stable from the beginning to mid-May, and increases from late May to the end of data window. There are a few revenue spikes around Valentine’s Day and Mother’s Day. Both holidays are explicitly captured in the model and discussed in the next Section.

<Insert Figure 4-4 about here>

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[8] Both 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.

The advertiser is given a fixed daily budget by the jewelry retailer and decides the daily bid on each keyword on behalf of the jewelry retailer. From the advertiser's perspective, the daily budget is set exogenously. Conditional on this daily budget, the decision variable for the advertiser is the bid on each keyword. However, the daily budget is a guideline rather than a binding constraint for the advertiser[9]. The total costs of all the search campaigns could sometimes exceed the budget given to the advertiser as shown in Figure 4-4.

If a customer clicks on multiple keywords before a conversion, the focal advertiser used the last-click attribution to assign conversion credits prior to May 2012, and used the first-click attribution from May 2nd, 2012 and onwards[10]. The change on the attribution metrics gives rise to a natural experiment which offers a unique opportunity to examine how the attribution metrics influence the imputed ROI of each keyword in leading to conversions. As a result, the imputed ROI of a keyword determine the advertiser's bid on this keyword in the next period, which determines the ad position among competing bidders accordingly, as illustrated in Figure 4-2 and 4-3. That is, the data allow me to observe how an exogenous shock (the changes in attribution metrics) triggers the changes in the endogenous system of paid search advertising, and allow me to examine the heterogeneous impact on different keywords.

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[9] Although the search engine allows the advertiser to set a "budget" and when the advertiser's spending reaches this "budget", their search ads will no longer be trigged by the customer's search queries. In this study, the focal advertiser sets the "budget" at the search engine twice of the budget given by the jewelry retailer to avoid censoring the possible conversions.

[10] For example, if a customer searches for the keyword "necklace" on May 3rd and then searches again for the keyword "necklace with gemstone" on May 5th. In both searches, the customer clicks through the advertiser's paid search ads and arrives at the advertiser's website. On the May 5th visit, the customer buys a $200 necklace. Since the advertiser uses first click attribution on May 3rd, the revenue is attributed to the first clicked keyword, i.e. the keyword "necklace" clicked on May 3rd.

The advertiser bids on about 200,000 keywords, but only 476 keywords get at least one click both before and after the change of attribution metrics. These 476 keywords account for more than 90% of the total click-throughs on the advertiser's keywords and more than 95% of the overall revenues[11]. Since the goal of this research is to investigate the role of attribution metrics, we only use these 476 keywords in the analyses.

4.4 Model

The focus of this research is to understand the impact of attribution metrics used by the advertiser on the ROI of paid search ads in leading to purchases. To advertise on a search engine, the advertiser first submits a bid for a keyword to the search engine. Meanwhile, the search engine may receive bids for the same keyword from many other advertisers. When the customer searches for this keyword, the search engine uses the bid and the quality score to rank all the ads on this keyword and assign a position to each ad. The customer then sees the paid search ads (i.e. the impressions) and decides to click on one of them (i.e. a click-through) or none of them. Once clicking on the ad, the customer is directed to the advertiser's website where they are able to make various conversions. In the next, I simultaneity model the advertiser's bidding decision, the search engine's ranking decision and the customer's click-through rate and conversion rate.

[11] When a customer clicks through a paid search ad to arrive at the advertiser's website, and later comes back to visit the advertiser's site again directly (i.e. by typing in the URL of the advertiser's website) and makes a purchase on this direct visit, the purchase credit is given to the previous click-through on paid search ads.

4.4.1 The advertiser's revenue outcome and bidding decision

The advertiser maximizes its expected revenue of keyword *i* on day *t*, R_{it}, which can be further expanded into $R_{it} = I_{it} * CTR_{it} * CONV_{it} * AR_{it}$.

I_{it} is the expected number of impression; CTR_{it} is the click-through rate (the number of clicks on the ad divided by the number of impression 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.

In equation (1), I model the log-revenue $\ln(R_{it})$ as the dependent variable, which should be influenced by I_{it}, CTR_{it}, $CONV_{it}$, and AR_{it}. The impression I_{it} is determined by how often the customer searches for keyword *i* on day *t* (influenced by the seasonality) and how often keyword *i* appears among the search results (indicating the competitiveness of the advertiser's bid on the keyword). The seasonality would be reflected in the daily budget, $Budget_t$, and the advertiser's competitiveness can be captured by their bid of keyword *i* on day *t*, bid_{it}. Since the observations of bid_{it} are not available, I instead use the average cost-per-click, CPC_{it}, as a proxy for the bid value in equation (1). The latter one is shown to be highly correlated with bid_{it} (Ghose and Yang 2009). For simplicity, I do not include the jewelry retailer into the model. Instead, the supply side of the paid search ads is the advertiser, who decides how much to bid on each keyword on a specific day (detailed in the next equation), based on an exogenously given daily budget.

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

The average revenue per conversion AR_{it} is influenced by the advertiser's attribution metric as well as the keyword characteristics. When a customer clicks on multiple keywords before a conversion, the total revenue is assigned to the last clicked keyword if the conversion happens before May 2nd, 2012, and to the first clicked keyword if the conversion happens on May 2nd, 2012 or afterwards. The particular attribution metric used by the advertiser on day *t* is denoted as FC_t, where FC_t is 1 when the first-click attribution is used and 0 when the last-click attribution is used. All else equal, a positive coefficient of FC_t implies the first-click attribution leads to a higher overall revenue.

Moreover, extant literature finds that the specificity of a keyword has an impact on its realized effectiveness (Agarwal, Hosanagar and Smith 2011; Ghose and Yang 2009; Rutz, Bucklin and Sonnier 2012). $Specificity_i$ in equation (1) is the number of characters contained in keyword *i*, reflecting the specificity of the keyword[12]. The number of characters in a keyword in the data ranges from 7 to 43, with the median at 19 and the mean at 19.76. Since the rest variables in equation (1)

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[12] In the Appendix V, I also provide the estimation results in which $Specificity_i$ is not standardized, or using alternative measures for $Specificity_i$, such as the number of words contained in a keyword or the judge rating on the keyword specificity.

are in a much smaller scale, I make a z-transformation of the number of characters in a keyword, so that the scale of $Specificity_i$ would not outweigh the other variables in the analysis. To account for the nonlinear effects of keyword specificity, I include the quadratic term $Specificity_i^2$. In addition, I capture the interaction effects of keyword specificity and the attribution metrics.

In sum, in equation (1) I model the impact of I_{it} (affected by CPC_{it} and $Budget_t$) CTR_{it}, $CONV_{it}$, AR_{it} (affected by the advertiser's attribution metric FC_t and keyword $Specificity_i$). The error term ε_{it} follows Normal distribution.

Conditional on the budget on day *t* and the expected revenue of keyword *i*, the advertiser can decide the bid_{it}. More specifically, the advertiser uses the lagged-revenue-per-click $rpc_{i,t-1}$ as a proxy of the expected revenue for keyword *i* in the current period. Then bid_{it} is proportional to both $rpc_{i,t-1}$ and $Budget_t$. At the search engine, the aposition of a paid search ad is determined by bid_{it} and its quality score, QS_{it}. Thus, the advertiser decides bid_{it} according to

$$bid_{it} * QS_{it} \propto \lambda * rpc_{i,t-1} * Budget_t,$$

Take the log transformation of this relationship and rearrange it to get:

$$\ln(bid_{it}) \propto \ln(\lambda) + \ln(rpc_{i,t-1}) + \ln(Budget_t) - \ln(QS_{it}).$$

This relationship is modeled in equation (2). Again, I use CPC_{it} as a proxy for bid_{it} and the error term ξ_{it} follows Normal distribution.

$$\ln(CPC_{it}) = \beta_0 + \beta_1 \ln(rpc_{i,t-1}) + \beta_2 \ln(Budget_t) + \beta_3 \ln(QS_{it}) + \xi_{it} \quad (2)$$

When the advertiser allocates the daily budget on keywords according to $rpc_{i,t-1}$, the keyword with higher $rpc_{i,t-1}$, i.e. higher expected ROI, gets a larger portion of the total budget. However, the absolute value of $rpc_{i,t-1}$ depends on, the budget level on time *(t-1)*, $Budget_{t-1}$. Thus, I standardize $\ln(rpc_{i,t-1})$ in equation (2) to get rid of its scale, so that $\ln(rpc_{i,t-1})$ is not highly correlated with $Budget_t$.

4.4.2 The search engine's position decision

I model the search engine's decision on ad position in equation (3). 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, Hosanagar and Smith 2011), I 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. The advertiser bids for keywords at both Google and Bing. I use a dummy variable $Google_i$ to capture the different competition environment at two search engines. In addition, I control for different competition levels between the branded keywords and other keywords with the dummy variable $Brand_i$. I also control the possible seasonality with the dummy variables for Valentine's Day (equal to 1 during the two weeks prior to Valentine's

Day) and Mother's Day (equal to 1 during the two weeks prior to the Mother's Day)[13]. The error term ζ_{it} follows Normal distribution.

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

4.4.3 The customer's click-through rate and conversion rate

On the customer's side, I model the click-through rate and the conversion rate, both of which influence the revenue in equation (1).

The click-through rate of keyword *i* on day *t* is modeled in a logistic regression as follows:

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

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

The click through rate CTR_{it} depends on the ad position ($Position_{it}$), the expected quality of the ad (I use QS_{it} as a proxy, cf. Agarwal, Hosanagar and Smith 2011), whether keyword *i* is a branded keyword ($Brand_i$), and the keyword specificity ($Specificity_i$ and $Specificity_i^2$). In addition, seasonality is controlled with the dummy variable $Valentine_t$ and $Mother_t$. The error term η_{it} follows extreme value distribution.

Furthermore, I model the conversion rate of keyword *i* on day *t* as follows:

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[13] I also tried including one more dummy variable for weekend (Friday, Saturday, and Sunday), but this weekend dummy was not significant in any of equation (3) – (5).

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

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

Several studies have shown that the conversion rate $CONV_{it}$ is influenced by $Position_{it}$ (Agarwal, Hosanagar and Smith 2011; Ghose, Ipeirotis, and Li 2014; Ghose and Yang 2009; Yang and Ghose 2010). In addition, I control the presence of brand name ($Brand_i$),the nonlinear effects of keyword specificity ($Specificity_i$ and $Specificity_i^2$), and the seasonality ($Valentine_t$ and $Mother_t$). I do not include QS_{it} into the conversion decision in line with previous studies (Agarwal, Hosanagar and Smith 2011; Ghose, Ipeirotis, and Li 2014) and assume that once the customer arrives at the advertiser's website and starts shopping, the quality of the search ad is no longer relevant. The error term δ_{it} follows extreme value distribution.

In order to capture the unobserved covariation among the advertiser's bidding decision, the search engine's position decision, and the customer's click-through rate and conversion rate, I allow the error terms in equation (1) – (5) to be correlated as follows:

$$\begin{pmatrix} \varepsilon_{it} \\ \xi_{it} \\ \zeta_{it} \\ \eta_{it} \\ \delta_{it} \end{pmatrix} \sim MVN \left(\begin{pmatrix} 0 \\ 0 \\ 0 \\ 0 \\ 0 \end{pmatrix}, \begin{matrix} \Sigma_{11} & \Sigma_{12} & \Sigma_{13} & \Sigma_{14} & \Sigma_{15} \\ \Sigma_{21} & \Sigma_{22} & \Sigma_{23} & \Sigma_{24} & \Sigma_{25} \\ \Sigma_{31} & \Sigma_{32} & \Sigma_{33} & \Sigma_{34} & \Sigma_{35} \\ \Sigma_{41} & \Sigma_{42} & \Sigma_{43} & \Sigma_{44} & \Sigma_{45} \\ \Sigma_{51} & \Sigma_{52} & \Sigma_{53} & \Sigma_{54} & \Sigma_{55} \end{matrix} \right) \tag{6}$$

The focus of this research is to explore the impact of attribution metrics on the realized ROI in paid search advertising. Note that the attribution variable, FC_t, is explicitly captured in only equation (1), while its impact indirectly influences equation (2) – (5). First of all, the attribution metrics directly affect the imputed revenue of a keyword as shown in equation (1). In equation (2), the revenue-per-click, $rpc_{i,t-1}$, is the imputed revenue in equation (1) at time *(t-1)* divided by the number of clicks in the same period. That is, $rpc_{i,t-1}$ has already incorporated the impact of the attribution. At the search engine's side, i.e. in equation (3), the ranking decisions at the search engine are solely based on the bids and the quality scores, regardless the attribution metrics used by the advertiser. In addition, at the customer's side, the attribution is reflected in neither equation (4) nor equation (5), because the customer is not aware of the change in the advertiser's attribution metrics. However, the indirect impact of attribution exists – the attribution metric 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 click-through rates in equation (4) and the conversion rates in equation (5).

4.4.4 Identification

The proposed equation system is as below:

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

$$\ln(CPC_{it}) = \beta_0 + \beta_1 \ln(rpc_{i,t-1}) + \beta_2 \ln(Budget_t) + \beta_3 \ln(QS_{it}) + \xi_{it} \tag{2}$$

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

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

$$z_{it} = \phi_0 + \phi_1 \ln(Position_{it}) + \phi_2 Brand_i + \phi_3 Specificity_i + \phi_4 Specificity_i^2 + \phi_5 Valentine_t + \phi_6 Mother_t + \delta_{it} \quad (5)$$

The proposed equations system has simultaneity bias, because some dependent variables are explanatory variables in at least one of the other four equations. For example, the dependent variable $\ln(CPC_{it})$ in equation (2) is an explanatory variable in equation (3) and the dependent variable $\ln(Position_{it})$ in equation (3) is an explanatory variable in both equation (4) and (5), and so on. In addition, the explanatory variables in the current period contain the dependent variables in the last period. For example, in equation (2), the current dependent variable $\ln(CPC_{it})$ depends on the lagged revenue-per-click, which is determined in equation (1) in the last period. Such dependence can create endogeneity problem and bias the estimation outcome. To account for such simultaneity and endogeneity issues, I use three-stage least squares (3SLS) method to jointly estimate all the parameters in equation (1) – (5).

Table 4-3 shows the endogenous variables included in equation (1) – (5) as well as the excluded exogenous variables in each of these equations. Note that although the quality score depends on some factors (e.g. click-through rates) 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 the value stays the same most of the time in the data. Only 57 out of 476 keywords have one or two changes in their quality scores during the six-month data window. Thus, the quality score is considered to be an exogenous variable in the equations system. In sum, the number of endogenous variables is strictly less than the number of excluded exogenous variables in each equation and thus it satisfies the order condition to identify all the parameters in this simultaneous equations system.

<Insert Table 4-3 about here>

4.5 Empirical Analysis

4.5.1 Results

Table 4-4 provides the coefficient estimates of equation (1). The positive and significant signs of CTR_{it} and $CONV_{it}$ indicate that improving the click-through rate and the conversion rate can increase the revenue. In addition, if the advertiser raises the bids, and thus the CPC_{it} increases accordingly, the revenue also increases. The coefficient of $\ln(Budget_t)$ is also positive and significant, indicating that more marketing dollars can lead to more revenue.

<Insert Table 4-4 about here>

The specificity of a keyword, $Specificity_i$ i, is measured by the number of characters included in a keyword and the value of $Specificity_i$ is standardized to be scale-free. Both $Specificity_i$ and $Specificity_i^2$ are positive and significant, which demonstrates a U curve with a turning point at -11.892, i.e. around 12 standard deviations below the mean. In fact, the result reveals a positive monotonic relationship between the keyword specificity and the revenue. That is, the realized ROI is higher for more specific keywords. For example, $Specificity_i$ is -0.992 for keyword “mother’s ring” (the specificity of this keyword is 0.992 standard deviation below the average), and the value of $\alpha_5 Specificity_i + \alpha_6 Specificity_i^2$ is -4.613. For a longer keyword, say “mother’s ring with birthstone”, $Specificity_i$ is 1.356 (1.356 standard deviation above the average), and the value of $\alpha_5 Specificity_i + \alpha_6 Specificity_i^2$ is 6.954. In sum, the specificity of a keyword has significant impact on its revenue.

Next, let us look into the impact of attribution metrics and its interaction with the keyword specificity. The coefficient of FC_t is negative and significant, indicating that switching from the last-click attribution to the first-click attribution hurts the advertiser’s overall revenue. This negative impact is more prominent for specific keywords. For example, when the advertiser uses the first-click attribution, $\alpha_7 FC_t + \alpha_8 FC_t * Specificity_i$ is 11.066 for keyword “mother’s ring” and -16.252 for keyword “mother’s ring with birthstone”. Assuming everything else being equal, the impact of keyword specificity, the attribution metric, and the interaction of both, i.e. $\alpha_5 Specificity_i + \alpha_6 Specificity_i^2 + \alpha_7 FC_t + \alpha_8 FC_t * Specificity_i$, is -4.613 for keyword “mother’s ring” under the last-click attribution and 6.454 when switching to the first-click attribution. The according value for keyword “mother’s ring with birthstone” is 6.954 under the last-click attribution and -9.298 when switching to the first-click attribution. In sum, the attribution and keyword specificity has a significant impact on the realized revenue of a keyword.

Customers click through different keywords to visit the firm’s website. These keywords reflect their current need. As the consumers move forward in their purchase journey, they tend to search with more specific keywords (Rutz and Bucklin 2011) and the more specific keyword are usually longer than the broad keywords. Using the first-click attribution, the broad keywords which appear at the early stage of the purchase journey get more conversion credits than they can get in the last-click attribution, and therefore, these broad keywords would be bid higher in the next period due to their higher imputed revenue. The higher bid as a result positions these broad keywords at more advantageous places among the paid search results and thus could bring in more customers who are at their early stage in the purchase journey. In sum, the first-click attribution creates a positive loop between the investment and returns for broad keywords. On the other hand, customers visiting through specific keywords may reach the late stage of their purchase journey and are already very clear what they intend to purchase. If the advertiser uses the last-click attribution, then the specific keywords get more credits than they could get in the first-click attribution. More credits on specific keywords lead to higher bid and thus better ad position, in turn higher click-through rates and conversion rates for specific keywords in the next period.

Whether or not the overall revenue increases, when the advertiser switches from the last-click to the first-click, depends on the mix of their keywords. If the advertiser's keywords are mainly broad keywords, then they would benefit from switching to the first-click attribution. On the other hand, if their keywords are dominantly specific keywords, using the first-click attribution would lead to underinvestment on these specific keywords and hurt the overall revenue. The negative and significant coefficient of FC_t and the negative and significant coefficient for the interaction of FC_t and $Specificity_i$ implies that the focal advertiser's keywords are mainly specific keywords.

The advertiser uses the lagged revenue-per-click as the expected revenue of a keyword to determine the current bid on a keyword in equation (2). The coefficient estimates are presented in Table 4-5. The results reveal a positive and significant relationship between the current bid on the keyword (proxied by the cost-per-click) and its lagged revenue-per-click. 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. Note that each day's lagged revenue-per-click is standardized, i.e. free of scale, so it is not highly correlated with the budget level. Furthermore, when the quality score of a keyword is higher, i.e. the chance to win a good ad position with the same bid is higher, the advertiser tends to bid less on the keyword. In sum, all the signs of the coefficient estimates in Table 4-5 are as expected.

<Insert Table 4-5 about here>

The estimation results of equation (3) are shown in Table 4-6. The dependent variable is $\ln(Position_{it})$, the larger value of which means the ad is placed to a less advantageous position. The negative coefficient of $\ln(CPC_{it})$ and $\ln(QS_{it})$ indicates that as the advertiser bids more on a keyword or the expected quality (in terms of quality score) of this keyword is higher, the value of $\ln(Position_{it})$ is smaller. That is, the ad is placed to a better position. The coefficient of $Google_i$ is negative and significant, indicating that with the same cost-per-click and quality score, the advertiser can get a better ad position at Google than at Bing. Furthermore, at the mean level, the presence of the brand name in the keyword can improve the ad's position by 1.852. For example, say the advertiser's ad for keyword "mother's ring" is positioned at the 5^{th} best position. The keyword "XYZ mother's ring", where XYZ is the brand name, could be positioned to the 3^{rd} best position with everything else equal. Including the brand name into the keyword can reduce the competition level and save costs for the advertiser. However, the potential audience of a branded keyword is narrower than that of a generic keyword. As for the seasonality, during the two weeks before the Valentine's Day or the two weeks before the Mother's Day, the position is less advantageous at the same cost-per-click than during other time, reflecting a more competitive jewelry market before these two holidays.

<Insert Table 4-6 about here>

Table 4-7 provides the coefficient estimates of equation (4). The coefficient of $\ln(Position_{it})$ is negative and significant, indicating that when the paid search ad moves to a less advantageous position (the value of $\ln(Position_{it})$ becomes larger), the click-through rate would decrease, consistent with previous finding (Agarwal, Hosanagar and Smith 2011; Ghose, Ipeirotis, and Li 2014; Ghose and Yang 2009; Rutz, Bucklin and Sonnier 2012). In addition, the coefficient of $\ln(QS_{it})$ is positive and significant, implying a 5.884% increase in click-through rate when the quality score increases by 1. Further, the presence of the brand name in the keyword increases the click-through rate by 12.608%. Although the click-through rate during the two weeks before Valentine's Day is higher, I do not find positive and significant impact before Mother's day, which means that customers are more actively search for a gift for Valentine's Day than for Mother's Day. The coefficient of $Specificity_i$ and $Specificity_i^2$ shows an inverted-U curve with respect to the click-through rate, with the turning point at 0.675, i.e the number of characters is more than the mean by 0.675 standard deviation, which is around 24 characters. The corresponding implication is that for short keywords with less than 24 characters (e.g. mother's ring, silver necklace, etc.), more specific keywords have a higher click-through rate. However, when the keyword specificity reaches a certain point, more than 24 characters in this case (e.g. mother's ring with birthstone, amethyst diamond engagement ring, etc.), the click-through rate decreases as the keyword is longer.

<Insert Table 4-7 about here>

Table 4-8 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, echoing the finding by Agarwal, Hosanagar and Smith (2011). This has important implication for the advertisers: when the advertisers spend more to win a better ranking in the result list, i.e. a smaller value for $\ln(Position_{it})$, the click-through rate increases as shown in Table 4-7, but the change in conversion rate is very marginal and not significant according to the results in Table 4-8. Moreover, the presence of the brand name in the keyword can increase the conversion rate from 1.022% to 1.388%, about 1/3 lift in the conversion rate. Both Valentine's Day and Mother's Day have a positive and significant impact on the conversion rate, while neither $Specificity_i$ nor $Specificity_i^2$ is significant. That is, the specificity no longer affects the conversion rate when its non-linear impact on revenue and click-through rates has already been explicitly controlled in equation (3) and (4).

<Insert Table 4-8 about here>

4.5.2 Robustness check

The change of attribution metrics happened on May 2nd, 2012. For all the conversions before this date, the advertiser assigned the conversion revenue with the last-click attribution, while the conversions on or after May 2nd, 2012 was assigned to the first clicked keywords. Hence, in the first few days after May 2nd, 2012, the revenue could be assigned to the first keyword clicked after the change, but not necessarily the first keyword clicked by the customer on his/her purchase journey. That is, some of the purchase paths are left censored. Similarly, the data are also right-censored – some customers are still in the middle of their purchase journey and thus some revenues have not been realized by the end of the data window. The first-click attribution in this case could underestimate these potential revenues. To cope with this issue, I drop the first two weeks of data after the change in attribution metrics and the last two weeks of data in order to test the robustness of the proposed model. All the parameters in this robustness check show the same signs as those in Table 4-4 to Table 4-8, although the p-value of $Budget_t$ in equation (1) drops to 0.13 and the p-value of $Mother_t$ in equation (5) drops to 0.19 due to fewer observations.

The 476 keyword analyzed in this research are belonged to three match types: exact, phrase, and broad. To get rid of the noise due to broad match, I estimate equation (1) to (5) with only keywords belonged to the exact and phrase match type. In addition, I explicitly use a dummy variable to distinguish the exact and phrase match type. The results are close to those in Table 4-4 to 4-8. More details are provided in Appendix IV.

4.5.3 Model Predictions

In the next, I compare the predictive validity of the proposed model with Ghose and Yang's model (2009). There are two important differences between the proposed model and Ghose and Yang's model (GY Model): first, the revenue is not observed and thus not modeled in the GY model; second, the bidding decision is made based on the lagged position of a keyword in the GY model, while in the proposed model, the bidding decision depends on the lagged revenue-per-click (reflecting the focal advertiser's practice), so that the bidding decision (equation (2)) is linked with the revenue generation (equation (1)). In the following comparison, I reflect these differences in the modeling, but do not use exactly the same variables as in the GY model. For example, the GY model uses separate dummies for retailer and brand name, while these two are the same in my context. Moreover, I estimate both with 3SLS to make these two models comparable, although Ghose and Yang (2009) estimate their model with Seemingly Unrelated Regression (SUR).

Table 4-9 provides the mean absolute error (MAE) of these two models. The proposed model leads to smaller MAE than GY model for equation (2), (4), and (5), especially in predicting cost-per-click (equation (2)) and click-through rate (equation (4)). The MAE for equation (3) by the proposed model is also very close to that of GY model. In general, explicitly modeling the revenue generation and linking it to the bidding decision helps in improving the predictive validity in the proposed model.

<Insert Table 4-9 about here>

4.5.4 Policy Simulation: a combined attribution metric

The focal advertiser has experimented with the last-click attribution and the first-click attribution. Either metric assigns the conversion credit only to a single click on the paid search ads. In the next, I simulate a scenario where the advertiser uses a combined attribution metric, which considers the potential contribution of a keyword under both the last-click and the first-click attribution schemes and then allocate the budget accordingly. Note this is not an optimized attribution metric. Rather, I intend to show that with an improved attribution metric, which considers the potential contribution a keyword can make at both the early stage and the late stage of a purchase journey and assigns the conversion credit to more than a single click, the advertiser can reap more revenue with the same budget.

Table 4-10 illustrates how the new metric is used to determine the bid on a keyword. For each keyword, I calculate the average lagged revenue-per-click under both the last-click and the first-click attribution (Column 2 and Column 3 in Table 4-10). Column 4 contains the larger revenue-per-click between the values in Column 2 and Column 3 for each keyword. I standardize the revenue-per-click in Column 4 the way as it is done in the estimation and use them to decide the bid.

<Insert Table 4-10 about here>

Table 4-11 presents the performance of the new attribution metric, compared against the last-click and first-click metrics. The average cost-per-click and average position using the new metric are both in between that of the last-click and first-click metrics. However, thanks to the improved budget allocation, the average click-through rate is higher than that of both the last-click and first-click metrics. Although the conversion rate is the same as that of the last-click metric and is smaller than that of the first-click metric, the predicted total revenue with this new metric is 5.1% more than the revenue under the last-click attribution and 5.5% more than the revenue under the first-click attribution.

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 rest 15% visitors have two or three clicks, i.e., the change in attribution metric only affects the attributed revenues from 15% visitors to the advertiser's website. That being said, by merely attributing the conversion credit with an improved metric which accounts for the potential contribution of a keyword under the last-click and first-click attribution, the advertiser is able to improve their revenue by more than 5%.

<Insert Table 4-11 about here>

4.6 Conclusions and Managerial Implication

Paid search advertising accounts for around half of the overall spending on digital marketing (VanBoskirk et al. 2011, eMarketer 2014). In this research, I propose a model to examine the relationship among the advertiser, the search engine and the consumer, and how the attribution metric plays a role in this relationship. Using a six-month panel data of 476 keywords from the advertiser of an online jewelry retailer, I jointly model the relationship among the advertiser's revenue outcome and bidding decision, the search engine's ranking decision, and the consumer's click-through rate and conversion rate, cope with the potential simultaneity bias with simultaneous equations model, and address the endogeneity issue with 3SLS method.

The analyses shed light on the impact of attribution metric on the realized ROI of different keywords. Different attribution metrics assign conversion credits across keywords based on different weights, which affect future budget allocation, and in turn determines the ROI of future search campaigns. The impact of attribution would depend on the mix of the advertiser's keywords. In this research context, the focal advertiser switched from the last-click attribution to the first-click attribution. The revenue loss of their specific keyword from this change outweighs the gain of their broad keywords. Overall, changing from the last-click attribution to the first-click attribution has a negative impact on the advertiser's overall revenue, and this negative impact is stronger for more specific keywords. Based on the estimation results, I propose a combined attribution metric which accounts for the potential revenue from both the last-click and the first-click attribution. This combined attribution metric can increase the overall revenue by more than 5% with the same amount of budget. Note that only around 15% of the visitors to the focal advertiser's website make multiple clicks before a conversion, so the change in attribution metric only makes a difference to the revenue generated by these 15% visitors. However, the combined attribution metric, by merely reallocating the same budget, is able to lift the revenue by more than 5%. The revenue lift could be more prominent for high-involvement products and services, where the consumer tend to make more search click-throughs on their purchase journey. Therefore, I would recommend the paid search advertisers to consider the importance of attribution metrics in their paid search campaigns and adopt a more sophisticated metric to fully realize the ROI potential of their search campaigns.

In addition to the change of attribution metrics, another merit of the data is the detailed conversion and revenue information, with which I am able to explicitly model the advertiser's revenue generation and model how the daily revenue outcome is used to determine the bid on a keyword in the next period. By modeling the revenue outcome and the bidding decision, the proposed model demonstrates good predictive validity. As I illustrate in the Predictive Validity subsection, the proposed model outperforms Ghose and Yang's (2009) model in predicting the cost-per-click, click-through rate, and conversion rate, and is as good as Ghose and Yang's model in predicting the position of a paid search ad.

Another interesting finding in this research is the impact of the keyword characteristics on the realized ROI. I find that, with the same bid, the branded keywords get more advantageous positions, higher click-through rates and higher conversion rates. This is intuitive and consistent with previous findings (Ghose and Yang 2009; Agarwal, Hosanagar and Smith 2011; Rutz, Bucklin and Sonnier 2012). The analyses show that more specific keywords demonstrate better performance in the last-click attribution than in the first-click attribution. Furthermore, the keyword specificity has a non-linear relationship with respect to the click-through rates, while the difference in conversion rates for specific versus broad keywords is not significant. In sum, as the consumer moves forward in their purchase journey, they narrow and specify their search queries and type in more specific keywords at the search engines. The implication for the advertisers is that the click-through rates could first increase and then drop as the search queries become more and more specific, but the conversion rates would not change significantly.

One limitation in this analysis is that I collect the data from the advertiser, to whom the overall budget is exogenously given. However, when the firm sets the budget for the advertiser, there could be numerous factors including the seasonality, branding, etc., taken into account. In the supply side models, the budget is used as an exogenous variable. In the demand side models, where the budget is not an appropriate variable to directly explain the variation in the click-through rates and conversion rates, I use time dummies to control for the seasonality. Assessing to more information on the budget decision will allow for suggestions on the optimized attribution metric to the advertiser.

The model can be adapted and applied to other marketing tools. For example, the proposed model can be used to analyze the ROI of real-time bidding display advertising, where the cost-per-click can be replaced by cost-per-thousandimpression, and the rest measures would be very similar. The proposed model can tease out the impact of revenue, cost, click-through rate and conversion rate which are simultaneously and continuously changing, and help the advertiser understand the impact of attribution in display advertising.

Tables and Figures

Table 4-1 Sample Data Observed by the Researcher

Keyword	Match	Day	Search Engine	Impressions	Clicks	CPC	Avg Position	Quality Score
engagement rings	Exact	1/21/2012	Google	18	3	0.29	2.05	7
engagement rings	Exact	1/22/2012	Google	29	3	0.34	2.00	7
engagement rings	Exact	1/23/2012	Google	36	3	0.39	2.20	7
engagement rings	Exact	1/24/2012	Google	21	2	0.36	2.00	7
engagement rings	Exact	1/25/2012	Google	35	5	0.42	2.74	7
engagement rings	Exact	1/26/2012	Google	21	3	0.39	2.81	7
engagement rings	Exact	1/27/2012	Google	24	3	0.46	2.13	7
engagement rings	Exact	1/28/2012	Google	28	4	0.33	2.47	7
engagement rings	Exact	1/29/2012	Google	34	2	0.55	2.73	7
engagement rings	Exact	1/30/2012	Google	28	3	0.54	1.32	7

Table 4-2 Summary Statistics

	All Keywords	Google	Bing
Number of Keywords	476	422	54
Total Impression	83,448,302	79,936,522	3,511,780
Daily Impression	463,602	444,092	19,510
Impression per Keyword	175,312	189,423	65,033
Total Clicks	1,000,507	946,239	54,268
Daily Clicks	5,558	5,257	301
Clicks per Keyword	2,102	2,242	1,005
Total Conversions (all four types)	25,689	23,985	1,704
Total Revenue*	613,805	576,159	37,646
Daily Revenue	3,410	3,201	209
Revenue per Keyword	1,290	1,365	697
Total Cost	1,658,999	1,561,924	97,076
Daily Cost	9,217	8,677	539
Cost per Keyword	3,485	3,701	1,798
Average CPC	1.48	1.48	1.46
Average Position	2.26	2.22	2.61
Average Quality Score	5.44	4.99	9.00
Average Click-through Rate	1.20%	1.18%	1.55%
Average Conversion Rate	2.57%	2.53%	3.14%

* The revenue is disguised.

Table 4-3 Endogenous and Exogenous Variables

	Endogenous Variables	Exogenous Variables Excluded
Eqn 1	$R_{it}, CTR_{it}, CONV_{it}, \ln(CPC_{it})$	$\ln(QS_{it}), Google_{it}, Brand_i, Valentine_t, Mother_t$
Eqn 2	$\ln(CPC_{it})$, $\ln(rpc_{it})$	$\ln(Budget_t), Specificity_i$, $FC_t, Google_{it}, Branded_i, Valentine_t, Mother_t$
Eqn 3	$\ln(Position_{it})$, $\ln(CPC_{it})$	$\ln(Budget_t), Specificity_i$, $FC_t, \ln(QS_{it})$
Eqn 4	CTR_{it}, $\ln(Position_{it})$	$\ln(Budget_t), FC_t, Google_{it}$
Eqn 5	$CONV_{it}$, $\ln(Position_{it})$	$\ln(Budget_t), FC_t, \ln(QS_{it}), Google_{it}$

Table 4-4 Coefficient Estimates from Revenue Model

	Estimates	
Intercept	-7.526	.
CTR_{it}	0.132	***
$CONV_{it}$	1.629	**
$\ln(CPC_{it})$	1.154	***
$\ln(Budget_t)$	0.958	*
$Specificity_i$	4.852	*
$Sq(Specificity_i)$	0.204	***
$First\text{-}Click_t$	-0.476	***
$First\text{-}Click_t*Specificity_i$	-11.635	**

Significance codes: *** (p< 0.001), ** (p< 0.01), * (p<0.05), and . (p< 0.1).

Table 4-5 Coefficient Estimates from Cost-per-click Model

	Estimates	
Intercept	-5.657	***
$\ln(rpc_{it})$	0.683	***
$\ln(Budget_t)$	0.731	***
$\ln(QS_{it})$	-0.530	***

Significance codes: *** (p< 0.001), ** (p< 0.01), * (p<0.05), and . (p< 0.1).

Table 4-6 Coefficient Estimates from Position Model

	Estimates	
Intercept	1.702	***
$\ln(CPC_{it})$	-0.613	***
$\ln(QS_{it})$	-0.341	***
$Google_{it}$	-0.357	***
$Brand_i$	-2.051	***
$Valentine_t$	0.097	***
$Mother_t$	0.024	***

Significance codes: *** (p< 0.001), ** (p< 0.01), * (p<0.05), and . (p< 0.1).

Table 4-7 Coefficient Estimates from Click-through Rate Model

	Estimates	
Intercept	-5.356	***
$\ln(Position_{it})$	-1.049	***
$\ln(QS_{it})$	1.332	***
$Brand_i$	1.907	***
$Valentine_t$	0.372	***
$Mother_t$	-0.025	
$Specificity_i$	0.142	***
$Sq(Specificity_i)$	-0.141	***

Significance codes: *** (p< 0.001), ** (p< 0.01), * (p<0.05), and . (p< 0.1).

Table 4-8 Coefficient Estimates from Conversion Rate Model

	Estimates	
Intercept	-4.566	***
$\ln(Position_{it})$	-0.014	
$Brand_i$	0.312	***
$Valentine_t$	0.020	***
$Mother_t$	0.024	***
$Specificity_i$	-0.002	
$Sq(Specificity_i)$	-0.002	

Significance codes: *** (p< 0.001), ** (p< 0.01), * (p<0.05), and . (p< 0.1).

Table 4-9 Model Comparison: Mean Absolute Error (MAE)

	DV	Mean	SD	Proposed Model MAE	GY Model MAE
Eqn (2)	ln(CPC)	0.182	0.775	0.668	1.286
Eqn (3)	ln(Position)	0.660	0.530	0.374	0.371
Eqn (4)	ln(CTR/(1-CTR))	-3.925	1.371	0.909	3.490
Eqn (5)	ln(CONV/(1-CONV))	-4.563	0.356	0.066	0.073

Table 4-10 A New Metric to Attribute the Conversion Credit

Keyword	Mean Lagged rpc with Last-Click	Mean Lagged rpc with First-Click	The Larger Lagged rpc
1	1.53	0.57	1.53
2	2.7	0.97	2.7
3	0.13	2.48	2.48
…			

Table 4-11 The Performance of the New Attribution Metric

	Last-Click	First-Click	New Metric
Predicted Average CPC	1.108	1.323	1.284
Predicted Average Position	2.072	1.777	1.864
Predicted Average CTR	1.854%	2.041%	2.044%
Predicted Average CONV	1.031%	1.034%	1.031%
Predicted Average Revenue	10.197	10.153	10.717
Predicted Total Revenue	4854	4833	5101

Figure 4-1 Search Results at Google

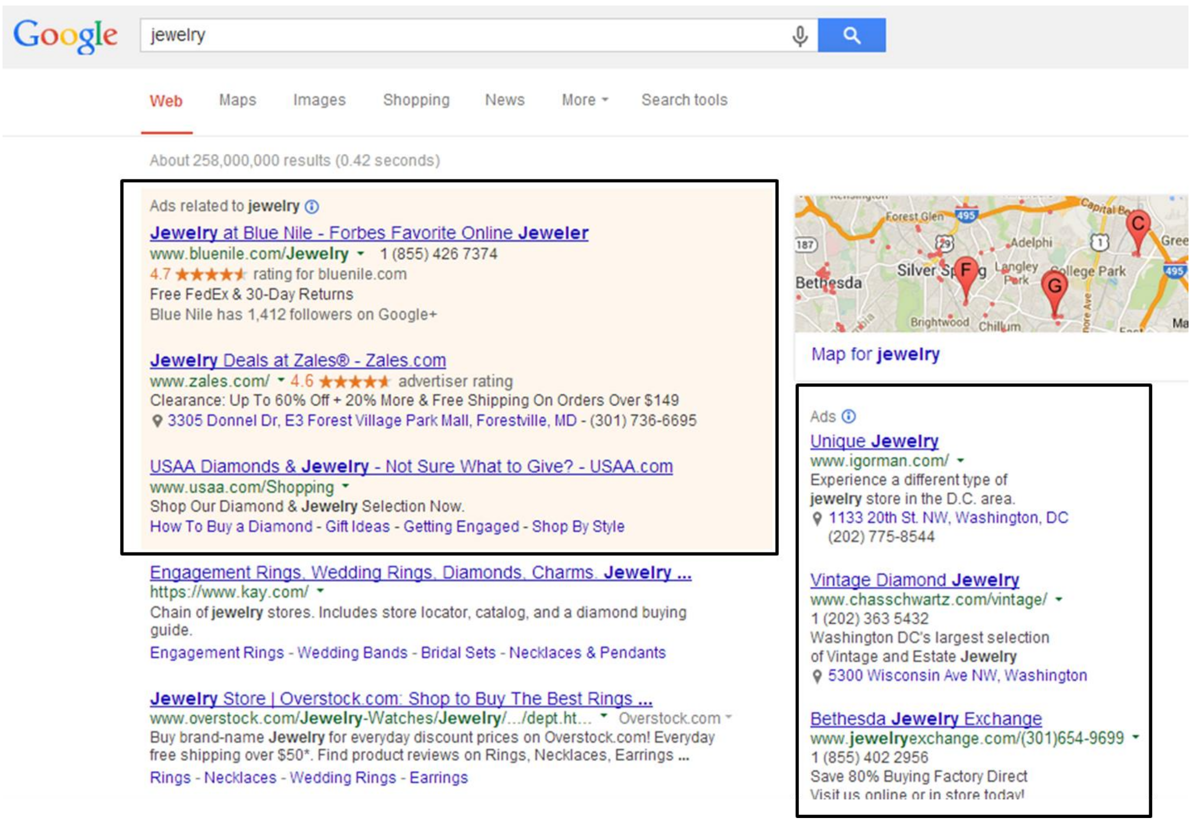


Figure 4-2 Institutional Context

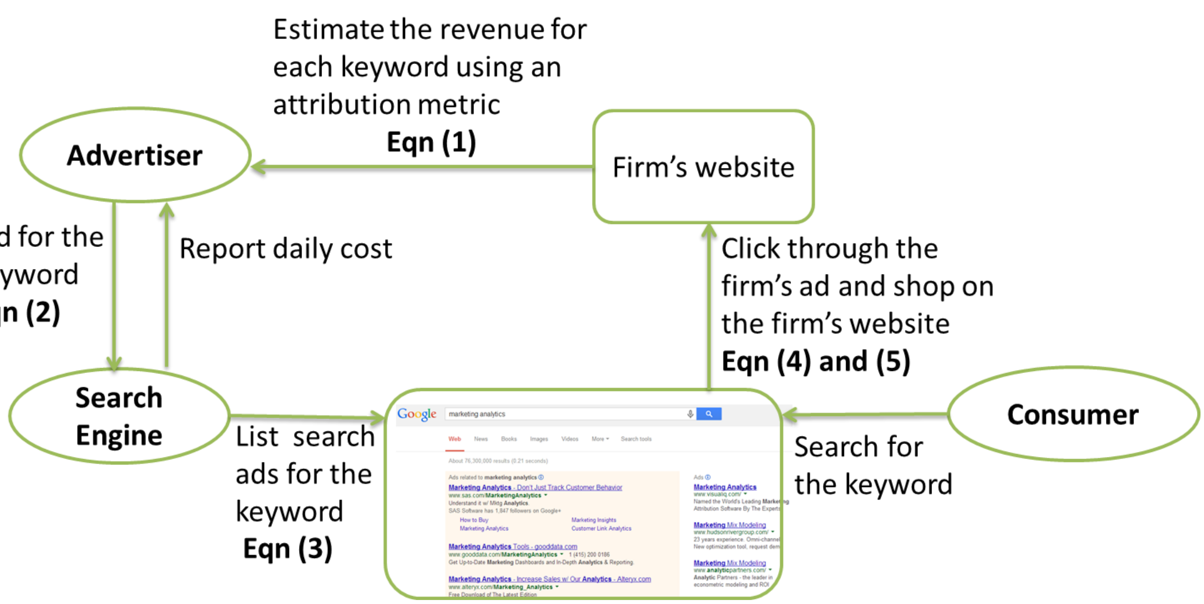
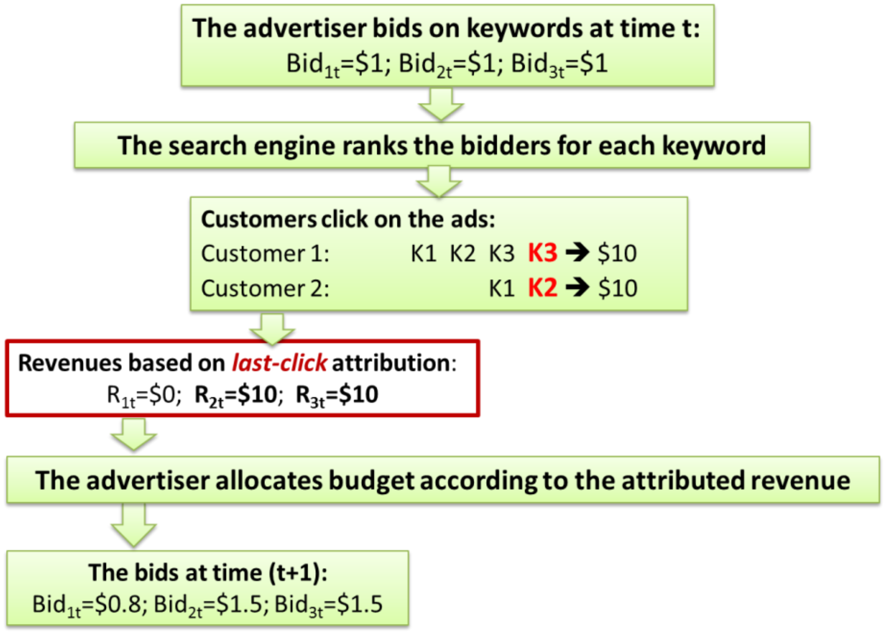
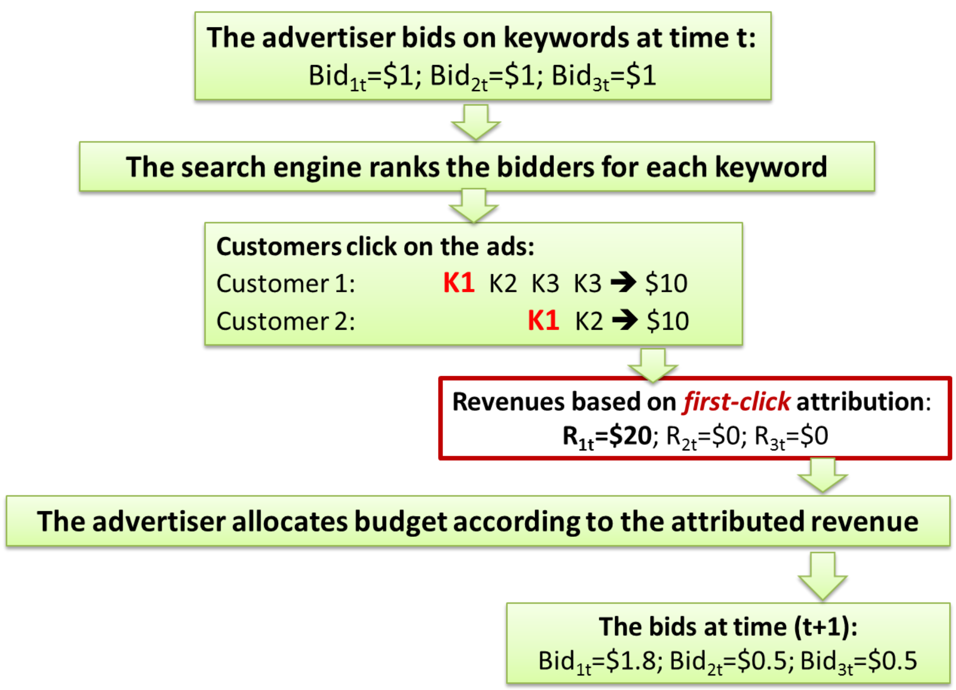


Figure 4-3 The Role of the Attribution Metric

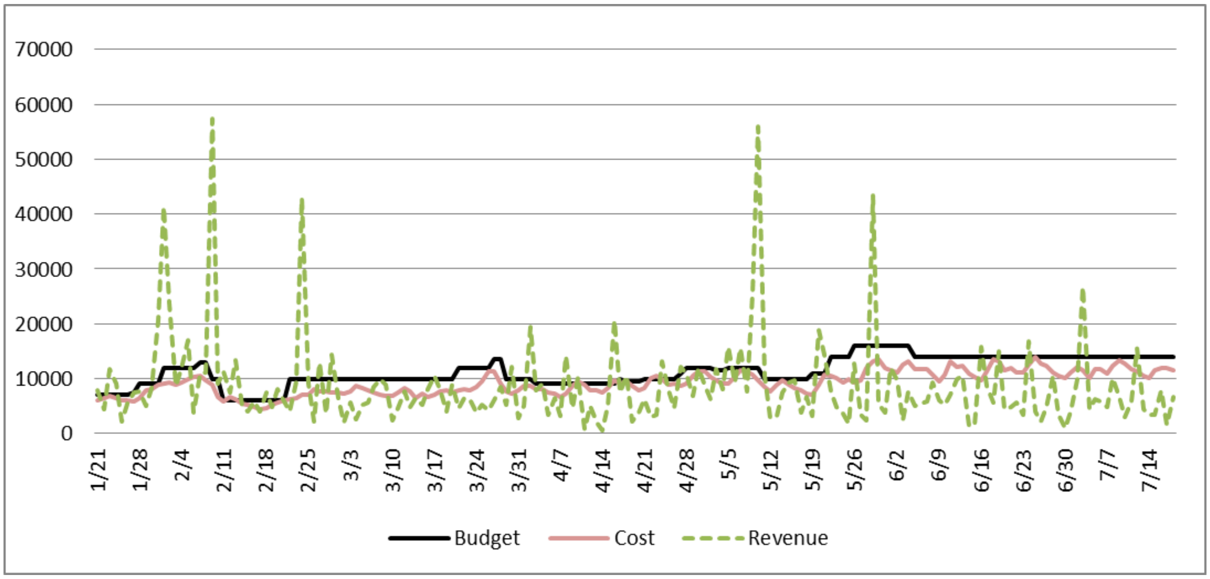


(a) Last-Click Attribution



(b) First-Click Attribution

Figure 4-4 Daily Budget, Cost, and Revenue



Chapter 5 : Conclusion

5.1 Summary of the dissertation

This dissertation proposes a conceptual framework and provides two empirical studies on the attribution modeling and marketing resource allocation in digital marketing. In this chapter, I summarize the previous chapters and discuss the contribution, limitation and potential future research of this dissertation.

Chapter II introduces the multi-channel marketing context and proposes a conceptual framework to understand the customer's browsing and purchasing behavior through different marketing channels. Based on the conceptual framework and extant literature, I propose four hypotheses of the carryover and spillover effects of the information collected during the customer's visit and conversion at the firm's website.

Chapter III provides a model of the customer's purchase funnel with three stages: (1) the customer's consideration of any number of channels, (2) their visit through a specific channel, and (3) their subsequent purchase at the firm's website. According to the modeling results, the contribution of search channel is inflated by the last-click and the 7-day average metrics, when referral, e-mail, and display channels deserve more credit than what the last-click and the 7-day average metrics suggest. For example, the last click metric overestimates organic search channel by 36% and paid search channel by 40%. On the other hand, it underestimates referral channel by 33%, e-mail by 58% and display by 75 %. To validate the model, the firm conducted a field experiment by pausing their paid search advertising for a week. The model predicts that paid search contributes 7.8% of conversion, while the observed drop in conversions is 6.6%. That is, the observed contribution from paid search is 1.2% less than the predicted contribution. My conjecture is that many of the branded keywords are recaptured by organic search during the pause of paid search. In addition, I use the data of customers who have received email from the focal firm and analyzed the firm's e-mail retargeting strategy based on the model estimates. Several cases are identified where e-mail retargeting can hurt the purchase probability when the customer makes touch points in certain orders.

Chapter IV investigates the impact of attribution metric on the ROI of search campaigns. The advertiser assigns conversion credits to each keyword according to a certain attribution metric. That is, the attribution metric influences the revenue assigned to a keyword and thus determine the future budget to be allocated on this keyword. I empirically examine the role of attribution in the relationship among the advertiser, the search engine and the customer with six-month data of 476 keywords used by an online jewelry retailer. In the model, I explicitly capture the advertiser's revenue generation and bidding decision, the search engine's ranking decision, and the consumer's click-through rate and conversion rate. The simultaneity and endogeneity in these decisions are dealt with 3SLS method. Half-way through the data window, the focal advertiser changed their attribution metric from the last-click attribution to the first-click attribution. This allows me to estimate the impact of the two alternative attribution metrics on revenue imputation and budget allocation. Given the mix of the keywords bid by the advertiser, the first-click metric leads to lower overall revenues and this negative impact is stronger for more specific keywords. Based on the estimation results, I simulate a scenario where the advertiser uses a new attribution metric. The new metric accounts for the potential contribution of a keyword both under the last-click attribution and the first-click attribution. With this new metric, the advertiser is able to improve their revenue by more than 5% by merely changing their attribution metric.

5.2 Contribution and Managerial Implications

The conceptual framework in Chapter II sheds light on the nature of carryover and spillover effects in the multichannel marketing context. Based on this framework, Chapter III offers the first study, to my knowledge, that examines these effects in the online multi-channel context at three distinct stages – consider, visit, and purchase. The results show that neither the last-click attribution metric nor the 7-day average metric is accurate measure for the incremental impact of online marketing channels. These metrics only consider the visits that result in conversion right away and bias the real impact of a marketing channel, especially for high-involvement products and services.

The model explicitly captures the customer's consideration stage and incorporates the heterogeneity and self-selection in customers' consideration of channels to use. It allows me to accurately predict the conversions through different channels when one of them (for example, paid search, as in this study) is not available. For example, the incremental value of Paid Search channel is not as high as what the last-click model suggests. When the Paid Search channel is paused in the field experiment, a significant portion of its impact can be recaptured by the Organic

Search channel. However, this finding depends on the brand strength of the firm and may not be generalizable for firms with a weak brand. In sum, the model proposed in Chapter III is able to provide directional suggestions in reallocating the marketing dollars, which has useful managerial implications for allocating marketing budget across marketing channels and for targeting strategies.

This attribution model can be applied to the paid search channel down to the keyword level. The marginal effectiveness of keywords can be used to allocate marketing budget selectively across keywords and the measures can be used for negotiation with search engine companies.

Chapter IV proposes a model to investigate the role of attribution on the ROI of search campaigns. The data in this research contains a natural experiment, where the focal advertiser switched from the last-click attribution to the first-touch attribution. This exogenous change in the attribution metric allows me to examine the impact of attribution metric in an endogenous system where the advertiser, the search engine and the consumer makes decisions simultaneously.

The proposed model gains predictive strength by capturing the revenue outcome and link it to the bidding decision. It outperforms Ghose and Yang's (2009) model in predicting the cost-per-click, click-through rate, and conversion rate, and is as good as Ghose and Yang's model in predicting the ad position of a keyword. Another interesting implication from Chapter IV is the impact of the keyword characteristics on ROI – more specific keywords are usually associated with the later stage of a purchase journey and lead to higher overall revenue in the last-click attribution than in the first-click attribution. As the consumers move forward in their purchase journey, they search for more specific keywords, and the click-through rates have an inverted-U relationship with respect to the keyword specificity. However, the conversion rates would not change accordingly.

Based on the estimation results, I propose a new attribution metric which considers the contribution of a keyword under both last-click and first-click regimes. This new attribution metric can increase the revenue by more than 5% with the same amount of budget. The revenue lift could be more prominent for high-involvement products and services, where the consumer tend to make more search click-throughs on their purchase journey. Therefore, I would recommend the paid search advertisers to consider the impact of attribution metrics in their search campaigns and choose a sophisticated attribution metric to reach the full ROI potential of their keywords.

5.3 Future Research

In Chapter II, I propose a conceptual framework of the customer's purchase funnel in the context of online shopping. Figure 2-1 illustrates the three distinct stages in a customer's online purchase journey - consideration, visit and purchase, which is from the customer's perspective. In Figure 5-1, I revisit this purchase funnel and investigate it from the firm's perspective. The customers are first drawn into the purchase funnel due to their awareness of the firm's products or services. Then the customers may research on the firm's product and compare it with competing products and finally make the purchase decision. That is, from the firm's viewpoint, the purchase funnel could contain three stages – awareness, research, and purchase, and the marketing implication for each stage would be different.

<Insert Figure 5-1 about here>

Different marketing channels could play different roles in this purchase funnel. In Chapter II, I have distinguished the firm-initiated channels and customer-initiated channels. The firm-initiated channels, such as display ads and emails, tend to help in building awareness of the firm's brand and drawing in traffic to the firm's website. On the other hand, the customer-initiated channels, such as search campaigns and referral links, usually provide the information to assist the customer's research on the firm’s product. There could be other dichotomies of marketing channels, such as outbound marketing channels versus inbound marketing channels, which are close to the definition of firm-initiated versus customer-initiated channels in this dissertation. Again, I would like to emphasize that each marketing channel falls onto a continuum from the most firm-initiated channel (email channel) to the most customer-initiated channel (direct visit channel). There could be carryover and spillover effects among the firm-initiated channels, among the customer-initiated channels, or between these two groups of channels.

In the next step of my research, I could expand the purchase funnel in Figure 5-1 horizontally to include the analyses of more marketing channels as shown in Figure 5-2. For example, new marketing opportunities became available on Facebook and Twitter a few years ago and quickly attract billions of dollars every year. Facebook reports the 2013 revenue to be $7.87 billion, increased 55% year-over-year, among which, 53% is from mobile ads. New technologies may bring in even more marketing opportunities in the near future. As more marketing dollars are shifted to online marketing and mobile marketing channels, marketing managers need to choose the right attribution model to measure the ROI of their marketing spending on these new marketing channels. My research can be extended to these new marketing channels and provide sophisticated models to evaluate these new marketing channels and help the marketing managers to have a better sense of the effectiveness of their marketing tools in a multi-channel multi-screen environment.

<Insert Figure 5-2 about here>

Additionally, technology advances make granular data available for some offline traditional marketing channels. For example, some marketing analytics companies are collecting offline data (for example, TV ad impressions and brick-and-mortar traffic) and trying to link these data with household online and mobile browsing behaviors. Including the offline observation into my research can help me vertically expand my research on the purchase funnel in Figure 5-1 and bring my research up to a strategic level on the media mix allocation as shown in Figure 5-2.

Apart from the possible future research on substantive issues, the nature of my research area may bring in the opportunities to make methodology contribution to the research of digital marketing. My research involves granular data on customer behavior at the individual level and the data formats of different marketing channels are usually incompatible. This inevitably requires the analyses of large datasets and merging datasets in different formats. My future research has the potential to provide better solutions to organize and analyze data in a data-rich environment.

Figures

Figure 5-1 Framework for Future Research

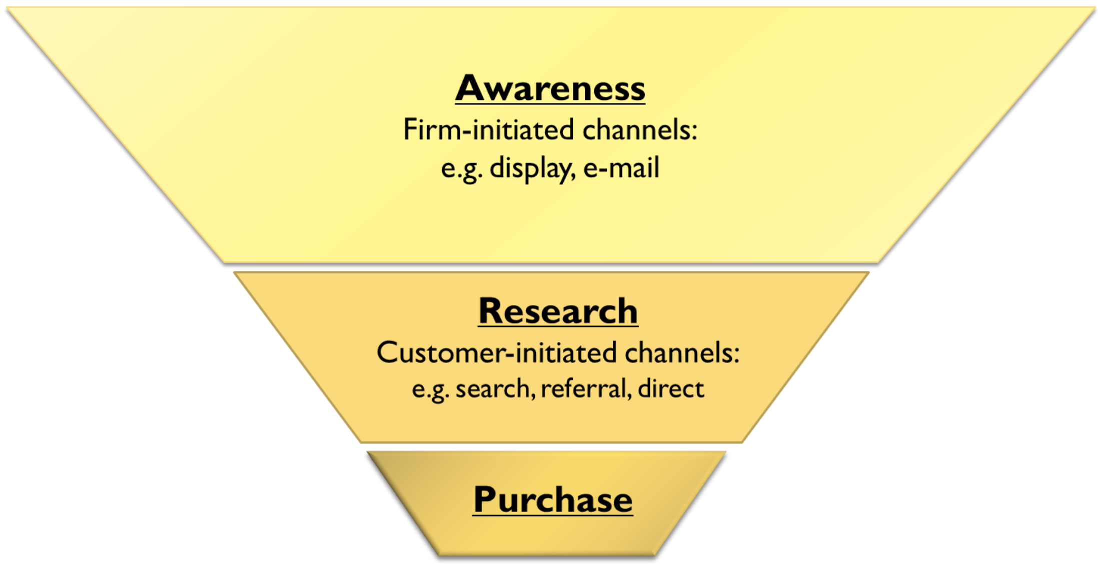
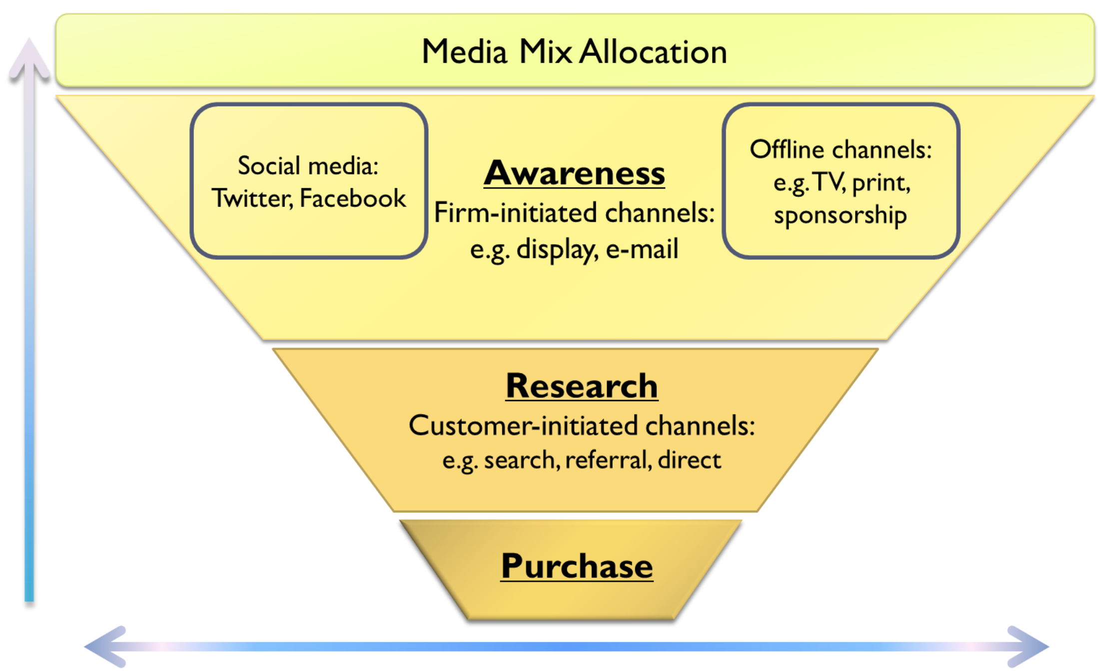


Figure 5-2 Two Directions for Future Research Extension



Appendices

Appendix I Full Conditional Posterior Distributions

1. Sample c_{iq}^*

$c_{iq}^* = R_i \alpha_{iq} + \varepsilon_{iq}$, with $\varepsilon_i = \left(\varepsilon_{i1}, \ldots, \varepsilon_{iQ}\right)' \sim N(0, \Sigma)$. The diagonal of Σ are set to be 1 for identification purpose. $\alpha_i = \left(\alpha_{i1}, \ldots, \alpha_{iQ}\right)' \sim N(0, \Sigma_\alpha)$, where Σ_α is diagonal, and $V(c_i^*) = R_i \Sigma_\alpha R_i' + \Sigma$.

2. Sample Σ

The full posterior distribution of Σ is not a standard distribution. Thus I use the Metropolis-Hastings algorithm with a random walk chain to generate draws of Σ (see Chib and Greenberg 1995, pp 330, Method 1). The prior of Σ is $p(\Sigma) \sim N(\mathbf{0}, I)$ and the likelihood is

$$L(\Sigma) \propto \exp\left(-\frac{1}{2}\sum_{i=1}^{I} N_i \left((c_i^* - R_i\alpha_i)'\Sigma^{-1}(c_i^* - R_i\alpha_i)\right)\right).$$

The posterior is proportional to $L(\Sigma)p(\Sigma)$.

3. Sample U_{in} and W_{in}.

I use the Metropolis-Hastings algorithm with a random walk to generate U_{in}. If U_{in}^{old} is the previous draw, I draw $U_{in}^{new} = U_{in}^{old} + \Delta$, with $\Delta \sim N(0, 0.01)$. The accepting probability is

$$\min\left[\frac{\exp\left(-\frac{(U_{in}^{new} - \bar{U}_{in})^2}{2}\right) L\left(U_{in}^{new}\right)}{\exp\left(-\frac{(U_{in}^{old} - \bar{U}_{in})^2}{2}\right) L\left(U_{in}^{old}\right)} \quad , \quad 1\right]$$

W_{in} can be sampled in the same manner.

4. Sample β_i, β_0, Σ_β, γ_i, γ_0, and Σ_γ

$U_{in} = \beta_{0,i} - S_{in}^{'}\beta + \tau I_{in} + \eta_{in}$, with $\eta_{in} = \left(\eta_{i1n}, \ldots, \eta_{iJn}\right)' \sim N(0, \Omega_\eta)$. Since the off-diagonal elements are not well identified empirically (Keane 1992), I assume Ω_η to be diagonal with the first element being normalized to 1 for identification.

Assume $\beta_{0,i} \sim MVN(\bar{\beta}, \Sigma_\beta)$. The posterior distribution of $\beta_{0,i}$ is $MVN(A_i, B_i)$, where

$$A_i = B_i\left(\Sigma_\beta^{-1}\bar{\beta} + \frac{u_i + S_{in}^{'}\beta - \tau I_i}{\sigma}\right) \text{ and } B_i = \left(\Sigma_\beta^{-1} + \frac{1}{\sigma}\right)^{-1}.$$

$\bar{\beta} \sim N(A, B)$, where $A = \dfrac{\sum_i \beta_{0,i}}{N}$ and $B = \dfrac{\Sigma_\beta}{N}$.

$\Sigma_\beta \sim IW(\sum_i (\beta_{0,i} - \bar{\beta})(\beta_{0,i} - \bar{\beta})' + 10I, N + 10)$.

Use similar steps to sample γ_i , γ_0, and Σ_γ.

5. Sample λ

Assume $\lambda = \left(\lambda_1, \ldots, \lambda_J\right)' = \dfrac{\exp(\varphi)}{1 + \exp(\varphi)} \in [0,1]$, so that $\varphi = \log\left(\dfrac{\lambda}{1-\lambda}\right) \in (-\infty, +\infty)$.

The prior of φ is $p(\varphi) \sim N(\mathbf{0}, I)$ and the posterior is proportional to $L(\varphi)p(\varphi)$. I use the Metropolis-Hastings algorithm with a random walk chain to generate draws of φ.

6. Sample μ

Assume $\mu = \left(\mu_j, \mu_{j,1}, \ldots, \mu_{j,J}\right)', j = 1, \ldots, J$, and the prior of μ is Normal. The posterior is proportional to $L(\mu)p(\mu)$. I use the Metropolis-Hastings algorithm with a random walk chain to generate draws of μ.

7. Sample τ

τ is not only the coefficient of the inclusive value, but also the parameter determining the nested logit model of the visit-purchase decision. The prior of τ is assumed to be Normal, and the posterior is proportional to $L(\tau)p(\tau)$. I use the Metropolis-Hastings algorithm with a random walk chain to generate draws of τ. The step is drawn from $N(0, 0.005)$.

Appendix II An illustration of using Shapley value to calculate the marginal contribution of a channel

The Shapley value is one way to distribute the total gains to the players in cooperative game theory, assuming that all players are collaborating. It tells the importance of each player to the overall gain and how much payoff should be given to each player. The basic idea in the application of Shapley value in this context is to calculate the marginal contribution of a channel in all possible permutations of channels and then take an average over all these marginal contributions of a specific channel.

As a simplified illustration, I assume there are only 3 channels: channel 1, 2 and 3. The conversion rates, i.e. the value functions of this game, are as below:

R_1: the conversion rate when only channel 1 is available.
R_2: the conversion rate when only channel 2 is available.
R_3: the conversion rate when only channel 3 is available.
R_{12}: the conversion rate when both channel 1 and channel 2 are available, which is equal to R_{21}.
R_{13}: the conversion rate when both channel 1 and channel 3 are available, which is equal to R_{31}.
R_{23}: the conversion rate when both channel 2 and channel 3 are available, which is equal to R_{32}.
R_{123}: the conversion rate when all three channels are available, which is equal to R_{132}, R_{213}, R_{231}, R_{312} and R_{321}.

In this context, when a firm is running multiple channels, I do not know in which order the firm adopts each marketing channel into their portfolio. Thus, I do not distinguish the conversion rates R_{12} and R_{21}. This reduces the calculation burden from calculating 15 conversion rates to only $(2^N-1)=7$ conversion rates in this example.

The first column in Table A-1 shows all the possible permutations of channels. Columns 2 to 4 show the marginal contributions of each channel in each permutation. Depending on the entering order in a permutation, I can calculate the marginal contribution of each channel. Take the last cell in column 2 for example. The company adopts marketing channel 3 first, then adopts channel 2 and then channel 1 at last. Before channel 1 is adopted, channel 2 and 3 together lead to conversion rate R_{23}. After channel 1 is adopted, the new conversion rate is R_{123}. Thus, the marginal contribution in this case is (R_{123}-R_{23}). The Shapley value of channel 1, i.e. the contribution that should be credited to channel 1, is summing up all the conversion rates in column 2 and dividing it by the number of all possible permutations (N!=6 in this example), as below:

$$\frac{R_1 + R_1 + (R_{12} - R_2) + (R_{123} - R_{23}) + (R_{13} - R_3) + (R_{123} - R_{23})}{6}$$

Table A-1 Marginal Contribution of Each Channel in All Possible Permutations

Entering Order	*Marginal Contribution of Channel 1*	*Marginal Contribution of Channel 2*	*Marginal Contribution of Channel 3*
1, 2, 3	R_1	R_{12}-R_1	R_{123}-R_{12}
1, 3, 2	R_1	R_{123}-R_{13}	R_{13}-R_1
2, 1, 3	R_{12}-R_2	R_2	R_{123}-R_{12}
2, 3, 1	R_{123}-R_{23}	R_2	R_{23}-R_2
3, 1, 2	R_{13}-R_3	R_{123}-R_{13}	R_3
3, 2, 1	R_{123}-R_{23}	R_{23}-R_3	R_3

Appendix III Competition effects

This research does not consider competitive effects and reactions. The visit traffic and purchases through all channels during the calibration window are illustrated in Figure A-1. There are no obvious shocks appearing in any cyclic trends. In Figure A-2, I present the Google search volume of the branded keywords versus the generic keyword “hotel”, where these two trends fluctuate in the same direction other than the two dips of branded keywords in November and December, when the focal firm conducted two experiments by shutting off the paid search. This implies that there might not be any significant changes in customers' interests in the focal company versus other competitor firms. Note that one of the critical contributions of the proposed model is shedding light on the attribution of visits and conversions back to each marketing channel. Even if the influence from competitors is powerful enough to scale up or down the market share of the focal firm, it still should not change the proportion of each channel’s contribution towards the visits and conversion.

Figure A-1: Visits and Purchases over the two month window

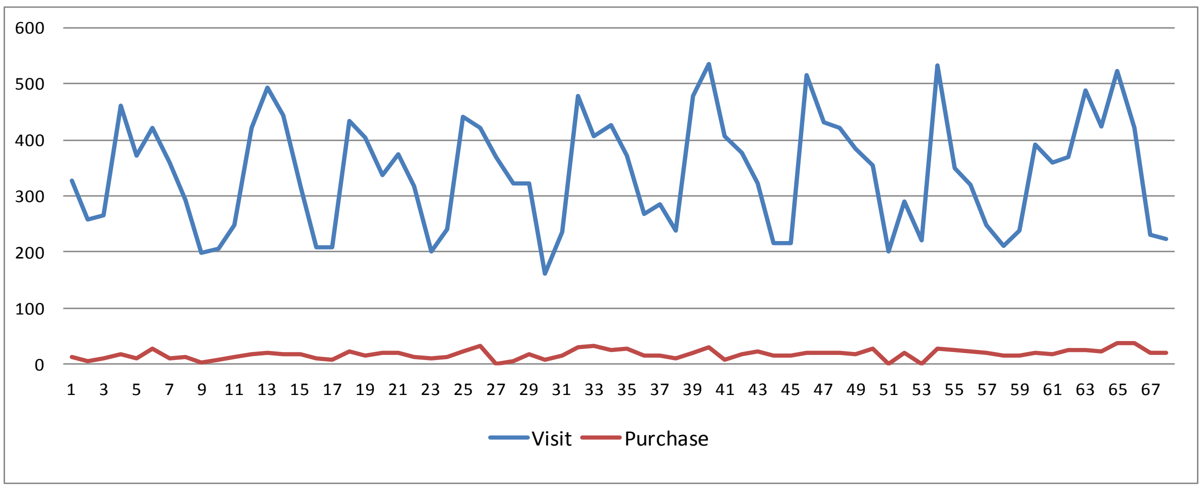
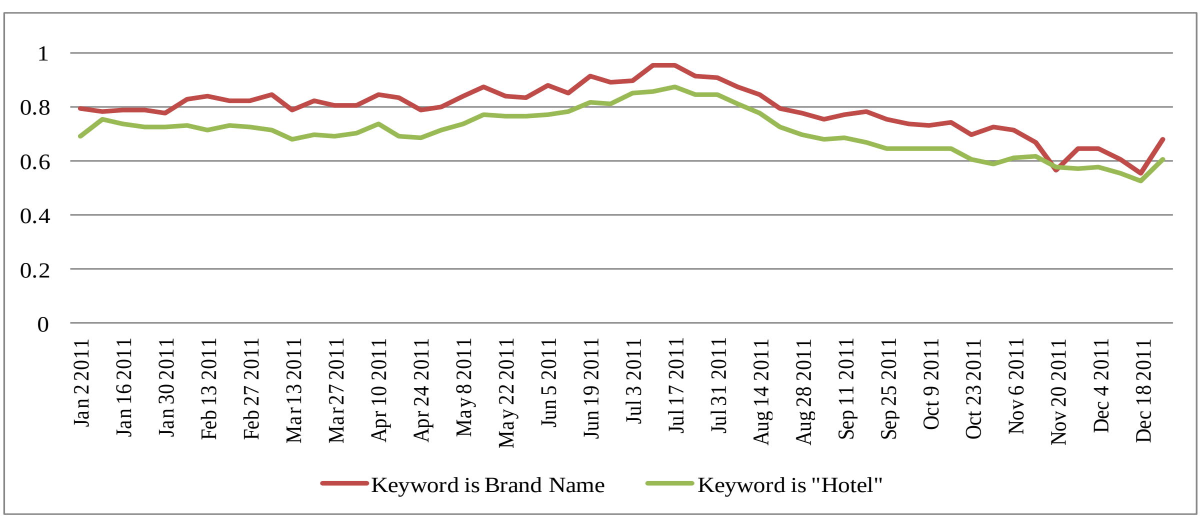


Figure A-2: Search Volume of Branded versus Unbranded Keywords at Google



Appendix IV Match Type

Determining the match type of a keyword is a basic but important task for the advertisers. The match type affects the size of the possible audience that a keyword can reach. Both Google and Bing offer five match types – broad match, broad match modifier, phrase match, exact match and negative match[14].

Table A-2 shows the examples of the same keyword "women's jewelry" with all but negative match types. Broad match allows for misspellings, synonyms and relevant variations of the term. For example, search queries like "buy ladies jewelry" could trigger the search ads on keyword "women's jewelry" with broad match. The exact match only allows close variation of the exact term "women's jewelry", while phrase match allows one or more words before or after (not in the middle of) that exact term, such as "buy women's jewelry". The broad match modifier is a match type that combines the broad and exact match, where the advertiser can use the broad match modifier specifies a term which (or the close variation of which) must be contained in the search queries, but the order of the terms could vary, such as "jewelry for women". The negative match means the search queries should not contain the keyword, which can help the advertiser avoid wasting investment on the audience with certain search queries.

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[14] Based on Google AdWords Help document online: https://support.google.com/adwords/answer/2497836?hl=en, and Bing ads training document online: http://advertise.bingads.microsoft.com/en-us/cl/246/training/keyword-match-options. Last Accessed on April 7, 2014.

Table A-2 Examples for Different Match Types

Match Type	Example search queries that can trigger "women's jewelry"	Example search queries that cannot trigger "women's jewelry"
Broad match	*buy ladies jewelry, women's necklace jewelry, women's jewelry*	*Women's, jewelry*
Exact match	*women's jewelry*	*Ladies jewelry, women's necklace, jewelry women's*
Phrase match	*buy women's jewelry, women's jewelry*	*Women's necklace, jewelry women's*
Broad match modifier	*jewelry for women, women's jewelry*	*Women's necklace, jewelry women's*

The focal advertiser runs search campaigns with three different match types (broad, exact, and phrase) at Google and all of their search campaigns at Bing are with broad match. In the model, the 476 keyword are from both search engines and include all three match types. To examine the influence of match type on the results and remove the noise due to the mismatch between the customer's search queries and the advertiser's keyword when using the broad match type, I estimate equation (1) – (5) again with only the data of keyword with exact and phrase match type. In addition, I add a dummy variable for exact match type to distinguish it from phrase match type. Since all the keywords with exact match are from Google, I remove the independent variable $Google_i$ in equation (3). The results are in Table A-3 to Table A-7. The coefficients of $Specificity_i$ and $Specificity_i^2$ are still positive and the impact of first-click is still negative, especially for the more specific keywords. In addition, the advertiser tends to bid less on exact-match keywords and the ad position of exact-match keywords is better. Both show the competitive advantage of the exact-match keywords compared with phrase-match keywords. Moreover, the exact-match keywords lead to higher click-through rates than phrase-match keywords, but the conversion rates are not significantly different between these two match types. In sum, these coefficient estimates are very close to those based on the keywords with all three match types.

Table A-3 Coefficient Estimates from Revenue Model

	Estimates	
Intercept	-4.638	***
CTR_{it}	0.111	*
$CONV_{it}$	0.955	***
$\ln(CPC_{it})$	0.791	
$\ln(Budget_t)$	0.691	***
$Specificity_i$	1.984	***
$Sq(Specificity_i)$	0.428	***
$First\text{-}Click_t$	-1.777	***
$First\text{-}Click_t * Specificity_i$	-5.076	***

Significance codes: *** ($p< 0.001$), ** ($p< 0.01$), * ($p<0.05$), and . ($p< 0.1$).

Table A-4 Coefficient Estimates from Cost-per-click Model

	Estimates	
Intercept	-3.981	***
$\ln(rpc_{it})$	0.053	**
$\ln(Budget_t)$	0.584	***
$\ln(QS_{it})$	-0.681	***
$Exact_i$	-0.141	***

Significance codes: *** ($p< 0.001$), ** ($p< 0.01$), * ($p<0.05$), and . ($p< 0.1$).

Table A-5 Coefficient Estimates from Position Model

	Estimates	
Intercept	1.731	***
$\ln(CPC_{it})$	-0.789	***
$\ln(QS_{it})$	-0.508	***
$Google_{it}$		
$Brand_i$	-2.654	***
$Valentine_t$	0.064	***
$Mother_t$	-0.001	
$Exact_i$	-0.157	***

Significance codes: *** ($p< 0.001$), ** ($p< 0.01$), * ($p<0.05$), and . ($p< 0.1$).

Table A-6 Coefficient Estimates from Click-through Rate Model

	Estimates	
Intercept	-6.212	***
$\ln(Position_{it})$	-0.546	***
$\ln(QS_{it})$	1.851	***
$Brand_i$	1.762	***
$Valentine_t$	0.096	***
$Mother_t$	-0.005	
$Specificity_i$	0.301	***
$Sq(Specificity_i)$	-0.125	***
$Exact_i$	0.426	***

Significance codes: *** (p< 0.001), ** (p< 0.01), * (p<0.05), and (p< 0.1).

Table A-7 Coefficient Estimates from Conversion Rate Model

	Estimates	
Intercept	-4.557	***
$\ln(Position_{it})$	-0.024	
$Brand_i$	0.317	***
$Valentine_t$	0.030	***
$Mother_t$	0.029	***
$Specificity_i$	-0.010	**
$Sq(Specificity_i)$	-0.012	***
$Exact_i$	0.006	

Significance codes: *** (p< 0.001), ** (p< 0.01), * (p<0.05), and (p< 0.1).

Appendix V Alternative measures of the keyword specificity

In the main text, I measure the keyword specificity with the z-value of the number of characters in a keyword. The purpose of such standardization is only to make the specificity measure comparable with the other variables in the analysis and easier for interpretation. In the next, I present the estimation results using the absolute number of characters contained in a keyword, the number of words contained in a keyword, and the judge ratings, respectively, as the measure of specificity.

1. **Using the absolute number of characters in a keyword as the specificity measure**

Table A-8 shows the coefficient estimates of equation (1). Compare with Table 4-4, the sign of First-Click$_t$ flips to be positive, while the rest coefficients have the same signs as those in Table 4-4. At the mean specificity, i.e. 19.76 characters, $\alpha_7 FC_t + \alpha_8 FC_t * Specificity_i$ =-0.463, which is very close to the mean effect (-0.476) in the main text. That is, the impact of first-click on most of the keywords is still negative. The revenue demonstrates a U curve with respect to the keyword specificity and the turning point is at -67.5. However, all the values of $Specificity_i$, i.e. the number of characters, are positive. In fact, the results reveal a positive monotonic relationship between the number of characters and the revenue. That is, the ROI of more specific keywords are higher.

Table A-8 Coefficient Estimates from Revenue Model (Specificity measure is the number of characters)

	Estimates	
Intercept	-19.032	*
CTR_{it}	0.124	***
$CONV_{it}$	1.566	**
$\ln(CPC_{it})$	1.135	***
$\ln(Budget_t)$	0.875	.
$Specificity_i$	0.540	*
$Sq(Specificity_i)$	0.004	***
First-Click$_t$	32.833	**
First-Click$_t$*Specificity$_i$	-1.685	**

Significance codes: *** ($p< 0.001$), ** ($p< 0.01$), * ($p<0.05$), and . ($p< 0.1$).

The coefficient estimates of equation (2) – (5) are presented in Table A-9 to A-12, which remain the same signs when significant as the results in Table 4-5 to Table 4-8 in the main text.

Table A-9 Coefficient Estimates from Cost-per-click Model (Specificity measure is the number of characters)

	Estimates	
Intercept	-4.046	***
ln(rpcit)	0.201	***
$\ln(Budget_t)$	0.581	***
$\ln(QS_{it})$	-0.439	***

Significance codes: *** ($p < 0.001$), ** ($p < 0.01$), * ($p<0.05$), and ($p < 0.1$).

Table A-10 Coefficient Estimates from Position Model (Specificity measure is the number of characters)

	Estimates	
Intercept	1.780	***
$\ln(CPC_{it})$	-0.690	***
$\ln(QS_{it})$	-0.374	***
$Google_{it}$	-0.358	***
$Brand_i$	-2.227	***
$Valentine_t$	0.080	***
$Mother_t$	0.003	***

Significance codes: *** ($p < 0.001$), ** ($p < 0.01$), * ($p<0.05$), and ($p < 0.1$).

Table A-11 Coefficient Estimates from Click-through Rate Model (Specificity measure is the number of characters)

	Estimates	
Intercept	-7.134	***
$\ln(Position_{it})$	-0.920	***
$\ln(QS_{it})$	1.287	***
$Brand_i$	2.085	***
$Valentine_t$	0.361	***
$Mother_t$	0.017	
$Specificity_i$	0.150	***
$Sq(Specificity_i)$	-0.003	***

Significance codes: *** ($p < 0.001$), ** ($p < 0.01$), * ($p<0.05$), and ($p < 0.1$).

Table A-12 Coefficient Estimates from Conversion Rate Model (Specificity measure is the number of characters)

	Estimates	
Intercept	-4.569	***
$\ln(Position_{it})$	-0.016	
$Brand_i$	0.310	***
$Valentine_t$	0.021	***
$Mother_t$	0.024	***
$Specificity_i$	0.001	
$Sq(Specificity_i)$	0.000	

Significance codes: *** (p< 0.001), ** (p< 0.01), * (p<0.05), and (p< 0.1).

In Table A-13, I calculate the change in revenue when the advertiser switches from last-click to first-click attribution. According to the coefficient estimates of equation (1), the change in revenue is $\Delta = \alpha_7 FC_t + \alpha_8 FC_t * Specificity_i$. The 2nd column of Table A-13 shows the summary statistics of the z-value of the number of characters in a keyword. The 3rd column shows the Δ values accordingly. Moreover, the 4th column shows the summary statistics of the absolute number of characters in a keyword while the according Δ values are presented in the 5th column. Although the values in the 2nd and the 4th columns are very different, the revenue implication in the 3rd and the 5th columns are very close. This implies that standardizing the number of characters in a keyword in the analysis, only renders ease for interpreting the coefficients with comparable scale of each variable, but does not change the scale of its impact on the dependent variable in equation (1), i.e. the log-revenue.

Table A-13 Changes in Log-revenue Due to the Change of Attribution Metrics

	Standardized Number of Characters	Δ	Number of Characters	Δ	Number of Words	Δ	Judgment Rating	Δ
Minimum	-1.872	21.305	7	21.038	1	24.553	1	8.702
1st Quartile	-0.845	9.357	14	9.243	2	11.047	2	2.587
Median	-0.111	0.819	19	0.818	3	-2.459	2	2.587
Mean	0	-0.476	19.76	-0.463	2.862	-0.595	2.476	-0.324
3rd Quartile	0.623	-7.719	24	-7.607	3	-2.459	3	-3.528
Maximum	3.411	-40.163	43	-39.622	6	-42.977	5	-15.758

2. Using the number of words in a keyword as the specificity measure

In the next, I use the number of words as the measure of the keyword specificity. Each keyword in the data set contains 1 to 6 words, with 2.862 words on average and the median is 3 words. Table A-14 shows the coefficient estimates for equation (1) when the specificity measure is the number of words contained in a keyword. There is a significant U curve for the revenue against the keyword specificity, with a turning point at -8.404. Since the value of the number of words is always positive, these estimates once again demonstrate a positive monotonic relationship between the keyword specificity and the revenue, the same as the finding in the main text. The interpretation of the positive coefficient of FC_t refers to the discussion on Table A-8. The coefficient estimates for equation (2) to (5) are shown in Table A-15 to Table A-18, from which the estimation results are very close to those in Table 4-5 to Table 4-8, other than that the $Specificity_i^2$ in Table A-18 is negative and significant. The summary statistics of the absolute number of words is in the 6th column of Table A-13 and the changes in revenue when switching attribution metrics are in the 7th column.

Table A-14 Coefficient Estimates from Revenue Model (Specificity measure is the number of words)

	Estimates	
Intercept	-23.341	*
CTR_{it}	0.148	***
$CONV_{it}$	1.902	**
$\ln(CPC_{it})$	1.376	***
$\ln(Budget_t)$	1.132	*
$Specificity_i$	4.202	*
$Sq(Specificity_i)$	0.250	***
$First\text{-}Click_t$	38.059	**
$First\text{-}Click_t * Specificity_i$	-13.506	**

Significance codes: *** ($p < 0.001$), ** ($p < 0.01$), * ($p < 0.05$), and . ($p < 0.1$).

Table A-15 Coefficient Estimates from Cost-per-click Model (Specificity measure is the number of words)

	Estimates	
Intercept	-4.010	***
ln(rpcit)	0.180	***
$\ln(Budget_t)$	0.572	***
$\ln(QS_{it})$	-0.438	***

Significance codes: *** ($p < 0.001$), ** ($p < 0.01$), * ($p < 0.05$), and . ($p < 0.1$).

Table A-16 Coefficient Estimates from Position Model (Specificity measure is the number of words)

	Estimates	
Intercept	1.881	***
$\ln(CPC_{it})$	-0.797	***
$\ln(QS_{it})$	-0.419	***
$Google_{it}$	-0.357	***
$Brand_i$	-2.468	***
$Valentine_t$	0.067	***
$Mother_t$	0.005	***

Significance codes: *** ($p < 0.001$), ** ($p < 0.01$), * ($p < 0.05$), and . ($p < 0.1$).

Table A-17 Coefficient Estimates from Click-through Rate Model (Specificity measure is the number of words)

	Estimates	
Intercept	-7.421	***
$\ln(Position_{it})$	-0.887	***
$\ln(QS_{it})$	1.302	***
$Brand_i$	2.277	***
$Valentine_t$	0.352	***
$Mother_t$	0.015	
$Specificity_i$	1.173	***
$Sq(Specificity_i)$	-0.167	***

Significance codes: *** (p< 0.001), ** (p< 0.01), * (p<0.05), and . (p< 0.1).

Table A-18 Coefficient Estimates from Conversion Rate Model (Specificity measure is the number of words)

	Estimates	
Intercept	-4.581	***
$\ln(Position_{it})$	-0.013	
$Brand_i$	0.316	***
$Valentine_t$	0.020	***
$Mother_t$	0.025	***
$Specificity_i$	0.012	
$Sq(Specificity_i)$	-0.002	.

Significance codes: *** (p< 0.001), ** (p< 0.01), * (p<0.05), and . (p< 0.1).

3. Using the judge ratings as the specificity measure

I also estimate equation (1) to (5) with judge ratings as the specificity measure. Two judges who are not aware of the research hypotheses are hired to evaluate the specificity of all the keywords. Each judge independently gives each keyword an integer specificity score with range [1, 5], where more specific keywords get higher scores. The mean of judge ratings is 2.476 and the median is 3. The inter-judge reliability according to Perreault and Leigh's (1989) index of reliability is 0.84, well above the 0.7 threshold recommended for exploratory research (Rust and Cooil 1994). The summary statistics of the judge ratings are in the 2nd last column of Table A-13 and the difference in revenue under two attribution regimes are in the last column.

The coefficient estimates for equation (1) to (5) are shown in Table A-19 to Table A-23, which are very close to those in Table A-3 to Table A-7. Although the coefficient of $Specificity_i^2$ in Table A-19 is not significant, the underlying positive monotonic relationship between the revenue and the keyword specificity is the same as what I find in the main text.

Table A-19 Coefficient Estimates from Revenue Model (Specificity measure is judgment rating)

	Estimates	
Intercept	-7.416	.
CTR_{it}	0.085	**
$CONV_{it}$	1.498	**
$\ln(CPC_{it})$	1.371	***
$\ln(Budget_t)$	0.284	.
$Specificity_i$	2.528	*
$Sq(Specificity_i)$	0.011	
$First\text{-}Click_t$	14.817	*
$First\text{-}Click_t*Specificity_i$	-6.115	*

Significance codes: *** (p< 0.001), ** (p< 0.01), * (p<0.05), and . (p< 0.1).

Table A-20 Coefficient Estimates from Cost-per-click Model (Specificity measure is judgment rating)

	Estimates	
Intercept	-3.964	***
ln(rpcit)	0.220	***
$\ln(Budget_t)$	0.577	***
$\ln(QS_{it})$	-0.447	***

Significance codes: *** (p< 0.001), ** (p< 0.01), * (p<0.05), and . (p< 0.1).

Table A-21 Coefficient Estimates from Position Model (Specificity measure is judgment rating)

	Estimates	
Intercept	1.935	***
$\ln(CPC_{it})$	-0.699	***
$\ln(QS_{it})$	-0.427	***
$Google_{it}$	-0.433	***
$Brand_i$	-2.207	***
$Valentine_t$	0.077	***
$Mother_t$	0.002	***

Significance codes: *** (p< 0.001), ** (p< 0.01), * (p<0.05), and . (p< 0.1).

Table A-22 Coefficient Estimates from Click-through Rate Model (Specificity measure is judgment rating)

	Estimates	
Intercept	-5.835	***
$\ln(Position_{it})$	-1.369	***
$\ln(QS_{it})$	1.499	***
$Brand_i$	1.233	***
$Valentine_t$	0.444	***
$Mother_t$	0.045	
$Specificity_i$	0.291	***
$Sq(Specificity_i)$	-0.062	***

Significance codes: *** (p< 0.001), ** (p< 0.01), * (p<0.05), and . (p< 0.1).

Table A-23 Coefficient Estimates from Conversion Rate Model (Specificity measure is judgment rating)

	Estimates	
Intercept	-4.562	***
$\ln(Position_{it})$	-0.001	
$Brand_i$	0.315	***
$Valentine_t$	0.018	**
$Mother_t$	0.025	***
$Specificity_i$	-0.007	
$Sq(Specificity_i)$	0.001	

Significance codes: *** (p< 0.001), ** (p< 0.01), * (p<0.05), and . (p< 0.1).

In sum, I estimate equation (1) to (5) with three alternative specific measures (the absolute number of characters in a keyword, the number of words in a keyword, and the judge ratings), and always find a positive monotonic relationship between the keyword specificity and the revenue in equation (1), and always find a significant inverted-U shape of the click-through rates with respect to the keyword specificity (the turning point is 25 characters, 3.51 words, or judge rating equals to 2.35). The impact of keyword specificity on the conversion rate is not significant, other than one case where the coefficient of $Specificity_i^2$ is significant at the 0.1 level when I use the number of words as the specificity measure. These results validate the robustness of the analysis in the main text.

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