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Technology enables a firm to produce a granular record of every touchpoint consumers make in their online purchase journey before they convert at the firm's website. However, firms still depend on aggregate measures to guide their marketing investments in multiple online channels (e.g., display, paid search, referral, e-mail). This article introduces a methodology to attribute the incremental value of each marketing channel in an online environment using individual-level data of customers' touches. The authors propose a measurement model to analyze customers' (1) consideration of online channels, (2) visits through these channels over time, and (3) subsequent purchases at the website to estimate the carryover and spillover effects of prior touches at both the visit and purchase stages. The authors use the estimated carryover and spillover effects to attribute the conversion credit to different channels and find that these channels' relative contributions are significantly different from those found by other currently used metrics. A field study validates the proposed model's ability to estimate the incremental impact of a channel on conversions. In targeting customers with different patterns of touches in their purchase funnel, these estimates help identify cases in which retargeting strategies may actually decrease conversion probabilities.

Keywords: attribution modeling, multichannel marketing, purchase funnel, online advertising, touchpoint management

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Attributing Conversions in a Multichannel Online Marketing Environment: An Empirical Model and a Field Experiment

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 $.24 billion, respectively (eMarketer 2012). These figures indicate the overall popularity of online marketing interventions to draw traffic to firms' websites. Customers also visit the websites on their own initiative either directly or through different sources, such as search engines and referral sites. Customers' responses—such as clicking on display ads, e-mail links, or firm's paid search ads or choosing any other sources on their own (e.g., typing in the website URL, clicking on organic search links or referral links)—cause these communications, interventions, or links to become the conduits or "channels" through which customers visit and convert at the firm's website (Martin 2009; Mulpuru et al. 2011).

In many product and service categories, customers visit a firm's website several times through multiple channels before a conversion occurs. A visit to the firm's website through a specific channel (e.g., web search, referral site) exposes customers to additional information about the attractiveness of the product and service in relation to competing and complementary offers. This visit experience can

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influence subsequent visits to the website through the same channel as well as possible conversions through that channel (i.e., carryover effects at the visit and purchase stages, respectively). Similarly, it could lead to visits and conversions through other channels; for example, a search visit might lead to a subsequent click-through on a display ad and possibly a conversion (i.e., spillover effects at the visit and purchase stages). These effects can also vary across customers who tend to be heterogeneous in how they use different channels and/or respond to online marketing interventions (Mulpuru et al. 2011).

In practice, the multiple touches a customer makes before a conversion are rarely taken into account when measuring campaign effectiveness across communication channels. For example, consider a hypothetical online purchase scenario of a sample of customers going through the purchase decision hierarchy (see Table 1). The "Current Visit-Through Channel" column indicates the channel each customer used for the current visit to the website, the "Conversion Status" column notes whether the customer converted on that current visit, and the "Prior Channel Touches" column lists the customer's prior visits through different channels. The channel alternatives through which a customer reaches the firm's website include directly entering the URL to the firm's website (D), search (S), referral sites (R), e-mails (E), and display banner ads (B). In addition, customers may encounter display impression (I) but choose not to click through it.

Applying the metric commonly used in practice—the last-click metric—to the data, the firm would attribute 50% (two of four) of the conversions to direct channel and 25% each to display and search. However, this last-click metric ignores the prior channel touches. For example, both of the current direct visits that resulted in conversions were preceded by visits through a referral channel (Customers 1 and 3), and the two current direct visits that did not convert were preceded by visits through the search channel (Customers 7 and 8). Thus, unless these prior channel encounters have no impact on current visits, ignoring such spillovers could lead to biased estimates of attribution. Realizing this limitation of the last-click metric, some practitioners have proposed other metrics, such as the first-click metric, which assigns the credit to the first touch, and the uniform, weighted, or exponential metric, which considers all the touchpoints leading up to a conversion and allocates the credit for the conversion accordingly. However, these metrics still only consider the paths that result in conversions and disregard the paths of touches that do not (Petersen et al. 2009). The cases of Customers 4 and 5 in Table 1 illustrate the pitfalls of these metrics. They have the same paths—one resulting in conversion and the other, not—and yet the existing metrics in practice do not use the valuable information contained in the paths with no conversions.

Thus, aggregate metrics used in practice do not take into account the timing and sequence of earlier communications and the resulting carryover and spillover effects, nor do they reflect these effects' relative incremental impact in leading to website visits and conversions. Therefore, using such metrics to determine the level of investment (e.g., bids for search keywords) for future marketing campaigns could lead to biased and misleading inferences and suboptimal allocation of marketing budgets across channels and campaigns (Martin 2009). In addition, these channels are typically managed and measured using separate systems, often by different teams within an organization (e.g., one team manages display and paid search channels, another team runs e-mail campaigns), which produces incompatible data and double-counting across different sample frames (Atlas 2008; Green 2008). An integrated model to estimate the carryover and spillover effects of prior touches at both visit and purchase stages is necessary to correctly measure the incremental contribution of multiple channels and overlapping campaigns and to assist decisions on optimizing marketing budgets. This is the focus of our article.

Given individual-level data on customers' touches (visits and purchases through commonly used multiple online channels over time), we propose a three-level measurement model for estimating the carryover and spillover effects of prior visits to a firm's website, at both the stage of visiting the website and the stage of purchasing on the website. This measurement model, based on individual-level path data of customers' touches in their purchase decision hierarchy or funnel, accounts for (1) the heterogeneity across customers' consideration of channels through which to visit the website, (2) the carryover and spillover effects of prior marketing interventions that contribute to the website visits, and (3) the subsequent purchase conversions. Note that 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-mail communications but others are not. The model provides the basis for measuring the incremental impact of a channel on conversions at a firm's website in a multichannel online marketing context.

Our research falls within the realm of multichannel marketing. Previous research in multichannel marketing in both offline and online contexts has focused on customer lifetime value, total spending across channels and cross-selling, and dynamics among media (Abhishek, Fader, and Hosanagar 2012; Dinner, Van Heerde, and Neslin 2013; Kireyev, Pauwels, and Gupta 2013; Kumar and Venkatesan 2005; Kushwaha and Shankar 2013; Li, Sun, and Montgomery 2011; Stephen and Galak 2012; Venkatesan and Kumar 2004, Zhang et al. 2010). Extant studies have also highlighted the importance of researching the different roles of various channels in a customer's purchase (e.g., Neslin and Shankar, 2009; Verhoef 2012). However, none have (1) examined the issue from the viewpoint of understanding the impact and synergy of online marketing communications

Table 1

CONSUMER TOUCHPOINTS 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

Notes: D = direct, S = search, R = referral, E = e-mail, I = display impression, and B = display.

and touches at different stages of individual customers' online purchase decision hierarchy and (2) attributed the conversion credit to multiple channels (for a comprehensive survey on the extant studies on multichannel marketing, see Neslin et al. 2006; Neslin and Shankar 2009).

Our research is also related to studies that analyze the impact of individual channels *outside* the website (e.g., display ads, e-mails, search engines) in enabling conversions at the website (Chan, Wu, and Xie 2011; Chatterjee, Hoffman, and Novak 2003; Ghose and Yang 2009; Manchanda et al. 2006; Rutz and Bucklin 2011). Instead of focusing only on a specific marketing channel, as in the preceding work, we integrate the effects of a variety of marketing communications and interventions (e.g., search, display ads, e-mails, referral engines) on website visits and conversion (cf. Ansari, Mela, and Neslin 2008; Lewis and Nguyen 2012; 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 affecting the 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, we account for the influence of a preceding marketing communication or intervention that visitors might have had before reaching the website that could affect their subsequent purchasing behavior. In the context of the aforementioned studies, our study fills a unique niche by proposing a methodology to apportion and allocate the credit for conversions that occur at the firm's website to multiple marketing channels by estimating the carryover and spillover effects in the online environment.

We estimate our model using individual-level customer path data from a firm in the hospitality industry. Our empirical analysis shows that there are significant carryover and spillover effects at both the visit stage and purchase stage, the magnitude of which varies significantly across channels. For example, whereas both e-mails and display ads trigger visits through search and referral channels, e-mails lead customers to purchase through search channels. The empirical analysis also shows that the attribution based on our measurement model paints a much different scenario of these channels' relative contributions compared with the metrics conventionally used in practice. For example, the last-click metric significantly undervalues e-mail, display, and referral channels while significantly inflating the contribution of search channels compared with their actual contribution. A field study conducted on the participating firm's website by pausing paid search for a week provides strong validation for our model's ability to estimate the incremental effect of a channel on conversions. We highlight the implications of our results for budgeting marketing investment across these channels. In addition, we demonstrate the usefulness of our results through an illustration of whether the firm should retarget its customers with e-mails according to the path of customers' prior visits.

MODEL

Model Preamble

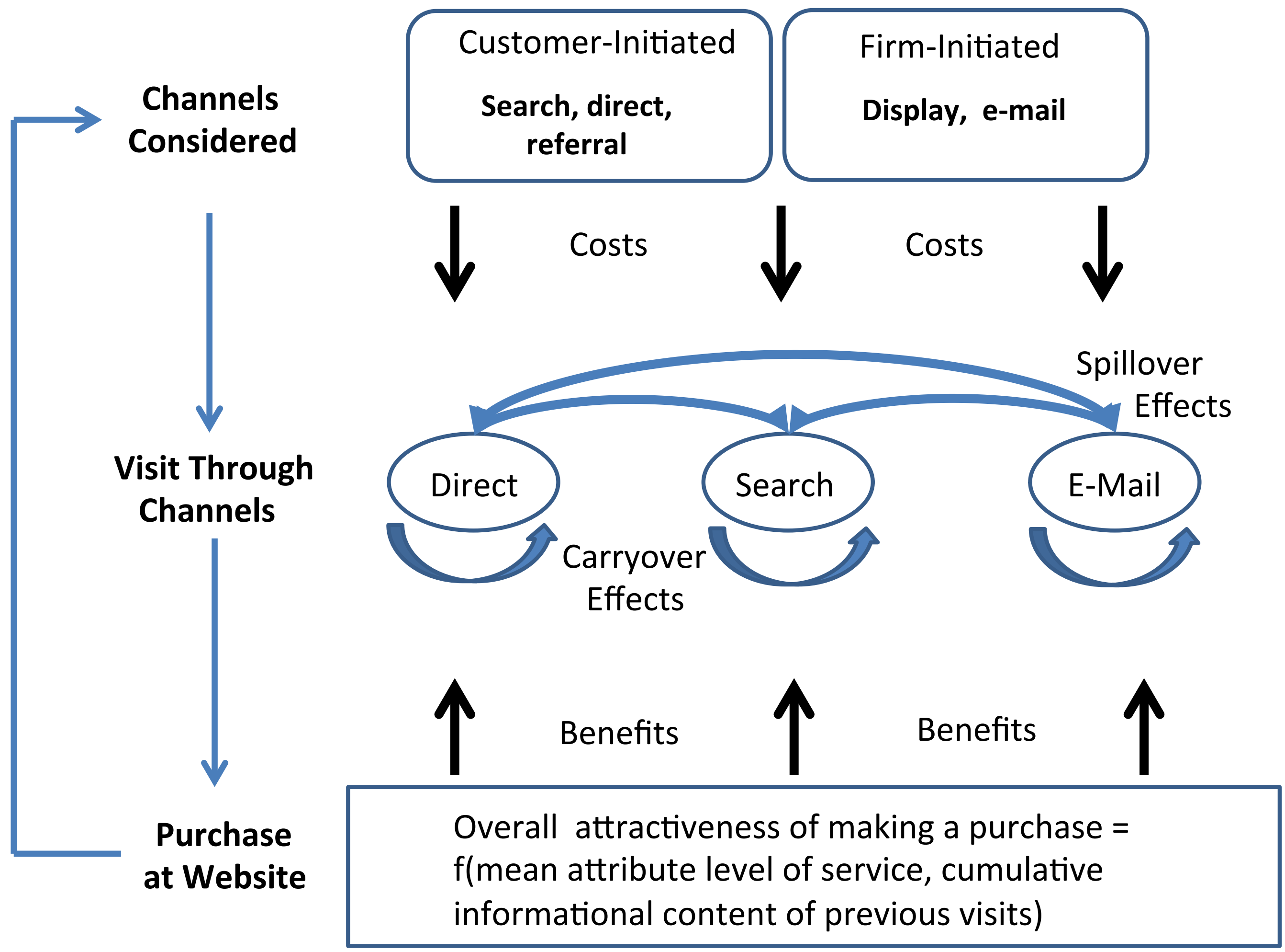
Our measurement model focuses on the decision hierarchy in the context of online purchases of high-involvement goods or services. The purchase decision hierarchy involves a series of stages (Figure 1) that a customer moves through when making a purchase: (1) the consideration stage, in which the customer recognizes his or her needs and considers different channels for information search; (2) the visit stage, in which the customer visits the website through a specific channel for information search and evaluation of alternatives; and finally, (3) the purchase stage, in which the customer makes a purchase (see, e.g., Wiesel, Pauwels, and Arts 2011). Given people's 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 firm and consider visiting the website directly, whereas others may consider the search channel for better prices and options. Some may consider both. Although firms may intercept customers with e-mail and display ads, consumers also take control of their purchase decision by seeking helpful information themselves (Court et al. 2009).

We make a distinction between customer-initiated channels, in which consumers seek out information on their own initiative, and firm-initiated channels, in which firms initiate marketing communications (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). From their awareness, experience, and expectations about these channels, customers 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 costs and arrive at a smaller set of channels that 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 "predecisional constraints" (Punj and Brookes 2002) to simplify the customer-initiated search process when a purchase must be made. In contrast, in firm-initiated channels, the firm initiates marketing interventions by targeting customers through e-mails and display ads.[1] Extant research has indicated that online display ads tend to have little behavioral impact and play an insignificant role in ad recall (Goldfarb and Tucker 2011), suggesting that customers consider them only at the time of encounter. Thus, the firm-initiated channels enter into customers' consideration sets only when customers encounter them as a result of a firm's targeting.

Conditional on their consideration sets, customers visit the firm's website through these channels and make a decision on purchase. Customers' prior visits through a specific channel have carryover effects in the same channel (e.g., prior click-throughs on referral links could lead to greater probability of clicking on another referral link) and

[1]Our distinction between customer-initiated channels and firm-initiated channels is more of a continuum than a dichotomy. Thus, a direct visit to the firm's website by entering the URL is entirely customer initiated, whereas a visit through an e-mail is at the other end of the spectrum. Other channels lie between these extremes. Display ads enable firms to target visitors at many sites online and thus are considered more firm initiated, whereas paid search requires customers to visit a search engine and type in a specific keyword(s) and thus are considered more customer initiated. We thank an anonymous reviewer for highlighting this distinction.

Figure 1
CONCEPTUAL FRAMEWORK



spillover effects across other channels (e.g., prior click-throughs on referral links could lead to greater probability of a visit through the search channel) at both the visit and purchase stages. At the visit stage, we define the carryover (spillover) effect as the impact of prior visits through a given channel on the probability of a visit through that specific (a different) channel. At the purchase stage, we define the carryover (spillover) effect as the impact of prior visits through a given channel on the probability of making a purchase through that specific (a different) channel.

A customer's decision to visit the firm's website through a specific channel depends on the marginal benefits derived in the visit relative to the marginal costs incurred. The benefit is the perceived attractiveness of making a purchase decision through the channel. The costs include the effort required to find the necessary information (Shugan 1980), which can be viewed as opportunity costs (Kim, Albuquerque, and Bronnenberg 2010), and the cognitive costs in processing the information (Johnson, Bellman, and Lohse 2003), which could be moderated by other factors (explained subsequently). As customers make multiple visits to the firm's website through various channels over time, the carryover and spillover of prior visits either increase or reduce the costs of the current visit. As customers gain familiarity in visiting through a channel and obtaining informational content, we expect the carryover of previous visits to reduce the costs of visiting the same channel as a result of cognitive lock-in effects (Bucklin and Sismeiro 2003; Johnson, Bellman, and Lohse 2003), risk reduction over multiple visits, and self-reinforcement effects (Song and Zahedi 2005). The spillover across channels could reduce costs to the extent that the channels are similar and to the extent that customers seek similar reinforcing information. If the channels are very different or if customers seek different types of information, the spillover could increase costs because customers may incur switching costs in breaking cognitive lock-in and adjusting to different types of channels. Thus, at the visit stage, we model carryover and spillover through their impact on the costs of visiting a channel. Here, costs reflect not only search costs, opportunity costs, and cognitive costs but also mere exposure effects, reinforcement learning, and risk reduction as customers gather information across visits. We use "cost" as a catchall term for the sake of modeling convenience, but we could also interpret this measurement term as inverse site familiarity.

At the purchase stage, as customers make visits through different channels over time, they derive contextual information from these channels (e.g., information about alternatives from a search engine, price and promotional details about complementary goods from a referral site) and compare this information with the website's offering. This cumulative informational stock accrued over previous visits manifests as a utility of all prior visits through the channel and is added to the overall 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 give more weight to later visits than to earlier ones (Ansari, Mela, and Neslin 2008; Terui, Ban, and Allenby 2011).

This framework provides the basis for our three-level measurement model, in which the conversion decision of a customer at an online site consists of three stages: the consideration of alternative customer-initiated channels and encountered marketing interventions, the visit decision, and the purchase decision. We use (1) "costs" as a catchall term to account for all the factors that influence a visit to the firm's website through different channels (both impediments and facilitators) and (2) "cumulative informational stock" to characterize the value of information gathered in prior visits through different channels relative to the firm's offering, which together influence the purchase probability during a visit. We develop an individual-level probabilistic model explicitly accounting for these stages, costs, and cumulative informational stock.

Consideration of Channels

Given the diverse individual habits in gathering information in the online shopping context, we expect to observe a significant variation in customers' consideration of which channels to use when visiting a firm's website. To control for individual heterogeneity in the consideration of channels, we allow customers in our model to have different consideration sets of channels, which could include both customer- and firm-initiated channels. We assume that a person's consideration of customer-initiated channels in visiting the firm's website is the same across all visits and purchase occasions, whereas the firm-initiated channels (display ad and e-mail), which enter into customers' consideration only when they encounter them, can vary across visit occasions. Because we collected the data within a short time frame during which the firm's marketing strategies and tactics remained constant, this assumption is justified. In addition, recent 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 customers 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. To study the consideration of customer-initiated channels, we assume that a person i (i = 1, ..., I) has a Q-dimension vector of latent utility, $\tilde{C}_i^*$, for considering each customer-initiated channel q (q = 1, ..., Q) in the visit decision (Van Nierop et al. 2010). The Q-dimension vector $\tilde{C}_i^*$ is jointly drawn from a multivariate normal distribution as in Equation 1. Furthermore, each element of latent utility c_{iq}^* is determined by customer-specific characteristics R_i 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 customer i's consideration set. We normalize all the diagonal elements in Σ to be 1 for identification purposes so that the off-diagonal elements are the correlations of considering two channels.

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

$$(2) \qquad c_{iq}^* = R_i\alpha_{iq} + \varepsilon_{iq}.$$

For the firm-initiated marketing interventions, we 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 his or her visit decisions. We exclude the empty consideration set from our model because we can observe a customer in the data only if he or she has made at least one visit to the focal firm's website. Define H_k as one combination of any positive number of channels out of J channels, where k = 1, ..., $(2^J - 1)$. The multivariate probits $C_i = (c_{i1} \ldots c_{iJ})^T$ are the same as H_k with a probability $P(C_i = H_k|\alpha, \Sigma)$.

Given the consideration of channels, we 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), customer i can choose to visit the firm's website through channel j, ($V_{in} = j, j \in \{c_{ij} = 1\}$) and gather new information with which to make a purchase, or he or she may not make any visit at all ($V_{in} = 0$) (outside option). Note 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, customer i may decide to make the purchase in the same visit ($B_{ijn} = 1$) or not ($B_{ijn} = 0$). We assume that an information search at the firm's website precedes the purchase stage in every occasion n because the consumer must at least determine the availability of a specific service (e.g., airline seat availability on a specific date) before purchasing.

Visit Decision

We posit that customer i's decision to visit channel j at occasion n depends on the perceived utility for that visit. This perceived utility U_{ijn} (Equation 3) is a function of customer i's perceived benefits of visiting channel j, $\beta_{0,ij}$ (e.g., the useful information he or she 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 costs $\beta_j S_{ijn}$. Customer i's inclusive value of the purchase or no-purchase option in channel j at occasion n is $I_{ijn} = \log\{1 + \exp(\overline{W}_{ijn}/\tau)\}$, where $\overline{W}_{ijn}$ is the expected utility of purchasing through channel j (detailed in the next subsection). The error term η_{ijn} follows a generalized extreme value distribution. The utility of not visiting, U_{i0n}, is normalized to 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 either visit the channel that offers the greatest net utility or not visit at all.

$$(3)\quad U_{ijn} = \overline{U}_{ijn} + \eta_{ijn} = \beta_{0,ij} + \tau I_{ijn} - \beta_j S_{ijn} + \eta_{ijn} \quad j = 1, ..., J.$$

The costs S_{ijn} are further parameterized in a logit form bounded between [0, 1], as in Equation 4. The costs S_{ijn} are captured only in the visit decision but are treated as sunk costs in the purchase decision, as we discuss in the next subsection. It is always costly to make a visit, but the total costs level off as the customer's experience and knowledge in a channel reach 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, which lends support to our S-shaped cost variables. In a recent study, Seiler (2013) uses the same specification to parameterize search costs.[2] T_{ijn} is the cumulative time spent at the website visiting through channel j, determined by the difference between the start- and end-time stamps associated with each visit/impression. This cumulative time is used to capture the long-term carryover effects in the visit stage. We also include a set of (J + 1) lag visit dummies, $\{L_{ik,n-1}, k = 0, ..., J\}$, indicating the channel visited by customer i at occasion (n – 1), with 0 representing no visit in the preceding occasion. This process can be viewed as a first-order Markov process to capture the short-term carryover and spillover effects.[3]

$$(4)\quad S_{ijn} = \frac{\exp\left(\mu_j T_{ijn} + \sum_{k=0}^{J} \mu_{j,k} L_{ik,n-1}\right)}{1 + \exp\left(\mu_j T_{ijn} + \sum_{k=0}^{J} \mu_{j,k} L_{ik,n-1}\right)} \quad j = 1, ..., J.$$

In the cost function (Equation 4), the coefficients μ_j capture the long-term impact of cumulative time spent at the website coming through j on the total costs S_{ijn}, while the $\mu_{j,k}$ terms capture the short-term carryover or spillover effects of the latest visit through channel k on the total costs S_{ijn}. Positive μ_j or $\mu_{j,k}$ terms imply that the corresponding variables can increase the costs S_{ijn}, whereas negative μ_j or $\mu_{j,k}$ terms imply that the costs will decrease. Meanwhile, the coefficient of costs β_j in Equation 4 determines the relative disutility of the costs S_{ijn} compared with $\beta_{0,ij}$ and τI_{ijn} in the utility function. Thus, with this formulation, we can compare the marginal impact of costs among different channels with β_j, and in a specific channel, we can compare the relative importance of long-term carryover versus short-term carryover and spillover with μ_j and $\mu_{j,k}$ terms. To identify the coefficient β_j as well as μ_j and $\mu_{j,k}$ terms, we set $\mu_{j,0}$ terms to be 1. Other than the short- and long-term impact captured in S, the cumulative information a customer encounters can influence the visit utility through the inclusive value I_{ijn} (detailed in the next subsection). Overall, the visit decision is a comprehensive decision, accounting for not only the short-term impact of lagged visit $L_{ik,n-1}$ in S_{ijn} but also the long-term accumulated time in T_{ijn} and cumulative information involved in the purchase decision through the inclusive value terms I_{ijn}.

Purchase Decision

Conditional on the consideration of and the visit through a certain channel, consumer i's perceived utility of purchasing through channel j at occasion n is W_{ijn} (Equation 5). The term τ is the scale parameter associating the visit decision with the purchase decision. We assume that the overall attractiveness of purchasing a product or service can vary along some mean attribute level of the offering (Erdem and Keane 1996). In our context, because the hospitality service in every purchase is unique and distinct and thus could be a new experience to the consumer, we construct a model in which consumers are imperfectly informed about these attribute levels of the service. At the outset, consumer i perceives the mean attribute level of his or her target service to be purchased in channel j as γ_{ij} in Equation 5. The error term ζ_{ijn} follows logistic distribution. The utility of no purchase is $W_{i0n} = 0$.

$$(5)\quad W_{ijn} = \overline{W}_{ijn} + \zeta_{ijn} = \gamma_{ij} + \sum_{k=1}^{J} \gamma_{j,k} G_{ikn} + \zeta_{ijn}, \quad j = 1, ..., J.$$

The intercept γ_{ij} is set by prior experiences and the expectations of the attractiveness of purchasing through a channel. For example, a customer visiting the firm's website through a display ad, e-mail, or coupon/referral site may have some mean expectation of the attractiveness of the purchases he or she might make. The customer then updates his or her perception of the overall attractiveness of making a purchase using information collected through channel visits, such as through search engines (e.g., Google, Yahoo), referral engines (e.g., TripAdvisor.com), or the focal company's website, and by the information conveyed in marketing interventions, such as display ads and e-mails he or she may encounter. For each of the J channels, the perceived overall attractiveness at occasion n is in Equation 5. The term G_{ikn} detailed in Equation 6 is the cumulative informational stock/content that contains the informational influence of all the preceding visits that consumer i has been exposed to in channel k through 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 1 if consumer i visits channel k at occasion h. The informational effect of previous 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 instantaneous influence of channel k compared with other channels can be picked up by the coefficients $\gamma_{j,k}$ in Equation 5.

[2]We have estimated the model with an alternative linear specification of the costs and find that the proposed specification leads to better model fits (as discussed in the "Model Estimates" subsection).

[3]We use visits lagged by one period, in line with Montgomery et al.'s (2004) finding that the first-order Markov process performs better than the zero-order Markov process. This process could also be viewed as behavioral reinforcement. In addition, in our empirical application when we accounted for the visits in (n – 2) occasion, the resultant second-order process did not significantly change the relative costs across channels or improve the model fit.

$$(6)\qquad G_{ikn} = \sum_{h=1}^{n-1} d_{ikh} \times (1-\lambda_k)^{(t_{ikn}-t_{ikh})}.$$

Overall, the joint likelihood function in Equation 7 takes into account the consideration, visit, and purchase stages. We estimated the model using the Markov chain Monte Carlo approach, which provides a computationally tractable estimation of the large number of parameters in the model. Web Appendix A provides details of prior and full conditional distributions.

$$(7)\quad L(B|\theta) = \prod_{n=1}^{N_i}\prod_{i=1}^{I}\prod_{j=1}^{J}\sum_{k=1}^{2^J-1} P(C_i = H_k|\alpha,\Sigma) \times \left[b_{ijn1}^{B_{ijn}} b_{ijn0}^{(1-B_{ijn})}\right],$$

where

$$b_{ijn1} = P(V_{in} = j|C_i;\ \beta, \mu, \tau)P(B_{ijn} = 1|C_i, V_{in} = j;\ \gamma, \lambda), \text{ and}$$

$$b_{ijn0} = P(V_{in} = j|C_i;\ \beta, \mu, \tau)[1 - P(B_{ijn} = 1|C_i, V_{in} = j;\ \gamma, \lambda)].$$

EMPIRICAL ANALYSIS

Data

The data for this study, provided by a franchise firm in the hospitality industry, consist of individual-level data on touches, visits, and purchases through multiple online channels over time. The firm uses a variety of online marketing channels, such as e-mails, search engines (both organic and paid search), display ads, and referral engines to attract visits to its website.[4] The average monthly visits to the firm's website in 2010 were approximately 26 million. The path data for each customer are developed by integrating data feeds from DoubleClick (display ad and search engines), Omniture Site Catalyst (visits from different sources using cookies and login IDs), affiliate websites, and an e-mail campaign management system. More specifically, when a web visitor is presented with 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 with a file of all display impressions, display clicks, and paid search clicks at the cookie ID level that contains 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 time stamp can help the firm successfully match the DoubleClick cookie ID with the firm's website visitor ID, and thus the data sets are merged.

For all e-mail campaigns, a unique tracking code is created for each campaign e-mail sent to every recipient. These tracking codes of campaigns and recipients are also embedded in the click-through URL and captured by the firm when the visitor enters the website. For referral engines, all inbound traffic to the firm's website has trackable referral information associated with the external referrer. Omniture Site Catalyst captures visits through the firm's website (direct), organic search, and other visits. Overall, the path data provide information on display impressions and e-mail drops to each customer (and whether he or she has clicked them), click-through visits from search engines (organic and paid), referral sites, and direct visits. The path data do not encompass visits to search engines that do not result in a click-through to the firm's website, but these cases are captured by the outside option in the visit stage of our model because they do not materialize in visits to the firm's website. The firm can also use cookies and login IDs to identify its rewards program customers and their specific rewards tiers (ordered from lowest to highest level): Rewards Level 1, Rewards Level 2, Rewards Level 3, and Rewards Level 4. We were not able to match approximately 4%–6% of the cookie IDs with any browsing information from the firm's website.

A concern of the firm-initiated channels is the potential endogeneity resulting from the strategic targeting. This problem is somewhat mitigated in our data because e-mails were not specifically targeted but sent to all previous purchasers and all visitors with e-mail registration, regardless of which channel they usually visit. With respect to display ads, targeting is an issue because the firm uses DoubleClick as a vendor. To determine whether such targeting is correlated with the channels customers often use, or with their rewards program levels, we estimated the incidence of display impressions and conversions across customers' visits through different channels as well as across loyalty tiers. We conducted a similar exercise with e-mail incidences and conversions. Both analyses revealed that the correlations were low.

The data are the visit history between late June and late August for a random sample of 1,997 unique visitors to the firm's website. We tracked each visitor's 68-day history,[5] which contained information about whether an online visit was made each day, the channel through which a visit was made, and purchase incidences, if any. In our data, the average time between the first visit after the last purchase and the current purchase was 9.2 days, indicating that a two-month window should be sufficient to capture all relevant historical data to explain visit and purchase decisions. We applied stratified sampling on the basis of the number of visits through each channel to ensure that the overall and channel-wise conversion rates in the sample are close to the firm's average of 4.5% and to ensure that we could reliably estimate the impact of various independent variables on conversion at the website. We treated all contiguous visits through the same channel within 30 minutes with the same campaign code as a single visit. Overall, 815 customers made 1,128 purchases during the study duration. As Table 2 shows, the conversion rates in each channel vary significantly, with display being the lowest and paid search being the highest.[6]

[4]Organic search and paid search represent the visits originated from a click on search engines such as Google, Bing, and Yahoo. Organic search provides free traffic to the firm's website, whereas paid search involves a fee per click for the firm. Referral engines include referral sites such as TripAdvisor.com and Kayak.com, business-to-business referrals, event management tools, and social media. The e-mail channel represents the visits by a web user who has received an e-mail and clicked the link embedded in that e-mail. It also includes visits from e-confirmation and prearrival e-mails. Finally, the display channel represents those visits made to the website by clicking on a display banner ad.

[5]We also estimate the model with only 30-day data and observe that the results are very close to the findings reported in the "Model Estimates" subsection. The data window does not make much difference, because the carryover and spillover effects wear out within 10–15 days depending on the decay parameters estimated.

[6]The number of visits for the display channel includes both display impressions and click-throughs.

Table 2
SUMMARY STATISTICS

Channel	*Channel Visits*	*Purchases*	*Purchase/Visit Conversion Rate*
Organic search	4,469	285	6.38%
Paid search	1,557	114	7.32%
Referral	3,980	201	5.05%
Direct	7,959	347	4.36%
E-mail	2,804	138	4.92%
Display	1,600	43	2.69%
Total	**22,369**	**1,128**	**5.04%**

Table 3 shows a matrix of current visit (n) versus last visit (n – 1). The large numbers on the diagonal reflect the stickiness of the customers' visit behavior to each channel. Meanwhile, the off-diagonals are not symmetric. For example, a direct visit preceding a display ad happens 84 times, but a display ad leading to a direct visit occurs 124 times. Table 4 shows a matrix of current visit (n) versus all prior visits (n – 1, n – 2, n – 3, ...). The first column presents the current channels through which the customer visits the website at occasion n, and each row shows the number of all prior visits. For example, before all the current organic search visits, 3,307 of prior visits originated from the organic search channel, 934 prior visits originated from a paid search channel, and the prior visits resulting from referral, direct, e-mail, and display are 1,445, 1,621, 862, and 862, respectively.

Model Estimates

Table 5 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. These estimates are posterior means based on 5,000 Markov chain Monte Carlo iterations, after 20,000 iterations were used as burn-in. To assess the convergence of the model estimates, we use the Geweke (1992) diagnostics, the Gelman and Rubin (1992) diagnostics, and the effective sample size (Kass et al. 1998). We investigate the iteration plots and use the Geweke convergence test, in which we compare the estimated parameters from the first 1,000 iterations, 2,001–3,000 iterations, and 4,001–5,000 iterations after the burn-in period, to confirm convergence to stationary posterior distributions of the parameters in the proposed model. We run two additional chains with two sets of initial values for the proposed model: the first has 25,000 iterations burn-in, and the second has 20,000 iterations burn-in. Then, we draw 5,000 iterations from posterior distribution. The average posterior marginal variance is very close to the within-chain variance. The average potential scale reduction factor (PSRF) is 1.062. The PSRF of 91% of the parameters ranges between 1 and 1.1, and the PSRF of all parameters is less than 1.2. Thus, the Gelman–Rubin diagnostics also support the convergence of the proposed model. The average effective sample size is 612.6 for all parameters. Most of the effective sample sizes are between 400 and 700, which shows that the samples from the posterior distribution are not highly autocorrelated with earlier samples.

Consideration stage. We model a consumer's consideration of customer-initiated channels (organic search, paid search, referral, and direct) as a function of his or her level of membership in the firm's loyalty program (nonmember and rewards levels 1–4). We expect the membership levels to act as a proxy for the consumers' experience with, affect toward, and commitment to the firm's brand and to capture their impact on the channels they would consider when visiting the website. As Table 5 shows, non–rewards program members are more likely to consider an organic search and paid search than rewards program members at any level, whereas they are less likely to consider referral and direct channels than rewards program members. Members of rewards levels 3 and 4 are more likely to consider direct visits than members of rewards levels 1 and 2. The estimate for

Table 3
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	2,071	557	542	463	295	186
Paid search	440	394	125	128	91	275
Referral	577	113	2,118	490	354	93
Direct	462	92	442	5,579	431	124
E-mail	329	69	360	434	1,345	81
Display	181	200	87	84	60	700
Total	**4,060**	**1,425**	**3,674**	**7,178**	**2,576**	**1,459**

Table 4
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	3,307	934	1,445	1,621	862	862
Paid search	1,220	903	583	590	396	967
Referral	1,777	432	3,391	2,211	1,088	580
Direct	1,694	410	1,721	6,532	1,425	548
E-mail	1,255	320	1,146	1,737	2,307	455
Display	738	539	366	437	315	1,127

Table 5
MODEL ESTIMATES

Variables	*Organic Search*	*Paid Search*	*Referral*	*Direct*	*E-Mail*	*Display*
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	**.35**					
Cost						
Cumulative time	–.77[a]	**–1.15**[a]	**–.99**[a]	**–1.41**[a]	–.78[a]	–.79[a]
Lag organic search	**–2.10**[a]	**–.18**[b]	**–.20**[b]	.07[b]	**–.30**[b]	**–.25**[b]
Lag paid search	**–.79**[b]	**–1.97**[a]	**–.19**[b]	.11[b]	**–.49**[b]	**–.43**[b]
Lag referral	**–.38**[b]	**–.13**[b]	**–2.43**[a]	.05[b]	.12[b]	.01[b]
Lag direct	**.47**[b]	**–.29**[b]	.03[b]	**–1.71**[a]	**.19**[b]	–.01[b]
Lag e-mail	**.74**[b]	**–.18**[b]	**–.21**[b]	**.24**[b]	**–2.04**[a]	**.49**[b]
Lag display	**–.27**[b]	**–.27**[b]	**.16**[b]	–.04[b]	.11[b]	**–1.26**[a]
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**[a]	**.17**[b]	**–.39**[b]	**.21**[b]	**–.21**[b]	–.12[b]
Info stock—paid search	.03[b]	**.44**[a]	.03[b]	**.23**[b]	.04[b]	**–.26**[b]
Info stock—referral	**.16**[b]	.03[b]	**.35**[a]	**.18**[b]	.11[b]	**.44**[b]
Info stock—direct	–.11[b]	**.22**[b]	**.70**[b]	**.73**[a]	**.22**[b]	**.47**[b]
Info stock—e-mail	**.28**[b]	**.61**[b]	–.15[b]	.08[b]	**.83**[a]	.06[b]
Info stock—display	.07[b]	**.16**[b]	**–.38**[b]	**.22**[b]	**.28**[b]	**.40**[a]
λ = (1 – decay rate)	**.73**	**.62**	**.57**	**.59**	**.69**	**.47**

[a]Indicates carryover effects.
[b]Indicates spillover effects.
Notes: Estimates are posterior means. Boldfaced figures indicate that the 95% posterior interval excludes zero. τ is the coefficient of the inclusive value.

direct visits is lower for rewards level 4 than that of rewards level 3 (.94 vs. 1.92). This counterintuitive result is a result of rewards level 4 memberships bestowed to many individual customers who have corporate affiliations, and thus, it may not truly reflect individual loyalty as much as rewards level 3. The estimated correlation matrix of consideration (not reported) indicates that customers are more likely to consider an organic and a paid search together (correlation coefficient .69) and referral and direct visits together (correlation coefficient .87). Overall, we find significant heterogeneity in the consideration of the customer-initiated channels.

Visit stage. The estimates of the visit stage in Table 5 provide (1) the long-term carryover effects of prior visits through the cumulative time spent going through each channel and (2) the 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 are significantly negative (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 DoubleClick'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 revisiting. That is, if a customer visited through a specific channel on the previous occasion (within the previous day or on the same day), the costs for the current visit through the same channel are reduced.

The lag effects of organic search on e-mail (–.30) and display channels (–.25) and 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. The spillover effect of a customer-initiated channel on other customer-initiated channels also reduces costs. 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"). In contrast, the lag effect of the e-mail visit increases the costs of visiting through organic search (.74), direct visit (.24), and display (.49). A possible explanation for this finding is that customers who visit the firm's website through e-mail links are more likely to come back through an 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 the costs of visiting through the other channel. However, we find that the spillover effects of paid search on organic search (–.79) are much stronger than in the reverse direction (–.18), contrary to Yang and Ghose's (2010) finding that organic search has a much stronger effect in leading to clicks in paid search than the reverse. Our result could be explained by the strong brand of the focal hotel chain, which leads to top placements in the organic search listings.

The coefficients for the costs of a 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 channels (–3.58, –3.11, and –3.58) are the highest in magnitude, indicating that a unit drop in costs of visiting is likely to affect repeat visits through these channels much more significantly than for the organic search, paid search, and display channels. These results highlight that the impact of carryover or spillover could be much higher for referral, direct, and e-mail channels than for 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 in the current visit. We find that the carryover effects of firm-initiated channels significantly contribute to increased purchase probabilities. These results are consistent with extant research that 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 result implies that for the focal firm, more repeated visits to the website through these channels are indicative of the greater attractiveness of the firm's offering relative to its competitors; thus, more repeated visits are indicative of a greater 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, we find that informational stock of organic search has a positive spillover on purchases through the paid search channel, but the reverse effect is not significant. Whereas informational stock of display has a positive spillover on purchases through the 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 the informational stock of display on the referral channel, which is significantly negative. This may indicate that customers who visit often through display click-through may use the referral channel to gather additional information but may not consummate the purchase through that channel. It is also notable that the spillover effects of informational stock of organic and paid search are negative (when significant) on purchases through referral, e-mail, and display channels. Given that, at the visit stage, the spillover of search channels contributes to reducing the costs of visiting in referral, e-mail, and display channels, we can similarly surmise that customers who visit the website through search channels often use these other channels mainly for gathering information but not for making purchases during those visits. In short, search can help bring in more visits, but it might not necessarily result in more conversions. In addition, the spillover effects of other channels on paid search and direct purchases are always positive, indicating that the informational stock of other channel visits leads to ultimate conversions during paid search and direct visits. Overall, our results show significant carryover and spillover effects at both the visit and the purchase stages.

The estimated decay rates of information gathered in a channel provide insights into how fast the informational stock accumulates in each channel. We observe that, in general, the decay rates are low for the search and e-mail channels (.27 for organic search, .38 for paid search, and .31 for e-mail) and high for the display channel (.53). Thus, a click-through from search or e-mail has a significantly long-lasting impact, whereas a display impression or click-through has the least enduring impact. From a complementary perspective, display retains only .5% of its original informational value after seven days, while organic search retains 11.0%, paid search retains 3.5%, and e-mail retains 7.4%. The corresponding values for referral and direct channels 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.

Model Fit

We compare the proposed model with alternative models on the dimensions of model fit (in-sample) and model predictions (out-of-sample), and it outperforms all of them (we also examined the fit across channels with posterior predictive check; see Web Appendix B). Table 6 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 include (1) Model 1, which has all three stages but does not include the decay parameters in the informational stock variables in the purchase stage (i.e., 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; (4) Model 4, which has all three stages but specifies costs as a linear

Table 6
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%	2,076%	33%
Overall	74%	20%	35%	24%	502%	1%
Log-marginal likelihood	–13,580	–14,692	–17,033	–13,629	–173,093	–12,521

Notes: All the percentage values in this table are MAPEs. Model 1 has all three stages but does not include the decay parameters in the informational stock. Model 2 has only the visit and purchase stages; that is, each consumer considers all channels. Model 3 has all three stages but does not include the lagged visits in the visit stage. Model 4 has all three stages but specifies costs as a linear form rather than a logit form of explanatory variables. Model 5 is a naive model with only channel-specific constants at the visit and purchase stages.

function of explanatory variables instead of in a logit form; (5) a naive model with only channel-specific constants at the visit and purchase stages; 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.[7] In addition, 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.

Model Predictions

We check the predictive validity of the proposed model and the best alternative model in terms of MAPE (Model 2) using two validation samples. Both are random samples of 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 who visited the firm's website during the last week of August 2011. The first validation sample is a holdout 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 7 compares the predicted number of purchases through different channels in the holdout sample using our estimates from the two models with the observed conversions. We observe that our proposed model predicts not only the total number of purchases but also the number of purchases in each channel fairly well, as does the alternative model (Model 2). This is not surprising; Van Nierop et al. (2010) find similar results when comparing a model with consideration sets with a model without consideration sets. In addition to the results reported in Table 7, we test the predictive power of the models using historical data for a seven-day forward forecast rather than for the next day, based on validation sample 2. That is, when we predict day 7, we still use the historical data through day 0 and do not use observed data from days 1–6 in the prediction. The reason for this test of predictive power is that we use the proposed model for prediction when paid search is turned off for a week (discussed subsequently in the "Field Study with Paid Search Off" subsection).

The advantage of our proposed model is evident in the seven-day forecast, in which it performs much better than Model 2. The observed purchases number in the first validation sample is 265; the proposed model predicts 259, and Model 2 predicts 287, indicating that the rich heterogeneity incorporated at the consideration stage in the model pays off well in out-of-sample predictions. Next, we 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 channels' relative contributions than what a last-click metric could provide.

[7]Other than the explanatory variables of visit stage and purchase stage reported in Table 5, we added the loyalty tiers into the visit stage and the purchase stage, and the log-marginal likelihoods were –14,703 and –14,147, respectively. We ran another alternative model using the cumulative time spent at websites as the explanatory variables in the purchase stage rather than at the visit stage. The log-marginal likelihood of this alternative was –14,897. In these cases, the proposed model fits the data better than the alternative models.

Table 7
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	2,905	2,860	2%	3,137	8%

Notes: Model 2 has only the visit and purchase stages; that is, each consumer considers all channels.

Estimating Contribution to Conversions

Given the calibration data and the estimates from Table 5, we can estimate the impact of a specific channel—say, e-mail—on predicted probabilities of conversion by excluding e-mail from the proposed model and predicting 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 the e-mail channel as well as other channels. However, these estimates are incremental, given that other variables (channels) already exist in the model and might already explain significant variance in the dependent variable. Therefore, using the idea of the Shapley (1953) value in game theory, we calculate the total contribution of each channel in leading to a conversion by averaging their incremental contributions in all possible channel combinations. (For an illustration using the Shapley value to calculate the marginal contribution of a channel, see Web Appendix C.) From this analysis, the last two columns in Table 8 show the contribution of each channel to purchase conversions, which we compare against the two most widely used metrics in the industry: (1) the last-click attribution metric, which gives all credit to the visit at which conversion occurred, and (2) the seven-day average attribution metric, which assigns the conversion credit equally to all the visits made in the previous seven days. Note that these metrics, unlike our model, use only path data that end in conversions and exclude all nonconversion data. We provide the Bayesian confidence intervals for the estimated contribution of each channel in Web Appendix D.

Although attribution percentages across channels differ between last-click and seven-day average metrics, their conversion ranks remain the same in both models. However, our proposed model provides 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% (a 36% reduction compared with the last-click model), and paid search decreases to 6% (a 40% reduction) and drops to the last rank. Moreover, referral channel climbs to the second-highest rank with 24% (a 33% increase in contribution), and e-mail and display attributions almost double their number of conversions credited in last-click metric.

Our results show that there are significant changes in attributions, which could have far-reaching implications for return on investment and budget allocations for marketing interventions such as paid search, display, and e-mail. In Table 5, all other channels have positive spillovers in enabling purchases through the direct channel, which could explain the drop in its attribution, although the direct channel also gains from spillovers to other channels. 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 highlight the importance of considering the path data of converters and nonconverters in estimating channel attributions and accounting for the carryover and spillover effects across channels on conversion. They also suggest that the firm could intervene with marketing actions that might play a positive role in effecting conversions at the website, which we discuss in the following subsections. Although extant research has found that the effectiveness of different types of marketing interventions may depend on customers' loyalty tiers (Rust and Verhoef 2005), we find that the contribution of a channel varies little across loyalty tiers in our context (see Web Appendix E).

Field Study with Paid Search Off

Our model helps managers understand the incremental effects of each channel and predict their impact on conversions. Even in situations in which one channel (say, paid search) was to be turned off, our model is still able to predict the reallocation of channel shares in leading to conversions. To test and further validate our model, we obtained a validation sample covering the period August–November 2011, in which the firm shut down the paid search option completely for one week (November 3 through November 9). Using this validation sample, we made two sets of predictions of conversions for this one-week period. We made the first set of predictions (paid search on) by assuming that all channels were available for this one week. Note that our model was calibrated on a sample with all channels available. We made the second set of predictions (paid search off) assuming that the paid search channel was not available for any customers to consider or visit. Because we have explicitly modeled the consideration set of consumers, we can constrain consideration probabilities of the paid search channel to be zero in estimating this set of predictions.

Table 9 provides the two sets of predicted conversions along with the observed conversions during this week. First, in comparing the total predictions with paid search on and paid search off, we find that overall conversions drop from 11,893 to 11,106, a decrease of 6.6%. 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

Table 8
CONTRIBUTION TO CONVERSIONS

		Last Click		*Seven-Day Average*		*Proposed Model*	
Channel	*Observed*	*%*	*Ranking*	*%*	*Ranking*	*%*	*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	1,128	100		100		100	

Table 9
PREDICTED CONVERSIONS: FIELD STUDY

	Assuming Paid Search On		*Assuming Paid Search Off*			
Channel	*Predicted*	*95% HPD Region*	*Predicted*	*95% HPD Region*	*MAPE*	*Observed*
Organic search	1,023	[869, 1,192]	1,711	[1,553, 1,854]	30%	2,453
Paid search	923	[782, 1,071]	0			0
Referral	2,775	[2,231, 3,226]	1,784	[1,376, 2,308]	21%	2,271
Direct	5,785	[4,204, 7,410]	6,269	[4,320, 7,426]	16%	5,398
E-mail	907	[782, 1,049]	1,260	[1,109, 1,349]	13%	1,114
Display	480	[378, 569]	82	[19, 207]	48%	159
Total	11,893		11,106		2.60%	11,395

when paid search is turned off. However, it is less than the 923 conversions (7.8% of total conversions) predicted for the paid search channel when assuming all channels are available. It seems that some of the paid search conversions are 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 predicted.

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%. Moreover, 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 finding validates our model's ability to predict conversions when a specific channel is not available and illustrates how our model can be used to estimate a channel's incremental contribution.

Third, comparing the predicted conversions with paid search off and the observed conversions channel by channel, we find that the amount of observed conversions through organic search is much higher (MAPE = 30%), referral conversions are higher (MAPE = 21%), but the number of direct conversions is lower (MAPE = 16%) than what our model predicted. Our model performs much better than a model that does not take the consideration stage into account. We 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%) occur through unbranded keywords. Because the firm has a very strong brand, the relative rank of its branded keywords in the organic search pages is almost always the highest; for many unbranded keywords the firm bids on, it also ranks within the first page of organic search results. Thus, when paid search is off, it seems that many of the conversions that previously stemmed from paid branded keywords are recaptured by free organic search, instead of being "lost," whereas a significant percentage of unbranded keyword conversions do get lost. This finding could possibly explain why the number of observed conversions through organic search is much higher (43%) and the number of observed overall conversions is somewhat higher (3%) than the model's prediction. In summary, given the firm's brand strength and 73/27 split between branded and unbranded keywords in paid search conversions, the recapture rate of paid search conversions when paid search is paused is higher than what the model predicts.

Purchase Decision Hierarchy and Marketing Interventions

A key insight that emerges from our results is the understanding of whether and when to intervene with marketing actions given a customer's path to the firm's website. Because the model provides the estimates of the impact of previous visits (the lag estimates in Table 5), it is possible to predict for a customer, given his or her visits to the firm's website to date, the probability of a visit through different channels for the next visit occasion and the probability of a purchase on that visit under different intervention scenarios. We illustrate this method with an example of e-mail intervention. In our calibration sample, e-mail interventions target a significant number of customers regardless of their rewards program status; specifically, 23% of the nonmembers and 45% of the members were targeted, with the same e-mail content across customers. To stay within the confines of the calibration model for our illustration, we focus our analysis only on customers who have already been targeted with e-mail interventions. Thus, our objective is to understand (1) under what path characteristics the firm can increase the overall probability of conversion for customers who have had a prior e-mail intervention in their paths by targeting them with another e-mail intervention and (2) under what conditions the firm is better off not targeting them with another e-mail.

Table 10 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 an organic search channel and makes another visit through an 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 occurring through an organic search. However, an e-mail intervention on Day T can increase 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.

Table 10 provides many scenarios in which the best option for the firm is not to intervene with e-mails. For example, when a visit on Day (T – 1) happens through the direct channel (Rows 3 and 6), e-mail intervention can only lower the likelihood of conversion. Rows 7–10 provide similar scenarios in which the advantage of e-mail targeting

Table 10
PATH SEQUENCE AND VISIT/PURCHASE PROBABILITIES

					Day T				
	Day (T – 4)	*Day (T – 3)*	*Day (T – 2)*	*Day (T – 1)*	*No Intervention*			*E-mail Intervention*	
Row	*Visit Through*	*Visit Through*	*Visit Through*	*Visit Through*	*Visit Probability*	*Purchase Probability*	*Visit Through*	*Click Probability*	*Purchase Probability*
1	X	X	OS	E-mail	.196	.447	OS	.185	.474
2	X	X	PS	E-mail	.193	.446	OS	.182	.473
3	X	X	E-mail	D	.421	.565	D	.208	.512
4	X	E-mail	OS	PS	.230	.356	PS	.184	.463
5	X	E-mail	OS	R	.238	.341	R	.184	.465
6	X	E-mail	OS	D	.421	.564	D	.208	.510
7	E-mail	R	X	X	.214	.137	OS	.188	.150
8	E-mail	D	X	X	.359	.335	D	.187	.149
9	OS	E-mail	X	X	.180	.172	OS	.217	.191
10	PS	E-mail	X	X	.190	.136	PS	.216	.121

Notes: OS = organic search, PS = paid search, R = referral, D = direct, and X = no visit.

is clearly contingent on the path a customer takes. This illustration indicates the utility of our approach for retargeting customers with marketing interventions. If the customers' history of touches is tracked when they enter the website for the first time, the firm can use the data to customize the price and promotion for each identified customer to maximize his or her purchase probability (for a more detailed discussion on targeted online promotion, see Grewal et al. 2011). For a full-fledged implementation of such individualized targeting, the criterion used for targeting, especially in the display channel, must be incorporated into a supply-side equation. In addition, 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.

CONCLUSIONS

In this article, we propose a conceptual framework to shed light on the nature of carryover and spillover effects across online marketing channels through which customers visit a firm's website. The framework forms the basis for estimating these effects and for attributing and allocating credit for conversions to both firm- and customer-initiated channels using individual-level data on customers' touches, visits, and purchases through these channels over time. To our knowledge, ours is the first study to examine these effects in the online channel context at distinctly different stages—visit and purchase. Our empirical study illustrates the importance of estimating these effects so that firms can accurately determine the attribution of each channel to the overall conversions at the website. It has useful managerial implications for allocating marketing budgets across marketing channels as well as for creating targeting strategies. We first examine the implications for the specific context we have studied and then discuss more general implications.

Implications for the Focal Firm

Our study finds significant spillover effects of firm-initiated channels to customer-initiated channels at both the visit and purchase stages. Firm-initiated interventions also affect visits through other channels in the short run with no long-term carryover effects, implying that managers must take a more inclusive and macro view of the returns to 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. In addition, the real impact of organic search on conversions is much lower than what the last-click metric shows. For the focal firm, it is evident that some customers, having visited the website through other channels previously, use organic search purely as a navigational tool to get to the website to complete purchases. Moreover, paid search and direct channels exhibit diminished impact. Given that the changes in attributions from our proposed model are considerably different (ranging from –40% to +75%), this implies a different optimal allocation of the marketing budget. The focal firm in our study uses the attribution estimates to charge its franchisees for marketing programs such as paid search, referrals, and other campaigns, so even if the attribution ranks were only marginally different, a sizable difference in revenues would still result for such appropriations. Attributions based on our model would render these appropriations in line with the incremental purchases that the franchisees actually observe at their properties. This would enhance franchisees' confidence in such metrics and the fairness perception of the firm in how it passes on marketing costs. We designed our attribution model to be estimated and run for each period—say, one month—so that it becomes the basis for allocating the marketing expenses and attribution for each channel each month. Our model can also form the basis for determining the acquisition costs through each channel and understanding the efficacies of each channel in each period.

Although our 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 website with the oft-used strategy of "retargeting," in which e-mails and displays follow visitors everywhere after they click on an e-mail or display ad or visit the website (Helft and Vega 2010). As our path analysis results show, retargeting visitors to the website with e-mails is not always the best strategy. Although e-mail retargeting increases the overall purchase probability for those customers in some cases, in others it actually hurts the purchase probability for the same segment of customers. This is consistent with Kumar, Venkatesan, and Reinartz's (2008) finding that contacting customers at the time they are predicted to purchase can lead to greater profits and return on investment 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. Our model can be used for customized targeting using path analysis to identify cases for which e-mail and display retargeting are likely to contribute to more conversions.

Our model enables us to estimate how conversions through different channels are affected when one channel is not available. We observe that a significant portion of the conversions that could have occurred through a paid search channel is recaptured through organic search. Because the firm in our example has a strong brand and ranks highly in an organic search, we 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 should reallocate marketing investments given the estimates of the incremental contribution suggested by our methodology.

Finally, we find that search and e-mail click-throughs have a significantly longer impact than a display-ad click-through. 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.

General Implications

It is evident from our study that neither the last-click attribution metric nor the seven-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 decision hierarchy (e.g., with one or two touch-points) and with fewer channels, they will invariably be misleading in product/service categories with a longer purchase decision hierarchy, as in high-involvement categories (e.g., consumer durables, travel services), as well as for firms with multiple channels, both customer and firm initiated. In the latter case, we also expect that the last-click model would underestimate the effectiveness of firm-initiated efforts, and it is imperative that firms use our 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.

Our results suggest that the incremental impact of the 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 could 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, such recaptures may not materialize because the firm's position in organic search may not be high enough. All else being equal, we conjecture that the stronger the brand, the lower the incremental effect of paid search on ultimate conversion. Our framework provides a useful tool with which to identify this incremental contribution and to determine whether the cost of effecting a conversion through paid search is less than the incremental revenue obtained through the channel. Because paid search makes up approximately 50% of the overall spending in the online marketing budget for many firms from 2011 to 2016 (VanBoskirk, Overby, and Takvorian 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 our model's useful features is that it incorporates customers' consideration sets of channels to use in visiting the firm's website. Because these consideration sets exhibit significant heterogeneity and self-selection, by modeling them endogenously, our modeling framework enables us to accurately predict the conversions through different channels when one of them (e.g., paid search, as in our field study) is not available. In addition, identifying customers who use fewer and more expensive (to the firm; e.g., paid search) channels enables the firm to offer them cheaper alternatives (e.g., e-mail).

Limitations and Further Research

Because we estimated our 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 greater propensity to purchase (Manchanda, Rossi, and Chintagunta 2004). Although our results are conditional on the firm's ongoing targeting strategies, we find no systematic pattern in targeting, at least not on the observed dimensions of channels and rewards program membership. We believe that the effects of strategic targeting are not likely to change the essential nature of our results. The focal firm provides a variety of substitutable products in a wide price range. Customers with different budgets can easily find an affordable choice within the target firm. To minimize selectivity bias, we can compare the results of our analyses with different cohorts of visitors separated by a period 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 Web Appendix F).

We 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. Our data lack detailed demographic information and prior purchase information. In addition, at the purchase stage we 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, we 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 our study, further research could examine long-term dynamic changes in search behavior and purchase decisions using structural models with appropriate long-term data. We 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, our 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 our research. We leave this undertaking for further research.

Finally, the model we have developed 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 our framework and methodology should be well suited to analyze such contexts.

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