Attributing Conversions in a Multichannel Online Marketing Environment:

An Empirical Model and a Field Experiment

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November 2013

(Forthcoming in JMR)

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Abstract

Current technology allows firms to produce a granular record of every touch point a consumer makes in their online purchase journey before they convert at a firm's website. However, firms still depend on aggregate measures to guide their marketing investments in multiple online marketing channels, such as display, paid search, referral, e-mail, and affiliates, which upon click-through become conduits, or "channels," to firms' websites. For example, the widely used "last-click" attribution metric assigns purchase credit to the last touched channel and entirely ignores all the other channels a customer might have touched prior to the purchase. Such aggregate and incomplete measurements bias the investment decisions for subsequent marketing campaigns. This paper provides a methodology to attribute the incremental value of each individual marketing channel in an online environment using individual-level data of customers' touches in their purchase funnel. We propose a three-level measurement model to analyze (1) customers' *consideration* of online channels, (2) their *visits* through these channels over time, and (3) their subsequent *purchases* at the website, and estimate the carryover and spillover effects of prior touches at both the visit and purchase stages. Based on customers' path data from a hospitality firm, we find significant carryover and spillover effects – for example, e-mails and display ads trigger visits through search and referral channels, while e-mails lead to significant purchases through search channels. Attributing the conversion credit to different channels based on the estimated carryover and spillover effects, we find that the relative contributions of these channels are significantly different from the contributions based on other metrics currently used in practice. A field study conducted at the firm's website by pausing paid search for a week validates the ability of our proposed model in estimating the incremental impact of a channel on conversions. In targeting customers with different patterns of touches in their purchase funnel, our estimates help in identifying cases where e-mail re-targeting may actually decrease the conversion probabilities.

***Keywords*:** Online multichannel attribution, attribution modeling, touchpoint management, online advertising, display ads, search, carryover, spillover, field experiment, path analysis, purchase funnel, nested logit model.

According to a recent forecast, the total US spending on search marketing is slated to grow from $15 billion in 2011 up to $24 billion by 2016, while the 2016 comparable figure for display ads is $25 billion, and for e-mail marketing is $0.24 billion (eMarketer 2012). The above figures indicate the overall popularity and potential of online marketing interventions to draw in potential customers to visit firms' websites. Customers also visit the websites on their own initiative directly or through different sources, such as search engines and referral sites. Upon the customer's response (such as clicking on display ads, e-mail links, firm's paid search ads, or choosing any other sources on their own – typing in the URL of the website, clicking on organic search links or referral links), these communications, interventions or links become the conduits or "channels" through which they 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, say a search or a referral site, exposes customers to additional information regarding the attractiveness of the product and service vis-à-vis competing and complementary offers. This visit experience *per se* can have an impact on subsequent visits to the website through the same channel and possible conversions occurring through *the same* 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 leading 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 very heterogeneous in how they choose to use different channels and/or respond to the various online marketing interventions (Mulpuru et al. 2011).

In practice, the multiple touches a customer makes prior to a conversion are rarely considered in measuring the effectiveness of campaigns across various communication channels.

For example, consider a hypothetical online purchase scenario of a sample of customers going through the purchase decision hierarchy as shown in Table 1. For each customer the channel used for the current visit to the website is indicated in column 3, whether they convert on that current visit or not in column 4, and the prior visits through different channels in column 2. The channel alternatives through which a customer reaches the firm's website include directly typing in the URL to "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 not to click through it. Applying the metric commonly used in practice – 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 prior channel touches. For example, both of the current direct visits that ended up with conversions were preceded by visits through a referral channel (customer 1 and 3), while the two current direct visits that did not convert were preceded by visits through search channel (customer 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 "first-click" metric which assigns the credit to the first touch, "uniform," "weighted" or "exponential" metric which considers all the touch points leading up to a conversion and allocates the credit for the conversion accordingly. However, these metrics still only consider the paths that have resulted 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 customers 4 and 5 in Table 1. They have the same paths, one resulting in conversion while the other not, yet the existing metrics in practice do not make use of such useful information contained in the paths with no conversions.

< Insert Table 1 about here>

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 reflect their relative incremental impact in leading to website visits and conversions. Given this, 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 sub-optimal allocation of marketing budgets 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 and double counting across different sample frames (Atlas 2008; Green 2008). It is clear that 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 precisely the focus of our paper.

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, both at the stage of visiting the website and at the stage of purchasing at the website. This measurement model, based on individual-level path data of customer 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. Extant studies in multichannel marketing have focused on customer lifetime value, total spending across channels and cross-selling, dynamics among media, in both offline and online contexts (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 papers have also highlighted the importance of researching how various channels play different roles in a customer's purchase (e.g., Neslin and Shankar, 2009; Verhoef 2012). However, none have examined the issue from the viewpoint of understanding the impact of online marketing communications and touches at different stages of the online purchase decision hierarchy and attributing the conversion credit to the multiple channels (See Neslin et al. 2006 and Neslin and Shankar 2009 for a comprehensive survey on the extant studies on multichannel marketing).

Our 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; 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, our paper integrates the effects of a variety of marketing communications/ interventions such as search, display ads, e-mails, referral engines, etc. 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 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, we account for the influence of a preceding marketing communication or intervention a visitor might have had before reaching the website that could affect their subsequent purchasing behavior. In the context of the above 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, e-mails and display ads trigger visits through search and referral channels, while e-mail leads to purchases through search channels. The empirical analysis also shows that the attribution based on our measurement model paints a much different scenario of relative contributions of these channels as compared to the metrics conventionally used in practice. For example, e-mail, display and referral channels are significantly undervalued by the 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 pausing paid search for a week provides a 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. We also highlight the usefulness of our results through an illustration of whether or not the firm should re-target their customers with e-mails based on the path of the 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 in making a purchase: (1) the consideration stage, where the customer recognizes his or 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).

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 firm and consider going directly, while some may consider search channel for better prices and options. Some may consider both. While 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*, where consumers seek out information on their own initiative, and *firm-initiated channels*, where 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). 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[2]. Extant research indicates that online display ads tend to have small behavioral impact and play an insignificant role in ad recall (Goldfarb and Tucker 2011), suggesting customers consider it only when encountered. Thus, the firm-initiated channels enter into customers' consideration sets as and when customers encounter them as a result of a firm's targeting.

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

< Insert Figure 1 about here>

Conditional on their consideration sets, customers make visits to 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 spillover effects across other channels (prior click-throughs on referral links could lead to greater probability of a visit through search channel) at both the visit stage and purchase stage. *We define the carryover (spillover) effect at the visit stage as the impact of prior visits through a given channel on the probability of a visit through that specific (a different) channel, while 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 vis-à-vis marginal costs incurred in the visit. The benefit is the perceived 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 opportunity cost (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 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 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 in visiting the same channel due to 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 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 the 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 we 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 customers gather information across visits. We use cost as a catch-all term for the sake of modeling convenience. We can also interpret this measurement term as inverse site familiarity.

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 that gets 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 weigh the later visits more than the earlier ones (Ansari, Mela, and Neslin 2008; Terui, Ban, and Allenby 2011).

The above framework provides the basis for our three-level measurement model where the conversion decision of a customer at an online site consists of three stages: the consideration of alternative customer-initiated channels and the encountered marketing interventions, the visit decision and the purchase decision. We use (1) costs as a catch-all term to account for all the factors that impact 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 impact 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 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, we allow individuals in our model to have different consideration sets of channels, which could include both customer-initiated channels and firm-initiated channels. We 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, can vary across visit occasions. Since the data were 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 $(J\text{-}Q)$ 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 an individual 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). Further, 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 individual i 's consideration set. We normalize all the diagonal elements in Σ to be 1 for identification purpose, so that the off-diagonal elements are 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, 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 their visit decisions.

We exclude the empty consideration set from our model, since we can observe a customer in the data only if 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 $k=1,\ldots,(2^J-1)$. The multivariate probits $C_i=(c_{i1}\ldots c_{iJ})^T$ are the same as H_k with a probability $P(C_i=H_k\mid\alpha,\Sigma)$.

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*$_i$) , 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). 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, individual 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 has to at least check the availability of a specific service (e.g., airline seat availability on a specific date) before purchasing.

Visit Decision

We posit that consumer *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*, $\beta_{0,ij}$ (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 $\beta_j S_{ijn}$. Consumer *i*'s inclusive value of the purchase or no-purchase option in channel *j* at occasion *n* is $I_{ijn} = \log\left\{1 + \exp(\bar{W}_{ijn} / \tau)\right\}$, where $\bar{W}_{ijn}$ 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 visit the channel that offers the greatest net utility or not visit at all.

$$U_{ijn} = \bar{U}_{ijn} + \eta_{ijn} = \beta_{0,ij} + \tau I_{ijn} - \beta_j S_{ijn} + \eta_{ijn} \qquad j = 1,\ldots,\mathrm{J} \tag{3}$$

The cost S_{ijn} is further parameterized in a logit form bounded between [0, 1] as in Equation (4). The cost S_{ijn} is captured only in the visit decision, but treated as a sunk cost in the purchase decision, discussed 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 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 our S-shaped cost variables. Recently, Seiler (2013) has used the same specification to parameterize search costs[3]. T_{ijn} is the cumulative time spent at the website visiting through channel *j*, determined on the basis of the difference between the start time stamp and the end time stamp 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, $\{L_{ik,n-1}, k = 0,\ldots, J\}$, indicating the channel visited by consumer *i* at occasion *(n-1)*, with 0 representing no visit in the previous occasion. This can be viewed as a first order Markov process to capture the short-term carryover and spillover effects[4].

$$S_{ijn} = \frac{\exp(\mu_j T_{ijn} + \sum_{k=0}^{J} \mu_{j,k} L_{ik,n-1})}{1 + \exp(\mu_j T_{ijn} + \sum_{k=0}^{J} \mu_{j,k} L_{ik,n-1})} \qquad j = 1,\ldots,\mathrm{J} \tag{4}$$

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 cost S_{ijn}, while $\mu_{j,k}$'s capture the short-term carryover or spillover effects of the latest visit through channel *k* on the total cost S_{ijn}. 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. Meanwhile, the coefficient of cost, β_j in Equation (4) 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, 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 $\mu_{j,k}$'s. In order to

[3] We 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 5).

[4] We 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 our empirical application when we accounted for the visits in (n-2) occasion, it did not significantly change the relative costs across channels. Neither did it improve the model fit.

identify the coefficient β_j as well as μ_j and $\mu_{j,k}$'s, we set $\mu_{j,0}$'s to be 1. Other than the short-term 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 coming through channel *j* at occasion *n* is W_{ijn} (Equation 5). τ is the scale parameter associating the visit decision with the purchase decision. We assume that the overall attractiveness of purchasing a product/service can vary along some mean attribute level of the offering (Erdem and Keane 1996). In our context, since the hospitality service in every purchase is unique and distinct, and thus could be a new experience to the consumer, we 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 his 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 $W_{i0n} = 0$.

$$W_{ijn} = \bar{W}_{ijn} + \zeta_{ijn} = \gamma_{ij} + \sum_{k=1}^{J} \gamma_{j,k} G_{ikn} + \zeta_{ijn}, \qquad j = 1, \ldots, \mathrm{J}, \tag{5}$$

The intercept γ_{ij} is set by prior experiences and the expectations of the attractiveness of purchasing through a channel. For example, a customer going to the firm's website through a click on a display ad or an e-mail or through a coupon/referral site may have some mean expectation of the attractiveness of the purchases the customer might make. The overall attractiveness of making a purchase is then updated by the information collected 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, 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 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 visits 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 instantaneous influence of channel k compared with other channels can be picked up by the coefficients $\gamma_{j,k}$ in Equation (5).

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

Overall, the joint likelihood function in Equation (7) takes into account the consideration, visit and purchase stages. The model is estimated using the MCMC approach which provides a computationally tractable estimation of the large number of parameters in the model. Details of prior and full conditional distributions are provided in Web Appendix A.

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

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

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 their website[5]. The average monthly visits 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 (display ad and search engines), Omniture Site Catalyst (visits from different sources using cookies and login IDs), affiliate websites, and and 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 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 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 campaign and recipient 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. Visits through firm.com (direct), organic search and other visits are captured by Omniture Site Catalyst. Overall, the path data provides information on display impressions and e-mail drops to each customer and whether they were clicked or not,

[5] 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, and social media. E-Mail channel represents the visits by a visitor who has received an e-mail and clicked the link embedded in the e-mail. It also includes visits from e-confirmation and pre-arrival e-mails. Finally, Display channel represents those visits made to the website by clicking on a display banner ad.

click through visits from search engines (organic and paid), referral sites, and direct visits. It does not consider visits to search engines that did not result in a click-through to the firm's website, but this is captured by the outside option in the visit stage of our 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. There were about 4% - 6% of the cookie IDs that we were not able to match with any browsing information on the firm.com.

One concern of the firm-initiated channels is the potential endogeneity due to the strategic targeting. This problem is somewhat mitigated in our data as e-mail is not specifically targeted, but sent to all past purchasers and all visitors with e-mail registration, irrespective of which channel they usually visit. With respect to display ads, 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 levels, we estimated the incidence of display impressions and conversions across customers' visits through different channels, and as well as across different loyalty tiers. A similar exercise was conducted 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 1997 unique visitors to the firm's website. We track each visitor's 68 day history[6] containing whether an online visit was made each day, through which channel, and purchases, if any. In our data, the average time between the first visit since the last 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 purchase decisions. We applied stratified sampling based on the number

[6] We also estimate the model with only 30-day data and find the results are very close to the findings to be reported in the "Model Estimates" subsection. The data window does not make much of a difference, because the carryover and spillover effects wear out within 10-15 days based on the decay parameters estimated (see subsection Model Estimation).

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 us to 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. Overall, 815 customers made 1,128 purchases over the study duration. As seen in Table 2[7], the conversion rates in each channel vary significantly with display being the lowest and paid search being the highest.

< Insert Table 2 about here>

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 leading to a direct visit happens 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*, while each row shows the number of all prior visits. For example, before all the visits in an organic search, 3,307 visits happened in organic search channel, 934 visits in paid search channel, and the prior visits in referral, direct, e-mail, and display are 1,445, 1,621, 862, and 862, respectively.

< Insert Table 3 and 4 about here>

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 MCMC iterations, after 20,000 iterations used as burn-in. In

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

order to check the convergence of the model estimates, we use the Geweke diagnostics (Geweke 1992), the Gelman and Rubin diagnostics (Gelman and Rubin 1992) and the effective sample size (Kass et al. 1998) to assess the convergence of the model estimates. We investigate the iteration plots and use the Geweke convergence test where we compare the estimated parameters based on the first 1,000 iterations, the 2,001-3,000 iterations, and 4,001-5,000 iterations after the burn-in period to confirm the convergence to stationary posterior distributions of the parameters in the proposed model. We run two additional chains with two different sets of initial values for the proposed model, respectively. One has 25,000 iterations burn-in and the other 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 range 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 (ESS) is 612.6 for all parameters. Most of the ESS are between 400 to 700, which show the samples from the posterior distribution are not highly auto-correlated with earlier samples.

< Insert Table 5 about here>

Consideration stage. We 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, and Rewards Level-1 through Rewards Level-4). We expect the membership levels to act as a proxy for the consumers' experience, affect and commitment towards the firm's brand and capture their impact on the channels they would consider when visiting the website. As shown in Table 5, a non-rewards program member is more likely to consider an 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 visits as compared to the Rewards Level-1 and Rewards Level-

2 members. The estimate for direct visits is lower for Rewards Level-4 than that of Rewards Level-3 (0.94 versus 1.92). This counter-intuitive result can be explained by the fact that Rewards Level-4 is bestowed to many individual customers who have corporate affiliations and 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 paid search together (correlation coefficient .69) and referral and direct visits together (correlation coefficient .87). Overall, we find a 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 coming 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 (reducing the costs). This could be due to cognitive lock-in effects (Johnson, Bellman, and Lohse 2003), mere exposure effects, reinforcement learning effects and risk reduction kicking in with increased experience in visiting through customer-initiated channels, thereby reducing the costs of re-visiting. 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 would do so at their first exposure rather than later ones 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. 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 cost 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 the 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 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). 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. 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 (-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 these channels much more significantly than 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 in the current visit. We find that the carryover effects of firm-initiated channels are significantly contributing to increased purchase probabilities. These results are consistent with extant research which suggests that the exposures to display banner ads seem to be processed at a pre-attentive level and may benefit ultimate purchase (e.g., Dreze and Hussherr 2003; Manchanda et al. 2006). Specifically, Manchanda et al. (2006) find the number of display impressions as well as the number of sites and pages containing the display ads all have a positive impact on the repeat purchase probability. A recent ComScore report also finds the banner ads impression could be more influential in leading to conversions than the click-throughs (Lipsman 2012). 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 are indicative of a higher likelihood of purchase. The carryover effect of direct visits is also positive, consistent with Bowman and Narayandas (2001)'s 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 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 the informational stock of display on referral channel which is significantly negative. This may indicate that customers who visit through display click-through very often may use the referral channel for gathering additional information but may not consummate the 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 spillover 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 leads to ultimate conversions during paid search and direct visits. Overall, our results have shown significant carryover and spillover effects both at the visit and purchase stages.

The estimated decay rates of information gathered in a channel provide insights on how fast the informational stock accumulates in each channel. We 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 channels are in the 2% range. While the informational value of an e-mail is understandable given that it can be retrieved and used again, the informational value of searches also having long-lasting impact is an interesting and useful finding. This may indicate that search, even if it occurs earlier in the purchase funnel, has some impact on the ultimate conversion.

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 out-performs all of them (we also examined the fit across channels with posterior predictive check in 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, 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[8]. 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 6 about here>

[8] Other than the explanatory variables of visit stage and purchase stage reported in Table 5, we added the loyalty tiers into the visit stage or the purchase stage, and the Log Marginal Likelihoods were -14703 and -14147, respectively. Another alternative model we ran was to use 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 -14897. In all above cases, the proposed model fits the data better than these alternative models.

Model Predictions

We check the predictive validity of the proposed model and the best alternate model in terms of MAPE (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 7 compares the predicted number of purchases through different channels in the hold-out 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, 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 7, we 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 we predict day 7, we still use the historical data up to day 0 and not using day 1 through day 6 observed data in the prediction. The reason for this test of predictive power is that we will be using the proposed model for prediction when paid search is turned off for a week (discussed later in the field study subsection). It is in the 7-day forecast that the advantage of our proposed model is evident as it performs much better than Model 2. While the observed purchases number 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 7 about here>

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

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 predict the probabilities of conversion without e-mails. The difference between the predicted number of conversions with and without e-mails should provide us 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 the Shapley value in game theory (Shapley 1953), we calculate the total contribution of each channel in leading to a conversion by averaging their incremental contributions in all possible channel combinations. See Appendix C for an illustration using the Shapley value to calculate the marginal contribution of a channel. Based on this analysis, the last 2 columns in Table 8 show 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) the 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 our model, use only path data which ended in conversions and exclude all non-conversion data. We provide the Bayesian confidence intervals for the estimated contribution of each channel in Web Appendix D.

< Insert Table 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, our 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% (a 36% reduction as compared to the last-click model), while paid search decreases to 6% (a 40% reduction) and drops to the last rank. While referral channel climbs to the second rank with 24% (a 33% increase in contribution), 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 would have far-reaching implications for ROI 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 direct channel, which could explain the drop in its attribution, although direct channel 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' loyalty tiers (Rust and Verhoef 2005), but we find 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 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, 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 through November in 2011, where for one week, November 3 through November 9, the firm shut down the paid search option completely. Using this validation sample, we 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. Note that our 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 visit. Since we have explicitly modeled the consideration set of consumers, we can constrain consideration probabilities of 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% 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. However, 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 9 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 our model in predicting conversions when a specific channel is not available, and illustrates how our 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, we 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 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%) 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 page of organic search results. Thus, when paid search is off, it appears that many 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 search conversions, the recapture rate of paid search conversions when pausing paid search 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. Since the model provides us the estimates of the impact of previous visits (the lag estimates in Table 5), it is possible to predict for a customer, given his/her visits to the firm's website to date, the probabilities 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 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 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 our illustration, we focus our analysis only on customers who have already been targeted with e-mail interventions in their past. Thus, our 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 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, 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 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 they spend the initial investment on their e-mail campaign system. Assume the revenue of one conversion is $100. The economic value of delivering an extra e-mail in this situation is (0.474-0.447)*$100 = $2.7. Considering the number of e-mails sent by the firm, identifying the right customer to target implies a significant size of revenues.

< Insert Table 10 about here>

Table 10 provides many scenarios in which the best option for the firm is to not 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 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 our approach for retargeting customers with marketing interventions. If the customers' history of touches 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 customer 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 incorporated 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.

Conclusions

We have proposed a conceptual framework to understand 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-initiated and customer-initiated channels, using individual-level data on customers' touches, visits and purchases through these channels over time. Ours is the first study, to our knowledge, which examines these effects in the online channel context at the distinctly different stages – visit and purchase. Our 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 budgets across marketing channels and for targeting strategies. We will first examine the implications for the specific context we have studied, and then discuss the more general implications.

Implications for the Focal Firm

Our 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 through other channels 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 to investments in firm-initiated interactions. Considering all the impact, the contribution of e-mail and display ads to conversions is significantly underestimated by the last-click metric. 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 to complete purchases. The impact of paid search and direct channels are also diminished. Given that the changes in attributions based on our proposed model are considerably different (ranging from -40% to +75%), it clearly implies a different allocation of the marketing budget. The focal firm in our 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 our 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. Our 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 understanding the efficacies of each channel, in each period.

While 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 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 our 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. Also, recent reports (Mattioli 2012) suggest that retailers are finding that overuse of e-mails actually annoy many customers and thus become less effective. Thus, our model can be used for customized targeting using path analysis to identify cases where e-mail and display retargeting are likely to contribute to higher conversions.

Our model allows us to estimate how conversions through different channels are affected when a 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 an organic search. Since the firm in our example has a strong brand and ranks very high in an organic search, we conjecture that many of the branded keyword searches that could have occurred through paid search are recaptured through organic 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 click-through and e-mail click-through have a significantly longer impact than a display-ad click-through. This implies that a search, even if it occurs earlier in the purchase funnel, had some impact on ultimate conversion. Identifying the specific search keywords having such impact early in the purchase funnel might be useful from the tactical viewpoint of increasing customer acquisition.

General Implications

It is clear from our study that the last-click attribution metric or the 7-day average metric are not 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. While they may provide passable results in product categories with very short purchase decision hierarchy (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 – consumer durables and travel services – and for firms with multiple channels, both customer-initiated and firm-initiated. In the latter case, we also expect that the effectiveness of firm-initiated efforts will be underestimated using the last-click model, 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 spend, with the channels whose impact is underestimated by conventional metrics getting more budget allocation and those whose impact is overestimated getting lower allocation.

Our results suggest that the incremental impact of paid search channel may not be as high as what the last-click model suggests, 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. We conjecture that the stronger the brand, the lower the incremental effect of paid search on ultimate conversion. Our 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 the 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 our 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, our modeling framework allows us to accurately predict the conversions through different channels when one of them (for example, 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 allows the firm to offer cheaper alternatives to them (e.g., e-mail).

Limitations and Future Research

Given that our model is estimated using secondary data and not experimental data, there is a possibility 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). 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 their affordable choice within the target firm. To minimize selectivity bias, we can compare the results of our analyses on different cohorts of visitors separated by 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 (see Web Appendix F for the discussion on competition effects).

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. Additionally, 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 lacks detailed demographic information and prior purchase information. In addition, at the purchase stage we do not use data on prices and promotion, and the attributes of the property that visitors could view before making their choices. Future research with such data can extend the analyses of carryover and spillover effects to different segments of customers, accounting for customers' heterogeneity in preference and price response parameters and provide managers with actionable guidance with respect to each segment.

We have currently 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. Long term dynamic changes in search behavior and purchase decisions can be examined using structural models with appropriate long term data. This could be a possible extension to our study. We do not model the supply-side decision such as targeting customers in e-mail campaigns, selecting locations for banner ads, or the keywords to bid on for paid search, yet the data of the conversion path is conditional on the above decisions that the firm has already made. Given this endogeneity, our model measures the relative effectiveness of these channels, conditional on the decisions made by the firm. To examine the impact of marketing interventions under policies very different from the ones being used, modeling supply-side decisions would be very useful. We leave this for future research.

Finally, the model we have developed has a broader application beyond the B2C context. For example, in business markets, sales conversion is often preceded by multiple vehicles of marketing efforts such as trade shows, direct mails and e-mail campaigns, salesperson visits and so on, and our framework and methodology should be well suited to analyze such contexts.

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Tables

Table 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.

Table 2
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
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 4
n^{th} 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 5
MODEL ESTIMATES

Channels	*Organic Search*	*Paid Search*	*Referral*	*Direct*	*E-Mail*	*Display*
Variables	*(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.
† indicates carryover effects.
‡ indicates spillover effects.

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%	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)
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 na ïve model with only channel specific constants at the visit stage and purchase stage.

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	2905	2860	2%	3137	8%

MAPE is mean absolute percentage error.
Model 2 has only the visit and purchase stages; that is, each consumer considers all channels.

Table 8
CONTRIBUTION TO CONVERSIONS

Channel	***Observed***	***Last Click*** *%*	*Ranking*	***7-day Average*** *%*	*Ranking*	***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 9
PREDICTED CONVERSIONS – FIELD STUDY

	Assuming Paid Search On		***Assuming 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 10
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	.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.

Figure

Figure 1
CONCEPTUAL FRAMEWORK