

Which Clicks Lead to Conversions?

Modeling User-journeys Across Multiple Types of Online Advertising

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Keywords: Online Advertising, User-journey, Consumer Behavior, Purchasing Probabilities, Clickstream Data, Bayesian Analysis, Mixture of Normals.

Abstract: With an increase in the potential to allocate financial online advertising spending, managers are facing a sophisticated decision and allocation process. We developed a binary logit model with a Bayesian mixture approach to address consumers' buying decision processes and to account for the effects of multiple online advertising channels. By analyzing data from a medium-sized online mail order business, we found inherent differences in the effects of consumer clicks on purchasing probabilities across multiple advertising channels. We developed an alternative approach to account for the different attribution of success of advertising channels—the average success probability (ASP). Compared to standardized metrics, we found paid search advertising to be overestimated and retargeting display advertising to be underestimated. We further found that the mixture approach is useful for considering heterogeneity in the individual propensity of consumers to purchase; for the majority of consumers (more than 90%), repeated clicks on advertisements decrease their probability of purchasing. In contrast with this segment, we found a smaller segment of consumers (nearly 10%) whose clicks on advertisements increase conversion probabilities. Our approaches will help managers to better understand consumer online search and buying behavior over time and to allocate financial spending more efficiently across multiple types of online advertising.

1 INTRODUCTION

In the last decade, the options for online advertising have become increasingly complex. With the increase in options to allocate funds for online advertising, managers have sophisticated decisions to make. Standardized ratios that evaluate the profitability of advertising campaigns are only partly helpful in evaluating the short- and long-term effects of specific advertising channels; such ratios do not address the consumer process that begins with becoming aware of a product or brand through specific channels, such as display or paid-search advertising. This problem may be clearly illustrated with the following example.

Suppose we are a company that is engaged in online advertising and we follow a user in his daily routine of Internet surfing; he checks his email, visits his favorite website, reads his blogs, etc. He sees dozens of display advertisements, including video, social media and, retargeted advertisements. Perhaps he clicks one or more advertisements, and maybe he even clicks on one of *our* advertisements; unfortunately, he does not purchase anything. After a few

hours have passed, he sees a display advertisement on Facebook and clicks again on one of our advertisements but does not purchase. He might remember our company and our products and search for us using a search engine such as Google or Yahoo; finally, that *specific* user buys something from our company, and our advertising activities have been effective. Such a user-journey across multiple types of online advertising is illustrated in Figure 1.

However, to measure the overall effectiveness of specific online advertising channels it is important to evaluate which advertisement was crucial for the user to become aware of our company and products. On which type of online advertising should we spend more to increase our chances of acquiring new consumers in future?

Companies often use standalone metrics to evaluate the profitability of specific online advertising campaigns. However, these metrics do not capture consumers' decision-making processes over time and do not account for the interaction effects between multiple advertising activities.¹ Although there have been

¹The profitability and effectiveness of online advertising

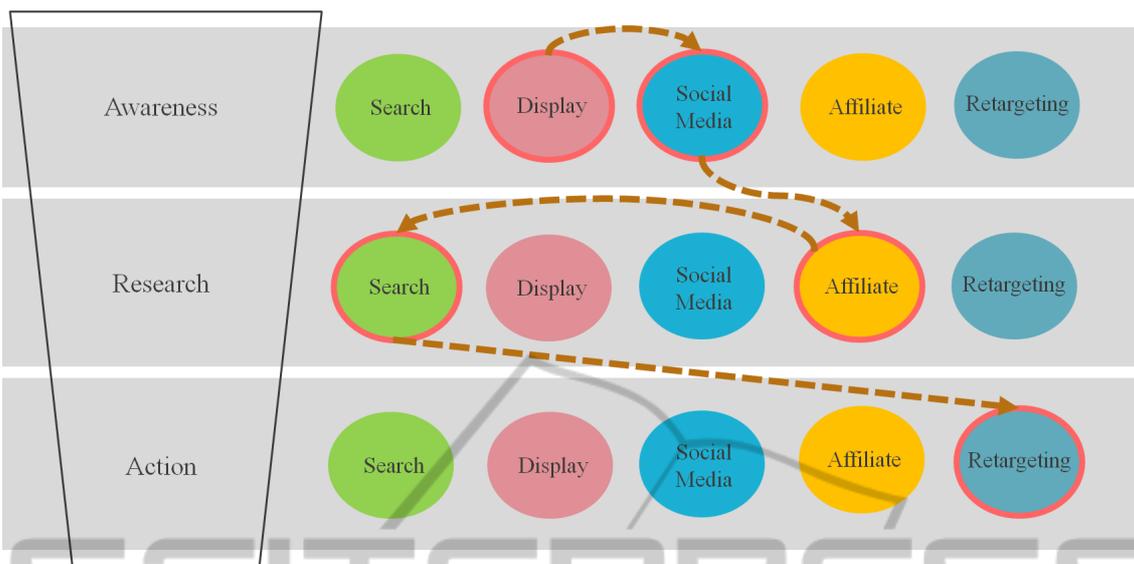


Figure 1: Illustration of a User-Journey Across Multiple Types of Advertising.

attempts to attribute online sales success to multiple types of online advertising (uniquedigital, 2012), the effect of advertising on the individual behavior of consumers has not yet been comprehensively analyzed.

We build on the specification of Chatterjee et al. (2003), who model the probability of a consumer to click on a display advertisement using a binary logit with a normal prior distribution. However, we extend their specification in two principal ways. First, we model the probability of consumers purchasing by including *multiple* advertising channels to address the complex allocating processes used by companies today to manage online advertising campaigns (such as display advertising, social media, and paid search advertising). Second, we employ a Bayesian mixture of normals approach, which offers more flexibility to address consumer heterogeneity than standard normal prior distributions (Nottorf, 2013; Rutz and Bucklin, 2011). The proposed model uses anonymized user-level data to help managers understand the effects of specific advertising channels on individual consumer behavior and online purchasing processes.

This paper is structured as follows. First, we will briefly review previous research related to this work. Second, we will examine the general model specifica-

campaigns may be assessed by using different ratios, such as click-through rate (CTR), which is the ratio of clicks to impressions for a specific type of advertising; conversion rate (CVR), which is defined as the number of purchases in relation to the number of clicks; and cost per click (CPC) and cost per order (CPO) as measures of the efficiency of promotional activities (Athey and Ellison, 2009; Nottorf and Funk, 2013a).

tion and extend the previous work of Chatterjee et al. (2003) to model consumer probabilities of purchasing after clicking on multiple advertising channels. This section is followed by the introduction of our unique dataset that includes detailed user-journeys and consumer interactions with multiple types of online advertising. After outlining our findings and discussing our results, we conclude this work by highlighting its limitations and providing suggestions for future research.

2 RELATED WORK

This work is related to several streams of research because we analyze *multiple* online advertising channels and their influences on consumer online purchasing behavior.

An emerging stream of research is analyzing paid search advertising from the advertiser's perspective and providing important initial insights into consumer clicking and purchasing behavior (see, for instance, Ghose and Yang (2009), Rutz et al. (2012), or Rutz, 2011c). For example, Rutz et al. (2011) analyze the long-term effects of consumers' online search activities on subsequent direct-type-in visitors and develop a hierarchical Bayesian elastic net to address the "large p, small n" problem. The authors demonstrate that normal ridge and LASSO regressions push the limits when analyzing the effects of thousands of keywords that are normally used in companies' paid search advertising campaigns.

Focusing on display advertising, Chatterjee et al. (2003) and Rutz and Bucklin (2011) find signifi-

cant heterogeneity in the propensity of consumers to click on banner advertisements. In addition, Danaher and Mullarkey (2003) introduce user involvement as an important factor that influences the effectiveness of banner advertising; characterizing user intentions as either goal-directed or in surfing mode indicates that there will be significant differences in the effectiveness of banner advertising. Goldfarb and Tucker (2011) show that the synergies between different types of banner advertising are negative; targeted and obtrusive banner advertising campaigns independently increase the purchase intent of consumers, whereas combining them is less effective.

Limited research has investigated the online behavior of users while considering multiple advertising channels simultaneously (Neslin et al., 2006; Neslin and Shankar, 2009). Previous research on media synergy effects has primarily focused on within-media interaction effects of offline advertising efforts, such as television, radio, and print (Bass et al., 2007; Naik and Raman, 2003), or model cross media synergies between offline and online advertising types (Ansari et al., 2008; Deleersnyder et al., 2002; Ilfeld and Winer, 2002; Naik and Peters, 2009).

Although studies of paid search advertising have increased significantly over the last several years, there have been few attempts to examine an integrated model of online advertising efforts, for example, to explain the effects of the interaction between display and paid search advertising. Although various types of online advertising arrived in the last decade, scientific works on cross channel advertising effects focused on modeling data that is aggregated on a specific time scale (e.g., week or day) on a specific type of advertising channel (e.g., “display” or “search”).

Although certain studies have focused on the effects of several types of online advertising, such as display and paid search advertising (Dinner et al., 2011; Wiesel et al., 2011), such studies do not investigate the influence of these types of advertising on the online behavior of individual consumers as a result of aggregation biases (Abhishek et al., 2011), and they do not consider the interaction effects of different types of online advertising activities on consumers. The possibility of “following” individual users across multiple types of online advertising is relatively new; user-level data is collected through cookie tracking by companies’ advertising-servers. Nottorf (2013) and Nottorf and Funk (2013b) employ such data to analyze the effects of repeated paid search advertisements and banner, video and retargeted display advertising on consumer click probabilities; they find both differences in the effects of repeated advertising exposure across multiple types of display advertising

and positive interactive effects between display and paid search advertising in influencing consumer click probabilities.

We also use such user-level data to distinguish multiple types of advertising at the level of individual consumers. As opposed to Nottorf (2013) and Nottorf and Funk (2013b), we analyze the effects of multiple advertising-specific clicks on consumers’ individual conversion probabilities. Therefore, we contribute to existing research at several junctures because we analyze the effects of *multiple types* of online advertising—such as paid search advertising, display advertising, and newsletter mailings—on consumer *purchasing* behavior at the *individual user-level*.

3 MODELING INDIVIDUAL CONVERSIONS ACROSS MULTIPLE ONLINE ADVERTISING CHANNELS

3.1 General Specification

We extend the specification of Chatterjee et al. (2003) and follow Nottorf (2013) to model the probability of consumer i purchasing at time t in session s , and we consider multiple advertising channels. Therefore, we specify the following:

- advertising-specific *intercepts*, I_{ist} ,
- variables accounting for *short-term* advertising-specific effects, X_{ist} , and
- variables accounting for *long-term* advertising-specific effects, Y_{is} .

I_{ist} : *Advertising-specific Intercepts*

First, we define multiple advertising-specific intercepts that account for the probability of consumers purchasing after clicking on a respective advertisement. We include these advertising-specific intercepts because we expect consumers’ likelihood of purchasing to vary strongly with the types of advertising a consumer may click on. For example, while a click on a paid search advertisement is followed by a consumer’s active search for specific terms, a click on a display advertisement may occur more or less by accident. Chatterjee et al. (2003) denote this intercept as consumers’ click-proneness. Because we model consumers purchasing probabilities across multiple advertising channels, we denote these terms as consumers’ *advertising-specific*

conversion proneness. These intercepts become 1 if a consumer clicks on a respective advertisement and remains at 0 otherwise.

X_{ist} : Short-term Advertising Effects

While a consumer may not purchase after his first click on an advertisement within a current session, that probability may increase with subsequent ones. Furthermore, that probability of purchasing might also vary with the type of advertising the consumer repeatedly clicks on. Therefore, we include the number of consumer clicks on specific advertising channels within a current session. These variables should capture the *short-term effects* (i.e., session-length of one hour) of advertisement-specific clicks on an individual consumer's conversion probabilities. If a consumer does not click on a specific type of advertising in a current session, the respective variable remains at 0.

Y_{is} : Long-term Advertising Effects

The *long-term effects* of advertising clicks on consumer conversion probabilities must also be modeled. We accomplish this because we account for the number of *all* advertising-specific clicks and not just those in a current session. We expect the long-term effects of clicks on conversion probabilities to strongly vary across consumers (Danaher and Mullarkey, 2003; Rutz and Bucklin, 2011); while we expect the effect of repeated clicks on specific advertisements to be positive for certain consumers (i.e., each click in their respective user-journey increases the awareness that a company might be relevant for their buying process), an increase in clicks on specific advertising channels may decrease the probability of purchasing for other consumers (i.e., no matter how often these consumers click on a specific ad, they cannot be convinced to purchase something). If a consumer does not click at all on a specific type of advertising, the respective variable remains 0.

To model the individual contribution of each advertising effort and its effect on consumer conversion probabilities, we specify a binary logit choice model (Chatterjee et al., 2003). The probability that consumer i converts subsequent to a click on an online advertisement at time t in session s is modeled as follows:

$$Con_{ist} = \begin{cases} 1 & \text{if user } i \text{ converts at time } t \text{ in session } s \\ 0 & \text{otherwise,} \end{cases} \quad (1)$$

with the probability

$$Pr(Con_{ist} = 1) = \frac{\exp(I_{ist}\alpha_i + X_{ist}\beta_i + Y_{is}\gamma_i + \varepsilon_{ist})}{1 + \exp(I_{ist}\alpha_i + X_{ist}\beta_i + Y_{is}\gamma_i + \varepsilon_{ist})} \quad (2)$$

where I_{ist} are advertisement-specific intercepts modeling the consumers' individual likelihood (prone-ness) of conversion after clicking on a respective advertisement. X_{ist} are variables varying within (t), across sessions (s), and across consumers (i), whereas Y_{is} are variables varying across sessions (s) and consumers (i), and α_i , β_i , and γ_i are consumer-specific parameters to be estimated.

3.2 Variable Specification

The variable X_{ist} includes the number of consumer advertising-specific clicks within a current session. Furthermore, we follow Chatterjee et al. (2003) and define the following additional variables incorporated in X_{ist} : $x_{is(t-1)}^{con}$ is the cumulative number of conversions until $t-1$ in the current session s for a specific consumer i , and $Con_{is(t-1)}$ is an indicator function that assumes the value 1 if a consumer has already purchased in $t-1$. We assume both variables to have a negative influence on subsequent consumer conversions; if a consumer has already bought something in $t-1$ or within his current session s , it might be highly unlikely that he will purchase again in the short-term. Furthermore, we define $TLCon_{ist}$ as the logarithm time since a consumer last made a conversion; if a consumer has never purchased, the variable remains zero.

Modern tracking software also allows companies to capture consumers' on-site clicks and on-site time. The former refers to the number of clicks a user has made on the company's website after he gets redirected by clicking on an advertisement, whereas the latter denotes the time the user browses through the company's website. Therefore, we include the cumulative number of on-site clicks of a user i within session s until time t as $x_{ist}^{Onsite-clicks}$ and the cumulative logarithm on-site time as $x_{ist}^{Onsite-time}$. We propose that a user shows a higher involvement in the purchasing process with increasing on-site time and clicks, which may increase the probability of a user to convert.

The same might hold true for the number of brand-related activities. We therefore also include x_{ist}^{Brand} , which refers to the cumulative number of brand-related clicks made by user i within session s until time t , and $Brand_{ist}$, which is an indicator function assuming 1 if a consumer i performs a brand-related activity at time t in session s . We define a brand-related activity as a click on an online advertisement

that accompanies prior brand-related knowledge. For example, if a user clicks on a paid search advertisement after searching for brand-related terms (i.e., the keyword includes the name of the company in question, such as “Staples pen” instead of just “pen”), we denote that click as a brand-related click. The same holds true for users’ direct visits to the company’s website (i.e., the user directly types the name of the company’s website into the web-browser or uses bookmarks).

Y_{is} accounts for the long-term effects of advertisement-specific clicks on consumers’ individual conversion probabilities, i.e., the cumulative number of clicks on a specific advertisement per consumer i until session s . Furthermore, $y_{i(s-1)}^{\text{con}}$ is the cumulative number of conversions in previous sessions. $y_{is}^{\text{onsite-clicks}}$ and $y_{is}^{\text{onsite-time}}$ refer to cumulative on-site clicks and time, respectively. The total cumulative number of brand-related clicks is modeled by y_{is}^{Brand} . IST_{is} is the logarithm of the intersession duration between session s and $s - 1$; it remains at zero if a consumer is active in only one session. Session_{is} refers to the number of sessions in which a consumer has already clicked on advertisements.

3.3 Data

We use a dataset from a regular online shop that will remain anonymous, at its own request. The dataset consists of information on individual consumers and the point in time at which they clicked on different ads, such as retargeted banner and paid search advertisements. Following consumers across multiple advertising channels and types is performed with cookie-tracking software and respective advertising servers. The data was collected within a one-month period (between 2012 and 2013). To analyze clickstream data, we take into account only those user-journeys that have more than three advertising touch points. The final dataset still consists several thousand users.²

Further, the dataset contains information about the following types of advertising that a user has clicked on:

- *Search*. If a user has searched for a keyword, if the company in question advertises on search engines such as Google, and if the user clicked on a respective *paid search advertisement* of that company, then we denote this interaction as a “search” click. Furthermore, the company in question is listed on the results page of a search engine if

²The datasets have been sanitized for reasons of confidentiality.

a user searches specific keywords for which the company has been classified as “relevant” by the search engine. If a user clicks on links of such *organic* results page listings, we also denote this interaction as a “search” click.

- *Price*. Companies might pay for becoming linked on *shopping comparison sites* such as Nextag. If a user compares the price of a product and clicks on a link of the company in question, we denote this interaction as a “price” click.
- *Retargeting*. Display advertisements, such as banners, may be individualized on a user-specific level. For example, if a user searches for a specific product and gets redirected to the website of a company, the company might individualize the display advertisements in a user’s later browsing routines to the extent that it *re-targets* the specific user and displays the specific (or related) product in the banner advertisement that the user was originally looking for at the company’s website. We denote users’ clicks on such retargeted display advertisements as “retargeting” clicks.
- *Direct*. If a user directly visits the website of the company in question, for example, via bookmarks or *direct-type-ins*, we denote this interaction as a “direct” click.³
- *Other*. There are other types of advertising contacts, such as *social media* or *newsletter mailings*. Because of their minimal total advertising contacts, we aggregate them and denote a user’s click on such types of advertising as an “other” click.

Table 1 lists the number of clicks on each type of online advertising.

Because there is no accessible information available on the number of consumer sessions and their duration, we manually define a session as a sequence of advertising exposures with breaks that do not exceed 60 minutes. Demographic information is not available. We report the descriptive statistics of our final dataset in Table 2.

3.4 Bayesian Mixture of Normals

Although the standard normal model as it has been applied by Chatterjee et al. (2003) to model consumers’ clickstream is capable of performing analyses with many consumers and properly accounts for heterogeneity (Allenby and Ginter, 1995; Lenk et al., 1996), we use a Bayesian mixture approach to account for

³Although direct visits are not any type of advertising, we will denote and treat it as an advertising channel for the sake of convenience.

Table 1: General Information on the Dataset.

clicks in total	100.00%
on search	51.42%
on price	16.15%
on retargeting	11.85%
on direct	14.95%
on other	5.63%
conversions	2.14%

Notes: We report the number of advertising-specific clicks, and the number of conversions within our dataset. For privacy reasons, the distribution of the advertising channels have been sanitized.

consumer heterogeneity and to determine the set of individual parameters. This mixture of normals approach enables us to find multiple cluster of users whose conversion probability is modeled *significantly* differently from those users of a different cluster (i.e., from a different normal distribution). For example, the conversion probabilities of one cluster of individual consumers may increase with each additional click on a specific type of advertising (wear-in effect), whereas the conversion probabilities of another cluster may decrease (wear-out effect).

For the sake of convenience, we denote the set of consumers' individual parameters to be estimated as:

$$\theta_i = \{\alpha_i, \beta_i, \gamma_i\} \quad (3)$$

Because we assume that the tendency of consumers to purchase will vary significantly (i.e., extensive vs. impulsive buying decision process), a mixture approach offers more flexibility for capturing heterogeneity than the standard normal approach (Rutz and Bucklin, 2011). This assumption is consistent with previous research that classifies the online searches of users according to navigational, transactional, or informational intentions (Broder, 2002) and indicates strong differences in the effectiveness of banner advertising with respect to consumer involvement levels (Danaher and Mullarkey, 2003; Nottorf and Funk, 2013a). We specify the Bayesian mixture approach, following Rossi et al. (2005):

$$\theta_i \sim N(\mu_{\text{ind}_i}, \Sigma_{\text{ind}_i}), \quad (4)$$

$$\text{ind}_i \sim \text{Multinomial}_K(\text{pvec}), \quad (5)$$

where ind_i is an indicator latent variable from which component observation i is derived. ind takes on values $1, \dots, K$, and pvec is a vector of mixture probabilities of length K . We use uninformative hyper-priors $\text{pvec} \sim \text{Dirichlet}(\alpha)$, $\mu_k \sim \text{Gaussian}(\mu_0, \Sigma_0)$, and $\Sigma_k \sim \text{Wishart}(\nu, V)$.

We apply a MCMC algorithm including a hybrid Gibbs Sampler with a random walk Metropolis step for the coefficients for each consumer and utilize the

Table 2: Descriptive Statistics of the Covariates.

Variables	min	max	mean	sd
Indicator Variables				
I_{ist}^{search}	0	1	0.26	0.44
I_{ist}^{price}	0	1	0.08	0.27
$I_{ist}^{\text{retargeting}}$	0	1	0.06	0.24
I_{ist}^{direct}	0	1	0.07	0.26
I_{ist}^{other}	0	1	0.03	0.17
Intraseession Variables				
x_{ist}^{search}	0	16	0.50	1.07
x_{ist}^{price}	0	286	1.23	13.96
$x_{ist}^{\text{retargeting}}$	0	13	0.09	0.44
x_{ist}^{direct}	0	46	0.12	1.00
x_{ist}^{other}	0	14	0.06	0.42
$x_{is}^{\text{con}}(t-1)$	0	3	0.01	0.11
$\text{Con}_{is}(t-1)$	0	1	0.01	0.09
TLCCon_{ist}	0	7.58	0.15	0.89
$x_{ist}^{\text{onsite-clicks}}$	0	450	2.31	8.95
$x_{ist}^{\text{onsite-time}}$	0	125	1.60	4.47
x_{ist}^{brand}	0	46	0.15	1.03
Brand_{ist}	0	1	0.09	0.29
Interseession Variables				
y_{is}^{search}	0	44	0.91	2.61
y_{is}^{price}	0	331	1.71	17.93
$y_{is}^{\text{retargeting}}$	0	33	0.31	1.66
y_{is}^{direct}	0	86	0.64	3.80
y_{is}^{other}	0	40	0.19	1.42
$y_{i(s-1)}^{\text{con}}$	0	65	0.11	1.92
$y_{is}^{\text{onsite-clicks}}$	0	510	6.28	24.64
$y_{is}^{\text{onsite-time}}$	0	364	4.08	15.24
y_{is}^{brand}	0	86	0.71	3.85
IST_{is}	0	7.66	1.26	2.02
Session_{is}	1	82	2.43	6.38

Notes: We report both the minimum/maximum and the mean/standard deviation of the covariates used in our study.

R-package bayesm by Rossi et al. (2005). We perform 40,000 iterations and use every twentieth draw of the last 10,000 iterations to compute the conditional distributions.

4 RESULTS

4.1 Benchmarking Alternative Models

We benchmark multiple model specifications by modifying the number of mixture components K . We compute the log likelihood (LL) and the Bayesian information criterion (BIC) to analyze fit performances. The latter criterion penalizes the incorporation of additional parameters—such as an additional number of

Table 3: Model Comparison: Benchmarking Fit Performances.

Model (Num. of Parameters)	LL	BIC
2 Mixture Components (56)	-253.9	374.4
3 Mixture Components (84)	-241.2	421.9
4 Mixture Components (112)	-241.2	482.2
Standard Normal Distribution (28)	-383.3	443.5

Notes: We report the log likelihood (LL) and the Bayesian information criterion (BIC) for both the proposed and alternative model specifications.

mixture components—in the model.

As reported in Table 3, the model with two mixture components performs best (BIC = 374.4). There seem to be *two cluster of consumers* who react differently to online advertising as the *two-mixture-components model* exhibits superior performance. The benefit of additional components does not increase the relative fit performance. As expected, the model that is reduced to a prior model with a standard normal distribution performs significantly more poorly than the models with multiple mixture components (BIC = 443.5).

4.2 Key Results

The parameter estimates for the two-mixture-component model specification are reported in Table 4. Our findings vary substantially across the two-component groups. The larger group, group 1, has a segment size of 91% and thus clearly represents the majority of consumers, whereas the second group, group 2, represents a segment size of 9%, which is a small number of consumers.

We report the results for the intrasession effects, intersession effects, and for the advertising-specific conversion proneness successively for both groups.

Intrasession Effects

Group 1, segment size of 91%

For the majority of consumers, represented by group 1 (the first component of the mixture model), we find the cumulative number of clicks on all types of advertising within a session to decrease purchasing probability (see $x_{ist}^{search} \dots x_{ist}^{other}$),⁴ i.e., the likelihood of consumers purchasing is highest after they have clicked for the first time on a particular advertisement and are redirected to the company’s website within a current session. For this segment of consumers, we

⁴The findings are significantly negative for x_{ist}^{direct} and x_{ist}^{other} .

find further differences in the effects of cumulative clicks during current sessions across different types of advertisements. For example, each additional *direct* visit ($x_{ist}^{direct} = -4.22$) and click on *other* advertisements such as newsletters or affiliate advertisements ($x_{ist}^{other} = -4.79$) significantly decreases consumers conversion probability, whereas we find that additional *search*, *price*, or *retargeting* clicks do not decrease the conversion probability significantly and are not as strong as the other two types. It seems that this group of consumers is either very goal-oriented (i.e., these consumers purchase immediately after they have clicked on an advertisement or directly visited the website of the company in question) or is insecure in their buying process because each additional click decreases their conversion probability.

As expected, the probability of consumers to purchase decreases if they have purchased in the last period ($Con_{is(t-1)} = -3.70$). The cumulative number of conversions within a current session is not significant and therefore does not affect further purchases (see $x_{is(t-1)}^{con}$). Contrary to expectations, both on-site time and on-site clicks have no significant influence on the conversion probability of consumers (see $x_{ist}^{Onsite-clicks}$ and $x_{ist}^{Onsite-time}$). Notably, information about brand-related activities does not influence consumers’ conversion probabilities significantly (see x_{ist}^{Brand} and $Brand_{ist}$). This result is surprising because we expected an increase in brand-related activities to reflect consumers’ intentions to purchase from the company.

Group 2, segment size of 9%

We now focus on the intrasession effects on consumer probability to purchase in the smaller segment represented by the second mixture component (see the right-hand side of Table 4).

For this small segment of consumers, we do not find the cumulative number of clicks on advertisements within the current session to significantly decrease conversion probabilities; we even find that each additional search with subsequent clicks significantly increases such consumers’ probability to purchase ($x_{ist}^{search} = 3.76$). Therefore, compared to the first segment of consumers, we uncover important differences in the effect of advertisements on consumer’s conversion probabilities.

Furthermore, both variables accounting for past conversions within consumers’ current session indicate a very strongly negative influence on future subsequent conversions (see $x_{is(t-1)}^{con}$ and $Con_{is(t-1)}$). As for the first segment, neither on-site clicks/time nor brand-related information significantly influences

Table 4: Parameter Estimates of the Two Component Mixture Model.

Variables	Group 1, segment size: 91%		Group 2, segment size: 9%	
	Mean	(95% cov. interval)	Mean	(95% cov. interval)
Indicator Variables I_{ist}				
I_{ist}^{search}	-6.09	(-9.17, -3.05)	-19.50	(-32.75, -6.49)
I_{ist}^{price}	-3.98	(-6.42, -1.57)	-13.30	(-26.01, -0.79)
$I_{ist}^{retargeting}$	-4.79	(-9.00, -0.57)	-12.44	(-29.65, 4.67)
I_{ist}^{direct}	-3.26	(-7.23, 0.68)	-15.00	(-33.92, 3.67)
I_{ist}^{other}	-4.06	(-7.40, -0.70)	-18.07	(-31.28, -5.02)
Intrasection Variables X_{ist}				
X_{ist}^{search}	-1.27	(-4.15, 1.59)	3.76	(0.54, 6.93)
X_{ist}^{price}	-2.38	(-6.02, 1.26)	0.44	(-20.43, 21.01)
$X_{ist}^{retargeting}$	-1.41	(-6.52, 3.69)	-6.87	(-21.61, 7.47)
X_{ist}^{direct}	-4.22	(-6.92, -1.52)	3.96	(-3.21, 11.06)
X_{ist}^{other}	-4.79	(-7.57, -2.00)	5.51	(-0.57, 11.57)
X_{ist}^{con}	0.38	(-2.66, 3.41)	-31.76	(-49.56, -14.23)
$Con_{is(t-1)}$	-3.70	(-6.38, -1.00)	-12.58	(-24.62, -1.07)
$TLCon_{ist}$ (logarithm hour)	-0.85	(-3.73, 2.13)	-10.67	(-27.27, 5.24)
$X_{ist}^{onsite-clicks}$	-1.05	(-2.95, 0.83)	0.46	(-1.61, 2.62)
$X_{ist}^{onsite-time}$ (logarithm hour)	-1.99	(-5.09, 1.02)	0.08	(-2.95, 3.16)
X_{ist}^{brand}	-1.94	(-6.35, 2.40)	0.86	(-3.31, 5.34)
$Brand_{ist}$	0.45	(-2.49, 3.40)	1.05	(-5.87, 8.05)
Intersession Variables Y_{is}				
y_{is}^{search}	-2.45	(-6.82, 1.91)	3.00	(-0.60, 6.63)
y_{is}^{price}	-3.76	(-8.73, 1.20)	4.83	(-2.19, 11.76)
$y_{is}^{retargeting}$	-1.20	(-6.41, 3.99)	5.71	(-2.24, 13.74)
y_{is}^{direct}	0.93	(-3.04, 4.93)	6.08	(2.03, 10.31)
y_{is}^{other}	1.83	(-1.66, 5.37)	-0.25	(-4.10, 3.64)
y_{is}^{con}	2.02	(-1.29, 5.33)	-19.27	(-45.00, 5.99)
$y_{is}^{i(s-1)}$	-1.57	(-3.74, 0.62)	-0.11	(-2.13, 1.85)
$y_{is}^{onsite-clicks}$	-0.67	(-3.39, 2.02)	0.42	(-2.42, 3.26)
$y_{is}^{onsite-time}$ (logarithm hour)	-1.45	(-4.59, 1.67)	-1.40	(-8.56, 5.78)
y_{is}^{brand}	-0.99	(-3.46, 1.47)	0.19	(-3.55, 3.99)
IST_{is} (logarithm hour)	-3.97	(-8.23, 0.23)	-1.58	(-6.30, 3.06)
$Session_{is}$				

Notes: We report the mean and the 95% coverage interval of the parameter estimates of our proposed model using two-mixture-component model. The estimates in boldface are significant as they lie in the 95% coverage interval.

consumers' conversion probabilities.

Intersession Effects

Group 1, segment size of 91%

We now focus on the long-term effects of clicks on consumers' conversion probabilities. By contrast to prior research that analyzed the long-term effects of repeated display advertisement exposures on consumers and found them to have a significantly positive influence on consumer click probabilities (Chatterjee et al., 2003), we do not find intersession clicks on any type of advertisement to significantly influence conversion probabilities for the large segment of consumers. There do not appear to

be any long-term effects of clicks on conversion probabilities for this group. On the one hand, this is extremely helpful information for the company in question because each consumer nearly has an identical conversion probability when entering a new session. On the other hand, if past clicks on online advertisements do not seem to affect consumer click probabilities, this information may lead managers to question what the long-term success rate of past advertising actually was.

As expected, there is no long-term negative influence of past conversions on future conversions (see $y_{i(s-1)}^{con}$). Furthermore, as for the short-term, there are no long-term effects of on-site clicks/time and brand-related activities on consumers' conver-

sion probabilities (see $y_{is}^{\text{Onsite-clicks}}$, $y_{is}^{\text{Onsite-time}}$, and y_{is}^{Brand}). Although the parameter estimates are barely not significant, an increase in the number of total sessions reduces consumers conversion probabilities ($\text{Session}_{is} = -3.97$).

Group 2, segment size of 9%

Compared to the first consumer segment, we again find inherent differences in the effects of clicks on conversion probabilities for the second consumer segment. For example, four out of five click types have a long-term positive influence influences the probability that they will purchase. For this small group of consumers, each *search*, *price*, *retargeting*, and *direct* click positively influences the probability that they will purchase.⁵ If we compare the influence of each click-type, we find that the cumulative number of *search* clicks does not have that strong of an effect on conversion probabilities as *retargeting* or *direct* clicks, for example (see y_{is}^{search} , $y_{is}^{\text{retargeting}}$, and y_{is}^{direct}). We consider these differences in the next section in formulating managerial implications.

Similar to the intrasession findings, the influence of conversions in prior sessions is negative on futures conversions ($y_{i(s-1)}^{\text{con}} = -19.27$). As with consumers in the first segment, the variables accounting for on-site clicks/time, brand-related activities and intersession time may be neglected (see $y_{is}^{\text{Onsite-clicks}}$, $y_{is}^{\text{Onsite-time}}$, y_{is}^{Brand} , and IST_{is}).

Advertising-specific Conversion Proneness

Group 1, segment size of 91%

Previous research indicates that the click proneness of consumers in response to display advertisement exposure is minimal (Chatterjee et al., 2003), and our findings also confirm this for advertising-specific conversion proneness. For the large segment of consumers, we find that the initial conversion probability is very small across all types of advertisement. Consumer proneness to purchase is smallest after consumers have clicked on companies' links through search engines ($I_{ist}^{\text{search}} = -6.09$). We find the highest probability of purchasing after consumers directly visited the companies website ($I_{ist}^{\text{direct}} = -3.26$) or after they clicked on comparison-shopping sites ($I_{ist}^{\text{price}} = -3.98$). This is not surprising because these two click types typically accompany a high level of intention to purchase

⁵Please note that only y_{is}^{direct} is significant, whereas the others are barely not significant.

(e.g., after comparing prices for a specific product or by directly visiting the company website to purchase).

Group 2, segment size of 9%

By contrast to the first segment that includes consumers with a low initial conversion probability that decreases with subsequent clicks, we find that the conversion probability of the second and smaller segment of consumers increases with subsequent clicks. By contrast to the first segment, consumers of the second segment show an even smaller initial probability to purchase. All five indicator variables accounting for the type of advertising show a much stronger initial and negative effect (see $I_{ist}^{\text{search}} \dots I_{ist}^{\text{other}}$). Our prior findings on the intrasession and intersession effects also have shown that this low conversion probability may be increased with subsequent clicks.

5 IMPLICATIONS

5.1 Real-time Bidding

The knowledge of a consumer's *individual* conversion probability and the respective degree of advertising-specific influence is vital to the relatively new and emerging field of real-time bidding (RTB) settings in which advertising is bought and displayed in real time on an individual consumer level. RTB provides a flexible option of matching individual consumers with suitable advertising content. Within milliseconds, advertisers place bids for individual advertisement impressions in an auction-based process (Way, 2012).

Assume that the company investigated here is active in a RTB setting and dynamically exposes consumers to display advertising. By accounting for consumers' complete user-journey and applying our parameter estimates, the company may be able to deliver display ads specifically to those consumers who have a higher probability of purchasing compared with consumers with a significantly lower probability of purchasing (i.e., consumers who clicked multiple times but never purchased).

5.2 Alternative Evaluation of Advertising Channels

In daily business, there are more- or less-simple heuristics to evaluate the success of multiple types of online advertising on an individual user-level (uniquedigital, 2012). In Table 5, we illustrate an alternative approach of evaluating the profitability of

Table 5: Alternative Approach of Evaluating Profitability of Advertising Channels.

Channel	Mean Estimates			Mean of Variables			ASP (<i>prop.</i>)		CVR (<i>prop.</i>)	
	α_i	β_i	γ_i	I_{ist}	X_{ist}	Y_{is}				
search	-7.30	-0.81	-1.96	0.26	0.50	0.91	1.65%	<i>(5.43%)</i>	1.65%	<i>(39.70%)</i>
price	-4.82	-2.13	-2.98	0.08	1.23	1.71	0.03%	<i>(0.03%)</i>	0.96%	<i>(7.25%)</i>
retargeting	-5.48	-1.90	-0.58	0.06	0.09	0.31	33.64%	<i>(25.46%)</i>	1.09%	<i>(6.04%)</i>
direct	-4.32	-3.48	1.39	0.07	0.12	0.64	54.23%	<i>(51.80%)</i>	4.86%	<i>(33.99%)</i>
other	-5.32	-3.86	1.64	0.03	0.06	0.19	48.01%	<i>(17.28%)</i>	4.94%	<i>(13.02%)</i>

Notes: We develop an alternative approach to evaluate the profitability of multiple advertising channels on the basis of individual user-level data and compare the average success probability (ASP) with the conversion rate (CVR). To calculate the proportional ASP (see the *italicized* number in the brackets), we take into account the total number of advertisement-specific clicks of the complete campaign/investigation period.

multiple advertising channels and contrast that approach with the conversion rate (CVR) of each channel type. We will develop that approach simplistically below because we are not focused on determining an *exact* success rate for each advertising channel. Instead we want to illustrate how it is generally possible to account for consumers' individual user-journeys and to evaluate multiple advertising channels in a more realistic way than companies currently are able. By so doing, we propose an alternative evaluation metric, the average success probability (ASP). The ASP can be interpreted as an advertisement- and campaign-specific contribution to companies' success probabilities because we account for both the short- and long-term advertising effects of the complete investigation period.

We begin the evaluation of each advertising channel by taking into account the mean (proportional for both mixture segments) of each advertising-specific parameter. For example, to calculate the mean estimates for the *search* channel, we take the sum of the mean parameter estimates for the respective parameter (I_{ist}^{search} , x_{ist}^{search} , and y_{is}^{search}) times the segment size (91% and 9%, respectively) over both segments:

$$\begin{aligned}\alpha_i &= 0.91 * (-6.09) + 0.09 * (-19.50) = -7.30 \\ \beta_i &= 0.91 * (-1.27) + 0.09 * 3.76 = -0.81 \\ \gamma_i &= 0.91 * (-2.45) + 0.09 * 3.00 = -1.96\end{aligned}$$

As illustrated in Table 5, a first simplification is that we only take into account those parameters that measure the advertising-specific influence directly. That is, we take the advertising-specific intercepts ($I_{ist}^{search}, \dots, I_{ist}^{other}$), the cumulative number of advertising-specific clicks within consumers' current sessions ($x_{ist}^{search}, \dots, x_{ist}^{other}$), and the cumulative number of advertising-specific clicks across all sessions ($y_{is}^{search}, \dots, y_{is}^{other}$).⁶

⁶Please note that because of simplifications and for convenience, we do not distinguish between significant and non-significant parameter estimates.

We take the sum of the mean parameter estimates multiplied by the mean of the applicable variables of the dataset that are reported in Table 1 and Table 5, respectively. The logits of each advertisement-specific product are reported as the average success probability (ASP) in Table 5:⁷

$$\begin{aligned}\text{ASP}^{\text{search}} &= \frac{\exp(-4.09)}{1 + \exp(-4.09)} \\ \text{ASP}^{\text{search}} &= 1.65\%\end{aligned}$$

The ASPs differ significantly across multiple channel types. For example, the *price* channel performs very poorly compared to the *retargeting* channel. In analyzing the complete investigation period and evaluating the proportional success of each advertising channel, we take into account the total number of respective clicks (as reported in Table 1) to calculate the proportional ASP (see *italicized* number in brackets).

The standard CVRs and their proportional success rate within the investigation period are reported on the right-hand side of Table 5. The ASPs calculated here offer the first advice on how future advertising spending should be allocated. Compared to the CVRs, we find that the *search* channel is overestimated (5.43% vs. 39.70%) and that the *retargeting* channel is underestimated (25.46% vs. 6.04%). These differences may be ascribed to the circumstance that consumers seem to be attracted by display advertisements—such as retargeted advertisements—at the early stages of their search-and-decision process before they conduct later searches and click on links of the company. In a test-setting, the company might increase its retargeting advertising spending chargeable to the search channel and then analyze the campaign profitability.

⁷Note that we multiply the mean parameter estimates with the mean of the respective variables: $-4.09 = -0.26 * 7.30 - 0.50 * 0.81 - 0.91 * 1.96$

6 CONCLUSIONS

We develop a binary logit model with a Bayesian mixture approach to model consumer clickstreams across multiple types of online advertising and analyze the individual conversion probabilities of consumers. The mixture approach we utilize outperforms the standard normal approach and is useful for considering heterogeneity in the individual propensity of consumers to purchase; for the majority of consumers (more than 90%), repeated clicks on advertisements decrease their probability of purchasing. Thus, for this segment of consumers, the probability of purchasing is highest after consumers' first click on an advertisement. In contrast with this segment, we find a smaller segment of consumers (nearly 10%) whose clicks on advertisements increase conversion probabilities.

We successfully demonstrate how to simultaneously integrate and evaluate multiple types of online advertising to gain knowledge that is indispensable to allocating financial resources. The evaluation of consumers on an individual level along their complete user-journey is essential to optimize the auction-based process, particularly in the emerging new advertising technology of real-time bidding.

Furthermore, we are able to show inherent differences in the effects of consumer clicks on purchasing probabilities across multiple advertising channels. Therefore, on the basis of our parameter estimates, we develop an alternative approach of accounting for the success of advertising channels—the average success probability (ASP)—which may be interpreted as an advertisement- and campaign-specific contribution to companies' success probabilities as we take into account both short- and long-term advertising effects of the complete investigation period. Compared to standardized advertisement-specific conversion rates, we find the “search” advertising channel to be overestimated and the “retargeting” channel to be underestimated.

In this paper, we analyze a large dataset containing detailed individual consumer-level information. Tracking individual consumers across multiple online advertising types is accomplished by the application of cookies that are stored on the personal computer of each consumer. Thus, we do not have combined information regarding consumer usage of web browsers across multiple devices (i.e., personal computers at work versus at home) and are thus unable to model complete sessions for all consumers. Furthermore, modern web browsers give consumers the opportunity to deny websites access their personal computers to store cookies.

Another limitation of this work is that we do not have any information on consumers' isolated exposures to online advertisements that have not been clicked. The long-term effects of unclicked online advertisements are thought to be positive on conversions (Yoon and Lee, 2007) but have not been analyzed yet on an individual user-level while analyzing multiple online advertising channels. We leave this question open for future research.

Further, there is room for research analyzing the effects of specific online advertisements on consumer online behavior. For example, the integration of consumer-specific information, such as gender or interests, might uncover further insights into consumers' individual online click and conversion probabilities. We also see the combination of aggregated data (that does not suffer from the cookie-deleting problem) with consumer-level data (as it is analyzed here) as an important and interesting topic for future research.

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