Online Advertising Response Models: Incorporating Multiple Creatives and Impression Histories

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ABSTRACT

Online advertising campaigns often consist of multiple ads, each with different creative content. We propose a model that evaluates the effectiveness of each creative in a campaign given the targeted individual's ad impression history, as characterized by the timing and mix of previously seen ad creatives. We examine the impact that each ad impression has on both visitation and conversion behavior at the advertised brand's website. Our model is constructed at the individual level and takes into account correlations among the rates of ad impressions, website visits and conversions. We also allow for the accumulation and decay of advertising effects, as well as ad wear-out and restoration effects. Our results highlight the importance of accommodating both the existence of multiple ad creatives in an ad campaign as well as the impact of an individual's ad impression history. We demonstrate with a simulation how this modeling approach can be used for online ad targeting. Specifically, our results suggest that, using our model, online advertisers can increase the number of website visits and conversions by varying the creative content shown to an individual according to that individual's history of previous ad impressions. For our data, we show a 12.7% increase in the expected number of visits and a 13.8% increase in the expected number of conversions.

KEYWORDS: Online Advertising, Advertising Response Modeling, Online Visitation and Conversion Rates, Bayesian Models, Targeting

Online Advertising Response Models: Incorporating Multiple Creatives and Impression Schedules

During the past decade, online advertising budgets have grown steadily, often at the expense of offline advertising budgets (Interactive Advertising Bureau 2010). Many marketers now prefer to advertise online because the interactive medium allows for the precise targeting of individual consumers. In this paper, we focus on banner advertising. While online targeting strategies have improved banner ad performance (Beales 2010), they have done so by using fairly straightforward targeting policies. For example, online ad networks examine individual clickstream histories to identify customers with an interest in a specific product category or brand. Interest is typically determined by whether the individual has previously visited webpages related to that product or brand. At the next advertising opportunity for that individual, the ad network then exposes that individual to an advertisement that matches his/her interests (e.g., computer ads would be shown to individuals who have recently visited computer review websites while car ads would be shown to individuals who have recently visited car websites).

Current online targeting practices have achieved rather impressive results by leveraging the online data associated with an individual's history of page views. However, little consideration has been given to an individual's history of ad impressions. That is, online advertisers typically treat an individual who has repeatedly seen a given ad in the same way as an individual who has only occasionally seen it, but in all likelihood, the former will be less responsive to the *next* exposure than the latter (Chatterjee, Hoffman and Novak 2003). This dynamic affects not only the decision of which product category to feature in the next ad exposure but also which of the creatives (versions of an ad) in the advertiser's portfolio of ads to serve.

Therefore, in this paper, we develop an individual-level advertising response model that measures the effect of a given ad impression in the context of an individual's impression history. Additionally, since many online ad campaigns include multiple advertising creatives, we also allow the effect of each impression to vary depending on the creative content associated with that impression. We then examine the individual's response in terms of future visitation and conversion behavior at the advertiser's website. This approach allows us to develop an attribution model that provides a measure of ad effectiveness for each creative in the campaign. Although advertising agencies often pretest ad creatives for the affect, attitudes, and brand associations resulting from an ad exposure, these tests usually occur in a controlled testing environment. The ability to attribute observed behaviors of interest in the field (e.g., site vists or sales conversions) to specific ads once the campaign is launched continues to be a challenge.

Methodologically, we employ a hierarchical Bayesian approach that models an individual's ad impressions, visits to the advertiser's website (as opposed to the website on which the ad is placed), and conversion behavior at the website, as three separate but correlated processes[1]. In concert with a long history of research on offline advertising effectiveness, we incorporate an advertising goodwill construct that allows: (1) advertising

[1] Each process has a baseline rate, and the visit and conversion processes depend on a scaled advertising effect. The intercepts and coefficients are considered random effects, whose distributions are modeled as priors in the Bayesian hierarchical model.

goodwill to accumulate and decay, (2) ad impressions to contribute differentially to goodwill according to differences in creative content, and (3) ad wear-out and restoration effects when individuals are repeatedly exposed to the ad campaign.

We develop and test our model against a dataset provided by a leading online advertising agency. The data represent individual ad impressions, visitation behavior and conversion behavior for a single advertiser. The content of this dataset is typical of online advertising data that advertisers routinely collect. Therefore, we specify a model that is tailored for such online data, while still incorporating several important theoretical and behavioral constructs from the offline advertising literature.

The implications of our research for online advertisers are significant. First, we provide a tool with which advertising researchers can measure the effectiveness of specific ad creatives in a larger campaign. Currently, available methods allow marketers to measure only the aggregate sales impact of overall campaign expenditures or the average click-through rates for specific online ad impressions. However, advertising response models have difficulty evaluating specific creatives in the campaign, and click-through rates ignore indirect effects on future sales (Manchanda et al 2006, Dreze and Herscherr 2003). In other words, it is currently very difficult to attribute future sales increases to individual ad creatives. Our method helps with this attribution problem.

Second, our model allows us to compute, for each individual, the expected response to a specific ad creative, given that individual's unique impression history. This provides online advertisers the opportunity to further refine their advertising targeting policies by considering individual impression histories. We demonstrate this application of our model by simulating a campaign in which the creative content shown to an individual is determined by our proposed model and is dependent on that individual's ad impression history. We compare the results of this simulated campaign to those of the impressions observed in the data. In our empirical example, we show how the advertiser, by customizing the creative content of ads based on individual impression histories advertisers, can achieve a 12.7% increase in the expected number of visits and a 13.8% increase in the expected number of conversions, compared to the policy that was actually employed. This is a strong testament to the managerial value of our proposed model.

This paper will proceed as follows. In the next section, we review advertising research, both online and offline, with a focus on the elements of previous research that should be incorporated into any model of online advertising response. From there, we present a description of the data, the specification of the model, and model results. After discussing our empirical results, we present a simulation that underscores the potential benefits of modeling both creative-specific effects and individual impression histories for online ad targeting.

Offline Advertising

Research on traditional "offline" advertising campaigns has provided convincing empirical evidence that advertisements have both short term and long-term effects on behavior. In a large-scale field experiment, Lodish et al (1995) showed that a temporary increase in advertising expenditures can result in sustained sales benefits that extend beyond the advertising period. In some cases, elevated sales were observed two years into the future. In a meta-analysis, Tellis (2009) also documented long-term advertising effects. Specifically, his study concluded that advertising carryover effects were twice as large as any contemporaneous effects. These studies emphasize the importance of allowing for both short term and long term advertising effects by considering the impact of advertising on both current and future behavior.

From a methodological perspective, Nerlove and Arrow (1962) proposed an advertising response model that highlights the long-term effects of advertising through a construct that they referred to as *goodwill*. In their model, goodwill accumulates with advertising expenditures but also decays from period to period. This dynamic of accumulation and decay has also been applied to the effect of advertising on awareness (Mahajan and Muller 1986). Specifically, aggregate brand awareness increases with advertising exposure but decreases as a result of consumers "forgetting" in the absence of advertising.

Other research has shown that the effect of any single advertisement is dynamic, and its impact is subject to both *wear-out* and *restoration* effects[2]. Wear-out refers to the decreased effectiveness of advertising copy over time. Naik et al (1998) differentiates between repetition wear-out and copy wear-out. Repetition wear-out results from repeated exposure to the ad while copy wear-out results from the passage of time. When there is a hiatus in advertising, restoration effects can reverse the repetition wear-out effects. During the hiatus, any degradation in ad effectiveness resulting from repetition wear-out is restored gradually. Mahajan and Muller (1986) have shown that these countering effects (wear-out versus restoration) can have significant implications for ad scheduling decisions.

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[2] Wear-in effects refer to increasing ad effectiveness as the number of ad exposures increase. These effects have been shown to be negligible (Tellis 2009).

From a methodological standpoint, a variety of different modeling approaches have been proposed to capture the aforementioned advertising effects (e.g., Little 1979; Feinberg 1992; Feinberg 2001; Vakratsas, Feinberg, Bass and Kalyanaram 2004). However, most studies, including those mentioned above, have been limited to aggregate response models, for which the dependent variable is total sales per time (and possibly per market). Although these aggregate response models can be valuable in planning offline media schedules at a market level, they are unable to address the online advertising challenge of measuring advertising effects when each individual is exposed to a unique ad schedule. Additionally, most advertising models have focused on examining the response to total advertising expenditures, despite the fact that many ad campaigns consist of a variety of different creative copy (different "versions" of the ad within a campaign). To our knowledge, there are no extant models that examine the effectiveness, or associated dynamics, of a specific advertising creative within a campaign[3]. This is again likely due to the fact that available offline advertising data is often aggregated across multiple ad creatives.

Online Advertising

Despite the shared interest in advertising, online advertising research shares few similarities with its offline counterpart. While advertisers in the offline environment tend to focus on long-term effects and brand building, online advertisers diligently (and almost exclusively) monitor performance metrics that can be observed immediately. Metrics such as

[3] We differentiate such attribution models that credit observed behaviors of interest to specific ad impressions from the practice of pretesting ads. In pretests, ads are evaluated in terms of how they affect attitudes, brand associations, etc. in a controlled testing environment. Our focus is on the advertisement's effect on observable behaviors after the campaign has been launched in the market.

click-through rates and conversion rates indicate an individual's immediate reaction to an advertising impression, but ignore any indirect effects that may result in changes in an individual's future behavior. Highlighting the limitations of these metrics, Dreze and Hussherr (2003) show that despite the fact that many individuals do not consciously attend to online ads and therefore do not click through on them, online ads still have a positive effect on brand measures which, in theory, translates to increased future sales.

Manchanda et al (2006) explore the delayed effects of banner ads on individual purchasing behavior. Rather than focusing on click-through or conversion rates, they show that increased exposure to banner ads shortens an individual's repeat purchasing rate[4], providing empirical evidence of the indirect effects of online advertising. They also show that the number of unique creatives an individual sees has a negative effect on repeat purchasing rates. This result seems to contradict the idea that advertising copy is subject to repetition wear-out.

One possible explanation for this negative effect of ad copy "variety" is that, like many of the offline advertising expenditure models, the Manchanda et al (2006) study does not accommodate differences in relative effectiveness across "creatives" in the ad campaign. Suppose, for example, an advertiser has developed two versions of an ad for a particular campaign, and that one of these versions is more effective than the other[5]. Then, an individual who is exposed to multiple creatives is more likely to have seen the less effective ad at the expense of an additional exposure to the more effective ad, than an individual who is exposed

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[4] Specifically, Manchanda et al (2006) model all repeat purchases irrespective of whether they resulted from a direct ad click-through or from manually entering the URL for the online retailer at a later time after being exposed to the ad.

[5] Many advertisers create campaigns that include multiple versions of the ad with the belief that increased variety will minimize advertising wear-out effects and therefore increase overall campaign effectiveness. In these cases, it is likely that each advertisement in the campaign varies in effectiveness.

to only one ad creative (assuming the advertiser planned more impressions of the more effective version of the ad).

Another complicating factor in the online advertising environment is the potential correlation between an individual's online behavior and advertising exposure. For example, a highly active browser will probably see more ads simply because he visits more sites (including the advertiser's site). Additionally, some online advertisers employ targeting policies that also lead to correlations between advertising exposure and behavior at the advertiser's site. For example, advertisers may target specific websites on which to place their ads based on the types of visitors the site attracts (e.g., an automobile brand will target potential car purchasers by advertising on automobile related sites). As a result, a car shopper is both more likely to be exposed to an ad and more likely to visit the advertiser's website[6]. In these cases, researchers need to careful to separate the causal effect of ad impressions on behavior from simple correlated effects.

Model Development

To address these issues and challenges, we propose an individual-level advertising response model that allows for (1) creative specific advertising effects; (2) wear-out and restoration effects on ad copy; (3) non-immediate and sustained effects of advertising on behavior; and (4) correlation between ad impression rates and site visit and conversion behavior. We examine these effects with respect to both visitation and conversion behavior.

[6] Some online advertising networks will employ more sophisticated (and costly) "behavioral targeting" practices, in which an individual is exposed to ads based on more detailed browsing histories across multiple websites. This kind of targeting could also result in similar correlations. The advertiser represented in our dataset did not employ these kinds of behavioral targeting techniques for this campaign.

To that end, we incorporate a goodwill construct, similar to that used by both Naik, Mantrala and Sawyer (1998) and Nerlove and Arrow (1962), that allows for both the accumulation and decay of advertising effects over time. Rutz and Bucklin (2011) use a similar construct that they call "Ad Stock" in their model of paid search advertising.

Ad Stock and Ad Effect

Specifically, we define E_{it} as the contemporaneous effect of an ad impression at time *t*, and A_{it} as the accumulated Ad Stock for user *i* at time *t*, such that:

(1) $$A_{it} = \alpha A_{i,t-1} + E_{it}$$

This formulation allows the overall advertising effect, A_{it}, to carry-over into future periods subject to geometric decay with rate α. Ad Stock accumulates over time as individual *i* is exposed to additional advertising impressions, each with an effect represented by E_{it}. Modeling advertising effects through the Ad Stock specification above allows us to capture both direct and indirect effects of advertising. Note that if advertising has only a contemporaneous effect (i.e., there are no long-terms effects) then we would expect α=0.

We define E_{ijt} as the net ad effect for an impression of creative *j* on individual *i* at time *t.* E_{ijt} varies across individuals and evolves over time, based on both which creative is served to that individual and the individual's ad impression history. We allow for four types of effects:

1. an advertising campaign effect *AD* where exposure to any ad in the campaign contributes to Ad Stock,
2. a creative specific marginal effects C_j that allows for various creatives (indexed by *j*) to vary in effectiveness;

3. repetition wear out effects δ that allows for diminishing marginal effects of each exposure to a particular creative ($0<\delta<1$) ; and

4. restoration effects R that allows for the mitigation of wear-out effects as time since the last ad impression increases ($R>1$);

In specifying the contemporaneous ad effect, E_{it}, aggregated across the J creatives, we include a baseline ad effect (AD), creative-specific effects of ads (C_j), wear-out (δ) and restoration (R). We consider two types of wear-out and restoration effects: (1) wear-out/restoration associated with repeated exposures to any ad in the campaign and (2) wear-out/restoration associated with exposures to a specific ad creative.

$$E_{it} = AD[1-(1-\delta_1^{x_{it}})+R_{1ijt}(1-\delta_1^{x_{it}})]+C_j[1-(1-\delta_2^{y_{ijt}})+R_{2ijt}(1-\delta_2^{y_{ijt}})] \quad (2)$$

Overall, the effectiveness of each impression is determined by the baseline advertising effect, AD, less any campaign-level wear-out $(1-\delta_1^{x_{it}})$ plus any restoration of that wear-out $R_{1it}(1-\delta_1^{x_{it}})$ and the effect of the creative itself, C_j, less any creative-specific wear-out, $(1-\delta_2^{y_{ijt}})$ plus any restoration of that wear-out $R_{2ijt}(1-\delta_2^{y_{ijt}})$.

Ad wear-out effects are represented by the expressions $(1-\delta_1^{x_{it}})$ and $(1-\delta_2^{y_{ijt}})$ where x_{it} is the number of previous impressions of any ad in the campaign seen by individual i at time t and y_{ijt} is the number of previous impressions of creative j seen by individual i at time t. The δ parameters are to be estimated and represent the proportion of the ad's effectiveness that is retained with each repeat impression.

Restoration effects are represented by the expressions $R_{1it}\left(1-\delta_1^{x_{it}}\right)$ and $R_{2ijt}\left(1-\delta_2^{y_{ijt}}\right)$ where the rates of restoration are captured by R_{1it} and R_{2ijt}. That is, R represents the percent of ad wear-out that is restored each week since the last ad impression. Since the restoration effect must be positive and cannot exceed the wear-out, R_{1it} and R_{2ijt} must be between 0 and 1. Thus we specify R_{1it} and R_{2ijt} as follows:

(3) $$R_{1it}=\frac{\rho_1\tau_{1i}}{1+\rho_1\tau_{1i}} \text{ and } R_{2ijt}=\frac{\rho_2\tau_{2ij}}{1+\rho_2\tau_{2ii}}$$

where ρ_1 and ρ_2 are nonnegative restoration parameters to be estimated, τ_{1i} is the time that has elapsed since person *i* was last exposed to any ad in the campaign and τ_{2ij} is the time that has elapsed since person *i* was last exposed to ad creative *j*. (τ is zero if there is no previous ad exposure, or if time *t* is the time of the first exposure).

Impression, Visit and Conversion Models

Our Bayesian hierarchical model is based on three separate but related processes for the arrival of ad impressions, visitations, and conversion behavior. Each individual has a rate at which he is exposed to ads from the advertiser, a baseline rate at which he visits the advertiser's website, and a baseline probability at which a visit "converts" and is accompanied by a target behavior. As the Ad Stock variable A_{it} evolves from period to period, it shifts the baseline visit rates and conversion probabilities. To account for correlation among the baseline visit rates, conversion probabilities and ad impression rates, we allow for correlation in the mixing distribution of these rates across the population. From our conversations with the advertiser represented in our data, we know that ads were placed on specific websites, but were not targeted directly to specific visitors to those websites. (we will discuss details of the ad campaign later in the Data section of the paper). That is, individuals were not targeted based on potential interest in the advertiser or by using other behavioral constructs. Therefore, we treat the specific schedule of creatives as exogenous.

Table 1 provides an overview of our model specification. We define m_{it} as the number of ad impressions seen by i in time t, v_{it} as the number of visits by i in time t to the advertiser's website and s_{it} as the number of "converted" visits. While many online marketers equate a converted visit with purchase, the concept of conversion can be extended beyond just purchasing behavior to examine any behavior of interest. Purchasing may be the most relevant behavior to understand for online retailers such as Amazon. However, for many product categories, purchasing typically does not occur online. Instead, the brand's online presence simply supports the purchasing process. For example, most new car sites are not designed to complete purchase transactions. However, they do encourage visitors to submit contact information so that a sales person can call or email them to facilitate a sale. Therefore, in this research, we focus on the conversion of visits in a general sense and do not restrict our analysis to purchase conversion.

***Table 1**. Overview of Model Specification*

Observed Event	Symbol	Individual Model
Impressions	m_{it}	zero-inflated (r_m) Poisson(λ_i)
Visits	v_{it}	zero-inflated (r_v) Poisson (μ_{it})
Conversions	s_{it}	zero-inflated (r_s) Binomial (p_{it}, v_{it})

When modeling impressions and visits, we employ a zero-inflated Poisson model while using a zero-inflated Binomial to model conversions. By "zero-inflating" the Poisson/Binomial distribution, we allow each distribution to have a mass point at zero. This allows for a larger number of individuals who receive zero impressions, make zero visits the site or convert zero times at the site than the Poisson/Binomial would normally predict. When modeling purchasing behavior, previous researchers have interpreted this zero-inflation parameter as a "hard-core never buyer" construct (Morrison 1969, Morrison and Schmittlein 1981). We could similarly interpret our zero-inflation parameters (r_m, r_v and r_s) as individuals who will never receive an ad impression, never visit the website or never convert.

We start by modeling ad impressions. We model m_{it}, the number of ad impressions from this particular seller that user *i* sees at time *t*, by a zero-inflated Poisson distribution, where r_m is the probability that $m_{it}>0$, and λ_i is a heterogeneous impression rate.

(4) $$f(m_{it}) = (1 - r_m)\mathrm{I}(\textstyle\sum_{t=1}^{T} m_{it} = 0) + r_m \frac{e^{-\lambda_i}{\lambda_i}^{m_{it}}}{m_{it}!}$$

We include zero-inflation in this distribution to accommodate individuals in the dataset who might never be exposed to any of the ads in the campaign.

To model visitation behavior, the probability of user *i* making v_{it} visits to the site also follows a zero-inflated Poisson distribution, where r_v is the probability that $v_{it}>0$, and μ_{it} is a heterogeneous, time-varying visit rate.

(5) $$f(v_{it}) = (1 - r_v)\mathrm{I}(\textstyle\sum_{t=1}^{T} v_{it} = 0) + r_v \frac{e^{-\mu_{it}}{\mu_{it}}^{v_{it}}}{v_{it}!}$$

Similarly, the probability of having the s_{it} successes out of the v_{it} visits is expressed as a zero-inflated binomial distribution, where r_s is the probability that $s_{it}>0$ for all *t*, and p_{it} is a heterogeneous, time-varying probability that a particular visit is a success.

(6) $$f(s_{it}) = (1 - r_s)\mathrm{I}(\textstyle\sum_{t=1}^{T} s_{it} = 0) + r_s \binom{v_{it}}{s_{it}} p_{it}^{s_{it}}(1 - p_{it})^{v_{it}-s_{it}}$$

The data likelihood contribution for a single user in our dataset is the joint probability of the observed impression, visit and conversion data, across all observed time periods, conditional on model parameters. However, for our dataset (and most other datasets available to online advertisers), we need to control for potential selection effect. All individuals in our dataset either have been exposed to at least one ad or visited the website (either on their own or as a result of an ad impression) at least once during the observation period. Therefore, the data likelihood is conditional on having met one of these two criteria, and is expressed as:

$$l_i = \frac{\prod_t f(m_{it}|\lambda\_it) f(v_{it}|\mu\_it) f(s_{it}|v_{it}, p\_it)}{1 - Pr(\sum_t m_{it} = 0, \sum_t v_{it} = 0 | \lambda_i, \mu\_i)} \tag{7}$$

To measure the effects of advertising on behavior, we model the visit rate μ_{it} and the conversion probability p_{it} as a function of accumulated Ad Stock, A_{it}. Ad Stock varies over time according to individual i's schedule of ad impressions up to time t. Additionally, we allow for time-varying effects in the frequency of ad impressions, site visitation and conversion behavior as follows:

$$\log \lambda_{it} = log\ \lambda_{0i} + \boldsymbol{\gamma_\lambda} X_t \tag{8}$$

$$\log \mu_{it} = log\ \mu_{0i} + \beta_{\mu i} A_{it} + \boldsymbol{\gamma_\mu} X_t \tag{9}$$

$$\operatorname{logit} p_{it} = \operatorname{logit} p_{0i} + \beta_{pi} A_{it} + \gamma_p X_t \tag{10}$$

where X_t is a vector of weekly indicator variables to control for potential time-varying fixed effects, and γ_λ , γ_μ , and $\boldsymbol{\gamma_p}$ are vectors of coefficients. These time-varying covariates allow us to control for any national offline advertising or promotional campaigns that would affect all individuals in that week equally. After controlling for these covariates effects, any remaining variance can then be attributed to differences across individuals in terms of their advertising exposures. The coefficient $\beta_{\mu i}$ represents the sensitivity of person *i*'s visit rate to advertising, and β_{pi} captures the sensitivity of the conversion probability to advertising.

Moving up the hierarchical structure of the model, we let the baseline impression and visit rates, the baseline success probabilities, and the sensitivities to Ad Stock, be heterogeneous and correlated. Specifically, we assume that all parameters (or appropriate transformations thereof) follow a multivariate normal distribution.

(11) $$\log \lambda_i, \log \mu_{0i}, \text{logit}\, p_{0i}, \beta_{\mu i}, \beta_{pi} \sim MVN(\phi, \Sigma)$$

The elements of ϕ correspond to the mean log impression rate, log visit rate, logit conversion probability, marginal effect of Ad Stock on visit rate, and marginal effect of Ad Stock on conversion probability. Adding unobserved heterogeneity to the model allows for some individuals to be exposed to ads more frequently than others, for some to have a greater propensity to visit the site than others, for some to be more likely to convert than others, and for some to be more sensitive to the advertising effects than others. By modeling the distribution of these latent parameters jointly, we control for correlation between an individual's latent rate of exposure to ads and his visit rates and conversion probabilities. For example, an individual who is an active online car shopper is both more likely to visit a car manufacturer's website and more likely to be exposed to a car ad (assuming that car advertisers place their ads on webpages frequented by car shoppers). By explicitly capturing this potential correlation between ad impressions and visitation behavior through the multivariate Normal distribution in equation (11), we can then separate it from the effects of impression histories on visits and conversions.

The effects of advertising on individual behavior are revealed in posterior estimates of C_j, $\beta_{\mu i}$ and β_{pi}. For the visitation process, the element of the prior mean on ϕ that corresponds to $\beta_{\mu i}$ is constrained to be one. Otherwise, multiplying all C_j by a constant would be equivalent to multiplying the mean of $\beta_{\mu i}$ by that same constant. Thus, the creative-specific effects, Cj, represent the effects of impression histories on Ad Stock. For the conversion process, β_{pi} represents the effect of advertising on the probability of conversion. Note that there are two ways in which advertising can affect sales: increasing the rate at which individuals visit the advertiser's website and increasing the chance of conversion.

It is not immediately clear what the signs of β_{pi} should be. If $\beta_{\mu i}$>0 and β_{pi} = 0, then advertising drives more customers to the site, but has no effect on whether the customer converts. One could argue that individuals are less likely to convert on advertising-induced visits because those visitors were not intrinsically motivated to visit the site on their own. In this case, conversion rates would be lower for the advertising induced visitors and β_{pi} would be less than zero. Alternatively, conversion rates could be greater for advertising induced visits (compared to organic visits) if the ad copy effectively stimulated a purchasing need. A β_{pi} greater than zero would indicate such an effect. In fact, a possible extension to our model (with a richer dataset) might be one that allows for a particular creative to have a different effect on the visit rate than it does on the conversion probability.

To complete the model specification, we place a weakly informative normal prior on a single vector that contains $C_1,\ldots,C_J$, logit α, logit δ, log ρ, and the unconstrained elements of ϕ; and an inverse-Wishart prior on Σ. We then sample from the joint posterior distribution of the parameters of interest, conditional on the observed data and prior parameters, to collect an estimate of marginal posterior means and intervals of highest posterior density.

Data

Our data were provided by Organic, an online advertising agency which, as part of its services to clients, manages client websites and purchases online ad exposures. Our specific data set pertains to an advertising campaign run by a single automobile brand over a course of ten weeks from June 15-August 23, 2009. For our analysis, we will use nine-weeks to estimate the model and use the tenth week for holdout validation (and as a baseline to assess potential benefits of using the model).

Our data set describes the activities of 5,803 individuals drawn from a larger database collected and maintained by Organic. To be included in this database, each individual had to have been somehow observable by the advertiser. This means that each individual was either exposed to at least one ad or visited the advertiser's website at least once, regardless of whether this visit was organic or instigated by an online ad. Thus, the data includes individuals who were not exposed to any ads from the campaign in question. Our sample of 5,803 individuals provides a sufficiently large sample with which to estimate and test our proposed model. The implementation of the model on the complete data set requires data storage and computing powers beyond the scope of research, and thus we leave that to the analysts and programmers at Organic.

For each individual in our data, in each week, we observe three types of data:

1. the number of impressions of each creative that were served;

2. the number of browsing sessions that include at least one visit to the client website; and

3. the number of sessions that include a conversion behavior.

Table 2 describes the distribution of impressions, visits and conversions across users in the data. Note that there are a number of individuals who were not exposed to any advertising. Although we do not explicitly designate these individuals as a "control" group, their presence in the data allows us to establish a baseline for visits and conversion behavior when estimating the effects of advertising.

Table 2. *Observed impression, visit and conversion counts*

	Impressions	*Visits*	*Conversions*
Number in data	*23205*	*4631*	*1828*
Average per individual user	*3.999*	*.798*	*.315*
Number of individual users with…			
0 impressions/visits/conversions	*1399*	*2476*	*4497*
1 impressions/visits/conversions	*1612*	*2744*	*1059*
2 impressions/visits/conversions	*806*	*342*	*143*
3 impressions/visits/conversions	*450*	*109*	*46*
4 impressions/visits/conversions	*328*	*45*	*22*
5 impressions/visits/conversions	*199*	*29*	*15*
>5 impressions/visits/conversions	*1009*	*58*	*21*

During this campaign, the advertiser employed 15 unique banner ad creatives designed to promote awareness for the United States government's "Cash for Clunkers" program. In the summer of 2009, the U.S. government provided consumers with rebates if they traded in their old vehicles for newer, more fuel-efficient vehicles. The advertiser in our data ran ads, both online and offline, to promote the fact that their vehicles would qualify for the "Cash for Clunkers" rebate. Each ad creative shared the same strategic objective and had a strong call to action. Beyond that, differences across ads lie solely in the creative content. Each creative is a different version of an online ad within this campaign.

Table 3 summarizes the total number of impressions served of each creative and the number of unique users that each creative reached. Organic purchased banner ad space directly from websites and did not employ any behavioral targeting practices for this campaign. The process was very similar to a traditional offline “ad buy” in which ads are placed in specific newspapers, television programs, or other media outlets. Seven of the creatives in the campaign accounted for only 46 of the 23,205 total impressions in the data, so we pool them together and treat them as a single creative.

Table 3. *Observed creative counts*

	Number of Impressions	*# Unique Users Reached*
Creative A	*692*	*149*
Creative B	*13078*	*3595*
Creative C	*4809*	*1689*
Creative D	*3667*	*1382*
Creative E	*325*	*45*
Creative F	*135*	*29*
Creative G	*327*	*66*
Creative H	*126*	*85*
Creative I-O	*46*	*24*

In our data, 3,327 individuals visited the advertiser’s website at least once, for a total of 4,631 visits. Of these visitors, 1,399 visited the site even though they did not receive any ad impressions. We do not differentiate between visits generated directly through a click-through, search engine result, or direct URL entry. While ad click-through reflects the direct effect of advertising, there may also be indirect effects on future behavior through effects like increased brand awareness and more favorable brand associations. In the latter case, an individual may visit the website in the future by manually entering a URL or by using a search engine. Although this is not a direct click-through on the ad, the visit can still (at least in part) be attributed to the advertising, and restricting our focus solely on ad click-through would underestimate the ad effects. Like Manchanda et al (2006), we treat all future behaviors equally regardless of whether they were initiated by an ad click-through or by manually entering a URL.

Of the 4,631 visits to the seller's website, 1,828 ended in what the advertiser defines as a conversion behavior. For many product categories, a conversion is defined as a sale. But in the automotive categories, final sales rarely occur online. Instead, new car sites focus on other conversion behaviors, such as building and pricing a car, getting a quote, finding a dealer and searching inventory. In our analysis, we use the advertiser's definition of a conversion behavior. Because this is a fairly large set of activities, the overall conversion rate in our data (39 percent) is higher than the typical purchase conversion rate at most retail websites. However, the model we present can easily be applied to a dataset with a different and possibly narrower definition of conversion.

Results

Model Fit and Benchmark Comparisons

Before discussing our empirical results and applications of the model, it is important to determine if the model is a sufficiently good representation of the data and how model fit compares to a number of benchmarks.

To summarize, our proposed model allows for (1) advertising goodwill effects, (2) creative-specific ad effects, and (3) advertising wear-out and restoration effects. Therefore, we compare our proposed model to benchmark models that vary along each of these dimensions. Table 4 provides an overview of the comparison models.

Table 4. *Overview of Comparison Models*

Model	Advertising Goodwill	Creative-specific ad effects	Advertising wear-out and restoration effects
I	no	no	no
II	yes	no	no
III	no	yes	no
IV (proposed model)	yes	yes	yes

Model I is a baseline model assumes no advertising effects and includes only weekly indicator variables to capture changes in behavior over time. Model II allows for advertising effects (through a goodwill construct with wear-out and restoration) but assumes only campaign level ad effects. That is, all ad impressions, regardless of creative content, is assumed to have the same impact on behavior. This model is the one that is most similar to existing advertising response models that do not accommodate creative-specific variation in ad effectiveness. Model III allows for creative-specific ad effects, but the effects do not persist from period to period (i.e., no goodwill Ad Stock is incorporated into the model). Finally, Model IV is the proposed model that includes all components. Comparing the fit of the proposed model against the benchmark models allows us to evaluate the contribution of each component of the model.

Table 5 compares the above models in terms of model fit. Specifically, we compare model predictions of the number of visits and conversions against the observed number of visits and conversions. We evaluate the models in terms of mean absolute percentage error (MAPE) and compute MAPE for visits and conversions separately, where a small MAPE value represents a model that captures actual behavior with low error. The results presented in

Table 5 confirm that the proposed model provides the best fit. Also, the fact that Models II and III both show substantial improvement over Model I indicates the importance of incorporating advertising effects either through advertising goodwill, wear-out, or restoration effects at the campaign level or through creative-specific contemporaneous effects. The notable improvement of the proposed model over and above Models II and III show the value of incorporating creative-specific effects and advertising goodwill with both campaign and creative level wear-out and restoration together in an integrated model. Overall, MAPE decreases from 20.3% error for visits and 30.0% error for conversions in Model I to just 12.9% error for visits and 11.1% error for conversions in our proposed model (Model IV).

***Table 5**. Model Fit (MAPE) Comparisons*

Model	Visits	Conversions
I	.203	.300
II	.129	.184
III	.150	.186
IV (proposed)	.129	.111

We also examine how the models fit for different subsets of the data in order to demonstrate the ability of the model to discriminate according to different impression patterns. For example, even if one model fits better than the others in aggregate, a model that includes restoration effects should fit better among those customers with at least one hiatus in their impression histories. Table 6 provides a description of the different subgroups we constructed while Table 7 provides in-sample MAPEs for each group. Across virtually all subgroups (with just a few exceptions), the proposed model fits the behavior exhibited in our data better than the benchmark models.

Table 6. *Description of subsets used for posterior predictive checks*

Name	Explanation
(a) One impression	All users who received exactly one impression during the observation period
(b) Two impressions	All users who received exactly two impressions during the observation period.
(c) Three or more impression	All users who were exposed to three or more impressions during the observation period
(d) One distinct creative	All users who were exposed to exactly one distinct creative, but possibly with multiple exposures of that creative
(e) Two distinct creative	All users who were exposed to at least two distinct creatives during the observation period
(f) Three or more distinct creative	All users who were exposed to three or more distinct creatives during the observation period.
(g) Restoration	All users who experienced some kind of restoration effect (e.g., there was at least one incidence of a skipped week between exposures to the same creative)
(h) Two impressions, same week	All users who received two impressions in the same week

Table 7. *MAPE by Subgroup*

Model	(a)	(b)	(c)	(d)	(e)	(f)	(g)	(h)
Visits								
I	.860	.684	.319	.764	.393	.204	.297	.684
II	.726	.546	.168	.624	.254	.046	.136	.546
III	.787	.598	.203	.682	,294	.068	.166	.598
IV	.743	.545	.151	.634	.244	.017	.107	.545
Conversions								
I	.871	.726	.216	.754	.366	.240	.032	.726
II	.690	.530	.026	.564	.179	.134	.167	.530
III	.737	.554	.038	.606	.194	.136	.141	.554
IV	.607	.421	.066	.482	.082	.053	.025	.421

Table 8. *Baseline process estimates for ad exposures, visits and conversion behavior*

	2.5%	median	97.5%		
Ad impressions					
Baseline rate (λ_0)	.091	.087	.094		
Zero-inflation (r_m)	.423	.406	.387		
Week 1	--	--	--		
Week 2	.426	.526	.636		
Week 3	.999	1.086	1.174		
Week 4	1.105	1.183	1.260		
Week 5	1.510	1.593	1.670		
Week 6	1.864	1.953	2.021		
Week 7	1.756	1.841	1.917		
Week 8	1.741	1.822	1.904		
Week 9	1.595	1.688	1.761		
Visit behavior					
Baseline rate (μ_0)	.063	.068	.074		
Zero-inflation (r_v)	.198	.156	.114		
Week 1	--	--	--		
Week 2	-.310	-.197	-.068		
Week 3	-.423	-.296	-.152		
Week 4	-.657	-.558	-.456		
Week 5	-.750	-.592	-.462		
Week 6	-.740	-.643	-.514		
Week 7	-.319	-.187	-.077		
Week 8	-.172	-.062	.044		
Week 9	-.417	-.309	-.183		
Conversion behavior					
Baseline rate (p_0)	.524	.582	.639		
Zero-inflation (r_s)	.394	.358	.316		
Week 1	--	--	--		
Week 2	-.196	.134	.455		
Week 3	-.439	-.126	.264		
Week 4	-.600	-.217	.190		
Week 5	-.491	-.188	.170		
Week 6	-.584	-.222	.170		
Week 7	-.185	.098	.424		
Week 8	-.357	-.028	.253		
Week 9	-.462	-.135	.155		
Covariance Matrix (Σ)					
	log λ_i	log μ_{0i}	logit p_{0i}	$\beta_{\mu i}$	β_{pi}
log λ_I	3.034				
log μ_0	3.507	4.775			
logit p_{0i}	-.129	1.561	98.316		
$\beta_{\mu I}$	-.048	-1.447	1.027	3.988	
β_{pi}	3.386	4.051	19.353	.962	9.058

Parameter Estimates

Baseline process estimates for each component model are provided in Table 8. The baseline rates of impressions, visits or conversions are given in the first row of each section. The zero-inflation parameter is given in the second row. The coefficients (γ) for the weekly indicators are also provided in Table 8.

The zero-inflation parameter in the ad impressions model suggests that, in addition to what is predicted by the Poisson distribution, another 40.6% of the consumers represented in our data are never exposed to an ad. Of the remaining users, the rate of exposure (λ_0) according to the Poisson is .087 ads per week. In terms of visitation behavior, the zero-inflation is much smaller (.156). In the absence of any ad exposures, the average rate of visits (μ_0) for the remaining population is .068 visits per week. These numbers are consistent with the low ad click-through rates observed online. Finally, conversion model indicates a zero-inflation of .358. For the remainder of the population, the probability of conversion at each visit (p_0) is.582. Because the advertiser in our case includes a broad range of activities to be conversion activities, our conversion estimate is higher than the typical conversion rate observed with online retailers, but not out of line with the advertiser's expectations.

How effective is each ad creative? Table 9 provides the estimated posterior medians and 95% highest posterior density intervals, for each of the 9 creative-specific effects (the C_j parameters). These parameters are indicators of the relative marginal contribution of each ad creative, before adjusting for wear-out and restoration effects, on the contemporaneous ad effect. With the exception of Creatives I-O, there is a high probability that all creatives contribute positively to Ad Stock. Based on median posterior estimates, we expect Creatives G and H to be the most effective[7].

Table 9. Advertising impression effects

	2.5%	median	97.5%
Baseline effect of any ad in campaign (AD)	.585	.747	.871
Creative-specific effects (C_j)			
Creative A	.342	.543	.751
Creative B	.351	.454	.559
Creative C	.373	.507	.602
Creative D	.339	.436	.540
Creative E	.259	.511	.772
Creative F	.013	.336	.668
Creative G	.471	.789	.960
Creative H	.479	.774	1.110
Creative I-O	-.694	-.103	.540
$E[\beta_{pi}]$	.016	.113	.195

The effect of advertising on conversion is captured by the same creative-specific and scheduling effects but is scaled by the coefficient β_{pi} from Equation (10). The marginal posterior distribution of the mean of β_{pi} is in the last row of Table 9, from which we observe a significant positive mean effect of accumulated Ad Stock on conversion probabilities. These results suggest that advertising not only generates more visits, but also that the advertising-induced visits are more likely to convert than organically generated visits. This metric can have significant managerial implications as it provides an important tool for advertisers to assess whether the increased number of visits they obtain from advertising provides valuable customer leads or just curious browsers.

[7] Note the range around the effect of creative H is quite large. However, even the lower range of the estimate indicates that it is an effective ad.

How does the timing of ad impressions influence Ad Stock effects? The accumulation and decay of the advertising goodwill construct, Ad Stock, considers three separate effects: (1) the decay of Ad Stock over time, (2) wear out effects with repeated advertising exposures and (3) restoration effects over time in the absence of repeated exposures. Table 10 presents the marginal posterior distributions for these effects.

Table 10. Impression history effects

	2.5%	median	97.5%
Ad stock decay (α)	.337	.374	.421
Campaign level effects			
Wear-out effects (δ_1)	.130	.222	.380
Restoration effects (ρ_1)	.011	.028	.059
Creative level effects			
Wear-out effects (δ_2)	.507	.597	.693
Restoration effects (ρ_2)	.016	.096	.463

The Ad Stock decay parameter captures the extent to which the effect of seeing ads in previous weeks carries over into subsequent weeks. We estimate that about 37.4% of the effects are lost from week to week.

The wear-out effect δ describes the extent to which advertising will retain its incremental effect after repeated viewing. We estimate this effect at both the campaign level (where repeated exposures to any ad in the campaign will create ad wear-out) and the creative level (where repeated exposures of an ad with a given creative will result in wear-out for that specific creative only). On average, each subsequent exposure to this ad campaign results in substantial wear-out of all ad creatives ($1-\delta_1$=.778). Wear-out from repeated exposures to the same ad creative is also substantial ($1-\delta_2=.403$) but substantially less than the campaign level effects.

However, the wear-out is gradually restored as time passes between exposures. At the campaign level, 2.7% (.028/(1+.238)) of the wear-out is restored in each week for which there is a hiatus in advertising (i.e., the consumer is not exposed to any ad from the campaign). Creative-specific effects are restored at a slightly faster rate, with 8.8% (.096/(1+.096)) of the effect that was previously "worn out" being restored each week since the previous exposure of the same ad creative.

Targeting Creatives based on Impression Histories

The results presented in the previous section show clearly how advertising impression histories can affect the response to subsequent ad exposures. To illustrate how impression histories could impact advertising targeting decisions, let us consider a stylized example of a campaign consisting of only two ad creative: G (estimated to be one of the most effective) and A (substantially less effective). Table 11 shows the potential effect that each creative can have on Ad Stock. Based on those effects, the final column indicates the ad creative that would generate the greatest response.

The top half of Table 11 considers a situation in which the advertiser must be opportunistic. That is, we assume that advertising opportunities do not necessarily occur at regular intervals and that when an advertising opportunity presents itself, the advertiser must evaluate the potential effect of each creative before selecting it. In week 1, we assume that no ads from this campaign have been previously served, and thus the effects of G and A on Ad

Stock are equivalent to the sum of the baseline ad effect and the creative-specific marginal effects presented in Table 9. If an advertising opportunity presents itself in week 1, the advertiser should serve the more effective ad (G). However, if a second advertising opportunity then presents itself in week 2 or 3, the advertiser should serve creative A, since the previous impression of G makes any subsequent impression subject to creative-specific wear-out effects (in addition to campaign level wear-out). However, if that second advertising opportunity were to come in week 4, the effectiveness of creative G will have been restored to a level that is comparable to that of A (after accounting for both campaign level and creative-specific wear-out and restoration of both ad creatives).

Table 11. Creative effects on Ad Stock

Assuming occasional advertising opportunities…			
Week	G	A	Serve ad creative…
1 (1st impression)	1.536	1.290	G
2 (possible 2nd impression)	.681	.725	A
3 (possible 2nd impression)	.719	.740	A
4 (possible 2nd impression)	.753	.754	G or A
Assuming weekly advertising opportunities…			
Week	G	A	Serve ad creative…
1 (1st impression)	1.536	1.290	G
2 (2nd impression)	.681	.725	A
3 (3rd impression)	.578	.399	G

Next, we consider an alternative scenario, in which the advertiser has weekly advertising opportunities. In the bottom half of Table 11, we compare the effect of each creative on Ad Stock, assuming that an impression is served every week. Again, in week 1, the advertiser serves creative G. But once it is worn-out, by week 2 creative A is more effective. In week 3, the effects of creative G are partially restored, but creative A is worn-out, so G is the creative of choice for week 3.

This example demonstrates the ability of the proposed model to help advertisers with ad targeting decisions. Next, we consider the effects of different ad impression histories. In this example, we construct ad exposure schedules for six hypothetical users whom we treat as if they were sampled from the same population of users that are included in our dataset. We then simulated 5,000 posterior predictive datasets, conditioning on the data that is implicit in these profiles.

All six histories consist of at most two unique creatives (see Tables 12 and 13). The first two histories describe individuals who are exposed to one ad impression every week for four weeks. In the first history, all impressions are of ad G (the most effective creative in our sample) while in the second history, the impressions alternate between ads G and A. We also consider two additional impression histories for which impressions are concentrated in alternating weeks. In history 3, we examine the case where all impressions are of ad G, and in history 4, we consider the case where both G and A are presented each week. The final two impression histories are scenarios for which the impressions are highly concentrated in the first week and significant time passes before the next impression opportunity in week 5. Again, we consider both a single creative history and a two creative history for these highly concentrated impression schedules.

The effect of an additional ad in week 5 will depend on both the individual's history of ad impressions and the ad presented in week 5. Therefore, using our model results, we simulate the expected number of visits and success conversions for various impression histories and compare the effect that different creatives would have if shown in week 5 on behavior over the subsequent 5 weeks[8]. In addition to ads G and A (which are present in the simulated impression histories), we consider, for comparison purposes, the effect of ad C which has a baseline creative-specific effect comparable to that of A.

For each history, we compare the effects of each ad creative. In practice, the advertiser should favor the ad creative that generates the greatest number of visits and conversions, given the individual's history. We highlight these instances in bold in Tables 12 and 13.

Table 12. *Expected Visits for Various Ad Impression Histories*

	Wk1	Wk2	Wk3	Wk4	G	A	C
Impression History 1	G	G	G	G	.327	**.388**	.379
Impression History 2	G	A	G	A	.384	.347	**.401**
Impression History 3	GG		GG		.401	**.505**	.469
Impression History 4	GA		GA		**.511**	.476	.505
Impression History 5	GGGG				.403	**.489**	.458
Impression History 6	GAGA				.452	.412	**.469**

NOTE: G is the most effect ad with C_G=.789. Ads A and C are comparable in effectiveness with C_A=.543 and C_C=.507.

Table 13. *Expected Successes for Various Ad Impression Histories*

	Wk1	Wk2	Wk3	Wk4	G	A	C
Impression History 1	G	G	G	G	.109	**.150**	.134
Impression History 2	G	A	G	A	.143	.132	**.156**
Impression History 3	GG		GG		.133	**.192**	.188
Impression History 4	GA		GA		**.199**	.162	.187
Impression History 5	GGGG				.155	**.185**	.167
Impression History 6	GAGA				.184	.162	.188

NOTE: G is the most effect ad with C_G=.789. Ads A and C are comparable in effectiveness with C_A=.543 and C_C=.507.

When comparing histories in which only ad G was shown (histories 1, 3 and 5) to those where both G and A were shown (histories 2, 4 and 6), we see that histories with creative variety (histories 2, 4 and 6) result in more visits and conversions regardless of which ad

[8] We assume that no ads other than the ones described in Tables 12 and 13 are served.

creative is shown next. Additionally, after four repeated exposures, ad G is significantly worn-out by the fifth week while ads A and C are still fresh. As a result, in histories where only G is served (histories 1, 3 and 5), the advertiser would benefit similarly from showing ad A or ad C in the fifth week since they are comparable in baseline effectiveness (C_A=.543, C_C=.507), and both would produce better results relative to a worn-out ad G. In contrast, in histories where both ads G and A are subject to wear-out effects (histories 2, 4 and 6), ad C would generate better results than ad A.

Furthermore, the highly concentrated impression schedules in histories 5 and 6 provide an interesting illustration of ad restoration effects. In both of those cases, the 3 week hiatus in weeks 2 through 4 have allowed the ads to gradually regain their effectiveness to a point where they are almost comparable to the unworn ad C.

While the results presented in Tables 12 and 13 represent stylized examples of how different ad histories and ad creatives impact behavior, they begin to illustrate how advertisers can utilize the modeling approach presented in this paper to customize ad creatives for an individual's impression history. To further test this application of our model, we next present a larger simulation in which the individuals observed in our data are exposed to alternative ad content, chosen by different advertising policies. We specifically examine the simulated outcome of an ad policy where the ad creative served is determined with the aid of our proposed model.

Simulation

Thus far, we have used weeks 1-9 of our data for model testing and estimation. We have held out a tenth week of data for use in this simulation. In week 10 of our data, 645 individuals (out of a total of 5803 in the entire data set) were exposed to an advertisement, resulting in a total of 1884 impressions. The creative content served in these impressions are presented in first column of Table 14.

Table 14*. Number of Impressions by Ad Creative in Week 10*

	Observed	Naïve	Simulated
Creative A	77	0	256
Creative B	906	0	57
Creative C	443	0	145
Creative D	437	0	59
Creative E	5	0	143
Creative F	11	0	47
Creative G	5	1884	413
Creative H	0	0	746

As a benchmark scenario, we first consider a naïve advertising strategy in which the most effective ad creative in the ad campaign is chosen to be the only ad in the campaign. In other words, all impressions are of a single ad creative (in our case, creative G). The second column of Table 14 describes this scenario.

To test the managerial value of our proposed model, we simulate, for each of the 645 individuals, alternative ad impressions in week 10 based each of their unique impression histories. Like in the stylized examples presented above, we calculate the potential effect of each available creative, if it were served in the next impression. After accounting for wear-out and restoration effects (at both the campaign and creative levels), the effect of each creative will vary across individuals depending on his or her impression history. For each individual, our simulation will assume that the creative with the highest marginal effect will be served in the next impression opportunity. The last column of Table 14 summarizes the impressions that result from this process.

For the scenarios described in Table 14, we calculate Ad Stock for each individual based on his or her impression history. We assume that no other ad impressions were served after week 10. One could, in practice, relax that assumption, but for the purposes of this paper, this assumption allows us to more easily compare scenarios by limiting the number of factors that we vary across individuals in the simulation. Then, for each individual, we simulate the resulting visit and conversion behavior. The results of these simulations are provided in Table 15.

***Table 15**. Simulated Behaviors across Advertising Scenarios*

	Expected Visits per Individual			Expected Conversions per Individual		
	Observed	Naïve	Model	Observed	Naïve	Model
Week 10	.0545	.0568	.0614	.0298	.0311	.0339
Week 11	.0518	.0524	.0530	.0282	.0285	.0289
Week 12	.0509	.0511	.0513	.0277	.0278	.0279
Week 13	.0506	.0507	.0508	.0276	.0276	.0276
Total for weeks 10-14	.2078	.2110	.2165	.1133	.1150	.1183

The results in Table 15 highlight the value of using our proposed model to target ad creatives based on individual impression histories. The first four rows provide the expected number of visits and conversions per individual in each of weeks 10-13. These visits and conversions are based on the impression histories observed in weeks 1-9 and the impressions planned under each scenario in week 10.

In week 10, the advertising impressions actually observed in the data are expected to generate .0545 visits per individual and .0298 conversions per individual. If, however, the creative content of the ads served in week 10 were chosen based on our proposed model, the expected number of visits would increase to .0614, and the number of conversions would increase to .0339. In other words, the number of visits would increase by 12.7% and the number of conversions would increase by 13.8%. Note that, while less dramatic, the model-based ad policy also improves upon a naïve policy in which the single most effective ad is used exclusively. Additionally, because ad effects carry over from week to week via the Ad Stock construct, increases in visit and conversion behaviors are expected beyond week 10 even though our simulation assumes no additional ad impressions.

Overall, the simulation presented above demonstrates the managerial value of considering ad impression histories when targeting ad creatives to individuals. Thus, our model contributes to current research and to practice by providing (1) a method with which to measure advertising campaign effects, creative-specific effects, advertising goodwill and ad wear-out/restoration effects and (2) a tool with which advertisers can target specific ad creatives based on an individual's impression history.

Conclusion

Although most online advertisers focus on the effects of a single ad impression, we develop an individual-level advertising response model that examines the effect of an ad impression in the context of the individual's impression history. The individual-level nature of the model and data lends the method well to online targeting applications. That is, when an individual visits a website on which an advertiser has purchased space, the advertiser has a choice of ads to present. Ideally, the advertiser would present the most effective ad. However, it can be difficult to identify the "most effective" ad from a portfolio of ads when ads are subject to wear-out and restoration effects. Our model allows the advertiser to estimate the effect that each ad creative would have in the context of an ad impression history. These impression histories vary across individuals and over time, highlighting the importance of an individual-level model such as the one we present in this paper. Our results indicate that individuals with different impression histories will respond differentially to the same ad creative, suggesting to advertisers that online targeting policies should consider not only an individual's page view history but also his/her ad impression history.

Additionally, our proposed model provides a method with which online advertisers can evaluate the effectiveness of various ad creatives in a campaign. While this application can be very important to advertisers who are trying to evaluate their creative teams or trying to isolate effective elements of advertising content, the ability to attribute results to specific ad creatives has continued to be a challenge for advertisers.

One facet of online advertising that we were not able to consider is whether there may be interactions in the order in which different creatives are presented. That is, some creatives might be more effective when presented before or after others. This would have further implications for the construction of impression schedules that would extend beyond just the consideration of wear-out and restoration effects. We leave this modeling challenge to future research.

The implications of our model depend on the advertiser having served all creatives to a sufficient number of individuals, and using the full impression histories to choose the most effective creative for the next impression. A natural extension of the model is to consider optimal decision-making in the presence of more limited information. For example, choosing an ad for the next period makes that ad less effective in subsequent periods, so in the presence of wear-out it might be better to save that ad for the future. In addition, the advertiser might want to select a creative whose expected effectiveness is low, but for which the uncertainty of the effectiveness is high (e.g., a new creative). In this case, the advertiser might benefit by learning more about creatives that have been used less often, just in case they turn out to be more effective. Thus, there is a tradeoff between “exploration” and “exploitation.” One then might treat this problem as a Markov decision process that selects an impression schedule to maximize the total successes over time. The implementation of such an advertising policy resembles the classic “bandit problem” used to model reinforcement learning (Gittens, et. al., 2011), and extends well beyond the scope of this research. However, incorporating wear-out and restoration effects into such a forward-looking decision process would be a welcome addition to any future research.

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