Should We Wait to Promote?: The Effect of Timing on Response to Pop-Up Promotions

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ABSTRACT:

This paper highlights a large scale field experiment conducted at an informational website where the timing of pop-up promotions being offered were varied. Specifically, I examine the effect of these promotions during the course of a web user's online experience. Often, these promotions are viewed by the web user as a nuisance that interrupts his or her online experience. Other times, these offers are perceived as providing useful information, thereby enriching their website experience. This paper proposes that the internet user's response to the pop-up promotion will vary depending not only on his or her own information seeking objectives at a particular online site but also on the timing of the promotion itself, in terms of when during the online session it is offered. Models of the web user's reaction to the promotion in terms of (1) a direct response to the promotion (i.e., click-through on the pop-up) and (2) any indirect response in terms of changes in the user's probability of exiting the site (i.e., exiting either earlier or later than expected) are developed and estimated.

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1. Introduction

As the internet matures, marketers have been developing new and more creative ways to promote to consumers online. Additionally, the nature of the internet has provided marketers with vast amounts of consumer information that allow for better targeting and customization of promotional messages. For example, efforts have been made develop sophisticated recommendation engines that customize promotional message to consumers' tastes and preferences (Ansari, Essegaier, and Kohli 2000). Though the customization of the message itself is an important issue, there are other characteristics of promotions that can also be customized.

This paper will examine the customization of promotional activities by altering the *timing* of when these messages are offered. For example, a common practice is to pop-up a promotional window immediately when a user arrives the home page of a particular site. Web surfers may find that this practice is annoying and takes away from their experience at the site. As a result, these messages may be ineffective in generating the desired response (i.e., click-through) or may lead the user to exit the site earlier than otherwise expected. If we were to delay when the message was offered, perhaps after the user has had some time to process the information on the website and/or webpage, would that affect the user's reaction?

In particular, we conduct a field experiment at an informational site (i.e., no commerce) where the timing of a pop-up promotion, in terms of when during the user's visit it is offered, is varied. We manipulate both the page depth (i.e., is the message offered on the first or second page of the visit?) as well as the page delay (i.e., is the message offered immediately on a page or after a 15 second delay on that page?). Clickstream data from the site is then collected and analyzed.

These promotions may have both a direct and an indirect effect on the web user. First, the user may directly respond to the message itself by clicking through on the pop-up promotion. Second, there may be an indirect response where the effect of the pop-up manifests itself in a change in how quickly the user exists the site. To examine the direct effect of the promotion, we develop a logit model of promotional response to examine click-through rates. We then develop a separate model of the number of pageviews per session to evaluate the user's site exit behavior in reaction to the message. Both direct promotional response and site exit are modeled as a function of a number of promotional characteristics which include timing.

Additionally, past research has shown that users' motivations and objectives at websites can vary dramatically, often leading to differences in purchasing behavior (Moe 2003, Moe, Chipman, George, and McCullouch 2002). For example, people who are browsing a site for the hedonic utility of the experience are less likely to purchase than those who are seeking specific information about a particular purchase that they are considering. Consistent with this idea, we also believe that the user's objectives at a website will affect their reactions to promotional messages. Therefore, we develop a number of measures that capture characteristics of the visit during which the message is offered. We then allow for heterogeneity by estimating latent segments using these session-specific measures as concomitant variables.

The paper will proceed as follows. The next section will briefly discuss the many promotional tools available to an online marketer. Then, §3 reviews some of the relevant literature that may apply. An in-depth discussion of the field experiment, the clickstream data, and the measures derived from the data follows in §4. We then present the promotional response model followed by the site exit model in §5. We conclude with a discussion of our findings.

2. Online Promotional Tools

Several types of promotional tools are available online. The most commonly studied are *banner ads* which are ads that are embedded in the page being viewed. These are similar to print ads in the offline environment. Another class of promotional tools, *interstitial promotions*, has become increasing popular. By definition, interstitial is a term used in the sciences to refer to small spaces found between cells or particles. In the internet environment, this term was originally used to refer to the smaller windows that pop-up on the user's screen to fill the time when larger content pages were loading on the user's computer. As computers, web servers, and internet connections became more efficient, the term *interstitial promotions* started referring to a broader class of promotional messages including pop-up messages, pop-under messages, bridge pages, and in-page animations. *Pop-up messages* appear in windows that open in the foreground of the user's screen often blocking parts of the page that the user wishes to see. Because pop-up messages often interfered with the user's experience on the site that offered it (because it blocked visibility of part of the page), online marketers began to offer *pop-under messages*. Pop-under messages, instead, appear in windows that open in the background of the user's screen. Only when the user closes the main window does the user see the pop-under message window beneath it. Because pop-unders are so discrete and easy to ignore while surfing online, it is difficult to integrate these messages with the user's experience on the site, if desired. Another promotional tool that is available which overcomes this disadvantage is the *bridge page*. A bridge page is a page to which the user is redirected when navigating from one page to the next. These are unavoidable and impossible to ignore as the user is forced to view the bridge page while the site is loading the next page requested by the user. Finally, there are *in-page animations*. These are effectively promotional messages that "come to life." In other words, while viewing a page, an animated message appears on the user's screen much like a television advertisement. Like pop-up messages, these messages appear in the foreground and block parts of the page the user wishes to view.

The focus of this paper is on interstitial promotional messages. Specifically, pop-up messages are used in the field experiment. The defining characteristic of this class of promotional messages (especially when compared to banner ads) is the difficulty with which the web surfer can ignore them. These promotional messages are designed to attract attention and interrupt the user's experience at the web site. Therefore, in the next section, we highlight some of the research that has been conducted in both the marketing literature with respect to online consumer behavior and promotions as well as in the decision processes literature with respect to task interruption.

3. Literature Review

There are several related streams of research that may apply to the research question at hand. The first and most obvious is the research on online consumer behavior.

Online consumer behavior

The rapidly growing research on online consumer behavior has focused primarily on search and purchasing behavior across stores (Lynch and Ariely 2000, Johnson et al 2002, Winer et al 1997), over time (Moe and Fader 2002a), and within session (Bucklin and Sismeiro 2003, Moe et al 2002, Li et al 2002). Fewer studies have examined the use of and market response to marketing interventions such as pricing (Smith and Brynolffson 2000), recommendation engines (Ansari et al 2000), and banner ads (Dahlen and Bergendahl 2001). Little to no research has been done on the impact of interstitial promotions. By studying the effect of interstitial promotions on direct promotional response and site exit, we hope to contribute significantly to the online consumer behavior literature.

In terms of methodology and data collection, several studies have used clickstream data which is quickly becoming more widely available to both researchers and practitioners (see Bucklin and Sismeiro 2003, Moe and Fader 2002a, Moe and Fader 2002b, Johnson et al 2002, Li et al 2002). However, research on clickstream data is often handicapped by the descriptive nature of secondary data. Though clickstream data does contain a lot of information pertaining to the consumer buying process, it is often difficult to draw cause-and-effect conclusions. To overcome this weakness, several researchers have turned to simulating an online environment in an experimental lab setting (e.g., Lynch and Ariely 2000). However, this method is not without its disadvantages. Often these lab settings are unrealistic and do not reflect the true behavior of consumers. Because of the drawbacks of both clickstream and experimental data, researchers have called on marketing practitioners to conduct experiments on their web sites. However, many web sites are hesitant to do so in fear of annoying site visitors with an inconsistent experience. This paper fills that gap and highlights a large-scale field experiment at a high traffic web site.

Promotions

Another related stream of research involves the study of promotions. Narasimhan (1984) studied consumer use of coupons as part of a price discrimination theory. In his study, the coupon, used as a promotional tool, had an associated utility which determined how likely the consumer was to redeem the coupon and purchase the product featured. A later study by Heilman, Nakamoto, and Rao (2002) examined the effect of promotions on overall store behavior. Specifically, they found that in-store promotions and electronic coupons often had positive surprise or mood effects that would generate more sales in categories other than the one featured by the promotion. These two studies suggest that promotional activities have both direct effects that lead to promotion redemption as well as indirect effects on overall behavior at the store. Accordingly, in this paper, we will examine the effect of pop-up promotional messages on both the web user's clickthrough of the pop-up (direct effect) as well as the impact on overall behavior at the site (indirect effect), specifically site exit behavior.

However, this paper differs from the promotions literature in a significant way. In the promotions and couponing literature, the promotional message is often associated with a monetary value and therefore factors into the consumer's utility for redeeming the offer. In this paper, we are interested less in the utility value of the promotion and more in how the timing of the offer can affect reactions. Therefore, the experiment presented in this paper uses pop-up offers that have no monetary value but simply ask the user to sign up for a weekly newsletter.

Additionally, the site used for the study is an informational site and has no commerce. In that sense, the promotional tool used in this study is in some ways like an advertisement. But unlike advertising, there is a direct and immediate response to the message in the form of clicktroughs.

Task Interruption

One unique characteristic of interstitial promotions is that when it pops up, it interrupts the user's experience at the web site. Therefore, it is useful to review some of the decision processes literature that addresses the effect of task interruption. Several studies ask subjects to complete a task during which they are interrupted with other information. These studies have found a wide array of responses that differ depending on characteristics of the task itself as well as characteristics of the interruption. Zijlstra et al (1999) found that many people when faced with a goal-directed task will overcompensate when interrupted, that is, they tend to concentrate even more on the task at hand. Speier and Valacich (1999) examined task performance when people are interrupted and found that interruptions improved decision making performance on simple tasks but lowered performance on more complicated tasks. This, however, was mediated by the similarity of content between the task and the interruption.

The aforementioned studies seem to suggest that interruptions generate a wide variety of responses that vary depending on the (1) the task at hand and (2) characteristics of the interruption. Other studies further investigated specific characteristics of the task and the interruption that affected subjects' responses. Kirmeyer (1988) showed that characteristics of the interruption such as frequency, duration, context, complexity, and timing all had significant effects on subjects' responses. For this paper, we will focus only on the effect of timing and context. Speier and Valacich (1999), on the other hand, focused on examining the characteristics of the original task and its affect of subjects' responses to an interruption. Specifically, they found that the complexity of the task itself had a strong effect on one's reaction to the interruption.   They proposed an information overload perspective suggesting that subjects performing more complicated tasks are more likely to be overloaded by an interruption thereby reacting negatively. In other words, the information load associated with the task has an effect on the user's response to the interruption.

These studies of how characteristics of the task interruption as well as the task itself are analogous to the experience that web users face when presented with pop-up promotions. Web users visit a particular web site often times with a task in mind, be it browsing for entertainment purposes or searching for specific information. These visit sessions vary in terms of the amount and type of information the user views at the site. Pop-up messages effectively interrupt the process. How site visitors respond to this interruption will vary depending on their purpose at the site as well as characteristics of the pop-up promotion. Therefore, in the next section, we will describe the data and the website used in this study and then specify a number of measures designed to capture characteristics of the user's task at the site and characteristics of the pop-up promotion.

4. Data

Description of Site

The website studied in this paper is a purely informational site, that is, no commerce is transacted directly through the site at the time of the study. It is a well trafficked site (they boast over 2.7

million readers per month in 2002) that provides information about movies, both in the theatres and on DVD, including critic reviews, trailers, actor biographies, etc.

The organization of the site is best understood by categorizing its pages as either *content* pages or *gateway* pages. Content pages are pages that provide movie specific information. Each movie (or SKU) has multiple unique content pages that the user can drilldown and view. Gateway pages, on the other hand, are navigational pages that link the user to the content pages. For example, the home page is considered a gateway page since it provides no in-depth discussion of any specific movie but instead highlights a few new releases, upcoming movies, and/or actors. To read more about the featured information, the user must click through on the hyperlink which redirects the user to a movie specific content page. The site also provides pages that summarize the Top 10 movies for the week, a full listing of new releases for the month, etc. These pages would also be considered gateway pages since their purpose is purely navigational and is supposed to redirect the web user to a product specific page. This structure of gateway and content pages is common across informational websites. News sites, for example, also follow this format. When visiting the CNN.com homepage the user is faced with a number of headlines each of which is a hyperlink that redirects the user to the full story. In that case, the home page is a gateway page and the news story itself is a content page. The site also has other gateway pages that summarize world headlines or sports headlines that also redirect the browser to specific stories of interest.

Experimental Design

The experiment was run over a span of four days, Monday, December 18, 2000 through Thursday, December 21, 2000. For the experiment, a pop-up message was designed to solicit site visitors to subscribe to a weekly newsletter. There was no monetary value associated with this offer, only the promise of receiving weekly emails about movies. The pop-up was offered only to those visitors who have not previously registered with the site, signed up for the newsletter, or received a similar offer in the past.

The experiment itself was designed to manipulate the timing of pop-up messages. Timing was varied along two dimensions: (1) page-depth and (2) page-delay. Three levels of page-depth were used. Browsers were presented with the pop-up either on the first page of their session, on the second page of their session, or on the fourth page of their session. Page-delay also had three levels. The pop-up appeared either immediately on a given page, after a 15 second delay, or after a 30 second delay. The page delay allows for browsers to absorb some of the information on the page before being interrupted by the pop-up.

Another factor that is of interest and has been shown to have a significant effect on a user's response to task interruption is context. In our case, we will test whether the effect of the pop-up differs depending on the type of page (i.e., gateway versus content page) during which it is offered. This factor will not be actively manipulated as part of the experimental design, but will naturally vary across page-depth and page-delay conditions since each site visit follows a different navigational path. For example, if the experimental condition is one where the pop-up is offered on the second page of the visit, that could mean that it is offered on a content page for one visitor versus a gateway page for another visitor.

There is also reason to believe that online behavior varies by time of day (Telang, Boatwright, and Mukhopadhyay 2002). Someone searching for information online during the day is likely to exhibit very different behavior from someone searching in the middle of the night. Therefore, time of day is another factor that we must balance in our experiment. Ideally, we should randomly assign visitors regardless of time of day into one of our page-depth/page-delay conditions. However, due to technology constraints at the website, we had to define experimental conditions by time of day. Each calendar day was divided into daytime (9am – 5pm), evening (5pm – midnight), and nighttime (midnight – 9am) as requested by the website. Effectively, we had three factors to manipulate (page-depth, page-delay, and time of day) each with three levels. Therefore, a Latin square design was implemented. Table 1 describes each experimental condition and the number of observations collected in each condition.

TABLE 1: Experimental Design

	0s delay	**15s delay**	**30s delay**
1 page viewed	NIGHT n=6226	DAY n=8826	EVENING n=5788
2 pages viewed	EVENING n=3426	NIGHT n=1765	DAY n=5978
4 pages viewed	DAY n=2857	EVENING n=1583	NIGHT n=2385

Data Collection and Measures

For the duration of the experiment, clickstream data was collected via a cookie on the visitor's PC. The clickstream data recorded each and every page requested by visitors. That is, each line of data represented a page view. It provided the date and time of the pageview and contained information regarding the type of page (content versus gateway). If it was a content page, the data also included the specific SKU for which it provided information as well as the type of content on the page (e.g., reviews, images, previews, etc.). Each page view was also associated with a unique user number specific to the PC used to browse the site and a unique session number. Sessions were defined by the website as consecutive pages requested no more that one hour apart. If a user is idle for one hour or more, any subsequent page requested by that user would be considered a new session.

During the 4-day experiment, 83,136 non-registered users visited the website and were eligible for the experiment (i.e., they had not previously received a pop-up offer to register for the newsletter). On average, these visitors viewed 3.47 pages during a given session. Of these 83,136 visitors, 38,834 received a pop-up message during their visit. Others were eligible for a pop-up but were assigned to an experimental condition that did not trigger a promotion during their stay at the site. For example, a visitor may be assigned to the condition where a pop-up is offered on the fourth page but he/she exits after the second page. Though this visit was assigned to one of the experimental conditions, the pop-up itself was never triggered and therefore never seen by the visitor. As a result, promoted sessions will on average contain more pageviews than non-promoted sessions. In our data set, non-promoted sessions on average had 1.38 pageviews while promoted sessions had 5.86 pageviews. This is a bias that will need to be addressed in our model development. Overall, 0.81% of those who received the pop-up message responded and signed up for the newsletter. Though this response rate seems low, it is consistent with typical purchasing conversion rates observed at e-commerce retail sites.

From our page-level clickstream data, we develop a number of measures that are designed to reflect characteristics of the pop-up promotion offered (task interruption characteristics) as well as characteristics of each user's website visit (task characteristics).

Two categories of measures are used to represent promotion characteristics. The first is timing measures which include depth of offer (DEPTH=1, 2, or 4 pages), delay of offer (DELAY=0, 15, or 30 seconds), and time of day (DAY=0/1; NIGHT=0/1). The second is a measure of context. Specifically, the type of page on which the promotion is offered is coded as either a content page (CONTENT=1) or a gateway page (CONTENT=0).

From our previous discussion of task interruption studies, we know that the information load (both the amount and type of information) associated with the original task has an effect on response to the interruption. Therefore, measures of session characteristics will focus on representing the information being viewed, specifically, the amount of information, the breadth of information, and the depth of information. The *amount* of information being viewed is measured as the percent of all pages that are content pages (PERCONT). The *breadth* of information can be represented by the number of unique SKUs (or movies) for which the user obtains information (NUMSKU). Finally, the *depth* of information is captured by the average level of drilldown for each SKU in a given session. This is obtained by dividing the total number of unique SKU-specific content pages by NUMSKU (DRILLDOWN).

5. Models and Results

In this section, we develop two models to evaluate the user's response to a pop-up promotion that interrupts their website visit. The first models whether the user signs up for the weekly newsletter. The second examines site exit by modeling the number of pages viewed.[1]

Promotional Response Model

To examine the direct response to a pop-up promotion given that one was offered, we model, p_j, the probability of signing-up for the weekly newsletter during session j, as a logit function. Characteristics of the promotion mentioned in the previous section are included as explanatory variables.

$$p_j = \frac{\exp(u_j)}{1+\exp(u_j)} \quad \textbf{where} \quad u_j = \boldsymbol{\beta x}_j \quad \textbf{and} \quad \boldsymbol{x}_j = \begin{bmatrix} 1 \\ depth_j \\ delay_j \\ context_j \\ day_j \\ night_j \end{bmatrix} \tag{1}$$

However, the specified model above does not accommodate heterogeneity. There are several options available to introduce heterogeneity in this case. Rossi and Allenby (2000) provide an excellent review of the different methodologies used in marketing for this purpose. We will highlight just a few methods that lend themselves to this problem. One option is to use discrete mixture models. Kamakura and Russell (1989) introduced latent class models that provided a basis for segmentation according to model response parameters. However, segments resulting

[1] Two separate models are developed rather than a single integrated model because of sample size issues. As mentioned earlier, only 38,384 sessions out of 83,136 are offered promotional pop-ups. Any promotional response model would apply only to the 38,384 sessions while any exit model would apply to all 83,136 observations. Because of the large differences in sample sizes, any integrated model would be dominated by the site exit component while parameters driving the promotion model would have a significantly smaller effect on the likelihood.

from a basic latent class models are estimated in the absence of any demographic variables. Therefore, Bucklin and Gupta (1992) examined the correlation between latent segment membership and demographic characteristics. Gupta and Chintagunta (1994) took it one step further and developed a discrete mixture model with concomitant variables. Effectively, latent segment membership probabilities were driven by demographic variables. Advantages of discrete mixture models are that they are more easily estimated with a relatively simple likelihood function. However, discrete mixture models limit heterogeneity to a finite number of segments and therefore lacks the richness of some other methods available.

A more recent development in modeling heterogeneity is continuous mixture models, specifically hierarchical Bayes methods (Allenby and Lenk 1994). The unique characteristic of this method is that heterogeneity is allowed to vary at the individual level rather than constrained to vary across discrete segments. The drawback with Bayesian methods, however, is in estimation. Hierarchical Bayes models are often cumbersome to estimate and may take enormous amounts of computing time to generate results. This disadvantage is particularly relevant when working with the large datasets associated with internet clickstream data.

A fairly new method to accommodate heterogeneity that has been introduced is Bayesian tree models (Chipman, George, and McCullouch 2002, Moe, Chipman, George, and McCullouch 2002). Bayesian tree models generate segments whose memberships are driven by one set of explanatory variables, those that govern how the tree branches split. Behavior within each segment, or terminal node of the tree, is governed by its own model sometimes with an entirely different set of explanatory variables. This is an extremely flexible modeling method as the variables that are selected for segmentation purposes are not predetermined but instead result from a Bayesian estimation algorithm that probabilistically generates the best fitting tree. Again, the drawback of this method, like other Bayesian methods, is that it is extremely cumbersome to estimate.

When modeling heterogeneity, the researcher must make a trade-off between estimation efficiency and richness in individual level heterogeneity. With internet clickstream data, the draw back of cumbersome estimation is quite substantial given the size of the datasets often collected. Therefore, heterogeneity is included in this paper using discrete mixture models with concomitant variables:

$$p_j = \sum_{s=1}^{S} p_j \mid s_j \cdot P(s_j) = \sum_{s=1}^{S} \frac{\exp(\mathbf{ß_s x_j})}{1+\exp(\mathbf{ß_s x_j})} \cdot P(s_j) \tag{2}$$

where S is the total number of latent segments and $P(s_j)$ is the probability of session j belonging to segment s. This segment membership probability is a function of the session characteristics described in section 4 earlier. These x-variables characterize the task being performed at the site by summarizing the amount, breadth, depth of information being viewed in each session. These characteristics allow sessions to be segmented according to the task being performed during that session.

$$P(s_j) = \mathbf{a}_s \mathbf{y}_j \quad \text{where} \quad \mathbf{y}_j = \begin{bmatrix} 1 \\ percont_j \\ numsku_j \\ drilldown_j \end{bmatrix} \tag{3}$$

Results for Promotional Response Model

We first estimate the promotion model at the aggregate level, that is without any heterogeneity. This homogeneous model uses only promotion characteristics as explanatory variables. The results are presented in Table 2. We find that at the aggregate level, page-delay is the only significant explanatory variable in the promotion response model (β_{delay}=-0.028 with p<0.01). Specifically, the later a promotion is offered, the less effective it is. This supports the behavior of most websites that offer pop-up promotions immediately on the home page when the visitor first enters the site.

TABLE 2: Homogeneous Promotional Response Model

Coefficient	Parameter Estimate (std. error)
Baseline	-4.384 (0.155)
Depth	-0.005 (0.052)*
Delay	-0.028 (0.005)
Context	-0.098 (0.109)*
Day	0.101 (0.123)*
Night	-0.076 (0.149)*

* not significant at p=0.05

However, it is likely that significant heterogeneity exists in visitor behavior which may lead to different responses to pop-up promotions. Therefore, we next estimate a discrete mixture model with session characteristics as concomitant variables. Table 3 provides the likelihood fits as well as the BIC used for model selection. The model with the best fit after adjusting for the number of parameters is the three segment model (BIC=2427.9). Table 4 provides the estimation results for this model.

TABLE 3: Model selection

	1 SEGMENT	2 SEGMENTS	3 SEGMENTS	4 SEGMENTS
Log-Likelihood	-1807.19	-1295.91	-1092.43	-1073.01
BIC	3677.79	2739.76	2427.91	2484.17
# Parameters	6	16	26	36

TABLE 4: Three Segment Promotion Response Model Results

	SEGMENT 1	SEGMENT 2	SEGMENT 3
Promotional Response Parameters			
Baseline	-6.714 (0.993)	1.211 (0.676)	-5.722 (2.190)
Depth	0.100 (0.170)*	-0.258 (0.189)*	-3.201 (1.049)
Delay	-0.057 (0.014)	-0.041 (0.017)	0.005 (0.088)*
Context	0.594 (0.531)*	2.452 (0.525)	-1.884 (1.806)*
Day	0.051 (0.293)*	-0.125 (0.259)*	2.407 (0.965)
Night	0.476 (0.253)	0.045 (0.362)*	2.287 (1.155)
Segment Membership Parameters			
Baseline	-41.828 (7.514)	-5.442 (0.579)	
PERCONT	-3.281 (3.731)	-7.665 (3.401)	
NUMSKUS	3.833 (0.870)	3.981 (0.830)	
DRILLDOWN	44.095 (7.097)	4.770 (1.299)	

* not significant at *p*=0.05

The first thing to note regarding the results of the three segment model is that several promotion characteristic parameters other than page-delay are significant, unlike the homogeneous model. Additionally, parameter estimates for promotion characteristics vary across segments. For example, page-depth, which was not significant in the aggregate level model, has a significantly negative effect for segment 3 sessions ($\beta_{depth,3}$ = -3.201; p = 0.001). That is, these segment 3 sessions are more likely to respond to a pop-up promotion if it were offered immediately on the page rather than after a delay. The page-delay effect, which was significant in the aggregate level model, is significantly negative for segments 1 and 2 but not 3 ($\beta_{depth,1}$=-0.057 with $p < 0.01$; $\beta_{depth,2}$ = -0.041 with p = 0.008). That is, promotional response rates are lower for pop-up promotions offered later in the visit session for segments 1 and 2 and has no effect on segment 3 sessions. Context, which was also insignificant in the aggregate level model, had a significantly positive effect on promotional response among segment 2 sessions ($\beta_{context,2} = 2.452$ with $p < 0.01$). Note that the magnitude of this effect is much greater than that of page-depth for segment 2. This suggests that though waiting until later pages to offer the pop-up promotion may decrease response rates, waiting for a content page to be viewed before offering the promotion will increase response rates more so than the decrease associated with page-delay.

In addition to simply understanding how segments vary in promotional response, it is of value to understand what kinds of online behavior lead to sessions belonging to one segment or the next. The parameter estimates for the concomitant variables are what determine segment membership probabilities. Table 5 provides a descriptive summary of how the segments differ in terms of session characteristics that determine segment membership as well as how each segment responds (negatively or positively) to promotional characteristics.

TABLE 5: Descriptive summary of Promotional Response by Segment

	Segment 1	**Segment 2**	**Segment 3**
Description	Deeper	Broader	Shallow
Baseline	low	high	moderate
Delay to later pages	–	–	–
Delay within page	not signif.	not signif.	not signif.
Context	not signif.	++	not signif.

Drilldown of product specific information is the biggest determinant of segment 1 membership. Sessions belonging to this segment can be characterized by deep information gathering of a limited number of SKUs. This segment is has the lowest baseline promotional response rate. This is consistent with the idea that a pop-up will be seen as an unwelcomed interruption if performing a more complicated task which seems to be reflected by the fact that the web visitor is seeking a deep amount of rich product specific information. Additionally, delaying a pop-up offer to this segment has a negative effect on promotional response.

Segment 2 sessions tend to be a bit broader in scope with respect to the type of information viewed. Sessions with less drilldown across slightly more SKUs are more likely to belong to segment 2. Like segment 1, this segment negatively responds to any page delay in pop-up promotions. However, unlike segment 1, these sessions have a relatively high baseline promotional response rate. One explanation may be that because these visitors are open to more variety in information, as reflected by their session characteristics, pop-up promotions may be more welcomed and perceived as an interesting source of information. Additionally, this is the segment with the strong and positive effect of context. That is, promotions offered on content pages are more positively received, again reflecting their high level of information tolerance.

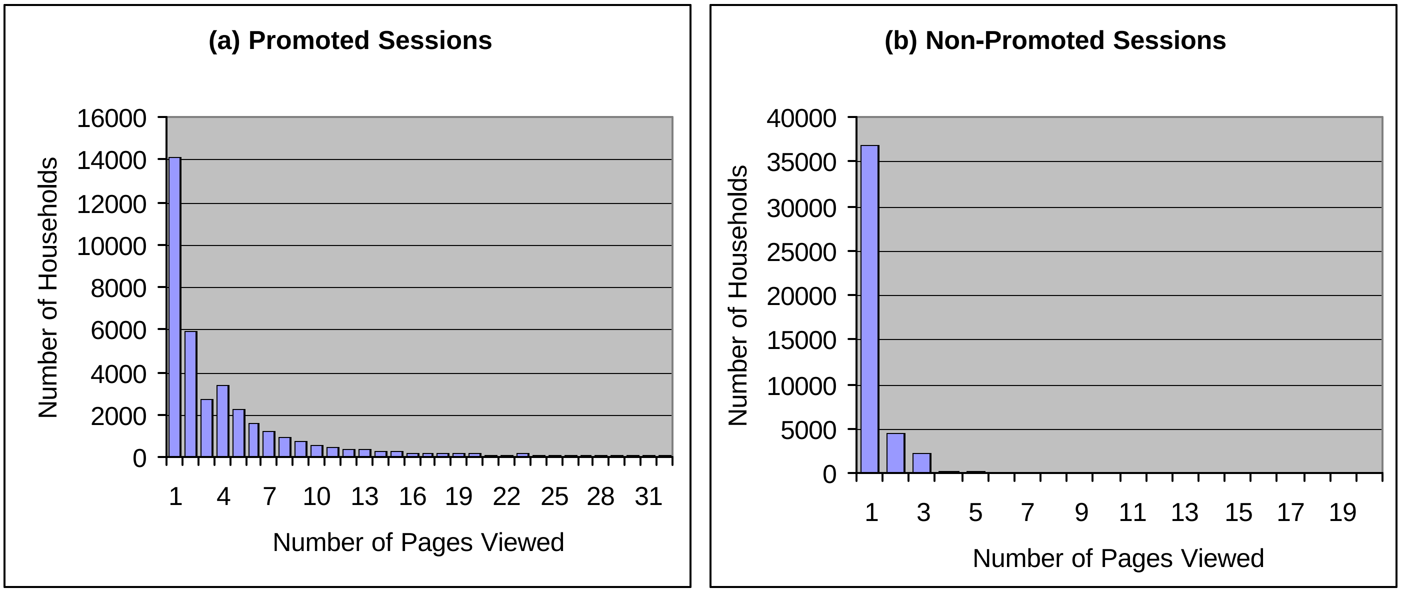
Segment 3 is our baseline session for our modeling exercise. In general, sessions with high probabilities of belonging in segment 3 are those more shallow visits characterized by a lack of content pages. These visitors are therefore more likely to be individuals who visit the site for a very specific but limited piece of information. Their behavior at the site is very much a hit-and-run kind of dynamic. Any interruption is likely to be viewed as an unwelcomed interruption.

Overall, waiting, both in terms of page-depth as well as page-delay, is not effective in increasing direct promotional response. For the most part, individuals seem to respond to these interruptions by ignoring the information presented in the pop-up promotions. Therefore, it is advisable for online marketers trying to increase direct response to pop-up promotions to offer them without any delay. The one exception to that rule is with segment 2, the segment that seeks out a breadth of information. Though these sessions still do respond negatively to any delay in a pop-up offer, this negative effect is well compensated for by waiting for appropriate content pages to be viewed when offering pop-up promotions. Therefore, when faced with a visitor seeking a broad level of information, the online marketer may want to offer the pop-up promotion on the first content page being viewed.

Site Exit Model

The promotional model presented above assessed the impact of timing and context on direct promotional response. However, that is only half of the story. There are also potential indirect effects of the interruption that are worth considering. Therefore, we next examine the impact of the promotional characteristics on site exit behavior by modeling the number of pages viewed per session. Figures 1 (a) and (b) provide histograms of the number of pages viewed for promoted sessions versus non-promoted sessions. One key challenge when analyzing pageviews is that of selection bias if one were to simply compare pageviews of promoted sessions versus non-promoted sessions. Promoted sessions, because they need to reach a certain number of pages to trigger the promotion, will by design have more pageviews than non-promoted sessions. This is a significant consideration when analyzing the data. Consequently, we must first develop an appropriate baseline model of site exit behavior before modeling the effect of a pop-up promotion.

Figure 1. Histogram of Pageviews



In the absence of any promotional activity, the number of pages viewed in session j, pv_j, can be viewed as a geometric process. This assumption is supported by the shape of the histograms in Figure 1.

$$P(pv_j) = (1-p)^{pv_j - 1} p \tag{4}$$

where p is the probability of exiting after viewing a given page. In this process, the probability of exiting, p, is constant from page to page. However, once the visit is interrupted by a pop-up promotion, this probability is likely to shift. To incorporate this change, we model pageviews as follows:

$$P(pv_j) = (1-p_0)^{depth_j - 1}(1-p_1)^{pv_j - depth_j} \; p_1 \tag{5}$$

where $depth_j$ is the page number during which the pop-up promotion was offered. Effectively, individuals enter the website with a latent probability of exiting, p_0. Once interrupted by a pop-up promotion, their exit probability shifts to p_1 based on promotional characteristics as follows:

$$p_0 = \frac{\exp(b_0)}{1+\exp(b_0)} \tag{6}$$

$$p_1 = \frac{\exp(\boldsymbol{bx})}{1+\exp(\boldsymbol{bx})} \quad \textbf{where} \quad x_j = \begin{bmatrix} 1 \\ depth_j \\ delay_j \\ context_j \\ day_j \\ night_j \end{bmatrix} \tag{7}$$

Again, we introduce heterogeneity though discrete mixture models with session characteristics as the concomitant variables driving segment membership.

$$P(pv_j) = \sum_{s=1}^{S} P(pv_j \mid s_j) \cdot P(s_j) = \sum_{s=1}^{S} \frac{\exp(b_{\boldsymbol{s}} \boldsymbol{x_j})}{1+\exp(b_{\boldsymbol{s}} \boldsymbol{x_j})} \cdot P(s_j) \tag{8}$$

$$\text{and } P(s_j) = a_s \boldsymbol{y}_j \quad \textbf{where} \quad \boldsymbol{y}_j = \begin{bmatrix} 1 \\ percont_j \\ numsku_j \\ drilldown_j \end{bmatrix} \tag{9}$$

Results for Site Exit Model

We begin our discussion of results by first examining the parameter estimates for the aggregate level model with no heterogeneity (Table 6). Unlike the promotional response model presented earlier, all parameter estimates are significant with the exception of the coefficient for page-delay. Based on the model coefficients, the later a promotion is offered, the more likely it will adversely affect the user's experience at the site and increase the likelihood of the visitor leaving earlier, at the aggregate level. Again, this is consistent with the common industry practice of offering pop-up promotions to visitors immediately upon site entry on the home page. Interestingly, unlike with the promotional response model, context adversely affects the user's experience at the site. If the visitor is interrupted with a pop-up promotion on a content page, he/she is actually more likely to exit the store site, despite the fact that at the aggregate level we see that offering the promotion on a context page increases direct promotional response. We will explore this relationship in more depth at the segment level.

TABLE 6: Homogeneous Exit Model Results

Coefficient	Parameter Estimates (std. error)
Baseline	0.115 (0.002)
Depth	0.472 (0.005)
Delay	0.001 (0.001)*
Context	0.307 (0.005)
Day	0.103 (0.006)
Night	0.061 (0.011)

* not significant at p=0.05

As with the promotional response model, it is important to accommodate heterogeneity when examining exit behavior as well. Table 7 provides fit statistics for the exit model with different segment specification. Using BIC as the criteria, the best model structure is one with four segments (BIC=216,436). Table 8 provides the parameter estimates for the four segment model[2].

TABLE 7: Exit Model Selection

	1 SEG	2 SEG	3 SEGS	4 SEG	5 SEG
Log-Likelihood	-157,806	-114,424	-109,012	-108,036	-108,024
BIC	315,669	229,008	218,286	216,436	216,514
# Parameters	6	16	26	36	41

[2] When interpreting the parameter estimates of the exit model, it is important to focus on the covariate effects. The baseline parameter is less interpretable since some correlation may exist between the baseline pageview level and segment membership variables. However, the coefficients that capture visitors' response to pop-up characteristics should be unbiased.

TABLE 8: Four Segment Exit Model Results

	SEGMENT 1	SEGMENT 2	SEGMENT 3	SEGMENT 4
Exit Model Parameters				
Baseline	3.396 (0.002)	-0.002 (0.001)	-2.961 (0.003)	-1.545 (0.006)
Depth	2.496 (0.001)	-0.040 (0.008)	0.073 (0.011)	0.158 (0.001)
Delay	-0.012 (0.004)	0.021 (0.005)	0.001 (0.038)*	0.006 (0.001)
Context	-1.888 (0.134)	-0.418 (0.001)	0.093 (0.005)	0.574 (0.005)
Day	-0.237 (0.114)	0.304 (0.055)	0.085 (0.017)	0.096 (0.019)
Night	-0.425 (0.005)	0.329 (0.077)	0.143 (0.014)	0.177 (0.027)
Segment Membership Parameters				
Baseline	2.503 (0.001)	1.654 (0.011)	-8.842 (0.016)	
Percont	74.985 (0.001)	41.336 (0.020)	6.935 (0.004)	
Numskus	-6.724 (0.007)	1.906 (0.008)	2.120 (0.001)	
Drilldown	-67.553 (0.065)	-44.186 (0.061)	-0.148 (0.006)	

Based on segment membership parameters, segments 1 and 2 can be described as sessions with very limited drilldown behavior. Specifically, segment 1 visits are characterized by visitors seeking only basic information on a single SKU. For these sessions, timing of the pop-up promotion can be critical in terms of its effect on site exit. Waiting, in terms of page-depth, can shorten already short visits (b_{depth} = 2.50) while waiting, in terms of page-delay, can lengthen a visit (b_{delay} = -0.12). From these results, it appears that these visitors, who are seeking one specific piece of information, respond positively to a delay within page as it may provide them time to complete the task of reading the information on that page. Additionally, offering the promotion on a content page decreases store exit probabilities ($b_{context}$ = -1.89), contrary to the results of the aggregate level model.

Segment 2 sessions also have limited drilldown but for a few more SKUs than segment 1. However, timing characteristics of the promotion have the opposite effect on exit behavior for segment 2 sessions. Specifically, waiting, in terms of page-depth, can decrease exit probabilities thereby increasing length of stay (b_{depth}=-0.12). However, waiting, in terms of page-delay, can increase exit probabilities and lead to a shorter visit (b_{delay} = 0.021). Like segment 1, offering the promotion on a content pages also decreases store exit probabilities but to a much lesser extent than is the case with segment 1 ($b_{context}$ = -0.42). Overall, for both segments 1 and 2, promotions, if timed correctly and presented on a content page, can decrease store exit probabilities. This presents an opportunity for marketers to customize the timing of promotions.

In contrast, segments 3 and 4 consist of sessions with deeper drilldown. The differentiating factor between segments 3 and 4 is the variety of SKUs for which this drilldown is performed. Segment 3 sessions are characterized by deep drilldown over a highly varied number of SKUs. These sessions can be described as thorough information gathering sessions. Though page-depth does not have a significant effect on exit behavior for this segment, page-delay has a signficant and negative effect on length of stay (b_{depth} = -0.07). In other words, waiting, in terms of page-depth, increases exit probabilities as the promotion is more likely viewed as an interruption of their complex information seeking task. Additionally, unlike the case with segment 1 and 2 sessions, offering the promotion on a content page significantly damages the user’s experience and increases the probability of exit ($b_{context}$ = 0.09). This suggests that these individuals, who are already acquiring large amounts of information, are overloaded by the information offered in the pop-up promotion and therefore react adversely to it, a risk that online marketers must manage.

Segment 4 sessions are also conducting complex tasks with deep drilldown but across fewer SKUs than segment 3. Any waiting, be it from page-delay or page-depth, increases exit probabilities (b_{depth} = 0.16; b_{delay} = 0.01) as it is viewed as an interruption of their primary task at the site, though the effect of page-delay is minor in terms of magnitude. Additionally, offering a promotion on a content page is viewed even more so as an unwelcomed interruption ($b_{context}$ = 0.57). Both segments 3 and 4 can be characterized as performing complex tasks (at least more complex than segments 1 and 2). As a result, interruptions are viewed unfavorably and seem to overload the user, as reflected by the earlier exit.

Table 9 provides a descriptive summary of the 4 segment exit model results. Overall, we find that for uncomplicated, though very directed, tasks (segments 1 and 2), interruptions can be more easily incorporated into the original task (as indicated by higher baseline estimates when compared to segments 3 and 4), enriching the experience and deterring site exit. This is especially the case if the promotion is offered on a content page. Additionally, timing becomes an important promotional characteristic to manage as it can be customized to these segments to keep the visitor at the site longer.

TABLE 9: Descriptive Summary of 4-Segment Exit Model Results

	Limited Drilldown		***Deeper Drilldown***	
	Segment1	**Segment 2**	**Segment 3**	**Segment 4**
Description	Single SKU	Few SKUs	Varied SKUs	Deep within fewer SKUs
Delay to later pages	–	+	–	–
Delay within page	+	–	not signif.	–
Context	+	+	–	–

For more complicated tasks with deeper drilldown (segments 3 and 4), there is a higher risk of information overload. Any delay in presenting the message leads to it being viewed as an unwelcomed interruption. Additionally, offering the pop-up promotion on a content page only adds to the information that the visitor must absorb on that page, potentially resulting in information overload and increasing his/her likelihood of exit.

6. Conclusion

Discussion

In this paper, two separate models were presented. One that examined a visitor's direct response to a pop-up promotion in terms of clickthrough and one that examined an indirect response in terms of site exit behavior. Both models accommodate heterogeneity and attempt to assess the effects of promotion characteristics such as timing (page-delay and page-depth) as well as page content.

The aggregate level models seem to support the common industry practice of offering a pop-up immediately once a visitor enters the website. However, this is deceptive since the effects vary greatly across segments. It would seem that waiting to present a pop-up promotion decreases promotional response regardless of the task being performed by the visitor. However, this alone does not support the conclusion that online marketers should offer all pop-up promotions immediately since the effect on site exit counters the decrease in promotion response among some segments. Though site exit probabilities increase as a result of waiting among visitors performing complex tasks, effects are more varied if the task is simpler. Depending on the segment, timing of pop-up promotions can be critical in not driving away these visitors, suggesting an opportunity for customization. Since sessions performing simpler tasks are more common, this is not an insignificant consideration for online marketers.

Additionally, the effect of offering a promotion on a content page is quite significant. By offering a promotion on a content page, online marketers can improve direct response rates among the segment that seeks information with limited depth but on a variety of items. Content also affects site exit behavior. For sessions performing simple tasks, offering the promotion on a content page can improve the visitors experience and decrease store exit. However, offering the promotion on a content page can have the opposite effect for more complex tasks since the risk of information overload is higher. Therefore, for complex tasks, there is a trade-off between increasing promotion redemption and managing store exit behavior.

Limitations and Future Research

This paper is an initial study of the effect of pop-up timing on the user's website behavior. In this effort, measures that characterized sessions, and used to assign them into segments, were design to provide a meaningful description of the session as a whole. As a result, these measures can only be calculated after the session has been concluded. Future research may want to explore methods that assign sessions into segments in real-time as the site visitor clicks from page to page.

Additionally, it has become increasingly popular to use pop-unders instead of pop-ups. Since these messages are typically not viewed by the web user until the visit session is complete and the browser window is closed, pop-unders can be considered pop-ups that have been delayed to an extreme. This extreme level of delay was not a condition in our field experiment but is an interesting condition to study further in future research. With a more complete continuum of delay levels, different functional forms can be tested to model response to promotional timing.

Currently, with the limited conditions in our experiment, we have used a linear function to describe a user's response to promotional timing. However, it is possible that the response function is an inverted-U with an optimal timing condition. If this is the case, a prescriptive model of response to promotional timing may be invaluable to internet marketers who may want to customize promotional timing to optimize the target user's response, be it clickthrough or site exit.

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