

**An Empirical Study of Long-run Impact of Internet
Advertising on Consumer Response Behavior**

By

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Submitted to the Sloan School of Management in Partial Fulfillment of the Requirement for the
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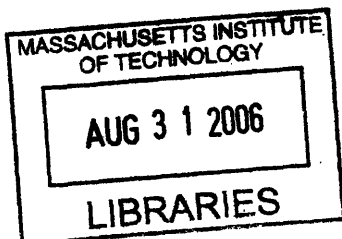
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Abstract

The long-run effect of banner advertisements is among the most complex topic in the internet world. Media spending on online marketing has grown from \$3 billion in 1999 to \$9 billion in 2004. Forecasts (*Jupiter Research 2005*) expect this growth to double in the next five years. The proportion of marketing budgets spent on online advertising is expected to grow from 4.6% in 2004 to 7% in 2010. Banner media costs contribute approximately 60% of the total online media spend across all industries. A portion of this increase can be attributed to the increasing acquisition cost of media/advertising space in the most frequently visited websites. Companies enter into bidding wars to acquire space in a restricted 15"/17" computer monitor screen from service providers like Google, Yahoo, AOL and MSN. Prices for banner advertisement space vary by the number of exposures and even by the time of the day. This directly begs a question on the effectiveness of online banner advertisement in influencing consumer behavior. Currently most firms track immediate response behaviors or the short-run effects. We use an experiment conducted with a student credit card campaign to explain the long-run impact on response behaviors across different audiences by exposing them to promotional advertisements on a public educational website.

Thesis Supervisor: Duncan Simester

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Keywords: Online Media; Online Banners; Long-Run Impact; Online Advertisement; Purchase behavior; Exposures, Control group

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1.0 Background

Advertising on the internet began in the middle of the past decade, when the first banner advertisements were placed on commercial websites. Although there are several forms of internet advertising, such as banners, interstitials and pop-up windows, banner ads are the most prevalent. Banner ads have dominated web advertising and become the standard advertising format on the internet. (George Baltas)

On-line advertising has become an important component of the Internet economy and the advertising industry, in general. Banner advertisements are active images on a web page that serve as a lead-in for the visitor to find out more by clicking on the banner (Raman & Leckenby 1998). Clicking on the banner takes the visitor from the current web page to the advertiser's web page. In this manner, banner ads are used as vehicles to bring prospective customers to a site, offering an automated link to the advertiser (Briggs & Hollis 1997; Bellizzi 2000). Clickable banner ads are believed to be the first gateway to entering the world of interactive electronic markets (Shamdasani et al. 2001).

A widely used measure for evaluating the effectiveness of banner advertising is the click-through rate, that is, the proportion of viewers who click on a banner to visit the advertiser's web site (Hanson 2000). It should be noted, however, that the advertising industry also uses alternative, well-established measures of banner success, such as acquisitions, branding and image change. The attraction of the click-through variable lies in its behavioral nature, measurability, and that it indicates immediate interest (Briggs & Hollis 1997). It is worth noting that the pricing of internet advertising is often based on click-through rates because advertisers demand results-oriented pricing and question the pricing model of traditional media, which is based on mere impressions; rather, they insist on paying for direct response results (Hofacker & Murphy 1998; Cho et al. 2001). It has been suggested that there is an explicit shift in online advertising strategy that favors deriving behavioral responses from selected target audiences over providing exposure to generic or random audience groups (Yoon & Kim 2001). These trends increase the importance of a banner's ability to induce direct responses and emphasize the problem of effective creative design and media planning (Shamdasani et al. 2001).

Tracking direct response results on the internet is simple since response information is electronically captured and reported through the ad serving process as well as by tracking visitors' activity once they have reached a site. In this manner, direct response data offer a great opportunity to empirically establish causal relationships (Broussard 2000).

In the early days of the internet, it was suggested that creative characteristics, in particular, animation, cryptic messages, and clichés such as 'click now' or 'free' tend to increase response rates (Hofacker & Murphy 1998). Now, the effectiveness of such simple ways on improving response rates is questionable, since over time the internet audience has gained considerable experience with banner ads. Perhaps more importantly, the impact of other design and media factors of the banner campaign remains empirically unexplored.

However, click-through rates vary owing to various and largely unknown factors related to design, execution and context of banner campaigns. Therefore, knowing about such determinants can help to improve campaign performance, but click-through rates are not the true measure for economic success of internet promotions. Companies are increasingly interested in tying spending on promotions to their marketing revenues. Unlike direct mail promotions, where individual coupons carry unique codes and purchases or responses can be tied directly to an individual consumer who is promoted, online banner advertisements offer challenges in establishing such relationships.

With the new technology procedures of placing web beacons (tiny invisible image placed on a web page), cookies, active advertisement banners (which actually sends a message to the servers when the banner is displayed to the users), tracking consumer activities on the internet has become increasingly easier and more interesting. Currently, almost all the internet service providers, ad agencies and corporations are able to track their consumer response behavior instantaneously from the moment an ad campaign is launched. Most of the published literature on this subject explains the responses or purchase behaviors of the campaigns. However, as discussed earlier in our abstract, almost

all of them fail to capture the long-run effects of the banner ads. Despite the importance of the topic, very little empirical work has been done on the long-run effectiveness of banner ads and, in particular, the effects on different visitor groups. The purpose of this study is to consider the long-run effects of a specific product campaign on the effectiveness of banner ads, drawing upon real response data.

The paper is organized as follows. The subsequent section presents the hypothesis, topography of the experiment, campaign design, campaign execution and an analytical framework for the empirical identification of banner effectiveness relationships. This is followed by analysis of the findings. Implications for advertising practitioners and researchers are considered next. A concluding section summarizes this paper.

2.0 Hypothesis

As an increasing amount of input floods consumers' lives and competes for their attention, consumers enhance their filtering mechanisms. Input that is not perceived to be of interest, relevance, or value is not committed to long-term memory and is quickly forgotten. Given the landscape of varying attentiveness to media, increasing clutter and dwindling attention span among consumers, how should we attribute response to banner advertisements in the long-run? While we didn't expect miracles (such as perfect recall of banner advertisement or everyone rushing out to purchase the product the moment they see the banner ad), we expected to see consistent responses from the banner advertising over time.

Our study tested this hypothesis by creating two random audience groups, Control and Treated, and measured their response behavior over several weeks after exposing both groups with different set of banner ads. The control group was exposed to charity banner advertisements and the exposed group was exposed to student credit card promotion banner ads. Because treated and control respondents were randomly assigned and identically matched, the hypothesis is that cumulative response rates from treated and control cells should be identical. A methodology of this type sets a high standard for measuring banner advertising effectiveness on the long-run because of randomness of the experiment.

3.0 Topography of the experiment

To test our hypothesis, we chose a high traffic student website, where several promotional banner ads are placed throughout the year. The website generates traffic through new paper advertisements, email campaigns and banner advertisements in several service provider home pages. On average, this site generates more than 20,000 visitors per day to the home page.

3.1 The World of Cookies

When a visitor first lands on the home page of the experiment web site, he/she was assigned a unique id (GUID, a 32 character text string) and it gets written as a cookie in the local machine. Any subsequent activity on the website by the user, who is using the machine, is tracked by this unique identifier. Since the association happens at a “machine level”, it is hard to identify a unique consumer or a household. The same consumer can also choose to use different machines at different times of the day. Unless consumers identify themselves with a log-in or personally identifiable information, there may be duplicate cookies. Tracking becomes more complex, as the time continuum is extended. In addition, we also observe higher a likelihood of losing consumers (or cookies) due to cookie cleaning and computer replacements. Another alternative to track the consumers is by using machine IP addresses; however this method is not popular because of the dynamic nature of IP address allocations.

Our study (*Atlas, Appendix -3*) on shelf lives of cookies indicates that more than 56% of the consumers retain cookies over a period of two months or above and cookies are the best way to track the individual’s behavior on the internet. Basing our experiment and analysis on cookies is rather a conservative approach since we will be reporting less on the positive side. In other words, we will have conservative false negative situations in the results we observe.

3.2 Information Exchange Mechanism

Information is exchanged between the web servers and the user's machine during every visit, every display of banner ad and every click. When a user lands on the page, either by typing URL or clicking a link from a sponsor's web page, the cookie information is sent to the web server that is serving the page. This information is captured and logged into the database and a unique session is created for the user. If a page is rendered with a banner ad, the image/banner add posts an impression message back to the server, with both the session information and the cookie id (GUID)¹. This records the fact that the page was rendered with the banner ad. Personalization of banner ads to consumers is also possible by matching the requestor's cookie id with the Web Server data. Similarly, all the click and response data can be tracked with the cookie id. In general, cookies are the unique identifiers that connect every event and user action in the internet world.

3.3 Response Definition

Another difficulty lies in the definition of a response. A definition of response from a consumer to an online banner advertisement depends on the purpose of the advertisements. If the ad is for a specific product promotion and if the product is sold exclusively through online channel then it is easier to collect the purchase data through the information transfer mechanisms discussed above. In some cases, the internet acts as a driver to product sales through multiple channels (phone or retail), in which case, associating the purchase behavior or response to the online activities of a consumer is quite cumbersome and some cases impossible. With many different channels to purchase a product in a distributed business model, we believe that the reported impact of internet on sales is lower than the actual impact.

1 - We use the term consumer, GUID, computer, and cookie identifier interchangeably for the sake of exposition. However, as mentioned earlier, our data only allow us to identify a unique computer and not a unique consumer.

In our experiment, we defined an online request for a student credit card (online application for the Student Credit Card) as a positive response from the banner advertisement. Each online application page carries the cookie id of the user machine. A valid response from the treated group in our experiment is an online application from an identifiable cookie id which had prior exposure to the promotional banner ad. Consumers typically respond in two different ways. Some click the banner ad (impulsive response) which takes them to an application page, where they can fill out their personal information and submit the application for approval. Others view the ad and later go to the application page directly by typing the URL or by other means, such as clicking the link from their favorite folders (delayed response). We tracked both responses from the audience through cookies. As discussed earlier, we saw responses coming from other channels (phones and paper) from those who were exposed to the online banner ads. However, we omitted such responses in our calculations, since we could not accurately tie them back to the banner exposures².

2 – Our dataset is based on the behavioral aspects and hence we are unable to control for the exact nature of exposure. In other words, we are making the assumption that if the consumer was on a specific page and the banner appeared on that same page, she/he actually viewed the advertisement. However, given that banner ads are probably even lower involvement than TV ads (small size, exposure in the presence of competing information), this argues against our finding any effects.

4.0 Experimental Design

4.1 Audience Profile

An important aspect we must consider is that a product specific web site generally reaches a specific type of consumer with a distinct audience profile. The traffic to product specific websites is driven mostly by the audiences that have relevant interests (*IAB Study, 2001*). Demographics of this audience may vary widely but the interest of the audience is very distinct. Our approach eliminates the influence of audience interest factors by creating a control group with similar interest profiles.

4.2 Creative Design

Our campaign ran for three weeks starting January 9th 2006. During these three weeks, different groups of audiences (discussed in our next topic) were exposed with different sets of promotional banner ads (*Appendix -1*) and several charity ads. These banner ads had active links which took them to landing page for applications in the case of the promotional ad and an appropriate charity organizations page in case of charity advertisements.

4.3 Advertisement Schedules

The promotional ads were run on all seven days of the week and during specific hours of the day. Based on our prior experience, we identified certain periods of time during a day when traffic to the website was relatively higher. We were also aware that the traffic to our websites was higher during the weekends and early part of the week. We selected specific times of the day to place the student card banner ads in order to maximize exposure and response. To simplify the implementation of the experiment, we did not vary the schedule by day of the week. The following table (Table 1) shows the day schedule for the different banner ads. The campaign was executed based on the following schedule.

Table – 1

Types of banner served during different periods of the day by audience

	<u>Existing Audience</u>		<u>New Audience</u>	
	<u>Control</u>	<u>Treated</u>	<u>Control</u>	<u>Treated</u>
8 AM – 10 AM	Charity Ad	Credit Card	Charity Ad	Credit Card
10 AM – 11 AM	Charity Ad	Other Ads	Other Ads or Charity Ad	Other Ads
11 AM – 3 PM	Charity Ad	Credit Card	Charity Ad	Credit Card
3 PM – 7 PM	Charity Ad	Other Ads	Other Ads or Charity Ad	Other Ads
7 PM – 1 AM	Charity Ad	Credit Card	Charity Ad	Credit Card
2 AM - 8 AM	Charity Ad	Other Ads	Other Ads or Charity Ad	Other Ads

Shaded rows represent the time of the day when student credit card promotion banners were served

In order to ensure that the control groups were significantly active, we served the charity banner ads until eight weeks after the promotion start date.

4.4 Control and Treatment Group Definition for Existing Audience

We had two distinctive groups; an existing consumer group and a new consumer group. Based on the prior discussions, the only way we can uniquely identify a consumer in the internet is through cookie id. We also noted earlier that the active shelf life of most of the cookies is approximately three months, with 40% of them get deleted or stay inactive after this time period. Hence we chose about 1.98 million random cookies that were created within three months prior to the beginning of the experimental campaign launch. In our selection, we observed that these cookies had at least one visit activity within a month prior to the beginning date of the campaign. We held this set of cookies as the

“Control Group of Existing Consumers (CGEC)”. We chose another set of random 444,000 existing cookies (GUID) with the same criteria as above and used them as “Treatment Group of Existing Consumers (TGEC)”.

4.4 Control and Treatment Group Definition for New Audience

We identified new audience group by the cookies that were created after the promotion start date. Some of new visitor’s cookies were created during the periods or hours when student card banner was served. We grouped these cookies into the treatment cell of new audience. Similarly, other new visitors visited our site during the periods or hours when student card banner was not served. We marked these cookies as control for the new audience. When the new control audience visited the site subsequently, they were either served charity ad or other advertisement. In summary, the new audience control was created on a daily basis and they were never exposed to the student card advertisement in their subsequent visits.

We classified them into two groups; “Treatment group of new consumers (TGNC)” are those who saw the banner ad and “Control Group of New Consumers (CGNC)” who visited the website but never saw our promotional ads. We had a total of 640,345 CGNC (Control group for new visitors) and 3,553,694 of TGNC (Treatment group of New Consumers) (Appendix – 2, Table -1).

We exposed the CGEC with charity ads and other two groups (TGEC and TGNC) with promotional banner ads. The CGNC, which is the Control group of new visitors were displayed either with Charity ads or other promotional ads not related to the Student Card. We tracked the visits, exposures/impressions, clicks and responses among these four groups (Appendix – 2, Table -2).

4.5 Campaign Execution

The campaign was set up to run with an ad server and different tables were set up to classify visitors. During the time of the day when student card promotion was served (refer Table -1), the web server first checked whether the computer requesting the web page has a cookie that already exists in the CGEC or CGNC tables. If it did, the page was

rendered with the Charity ad. If the ad server did not find this cookie in either one of these tables, it then served the Student Card promotional banner ad.

During the time of the day when student credit card promotion was not served, the existing visitors from control table (CGEC) were served with Charity ads. Visitors from other groups were rendered promotional ads sponsored or paid by other companies or charity ads.

4.6 Data Collection

We collected the data over a period of thirteen weeks since the start date of campaign. All the tables are keyed by cookie id. The five main subject areas of our database are Audience, Visits, Impressions, Clicks and Response. Each row in the Audience tables represents a consumer. The row also carries the date and time of the first visit and other relevant information related to the webpage. Each row in visit tables represents individual page visit data for each consumer. Similar to the Audience tables, the visit tables carry date and time of the visit, session identifier and IP addresses of the visitor's computer. Impression tables contain information about the banner ads served. Depending on the page design, a consumer may see any number of banner ads. Hence, each row in this table carries information about the type of banner ad, placement or location of the banner ad on the page and dimensional attributes of the banner ad.

Click data contains two sets of information. The first set contains the session and the date and time when user clicked the banner ad. The second set contains the information about the target URL. The information about target URL represents the landing page characteristics and some information about the actions that user had already performed prior to clicking. Response table contains information about the student credit card application, the date and time of application and cookie data.

5.0 Analysis of Results

5.1 Summary Statistics

We collected the data for a period of thirteen weeks since the beginning of the campaign. We measured the visits, impressions/exposures, clicks and responses from the four groups and analyzed the results. The following table shows summary statistics on all the four groups.

	Existing Visitors Control	Treatment Group of Existing Consumers	p-value	New Visitors Control*	New Visitors Treated	p-value
Unique Users	1,983,676	444,873		640,345	3,553,634	
Visits	7,148,829	5,094,431		5,969,370	19,524,345	
Total Exposures	5,894,693	1,501,447		-	9,721,353	
Clicks	7,785	128,553		-	756,251	
Responses	77	59		30	672	
Response/User	0.0039%	0.01323%	<0.001*	0.00468%	0.01891%	<0.001*
Response/User_Lift		3.42			4.04	
Response/Exposure	0.00131%	0.00393%	<0.001*	0.00050%	0.00391%	<0.001*
Response/Exposure_Lift		3.01			13.75	

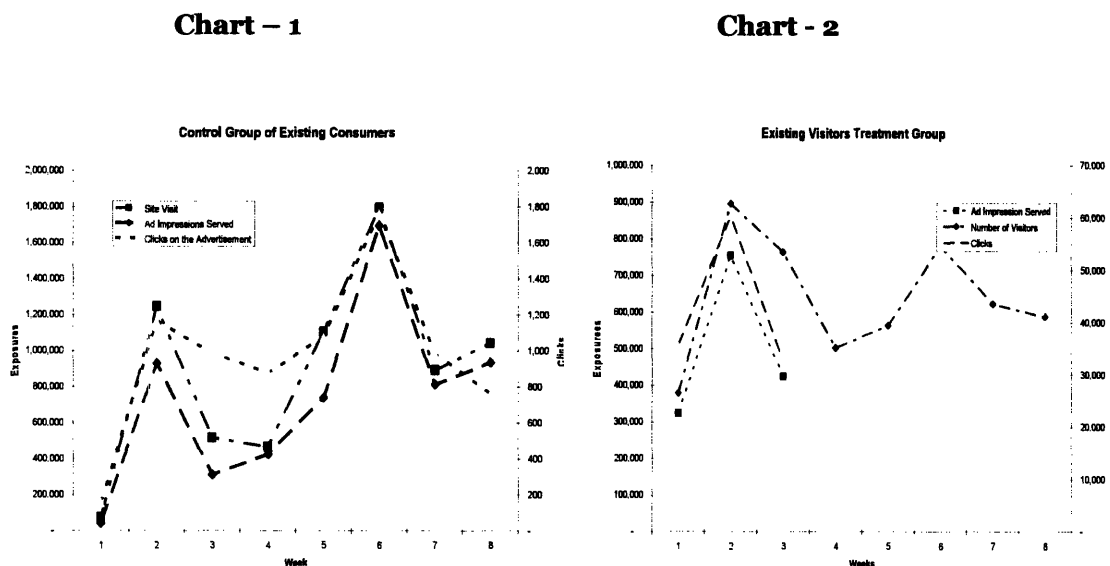
* New users who were never exposed to student ad campaign. The calculation of response rate for this group is based on the number of visits since this group was exposed to banners from other firms during the promotion.

Response rate measured in terms of unique visitor shows a lift of 4.04 for the new user group over control. The existing user group shows a lift of 3.42. The results indicate better performance from the new visitor group, although the difference in the lift is not highly significant. Response rate measured in terms of exposure shows a completely different result. A lift of 13.75 of the new consumers compared to 3.01 for the existing consumers is astonishingly different and this difference clearly arises due to the visiting behavior between these two groups. This situation is very similar to the retail shopping model i.e. the more the visits, the more the purchase tends to be. This implies that the internet media reach beyond the existing customer base is crucial in increasing the effectiveness of banner advertisements.

5.2 Visitor Behavior Analysis

5.2.1 Existing Consumers

The impressions were served uniformly across the treatment group during the visits. The following graph shows the pattern of visits, impressions/exposures and Clicks for the Control and Treatment groups of existing consumers (*note that the graph is plotted with two Y-Axes, number of exposure on the left Y and number of Clicks on the right Y. The data for these graphs are in Table 1 and 2 in Appendix 2*)



From the data we observed for the existing consumers, the click to impression or exposure ratio was significantly different between the control group and the treatment group. The Control group who were exposed to charity advertisements had a click to exposure ratio ranging from 0.1% to 0.4% (over eight weeks of ad serving) whereas the treated group had a click to exposure ratio of 7% to 11% (over three weeks of promotional ad serving). The lower click to exposure ratio of the control group clearly indicates the fact that consumer's interests and the contents are not clearly aligned. During the first three-week period, the pattern of visits is nearly identical between these two groups. After the third week, we continued to observe a slight decline in the website visit patterns from the treatment group, although we did not see any abrupt decline in visit behavior. Control group

continued to see the charity ads until the end of eighth week. Both control and treatment group showed a significant spike in the web site visit during sixth week. Cause for such increase in activity requires further exploration.

5.2.2 New Consumers

Since the control group for new consumers was not exposed to any advertisement related to Student Credit Cards, we could only track their visits and responses. The following charts shows the visits, exposures and clicks of new treated consumers and the visits of control group.

Chart – 3

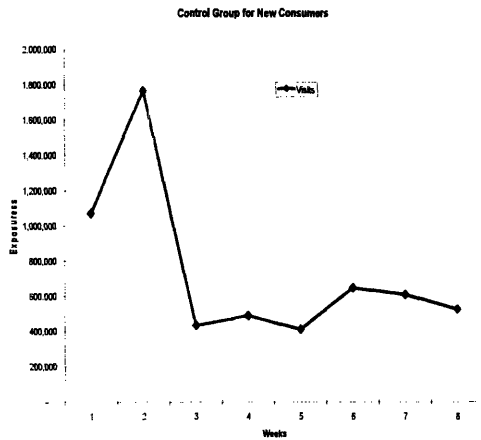
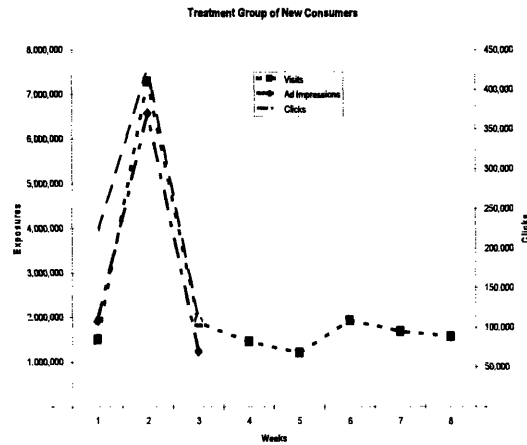


Chart - 4



The visit patterns were almost identical between these two groups. With the exception of the 2nd week spike in the number of visits of the new consumers (from both control and treatment cells), the traffic from the new visitors to the website is very steady. The spike may be attributable to seasonality effect or word of mouth within the student community about the promotional offers.

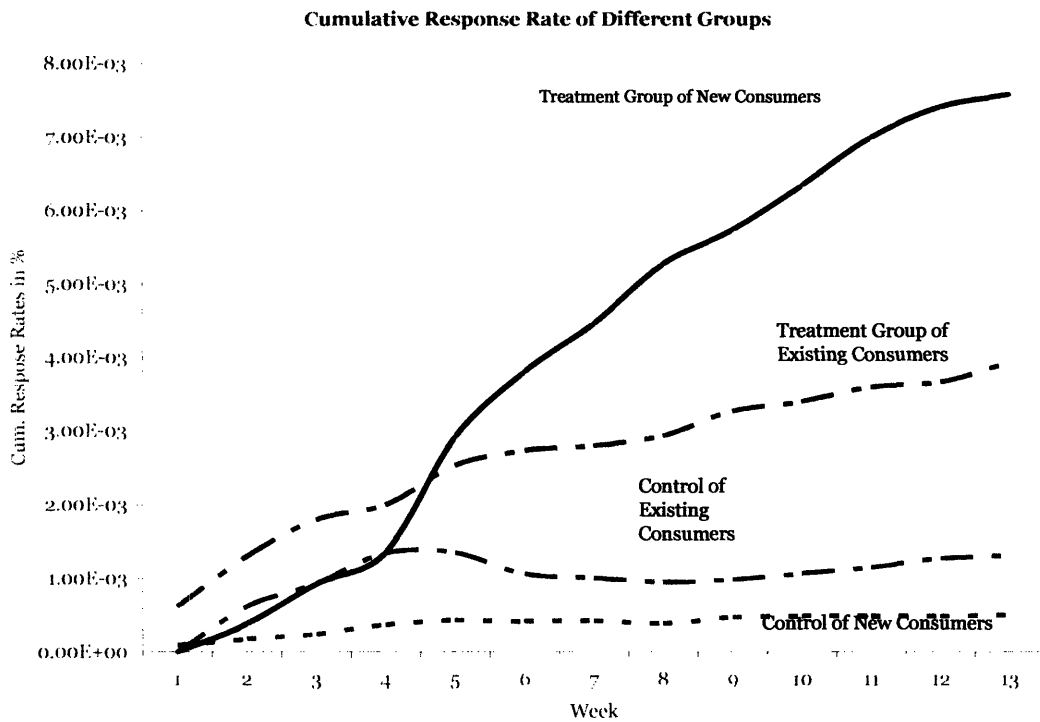
5.3 Cumulative Response Rate Analysis – Long-Run Effects

5.3.1 Cumulative Response Rate Definition

In order to analyze the long-run impact we introduced the cumulative response rate as a measure of normalizing the responses across different groups. The following chart (chart -5) shows the cumulative response rates of all four groups we analyzed. Cumulative response is calculated as follows

$$\text{Cum. Response Rate} = (\text{Sum of responses}/\text{Sum of exposures})_{\text{Week}}$$

Chart - 5



Clearly we observe a remarkable separation in the purchase behavior among the treated groups and control groups. It is important to note that the banner ad was stopped after the third week of the campaign.

5.3.2 Existing Consumers

The following table (Table -3) shows the cumulative response rates of treated and control group of existing consumers.

Table -3

Week	Existing Visitors Control 1983676			Existing Visitors -Treatment Group 444873			Lift	Significance Test(5%: threshold) between Control and Treated group for existing consumers
	Number of Respnoses	Number of Impressions or Exposures	Cumulative Response Rate in %	Number of Respnoses	Impressions Displayed	Cumulative Response Rate in %		
1	0	42,578	0	2	323,877	0.000618	NA	NA
2	6	930,103	0.000617	12	754,038	0.001299	1.105923	p < 0.05
3	6	911,974	0.000934	13	429,872	0.001799	0.925134	p < 0.05
4	11	425,770	0.001345	3		0.001999	0.495999	p = 0.158
5	10	739,954	0.001347	9		0.002531	0.879447	p < 0.05
6	11	1,699,339	0.001061	3		0.002731	1.572929	p < 0.05
7	8	813,290	0.001009	1		0.002797	1.774319	p < 0.05
8	6	935,780	0.000950	2		0.002931	2.094721	p < 0.05
9	2		0.000994	5		0.003264	2.316800	p < 0.05
10	5		0.001089	2		0.003397	2.178197	p < 0.05
11	5		0.001154	3		0.003597	2.117712	p < 0.05
12	7		0.001272	1		0.003663	1.879073	p < 0.05
13	2		0.001308	4		0.003930	2.009240	p < 0.05

In the first two weeks during the advertisement, we observed a significant difference in response rates of existing consumers compared to the control group. Subsequently, we continued to observe a significant lift in response rates of treated group over the control group at 5% threshold levels, with $p < 0.05$. Existing consumer's response rates were significantly higher than the control group in both short-run and the long-run.

5.3.3 New Consumers

When compared with the new consumer control group, the treated group showed no significant differences in the response behavior in the short-run (Table -4). After the exposure duration of three weeks, we observed significant activities of visits and applications from this group and the response rate increased during week four thru week six. The cumulative response table (Table – 4) shows the effect of long-run response from

the new consumers over an extended period of time. After the sixth week of the advertisement, the treated new consumers responded at higher rates than all other groups.

Table -4

Week	New Visitors Control 640345			New Visitors Treated 3553694			Lift	Significance Test(5% threshold) between Control and Treated group for existing consumers
	Number of Responses	Impressions Displayed*	Cumulative Response Rate in %	Number of Responses	Impressions Displayed	Cumulative Response Rate in %		
1	1	1,072,984	9.32E-05	-	1,081,335	-	1.000000	p = 0.317
2	4	1,768,957	0.000178	29	8,671,114	0.000390	1.153814	p = 0.053
3	3	435,190	0.000244	53	1,231,038	0.000925	2.789749	p < 0.05
4	8	491,562	0.000371	38		0.001354	2.644492	p < 0.05
5	4	413,094	0.000430	139		0.002911	5.762424	p < 0.05
6	2	649,232	0.000414	79		0.003802	9.184009	p < 0.05
7	3	610,994	0.000423	58		0.004456	9.544419	p < 0.05
8	0	527,377	0.000395	72		0.005238	12.674548	p < 0.05
9	5		0.000469	41		0.005731	11.218929	p < 0.05
10	1		0.000489	54		0.006341	12.051553	p < 0.05
11	0		0.000489	59		0.006995	13.399511	p < 0.05
12	0		0.000496	37		0.007412	14.257777	p < 0.05
13	1		0.000503	15		0.007582	14.085924	p < 0.05

6.0 Discussions

Banner advertisements are vehicles for contemporary businesses to increase web site traffic. Extensive demand for placements in high traffic web pages has lead to a sharp increase in banner advertisement costs. The short-run effects of banner ads are often measured by firms, but there is little evidence of the long-run impact of banner advertisements on consumer purchase behaviors. Without understanding the effect of banner ads in the long-run it is hard for firms to optimize their investments in banner ads. Our primary objective is to test the hypothesis that internet banner advertisements have long-run influence customers.

Cookie survival analysis reveals that the measurable the time window for the long run study is approximately eight weeks after the cookie's creation. Most of the users have

deleted or cleaned their cookies after this time period. This limits our measurability of long- run impact to eight weeks.

We find that banner advertising increases the response rates of exposed groups significantly. In the short-run (during the execution window for the campaign), existing customers are likely perform better than their control groups when exposed to advertisements. We also find that having internet media reach beyond the existing customer base is crucial in increasing the effectiveness of banner advertisements, as the lift in response rates of prospects when measured for an extended period of time is significantly higher than that of existing consumers.

In contrary, the prospects, who are forming their consideration set for selection through search, do not respond to the banner advertisements in the first few weeks of exposure. Subsequently, prospects tend to respond better than existing customers.

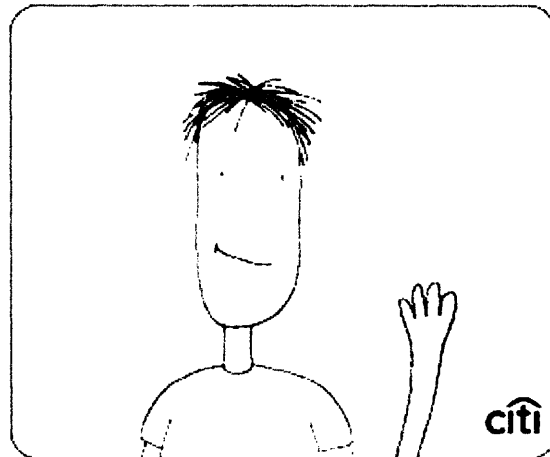
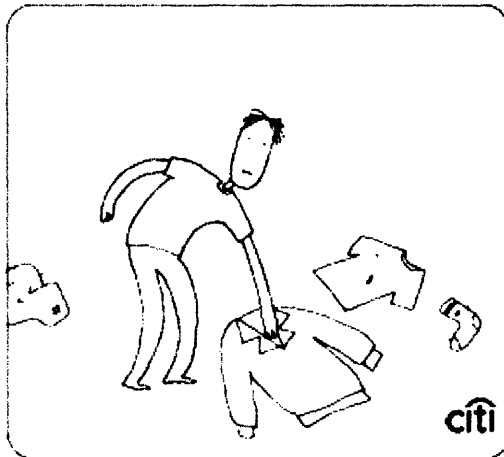
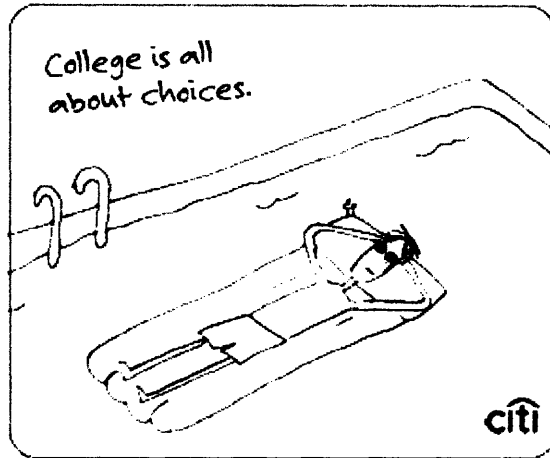
We infer the following two points from this empirical study. First, we can reject the null hypothesis that banner advertisements have similar effect between treated and control groups in the long-run. Second, the firms may be focusing on the wrong metric when they use short-run metrics such as click-through and immediate response to measure banner advertisement effectiveness.

7.0 Conclusion

Banner advertisements continue to dominate not only for online responses but also for brand awareness. There are several theories on the influence of banner ads on brand awareness but our empirical research proves that there is a strong correlation between the banner advertisement and delayed response across different groups. Also, we emphasize that our response measurements are completely conservative, because we have ignored response from other channels. We believe that the actual response rates from the banner advertisements are also underestimated in the industry because of the limited shelf life of cookies. Despite the conservative nature of the setting, the strong evidence of long-run effects indicates, that the banner advertisements have significant positive influence on the consumer purchases in the long-run.

Appendices

Appendix – 1

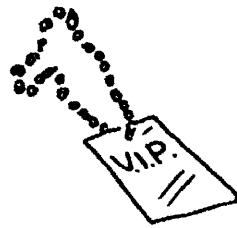


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Meeting your
roommate
can be great.

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Appendix – 2

Table - 1

Unique Users				
	Existing Visitors Control	Existing Visitors -Treatment Group	New Visitors Control*	New Visitors Treated
Unique Users	1,983,676	444,873	640,345	3,553,694

Table - 2

Advertisement Impression Data				
Week	Number of Advertisement Impressions			
	Existing Visitors Control	Existing Visitors -Treatment Group	New Visitors Control*	New Visitors Treated
1	42,578	323,677		1,919,231
2	930,109	754,038		6,571,114
3	311,974	423,672		1,231,038
4	425,770			
5	738,854			
6	1,698,338			
7	813,290			
8	935,780			

*New Visitors Control is a random selection of certain unique new visitors who were not served the Student Card campaign

Clicks Data				
Week	Number of Clicks			
	Existing Visitors Control	Existing Visitors -Treatment Group	New Visitors Control*	New Visitors Treated
	1,983,676	444,873	640,345	3,553,694
1	157	35,604		219,071
2	1,167	60,327		426,890
3	989	32,622		110,350
4	877			
5	1,078			
6	1,767			
7	988			
8	762			

Appendix – 3

This study addresses the recent survey-based studies on cookie deletion with an analysis that compares self-reported cookie-deletion estimates with the cookie “lifespan” of survey respondents. The behavioral data confirms that people who report deleting their cookies on a regular basis generally have short cookie lifespan. However, the analysis reveals some remarkable disparities between user responses to cookie deletion and their actual behavior. For example, 4 out of 10 respondents who claimed to delete their cookies weekly or monthly actually had cookie lifespan more than double their survey response.

The study compared cookie-deletion survey responses with the average cookie “lifespan” of the survey respondents. In this case, “lifespan” means the duration between the first and last instance that we saw the respondent’s cookie. Cookie lifespan is an excellent proxy for the stability of a user’s cookie because the data for the analysis was gathered from different corporations serving different demographic consumer segments, translating to almost 100 billion impressions, clicks, and page-views each year. Below is the cross tabulation of the self-reported data with the true behavioral data

How Often Do You Delete Internet Cookies?	% of Respondants	Lifespan of Respondent Cookies					
		0 Weeks	0-1 Week	1-2 Weeks	2-4 Weeks	4-8 Weeks	8+ Weeks
Every week	42.60%	17%	33%	10%	11%	8%	21%
Every month	13.70%	9%	15%	15%	12%	12%	46%
3 months +	43.70%	2%	14%	2%	5%	9%	68%
Overall	100%	8%	23%	8%	9%	9%	43%

Though the survey responses correlated with behavior, there were notable exceptions across the board. 40% of people who claimed to delete their cookies weekly had cookies that lived longer than two weeks, while 46% of people who said they delete their cookies every month had cookies that lived longer than two months. It’s also fair to point out that there were a significant number of people whose cookies lived far shorter than their responses.

In general, shorter shelf life of cookies has been a tremendous concern among the marketers, however hypothesis of many marketers is that the “Time-to-Convert Analysis” shows majority of conversions, generally 70%–90%, happens within a 12-hour to 24-hour of the window of the corresponding click or impression. Our study mainly focuses on testing the hypothesis of long-run effects. To estimate the long-run impact, understanding the shelf life of the cookies outside this short-run response behavior is important.

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