Is Combining Contextual and Behavioral Targeting Strategies Effective in Online Advertising?

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Online targeting has been increasingly used to deliver ads to consumers. But discovering how to target the most valuable web visitors and generate a high response rate is still a challenge for advertising intermediaries and advertisers. The purpose of this study is to examine how behavioral targeting (BT) impacts users' responses to online ads and particularly whether BT works better in combination with contextual targeting (CT). Using a large, individual-level clickstream data set of an automobile advertising campaign from an Internet advertising intermediary, this study examines the impact of BT and CT strategies on users' click behavior. The results show that (1) targeting a user with behavioral characteristics that are closely related to ads does not necessarily increase the click through rates (CTRs); whereas, targeting a user with behavioral characteristics that are loosely related to ads leads to a higher CTR, and (2) BT and CT work better in combination. Our study contributes to online advertising design literature and provides important managerial implications for advertising intermediaries and advertisers on targeting individual users.

CCS Concepts: • **Information systems → Online shopping**

Additional Key Words and Phrases: Targeted advertising, behavioral targeting, contextual targeting, online advertising

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1. INTRODUCTION

Targeted advertising, a marketing strategy in which advertisers target individual consumers with tailor-made content, has seen significant growth in the past few decades [Zhao 2012; Zhao and Xue 2013]. New online targeting approaches have been developed to deliver ads to the right person who most values the information in the ads at the right time when the person is most likely to act on the ads. Examples of the recent innovations in online targeted advertising include behavioral targeting (BT), contextual targeting (CT), retargeting, IP-based geo-targeting, explicit profile data targeting, and search targeting [IAB 2010; Lambrecht and Tucker 2013]. These techniques have been

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applied to a variety of online ad formats such as search ads, display ads, banner ads, and video ads. Borrel Associates projected that online advertising grows 44% in 2015, driven primarily by targeted display advertising [Smith 2014].

Two major targeting innovations that are widely used are *contextual* and *behavioral targeting*. CT refers to approaches that deliver online ads to a user based on the web content that he or she is viewing [Goldfarb and Tucker 2011a, 2011b, 2011c; Zhang and Katona 2012], which essentially aims to target consumers at the right time. A recent survey by the Digital Advertising Alliance found that 41% of respondents reported that they preferred online ads directed toward their interests whereas only 16% of respondents preferred random ads.[1] The premise of CT is that a user's interest in a particular content topic may be indicative of his or her preference for a type of product [Zhang and Katona 2012]. For example, a user who is browsing a webpage about automobiles is more likely to be interested in cars at that time than a user who is browsing a webpage about health care. So in CT, an advertising intermediary displays the auto-related advertisements when a user is loading a webpage about automobiles.

BT refers to approaches where online ads are delivered to a user based on his or her historic online behavior data [Yan et al. 2009]. BT aims to identify consumers who are more interested in the information in the ads, that is, the right people [Yan et al. 2009; Farahat and Bailey 2012]. Advertising intermediaries are using consumer-tracking technologies such as cookies, beacons, and video cookies to record consumers' online behaviors across their partners' websites. According to a study by The Wall Street Journal, the 50 most popular websites in the US installed more than 3,000 tracking files on a single computer [Angwin 2010]. Using users' online behavior data, such as specific pages visited, browsing trails from one site to another, searches made, or click-throughs to specific content or ads, advertising intermediaries can learn the users' interests and display ads to those who are likely to be interested in and respond to the ads [Beales 2010]. A survey of 12 advertising networks reported that the conversion rates of BT advertising were more than twice those of other standard advertising rates [Beales 2010].

BT enables advertisers to reach out to users no matter whether or not they are browsing specific content related to ads. When BT delivers ads to users while they are browsing content that is related to the ads, consumers' responses are essentially the consequences of both BT and CT. Prior research has shown that the use of BT in online advertising leads to higher click through rate (CTR) and/or conversion rates [Manchanda et al. 2006; Yan et al. 2009; Farahat and Bailey 2012; Breznitz and Palermo 2013]. It is unclear how CT contributes to the favorable performance of BT. This issue is further compounded by the mixed findings about the effectiveness of CT in prior literature [Moore et al. 2005; Goldfarb and Tucker 2011a, 2011b]. Considering one form of targeting but ignoring the other may overestimate or underestimate the effectiveness of a particular targeting approach. The study intends to address this issue by investigating whether BT works better in combination with CT. In addition, we examine how individual behavioral variables should be used to select users to achieve a higher response rate. In particular, is a user with behavioral characteristics that are closely related to an ad (i.e., a higher degree of matching) more likely to click the ad compared with one with behavioral characteristics that are loosely related to the ad (i.e., a lower degree of matching)?

The research makes important contributions. First, prior literature has examined the effectiveness of BT and CT separately [Moore et al. 2005; Goldfarb and Tucker 2011a, 2011b; Yan et al. 2009; Farahat and Bailey 2012; Breznitz and Palermo 2013; Lambrecht and Tucker 2013]. In practice, both forms of online targeting may work together in delivering ads, and the increases of CTRs may be attributed to CT or the

[1]http://blog.atex.com/the-atex-blog-1.1483/ad-targeting-101-eight-types-of-targeting-1.3028.

interaction between BT and CT. Our study fills the void regarding empirical investigation of the interaction effect of these two targeting approaches. The results show that the joint use of these two approaches can generate a higher CTR, and hence that BT and CT work better in combination. Second, prior studies took the use of BT as a blackbox (e.g., Goldfarb and Tucker [2011a, 2011b, 2011c] and Lambrecht and Tucker [2013]). It is not clear how individual-level consumer behavioral information was used by ad intermediaries to match consumers and ads, or how the matching was connected to CTRs. The unique individual-level data set in this study enabled us to closely examine individual BT variables. In particular, we showed that the BT variable with a lower degree of matching increased consumers' CTRs, whereas those with a higher degree of matching did not impact consumers' CTRs. Prior literature has shown that privacy concerns negatively impact the performance of online display advertising [Goldfarb and Tucker 2011a]. Our study shows that privacy concerns also had a negative impact on the effectiveness of BT. Our study helps guide advertising intermediaries in designing better targeting criteria and IT artifacts to execute these targeting criteria.

The rest of this article is organized as follows: Section 2 reviews the literature on online targeting. Section 3 develops the hypotheses. In Sections 4 and 5, we introduce the research context and describe the theoretical model, respectively. Section 6 presents the empirical results and discussion, followed by robustness tests in Section 7. The final section summarizes the limitations and contributions of this study.

2. LITERATURE REVIEW

The article relates to a very small but growing body of literature investigating the use of BT in online advertising. Manchanda et al. [2006] found that the repeated purchase probability was influenced by individual browsing behavior and individual advertising exposure, including the number of ads that an individual was exposed to, the number of sites, and the number of pages displaying the ads. Their findings provide empirical evidence that prior advertising exposure and browsing behavior have a positive effect on consumers' purchase decisions. Goldfarb and Tucker [2011b] found that consumers' purchase intent was lower after viewing online display advertising in the countries that enforced privacy regulations that restricted advertisers' ability to collect consumer data used for targeted advertising. The results show evidence of the value of consumer data and behavior targeting. Yan et al. [2009] technically examined whether and how BT could help online advertising using real-world ad click-through logs. They segmented users based on their past browsing and search behavior and compared ad responses across segments. The results suggested that if BT was used, CTRs of online advertisements could be improved by as much as 670%. Farahat and Bailey [2012] recognized the issue of selection bias in individual targeting, which potentially led to overestimating the effectiveness of targeted advertising. They employed a difference in differences methods to control the selection bias, and still found that CTRs of the targeted users were higher than those of the untargeted group, and the rise of CTRs was driven by identifying the users who had an interest in the brand. Breznitz and Palermo [2013] showed that targeted advertising investments, by exploiting better knowledge of a much smaller subset of potential consumers, were more effective than traditional advertising investments in reducing costs and enabling better price discrimination. These studies empirically illustrated that overall BT could have a favorable effect on consumers' purchase intent or actions. Our study takes one step further, examining and comparing the effectiveness of different BT criteria in different contexts.

Prior literature has also empirically examined the use of CT in online advertising and found CT may lead to a favorable or unfavorable effect on consumer attitudes. Rodgers [2003/2004] showed that consumers preferred relevant sponsors to irrelevant sponsors in the context of Internet sponsorships. Moore et al. [2005] found that congruity between the website and the ad had a more favorable effect on attitudes towards the brand because consumers were more capable of assimilating the information in a congruent advertisement into existing activated schemas. Goldfarb and Tucker [2011a] found that contextually targeting using non-obtrusive ads increased the purchase intent of the exposed consumers. The congruity theory argues that highly congruent information fits with consumers' category schemas and as a result consumers have a favorable attitude to such information [Mandler 1982]. These studies empirically demonstrated that consumers were more likely to tolerate contextually targeted ads because the ads potentially provided information. However, Goldfarb and Tucker [2011a] also illustrated that contextually targeting visitors with highly obtrusive ads has a negative impact on consumers' purchase intent compared with contextually targeting using non-obtrusive ads. The use of obtrusive ads may increase consumers' perception of targeting and manipulation, reducing purchase intent [Campbell 1995].

Prior studies on online targeting examine the effectiveness of BT and CT separately due to the difficulty in acquiring the data. In practice, BT may deliver ads to consumers when they are browsing content that is related to the ads. The performance of ads may be partly driven by CT or the interaction between BT and CT. Considering one form of advertising but ignoring the other one may result in overestimating or underestimating the performance of a targeting approach. Goldfarb and Tucker [2011b] showed that the performance of banner advertising on websites that had general content suffered more from the enforcement of privacy regulations compared to websites that had specific content. Websites that had specific content can deliver ads to interested consumers based on the webpage content and are, therefore, less impacted by privacy regulations. The findings in Goldfarb and Tucker [2011b] suggest that either CT is a substitute of BT or there is a positive interaction effect between BT and CT. While Goldfarb and Tucker [2011b] indirectly touched the issue, few studies directly examined the interaction between BT and CT. Our article fills this void.

3. HYPOTHESIS DEVELOPMENT

BT has the advantage of delivering ads to interested users even when they are visiting webpages that are not related to the products and services in the ads. The advantage is achieved by tracking users across websites and labeling them based on personal information collected. Prior studies have found that consumers are concerned about businesses collecting their personal data [Consumer Union 2008; Lebo 2014] and such information privacy concerns hampered the growth of e-commerce [Malhotra et al. 2004; Tucker 2014]. Pushing to users the ads that match their past behavior or interests may heighten the awareness of online tracking and privacy violation. Turow et al. [2009] shows that 66% of adult Americans do not want marketers to tailor advertisements to their personal interests. So users may have stronger reactance when they view ads that are closely related to their past behavior. For example, when users who frequently visit auto channels view auto ads on non-auto channels, they may suspect online tracking and ad manipulation. The lack of user confidence in information privacy would cancel out the potential gain from identifying the most interested users. Compared with simply targeting users who have more auto related behavioral characteristics, the return is likely higher by targeting the users who have less auto related behavioral characteristics but are still interested in automobiles. We, therefore, hypothesize the following:

HYPOTHESIS 1. *BT with a lower degree of matching is more effective than BT with a higher degree of matching.*

Even though online advertising has seen rapid growth in the past decade, low CTRs have raised significant concerns. Cho and Cheon [2004] found that perceived goal impediment is the most significant antecedent explaining advertising avoidance on the Internet. The rationale is that users are likely to be goal-directed when they use the Internet and Internet ads may interrupt their goals, resulting in negative attitudes and subsequent ad avoidance [Li et al. 2002; Krugman 1983; Cho and Cheon 2004]. Delivering the right message to the right people at the right time may increase the alignment between users' goals and advertising. In particular, advertisers could use highly targeted, customized, context-congruent advertising messages through user-profiling and systematic behavioral tracking to lessen users' avoidance of ad messages, i.e., the joint use of BT and CT [Cho and Cheon 2004]. An example of combing BT and CT is to display auto ads to users with auto-related behavioral characteristics when they are visiting auto channels. Such targeting approach aims at reaching out to the right person at the right time, which may generate a higher CTR.

From a privacy perspective, users' concerns about online tracking and privacy violations limit the effectiveness of targeting [Goldfarb and Tucker 2011b; Tucker 2014]. BT follows users from website to website to collect personal information, which inevitably leads to invasion of users' privacy [Laufer and Wofe 1977; Culnan 2000]. Ads delivered as a result of both BT and CT are less likely to be perceived as intrusive. Users may not suspect that they are being tracked and behaviorally targeted when viewing contextually congruent ads, e.g., viewing auto ads on auto channels. So privacy violations are less of a concern and users' level of reactance to personalized advertising is alleviated. Therefore, we hypothesize an interaction relationship between BT and CT.

HYPOTHESIS 2A. *Combining BT with a higher degree of matching and CT leads to a higher CTR.*

HYPOTHESIS 2B. *Combining BT with a lower degree of matching and CT leads to a higher CTR.*

4. RESEARCH CONTEXT AND DATA DESCRIPTION

4.1. Research Context

We obtained data from one of the largest online advertising intermediaries in China, founded in the United States in 2007 with its headquarters in Shanghai, China. Its advertising alliance network consists of more than 500 popular Chinese web portals, e-commerce, and social networking websites, with 432 million unique visitors per month. The intermediary's business model can be considered a two-sided market—on one side, the intermediary contracts with advertisers in various industries on conducting online ad campaigns, including ad design and delivery; on the other side, the intermediary buys ad space from partners' websites and displays ads for advertisers. Figure 1 illustrates the intermediary's business model.

The purpose of the ad campaign in this study was to promote a luxury automobile brand. The ads in the ad campaign were non-visitor-initiated pop-up videos about the auto brand, such as demonstrating a new car model or introducing a new feature. When a destination webpage was loading upon a visitor's request, a short video played in a pop-up floating window occupying a small portion of the screen (see Figure 2 for a demo). If the visitor clicked the pop-up window, he or she would be directed to the brand owner's website. This campaign ran for 25 days from March 7 to March 31, 2011. The consumers that the campaign targeted were 35- to 50-year-old men with relatively high incomes in China. Consumers in this segment are more likely to be able to afford the automobiles of this luxury brand.

Our data includes the contextual information such as the channels and websites on which the ads were displayed; visitors' responses, such as ad views and clicks; visitors' behavioral characteristics, such as past visits to the websites and channels; past clicks

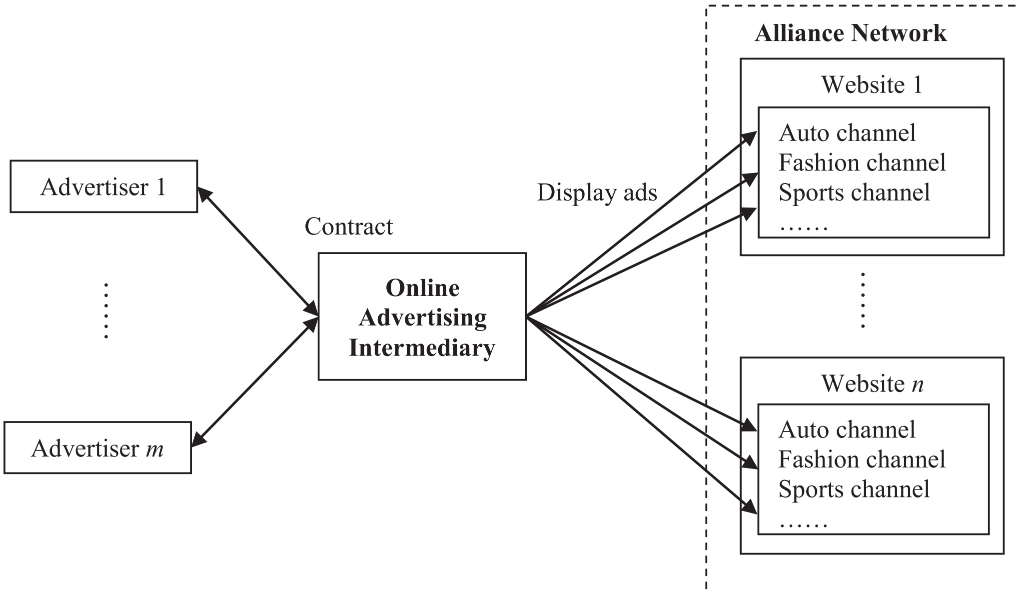

Fig. 1. Online adverting intermediary's business mode.

Fig. 2. Example of channels and video ad on website.

to ads; and individual, observable characteristics, such as visitors' cities and IP types. In this advertising campaign, the intermediary uses multiple creative ads (i.e., ads with different creative content). For example, an automobile ad campaign may have an ad demonstrating a new car model and another introducing a new feature. We also obtained the coded creative information.

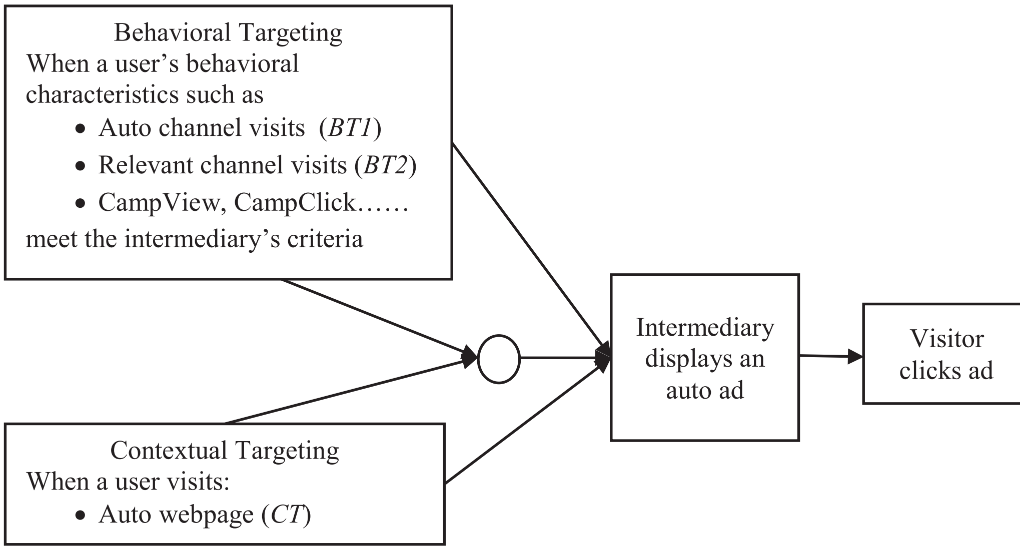

Fig. 3. Intermediary's behavioral and contextual targeting process.

In the ad campaign, the intermediary employed both BT and CT approaches. For BT, the intermediary tracked web users' online activities, such as website visits, channel visits, and ad clicks across its network of alliance websites using cookies, and maintained a database of behavioral characteristics at the individual level. When an identifiable user visits one of its partner websites, the intermediary made a real-time decision on whether or not to display one of the ads based on their targeting algorithms. The intermediary's BT criteria focused on individual users' past channel visit information. We defined two variables to capture the targeting strategies of the intermediary: BT1, the number of visits to auto channels (targeting with a higher degree of matching); and BT2, the number of visits to relevant channels (targeting with a lower degree of matching). In this ad campaign, the intermediary defined the relevant channels as the business, real estate, finance and investment, fashion and luxury goods, sports, and technology channels. According to prior studies, middle-aged men with medium to high income, i.e., the potential customers of the advertised automobiles, were more likely to visit these relevant channels [Weber and Jaimes 2011; China Internet Network Information Center 2014]. For CT, the intermediary displayed the auto ads when a user visited the auto channel of a website. To capture the intermediary's CT criteria, we used a dichotomous variable CT to indicate contextual matching between an ad and the channel where the ad was displayed. *CT=1* indicates that the ad was displayed on an auto channel and *CT=0* indicates that the ad was on other channels.

Meanwhile, because the consumers' interests change over time and the advertisers value consumers' recent interests most, advertising companies often use the recent consumer data in targeted advertising [Pancras and Sudhir 2007]. Yan et al. [2009] showed that BT using short-term user behavior was more effective than that using the long-term behavior. We, therefore, used the numbers of visits to the auto and relevant channels in the previous month for BT1 and BT2. In the robustness tests, we also examined the use of user historic behavioral data in the previous 2 months. The process of targeting is shown in Figure 3.

4.2. Variable Description

This study examined both the intermediary's ad display decisions and the users' click decisions. We used the *Display* variable to indicate whether or not an ad was displayed to a user. It is a dichotomous variable where 1 represents that an ad was displayed to a user and 0 otherwise. The *Click* variable was used to indicate whether or not the user clicked the ad. It is also a dichotomous variable where 1 represents that the user clicked an ad and 0 otherwise. The temporal unit in our analysis is "day."

We included several variables to control the other targeting criteria used by the intermediary. Following Lambrecht and Tucker [2013], we included a variable, *SiteVisit*, which recorded the number of visits in the past by a user to the website where the ad had been displayed. In addition, "ad view" and "ad click" were both important online behaviors that reflected users' idiosyncratic characteristics [Manchanda et al. 2006]. We, therefore, used the variable *PastAdView* and *PastAdClick* to capture a user's response (the numbers of views and clicks) in all ad campaigns run by this intermediary in the past. In addition, we defined an *AdClickProne* variable as the ratio of the number of *PastAdClick* to the number of *PastAdView*, which was used to capture a user's inherent propensity to click on an ad. Chatterjee et al. [2003] and Braun and Moe [2013] showed that individual advertising exposure had a significant impact on consumers' purchase probability. We, therefore, used the variables *CampView* and *CampClick* to capture the number of times that a user had viewed and clicked on the ads in the current campaign before he or she was exposed to an ad. In addition, the ad campaign consisted of multiple ad creatives for the auto brand. The intermediary did not share the content of the particular ad shown to a user during a visit but we acquired the coded creative information. The display of different ad creatives was mainly time-based. For example, in the first 5 days of the ad campaign, the intermediary displayed ad creative 1, ad creative 2, and so forth. We used four dummy variables *Creative* to control the creative-specific effect. In our dataset, individual characteristics included city and IP address information. We used a dichotomous variable *City* to represent the location of a user and let *City*=1 if the user was from a big city and 0 otherwise. We also included five dummy variables to represent six users' IP types, including education system, commercial web service provider, government, household, office, and others. The websites are also captured by two dummy variables, *SiteVisit*. Table I summarizes the variables used in this study.

4.3. Data Description

Our dataset describes the activities of 89,000 individuals who visited the websites when the intermediary was conducting the ad campaign. Table II shows the summary statistics of the data, and Table III reports the correlation matrix among these variables.

Table II shows that the number of unique users who were targeted in a visit during the campaign period was 49,055, and the number of unique users who were not targeted was 55,116. The total number of these two groups is larger than the number of unique users in the dataset (i.e., 49,055 + 55,116 > 89,192), indicating that some users were classified as both targeted users and non-targeted users. Overlap occurred because a user might have visited multiple channels during the campaign period, and ads were displayed only during some visits. Table IIIa examines the correlation matrix of the main variables for all users. Because the Click variable does not apply to the non-targeted users, it is not included in the matrix. Table IIIb examines the correlation matrix for the targeted users only. The Display variable is not included in this matrix because its value is always one for all targeted users. The result indicates that the correlation coefficients are all lower than 0.7. We have also computed the variance

Table I. Variable Description

VARIABLES	DESCRIPTION
Display	Whether an ad was displayed to a visitor Display = 1 if displayed, Display = 0 otherwise
Click	Whether a visitor clicked on an ad Click = 1 if clicked, Click = 0 otherwise
CT	Whether the channel is an auto channel CT = 1 if auto channel, CT = 0 otherwise
BT1	Number of visits to the auto channels by a user in the previous month
BT2	Number of visits to the relevant channels by a user in the previous month
CampView	Number of the ads in the current ad campaign displayed to a visitor
CampClick	Number of clicks that a visitor made on the ads in the current ad campaign
SiteVisit	Number of visits to the current site by a visitor
PastAdView	Number that the ads displayed to a visitor
PastAdClick	Number of clicks that a visitor made on ads
ClickProne	A visitor's inherent propensity to click on an ad $ClickProne = \frac{PastAdsClick}{PastAdsView}$
City	The cities that a visitor was from City = 1 if big city, City = 0 otherwise
Site	Dummy variables for websites
Creative	Dummy variables for ad creatives
IP	Dummy variables for IP types

Table II. Summary Statistics

	DISPLAY = 0 (OBS = 83,056 WITH 55,116 UNIQUE ID)				DISPLAY = 1 (OBS = 169,812 WITH 49,055 UNIQUE USERS)			
VARIABLE	MEAN	S. D.	MIN	MAX	MEAN	S. D.	MIN	MAX
Click					0.009	0.094	0	1
CT	0.029	0.168	0	1	0.044	0.204	0	1
BT1	0.047	1.652	0	252	0.057	1.316	0	252
BT2	47.300	84.108	0	2322	53.850	101.191	0	2322
CampView	0.042	0.327	0	16	1.402	2.058	0	45
CampClick	0.0001	0.0032	0	2	0.024	0.216	0	10
SiteVisit	2.010	15.863	0	54	1.370	6.872	0	47
PastAdView	366.700	334.716	1	16340	446.000	419.972	1	16340
PastAdClick	3.550	10.839	0	732	5.933	13.936	0	732
ClickProne	0.010	0.021	0	1	0.014	0.023	0	1
City	0.066	0.248	0	1	0.029	0.169	0	1

Table IIIa. Correlation Matrix of Key Variables for All Users

	BT1	*BT2*	*CT*	*SiteVisit*	*PastAdView*	*PastAdClick*	*Display*
BT1	1.000						
BT2	0.067	1.000					
CT	0.046	−0.061	1.000				
SiteVisit	0.134	0.118	0.031	1.000			
PastAdView	0.138	0.621	0.039	0.460	1.000		
PastAdClick	0.174	0.352	−0.005	0.397	0.616	1.000	
Display	0.003	−0.034	−0.038	−0.035	−0.102	−0.093	1.000

Table IIIb. Correlation Matrix of Key Variables for Targeted Users

	BT1	*BT2*	*CT*	*SiteVisit*	*PastAdView*	*PastAdClick*	*Click*
BT1	1.000						
BT2	0.063	1.000					
CT	0.079	−0.046	1.000				
SiteVisit	0.137	0.130	0.041	1.000			
PastAdView	0.142	0.569	0.088	0.498	1.000		
PastAdClick	0.193	0.331	0.015	0.420	0.629	1.000	
Click	0.000	−0.010	0.006	0.000	0.003	0.064	1.000

inflation factors (VIF) values for all these variables, and all of them are lower than 5, so the multicollinearity issue is not a concern in our study.

5. MODEL

The online targeted advertising process consists of two steps: (1) the advertising intermediary displays the ads to the users or does not (*display decision*); (2) the users click the ads or do not (*click decision*). Since each step involves a binary decision, we modeled each step using a Logit function. There is a sample selection issue in this setting—only the users who were targeted by the intermediary in the first step decided whether or not to click the ad. We, therefore, developed a two-step model to account for the sample selection issue [Woodridge 2010]. In the first step, we used a display equation to capture the intermediary's targeting and ad display decision. In the second step, we used a click equation to capture the users' click decisions.

Display decision: The display equation modeled the intermediary's display decision. The intermediary displayed an ad to the user when the expected value exceeded a threshold value. We used a random-utility framework to model the intermediary's decision. Specifically, for user i viewing channel j on website s at time t, we used $Display_{ijst}$ to denote the intermediary's display binary decision and ξ_{ijst} to denote the intermediary's expected value of the user. The choice of the independent variables for the display equation was largely guided by the intermediary. Even though the intermediary did not disclose the individual variables used in its targeting algorithms, it shared with us the types of variables that it was interested in. In addition to the BT and CT variables (i.e., $BT1_{it}$, $BT2_{it}$, and CT_{ijt}), we also included other variables that may have impacted whether or not user i was exposed to an ad based on our discussion with the intermediary. These variables were $SiteVisit_{ikt}$, $PastAdView_{it}$, $PastAdClick_{it}$, $City_i$ and IP_i. The dummy variables, $Site_s$, are also included to control the website-specific effect on ads display. η_{ijst} stands for the random error that follows the type-I extreme distribution. Therefore, the display equation is defined as:

$$\begin{aligned} y_{1ijst} &= Display_{ijst} = 1[\xi_{ijst} > 0] \\ \xi_{ijst} &= \alpha_{0i} + \alpha_{1i} CT_{ijt} + \alpha_2 BT1_{it} + \alpha_3 BT2_{it} + \delta_1 SiteVisit_{ist} + \delta_2 PastAdView_{it} \\ &\quad + \delta_3 PastAdClick_{it} + \delta_4 City_i + Site_s + IP_i + \eta_{ijst}, \end{aligned}$$

Click Decision: The click equation modeled a user's click decision. We, again, used a random-utility framework to model a user's decision. A user clicked on an ad when his or her utility of clicking exceeded a threshold level. Specifically, for user i viewing channel j on website s at time t, we used $Click_{ijst}$ to denote the user's click binary response and u_{ijst} to denote the latent value. For the click decision, we drew the independent variables based on the literature and the discussion with the intermediary. In addition to $BT1_{it}$, $BT2_{it}$, and CT_{ijt}, we included several groups of control variables. The first group of variables indicated users' past behavior on this ad. Chatterjee et al [2003] and Braun and Moe [2013] found that consumers might respond differently when they saw an ad for the first time or after several times. Multiple exposures may enhance the impression of ads and lead to a higher click rate. We, therefore, included two variables, $CampView_{it}$ and $CampClick_{it}$, into our model as users who repeatedly viewed or clicked on an ad might respond differently to those who occasionally saw it. The second group of variables was the visitors' proneness to clicking on the ads. We characterized a visitor's inherent disposition to click using the variable $ClickProne_{it}$. We assumed a user's click-proneness was associated with the probability of him/her clicking on the ads in this campaign. Users' click behavior is also associated with their familiarity with the website where the ad is displayed [Manchanda et al. 2006]. Thus, $SiteVisit_{ist}$ was also included in this model to control the impact of sites on users' click behavior. These above control variables are all cumulative data starting from the first day that users joined the network of this intermediary. Furthermore, a visitor may respond differently to different ad creatives in the same campaign [Manchanda et al. 2006; Braun and Moe 2013]. Hence, we included a set of dummy variables, *Creative*, to capture the heterogeneity of the ad creatives in this campaign. ε_{ijkt} stands for the random error that follows the type-*I* extreme distribution. The click equation is defined as:

$$
\begin{aligned}
y_{2ijst} &= Click_{ijst} = 1[u_{ijst} > 0], \\
u_{ijst} &= \beta_{0i} + \beta_{1i} CT_{ijt} + \beta_2 BT1_{it} + \beta_3 BT2_{it} + \gamma_1 ClickProne_{it} + \gamma_2 SiteVisit_{ist} \\
&\quad + \gamma_3 CampView_{it} + \gamma_4 CampClick_{it} + \gamma_7 City_i + Creative + Site_s + \varepsilon_{ijst}.
\end{aligned}
$$

To capture the heterogeneity at the individual user level, we adopted a random coefficient specification. Random coefficient models have been widely used to capture the heterogeneity among individuals in IS literature [e.g., Ghose and Yang 2009; Ghose et al. 2014; Yang et al. 2013] or address the multi-level data issue [Mithas et al. 2007; Ma et al. 2014; Kim et al. 2014]. By modeling the variation in intercepts and slopes across users on the basis of user's unique characteristics, the random coefficient model could capture the unique random effect of each visitor [Mithas et al. 2007]. In addition, the random coefficient model allows us to model the heterogeneity among subjects with unequal number of observations within subjects [Khare and Inman 2006]. Therefore, we model the constants, that is, the baseline display and click probability (α_{0i} and β_{0i}), as the random intercepts by allowing α_{0i} and β_{0i} to vary along its population mean $\bar{\alpha}_0$ and $\bar{\beta}_0$ as follows:

$$
\begin{aligned}
\alpha_{0i} &= \bar{\alpha}_0 + \nu_0 \\
\beta_{0i} &= \bar{\beta}_0 + \tau_0
\end{aligned}.
$$

We allowed the CT coefficients of the i^{th} user (α_{1i} and β_{1i}) to vary along the population means ($\bar{\alpha}_1$ and $\bar{\beta}_1$), and modeled them as functions of the individual behavior characteristics, which are represented by $\mathrm{BT1_{it}}$ and $\mathrm{BT2_{it}}$. This random coefficient specification also allows us to capture the interaction between the BT and CT variables. In addition, it allows the random utility term ν_0 and ν_1 (as well as τ_0 and τ_1) to be correlated, which offers better model flexibility than general interaction terms. The second level of our click model was constructed as follows:

$$
\begin{aligned}
\alpha_{1i} &= \bar{\alpha}_1 + \chi_{11} BT1_{it} + \chi_{12} BT2_{it} + \nu_1 \\
\beta_{1i} &= \bar{\beta}_1 + \mu_{11} BT1_{it} + \mu_{12} BT2_{it} + \tau_1
\end{aligned}.
$$

6. ESTIMATION AND RESULTS

In our case, the click decision was made only when an ad was displayed to a user. The Heckman model is the most frequently used method to address the above sample selection issue by assuming η and ε are not independent. However, because the dependent variables of both Equations (1) and (2) are binary response variables, the traditional Heckman model cannot be used to estimate the sample selection model

Table IV. Estimation Results of Display Equation

VARIABLES		MAIN MODEL COEFFICIENT	INTERACTION MODEL COEFFICIENT
CT Variables	CT	1.268***	1.296***
BT Variables	BT1	0.062***	0.0368***
	BT2	0.0197**	0.0185*
BT×CT	BT1×CT		0.137***
	BT2×CT		0.057***
Control Variables	PastAdView	–0.024***	–0.028***
	PastAdClick	–0.046***	–0.0457***
	SiteVisit	0.0311***	0.0297***
	City	–0.471***	–0.465***
	Website dummy	Included	Included
	IP dummy	Included	Included

Table V. Estimation Results of Click Equation

VARIABLES		MAIN MODEL COEFFICIENT	INTERACTION MODEL COEFFICIENT
CT	CT	–0.0087***	–0.0043***
BT	BT1	–0.00178	0.00144
	BT2	0.00195**	0.0031*
BT×CT	BT1×CT		0.0105*
	BT2×CT		0.00673**
Control variables	ClickProneness	0.0167***	0.0173***
	CampView	–0.0003	–0.00004
	CampClick	0.0285***	0.0285***
	SiteVisit	–0.0221***	–0.0242***
	City	–0.0216*	–0.0202*
	Website dummy	Included	Included
	Creative dummy	Included	Included
Log-Likelihood		38,830	38,470
Rho		0.089***	0.090***

[Dubin and Rivers 1989]. To estimate the display and click behavior simultaneously, we constructed a maximum likelihood estimation function and developed our own codes to estimate the parameters using *R* language (please see Appendix for the likelihood function used in the estimation algorithm). Tables IV and V report the estimation results of the display and click equations.

Table IV shows the estimation results of the display models, which captured the intermediary's targeting strategies. The first display model only considers the main effects of the BT and CT variables, and the second model considers both the main effects of and the interaction effects between the BT and CT variables. In both models, the coefficients of the BT and CT variables are positive and significant. The results suggest that the intermediary was more likely to target the users (i.e., display ads) when they were visiting the auto channels and those who had more frequently visited the auto and relevant channels. For the interaction model, the coefficients of the interaction terms between BT and CT variables were also positive, which suggests that the intermediary was more likely to target the frequent auto and relevant channel visitors when they were visiting auto channels. These results are consistent with the fundamental targeting criteria that the intermediary shared with the researchers.

We next examined the results of the click equation. Table V shows that the hypothesis that $\rho = 0$ is rejected ($p < 0.05$), indicating that the display equation and the click equation were not independent. This result confirms the need for using a selection model to adjust the sample selection bias in the click equation [Woodridge 2010].

In the click equation, the coefficients of BT variables are not qualitatively the same as those in the display equation. BT1 is statistically insignificant, suggesting that users who had more frequently visited the auto channels were not necessarily more likely to click on the ads on non-auto channels. A potential explanation is that frequent auto channel visitors, when viewing auto ads on non-auto channels, may have suspected online tracking. The privacy concerns may alienate consumers, canceling out the advantages of BT identifying the right consumers. Interestingly, the coefficient of BT2 was positive and statistically significant. The statistical test shows that the coefficients of BT1 and BT2 are statistically different ($F = 3.57$, $p < 0.000$), suggesting that BT2 has a larger effect on click than BT1. Therefore, H1 is supported. The results indicate that if the number of relevant channel visits increases one unit in the past 1 month, the probability of this user clicking the ads increases 0.195%. Although the magnitude of increase is small, given the mean value of CTR is only 0.9% (see Table II), the CTR of web users who had visited the relevant channels one more time could be 21% higher on average compared with those who had visited the relevant channels less frequently. Therefore, targeting to the right people could generate about 20% more clicks without increasing the budget. Frequent relevant channel visitors are often middle class with a high income [Weber and Jaimes 2011; China Internet Network Information Center 2014]. They are the potential consumers of this auto brand and have a greater interest in this brand than other consumers. Thus, they are more likely to be interested in the information provided by the ads. Since the channels that they frequently visit are not auto channels, auto advertising messages are unlikely to heighten these visitors' awareness of online tracking and privacy concerns. As a result, targeting these users' results in a higher CTR. Presumably, auto channel visit frequency may be a more accurate BT criterion than relevant channel visit. Our results, however, show that BT with a lower degree of matching may perform better than that with a higher degree of matching, suggesting the negative impact of online tracking and privacy concerns on the effectiveness of BT.

Table V shows that the coefficients of the interaction terms, BT1×CT and BT2×CT, were both positive and statistically significant. So H2a and H2b are both supported. The results suggest that the CTRs of the users who were both behaviorally targeting and contextually targeted were 0.011 and 0.0067 higher than those who were only behaviorally targeted respectively, representing about 122% and 74% increases of CTRs. There were two possible drivers that led to the positive interaction effects between BT and CT. First, displaying auto ads to frequent auto or relevant channel visitors when they were visiting auto channels was essentially targeting the right person at the right time. The perceived goal impediment of Internet ads would be alleviated, resulting in less ad avoidance and higher CTR [Li et al. 2002; Krugman 1983; Cho and Cheon 2004]. Second, users were unlikely to suspect online tracking when viewing auto advertising messages on auto channels; instead, they may have considered it as CT. So, privacy violation may have been less of a concern for these visitors.

We find that the coefficient of the CT variable was negative and significant. Particularly, if the ads are displayed on auto channels, the users who have never visited auto or relevant channels are 0.87% less likely to click the auto ads than on non-auto channels. The premise of CT is that a consumer's interest in a particular content topic may be indicative of his or her preference for a type of product [Zhang and Katona 2012] and prior literature has shown that CT leads to a favorable effect of ads on consumer attitudes [Rodgers 2003/2004; Moore et al. 2005]. It is worth noting that the ads in this campaign were non-visitor-initiated pop-up videos, which are often viewed as highly obtrusive by users. Our results are consistent with the findings in Goldfarb and Tucker [2011a], that contextually targeting visitors using highly obtrusive ads may reduce consumers' purchase intent. One possible driver of the negative effect is that the combination of CT

Table VI. Estimation Results of Display Equation (Ratio)

VARIABLES		MAIN MODEL COEFFICIENT	INTERACTION MODEL COEFFICIENT
CT	CT	1.242***	1.27***
BT	BT1 (%)	0.0649***	0.0416***
	BT2 (%)	0.0243*	0.024***
BT×CT	BT1×CT		0.137***
	BT2×CT		0.033**
Control variables	PastAdView	–0.0210***	–0.0257***
	PastAdClick	–0.0466**	–0.0463***
	SiteVisit	0.0439***	0.0433***
	City	–0.479***	–0.483***
	Website dummy	Included	
	IP dummy	Included	

and obtrusive ads may increase consumers' perception of targeting and manipulation [Campbell 1995; Goldfarb and Tucker 2011a]. Our study provides additional empirical evidence of the negative consequences using the obtrusive targeting approach—such targeting approach has an unfavorable effect on consumer behavior, i.e., less ad clicks.

We also observed some interesting results about the control variables. In the display equation, the coefficient of *SiteVisit* was positive and statistically significant, which means the intermediary tended to target the users who had visited the website before. However, we found the coefficient of *SiteVisit* was negative and statistically significant in the click equation. This suggests that the targeting strategy based on site browsing history actually did not generate more clicks, which is consistent with the findings of Lambrecht and Tucker [2013]. In addition, the click proneness of a user was positively correlated with the click behavior, suggesting that users were heterogeneous and click proneness could be a good predictor of ad-clicks. The coefficients of the variable *City* were negative in both the display and click equations. Note that *City*=1 if a visitor was located in a big city. The negative coefficient of *City* in the click equation suggested that users from big cities were less likely to click on the ads. Web users in large cities are often better educated and more informed about automobiles than those in small cities, so the former is less likely to acquire information from ads.

7. ROBUSTNESS TESTS

We checked the robustness of our results using different alternative specifications. In the main analysis, we measured the BT variables using the absolute number of visits to the auto channels and relevant channels in the previous month. Estimation results may be biased since the absolute numbers of visits vary significantly among visitors. In the first robustness test, we let *BT1* be the ratio of auto channel visits to all channel visits and *BT2* be the ratio of relevant channel visits to all channel visits in the previous month. Tables VI and VII show the estimation results. The coefficients of the interaction terms were both positive. Even though the coefficient of BT1×CT is not significant, the p-value is very close to the 0.05 cutoff value. Therefore, the joint use of BT and CT is still likely to lead to a higher response rate. The coefficient of CT was negative and significant, which is consistent with the main analysis. CT did not directly lead to a higher CTR, possibly due to the manipulation perception.

The intermediary did not share the exact time period that it used to define the BT variables. In the main analysis, the BT variables only recorded the user's visits to the auto channels or relevant channels in the previous month. This reflected the intermediary's practice, i.e., using the most recent users' behavioral history to predict their preference. To ensure that our definitions of the BT variables do not limit the generalizability of the results, in the second robustness test, we extended the length of

Table VII. Estimation Results of Click Equation (Ratio)

VARIABLES		MAIN MODEL COEFFICIENT	INTERACTION MODEL COEFFICIENT
CT	CT	–0.083***	–0.0709***
BT	BT1 (%)	–0.0195	–0.00285
	BT2 (%)	0.0013*	0.00095
BT×CT	BT1×CT		0.0076
	BT2×CT		0.0093**
Control variables	ClickProneness	0.016***	0.016***
	SiteVisit	–0.025***	–0.0244***
	CampView	0.00151*	0.0016*
	CampClick	0.0275***	0.0275***
	City	–0.0147	–0.0146
	Website dummy	Included	
	Creative dummy	Included	
Log-Likelihood		36,344	36,856
Rho		0.084***	0.090***

Table VIII. Estimation Results of Display Equation (2 Months of Data)

VARIABLES		MAIN MODEL COEFFICIENT	INTERACTION MODEL COEFFICIENT
CT	CT	1.27***	1.29***
BT	BT1	0.024***	0.0056*
	BT2	0.066***	0.071***
BT×CT	BT1×CT		0.0672**
	BT2×CT		0.0221*
Control variables	PastAdView	–0.0656***	–0.0758 ***
	PastAdClick	–0.0463***	–0.046***
	SiteVisit	0.0428***	0.044***
	City	–0.476***	–0.467***
	Website dummy	Included	
	IP dummy	Included	

the BT measures from the previous month to the previous 2 months (see Tables VIII and IX). Most of the findings of this study still held in this robustness test—the BT variable with a lower degree of matching still outperformed the BT variable with a higher degree of matching. And we still observed the positive interaction relationship between BT and CT as shown in Table IX.

8. DISCUSSION AND CONCLUSION

Using individual-level clickstream data, we examined how BT impacted users' responses to online ads and whether it worked better in combination with CT. We developed a two-step model to estimate the intermediary's display decisions and the users' click behavior. Our results show that BT with a lower degree of matching outperforms BT with a higher degree of matching in generating clicks; combining BT and CT has a favorable effect on consumer click behavior and, thus, BT and CT have a positive interaction effect. The findings of this study advance our understanding of online advertising and also help guide advertising intermediaries in designing better targeting criteria.

8.1. Theoretical Implication

Our study contributes to the literature on targeted advertising in several aspects. First, the unique data set allows us to open the "black box" of BT and compare the effect of different BT variables on user click behavior. We find that BT with a higher degree

Table IX. Estimation Results of Click Equation (2 Months of Data)

VARIABLES		MAIN MODEL COEFFICIENT	INTERACTION MODEL COEFFICIENT
CT	CT1:Auto channel	–0.0072***	–0.0079***
BT	BT1: Auto channel visits	–0.0034	–0.0042
	BT2: Relevant channel visits	0.0007**	0.0007**
BT×CT	BT1×CT		0.0005
	BT2×CT		0.0009**
Control variables	ClickProneness	0.017***	0.017***
	CampView	0.0016**	0.0016**
	CampClick	0.0279***	0.00279***
	SiteVisit	–0.00189***	–0.00189***
	City	–0.0145	–0.0146
	Website dummy	Included	Included
	Creative dummy	Included	Included
Log-Likelihood		45,742	46,350
Rho		0.065***	0.069***

of matching does not necessarily improve the CTRs on other channels (i.e., non-auto channels), but BT with a lower degree of matching directly generates a higher CTR on other channels. This result is in stark contrast to previous findings that BT always has a positive effect on CTR [Yan et al. 2009; Farahat and Bailey 2012]. Our study also contributes to the literature on privacy. Prior research has shown that privacy concerns have an adverse effect on the use of advanced information technologies, including targeted advertising [Edgcomb and Vahid 2013; Mathew and Obradovic 2013; Goldfarb and Tucker 2011a]. It is found that the enforcement of privacy regulations impacts the effectiveness of online display advertising [Goldfarb and Tucker 2011a], and the availability of consumer privacy controls enhances the performance of social network targeting [Tucker 2014]. Our study adds to the literature by providing empirical evidence that BT could raise the awareness of online tracking, and the associated privacy concerns have a negative impact on the effectiveness of BT.

Prior literature has shown that BT in online advertising can improve CTRs or conversion rates [Manchanda et al. 2006; Yan et al. 2009; Farahat and Bailey 2012; Breznitz and Palermo 2013; Lambrecht and Tucker 2013]. Our study further explores how the consumers' responses change when they are behaviorally targeted in different contexts. The interaction effect suggests that behaviorally targeting consumers using contextually congruent ads can lead to more ad clicks, i.e., BT and CT work better in combination. Our study provides an empirical foundation for further theory exploration about the drivers of the interaction effect between BT and CT. Experimental research may be desirable to further explore how privacy, ad avoidance, and other factors contribute to the interaction effect.

8.2. Practical Implication

Our study also has a number of important implications for advertising intermediaries pursuing online targeting opportunities to increase the CTRs. This study demonstrates that BT with a lower degree of matching outperforms BT with a higher degree of matching. The finding suggests that a higher degree of matching does not necessarily lead to a higher CTR or targeting precision. Contrary to the conventional wisdom, the intermediaries should restrain from directly targeting the users with behavioral characteristics that are closely related to the ads. Instead, they should focus on displaying ads to the consumers with characteristics that are loosely related to ads. The former group of users, although interested in the information in the ads, is averse to being spied on. Targeted ads can easily heighten their privacy concerns. The intermediaries may consider targeting them a couple of days after their most recent visits to the related websites.

The interaction between BT and CT suggests that when targeting individuals, the intermediaries should not only identify the right person but also choose the right time. Considering both the users' past behavior and the content of the webpages that they are requesting could improve the preciseness of targeting and generate a higher CTR. For example, displaying the auto ads to users who may be the potential buyers of the automobile when they are visiting auto channels may double the number of clicks than simply following them everywhere. Such targeting strategy could also help the intermediaries save by cutting ad display expenditure. From the advertisers' perspectives, more informative ads could have a favorable effect on brand image and consumers' attitudes towards the products and services.

8.3. Research Limitation and Contributions

As with any empirical work, our study has a few limitations. First, it used an ad campaign for an automobile brand. Automobiles are expensive products and consumers are highly involved in the shopping process. Consumers may be more sensitive to privacy violation for big-ticket items than products that they routinely buy. So BT with a higher degree of matching may be more effective and the interaction effect may be weaker for other less expensive or low-involvement products. Future research may examine other product categories. Second, this ad campaign only targeted 35- to 50-year-old men with relatively high incomes. The consumers in this segment may behave differently from those in other age and income groups in the network environment. This may limit the generalizability of this study. Future study may investigate the consumers' behavior in other groups. Third, this ad campaign employed video ads. The format of the ad may have influenced the results. Video ads are considered highly intrusive compared with banner ads in which only images are presented. Goldfarb and Tucker [2011a] found that obtrusive ads did worse in increasing purchase intent when matching them to website content. CT may be more effective and the positive interaction effect may be weaker for other ad formats. In addition, video ads often have attractive sound effects. Some users may click on the ads simply because of sound effects, which leads us to overestimate the return of advertising.[2] Future research may examine targeted advertising using other ads. Lastly, this study used the CTR, not actual purchase data, to measure the effectiveness of targeted advertising. It is possible that the type of product category and the format of advertising used may have a different effect on actual purchases.

Nevertheless, this research makes important contributions. First, our study empirically shows that BT and CT work better in combination. So, the positive performance of BT could be partly attributed to CT. Our study cautions the ads intermediaries and advertisers of the possible overestimation of BT. Second, this study compares direct effects of BT variables with different degrees of matching on ad clicks. It provides useful guidance for ads intermediaries and advertisers to use behavioral variables to select users to achieve a higher response rate. Lastly, this study illustrates that inconsistencies could exist between intermediaries' display decisions and the visitors' click behavior, suggesting that the intermediaries' targeting strategy might not be optimized to maximize the CTRs. Our study could guide advertising intermediaries in designing better targeting criteria and IT artifacts to execute these targeting criteria.

[2]We thank an anonymous reviewer for providing the alternative explanation.

APPENDIX

Maximum Likelihood Function Development in Estimation Procedure: We denote y_1 as the Display variable, and y_2 as the Click variable, then we have

$$\begin{aligned} y_1 &= 1[\xi > 0] = 1[Z\delta + \eta > 0] \\ y_2 &= 1[u > 0] = 1[X\beta + \varepsilon > 0] \end{aligned},$$

where ξ represents the intermediary's value of displaying the ad to the visitor and u represents the visitor's utility of clicking the ad. The vectors X and Z represent the independent variables that impact the intermediary's value and visitors' utilities. The variables η and ε are random disturbances. We assume that the intermediary will display an ad to a visitor when the intermediary's value of the visitor is greater than zero and the visitor will click the ad when his or her utility of clicking the ad is greater than zero.

We develop the maximum likelihood function of this model as follows:

(a) The probability that an ad is displayed to visitor i is given by:

$$\begin{aligned} Q(\delta) &= \Pr(Display = 1|Z_i) \\ &= \Pr(y_{1i} = 1|Z_i) \\ &= \frac{1}{1+e^{-\delta Z_i}} \end{aligned}. \quad \text{(A1)}$$

(b) The probability that an ad was displayed to visitor i and he or she clicked the ad is given by:

$$\begin{aligned} P_i(\beta,\delta,\rho) &= \Pr(Click = 1, Display = 1|X_i, Z_i) \\ &= \Pr(y_{1i} = 1, y_{2i} = 1|X_i, Z_i) \\ &= \Pr(y_{1i}^* > 0, y_{2i}^* > 0|X_i, Z_i) \\ &= 1 - \frac{1}{1+e^{-\beta X_i}} - \frac{1}{1+e^{-\delta Z_i}} + \frac{1}{1+(e^{-\beta X_i/\rho}+e^{-\delta Z_i/\rho})^{\rho}} \end{aligned}, \quad \text{(A2)}$$

where ρ is the correlation between η and ε.

(c) Finally, the probability that an ad was displayed to visitor i but he or she did not click the ad is given by:

$$Q_i(\delta) - P_i(\beta,\delta,\rho). \quad \text{(A3)}$$

Combining Equations (A1), (A2), and (A3), we obtain the log likelihood function as:

$$\begin{aligned} L(\beta,\delta,\rho) = &\sum_{i=1}^{n} y_{1i}(y_{2i}\log P_i(\beta,\delta,\rho) + (1-y_{2i})\log(Q_i(\delta) - P_i(\beta,\delta,\rho))) \\ &+ (1-y_{1i})\log(1-Q_i(\delta)) \end{aligned}$$

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