Impact of Retargeted Display Advertising
on Multichannel Customer Browsing & Purchase

by

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Abstract

Retargeted display advertising is one of the most popular and growing forms of digital marketing. The main problem in analyzing retargeted display ads is selection bias. I use data from a randomized field experiment to identify the causal impacts of an individually-targeted display advertising campaign on both digital and traditional channels. The field experiment was conducted on the cookie level and I aggregate the data to the individual level for the analysis. Overall, online visits decrease, but web and store purchases increase in response to retargeted display ad campaigns. I find the effect of the retargeted display advertising campaign is not only contemporaneous but also carries over for several days after a consumer leaves the treatment group. The retargeted ad campaign effect also depends on a consumer's distance from a store. Consumers living near a store tend to visit the website as a response to the retargeted ad campaign more than consumers who live farther from a store. In terms of purchasing, people tend to choose the lower cost channel to shop: nearby consumers go to the store as the purchase response to the retargeted ad campaign, and distant consumers go to the online website to place an order in response to the retargeted ad campaign. Methodologically, I provide a novel model to measure individual consumer response along the purchase funnel from consideration to purchase. The model takes into account the cumulative display advertising campaign effect using the ad-stock approach and allows for individual customer heterogeneity in both decay and response. Empirically, I find a significant lift attributable to contemporaneous and carryover effects. Further, this lift manifests both in purchases and across channels.

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1 Introduction

Display advertising is one of the most common forms of digital advertising around the world. It is the banner ads displayed at the top or side of the screen during online browsing. Nearly 44% of digital advertising spending is allocated to display advertising (PwC Advisory Services LLC 2017). The importance of this method has not gone unnoticed by academic researchers, and a growing body of work has explored its impact (Rutz and Bucklin 2012, Braun and Moe 2013, Hoban and Bucklin 2015, Johnson et al. 2017, Lambrecht and Tucker 2013, Sahni 2015, 2016). In the current digital advertising ecosystem, display advertising offers individual-level targeting in which specific individuals are targeted on specific websites at specific times. One such example is retargeted display advertising which delivers impressions to users who have previously visited one or more web pages on the advertiser's website. However, the full effects of retargeting remain less well understood. Some advertisers have expressed doubt about the strategy, arguing that the ads are shown only to an essentially self-selected cohort of customers who are likely to buy regardless of the ad's effect (CNBC 2018).

The existing literature on retargeted display advertising has focused on e-commerce visits and transactions, where researchers have found significant lift (Lambrecht and Tucker 2013, Bleier and Eisenbeiss 2015, Johnson et al. 2017). However, little is known about potential carryover effects or cross-channel impacts of retargeted display advertising. Moreover, researchers have generally assumed that cookies and individuals are equivalent, a confounding of variables that is known to bias estimates of response (Coey and Bailey 2016).

In this dissertation, I study the impact of a retargeted display advertising campaign in an omnichannel retail environment, in which customers can shop and complete purchases online through the retailer's website, or offline in brick-and-mortar stores. Specifically, I address the following research questions:

1. How does a retargeted display advertising campaign impact consumer online and offline behavior?

2. How does consumer type moderate the impact of the retargeted display advertising campaign?

3. How is individual channel choice affected by the retargeted advertising campaign?

The difficulty in addressing the research questions and measuring the impact of a retargeted display advertising campaign is selection bias. The ad-serving agent can select ads to serve to different consumers based on undisclosed individual-level data and algorithms. Ad-serving agents tend to select the type of consumers who are easier to convert for the focal advertiser. It is highly likely that ad-exposure consumers have a history of frequent online shopping while non-ad-exposure consumers are less active online, so I cannot measure ad campaign effectiveness by the difference in response of those two types of consumers. This difference is determined by both ad campaign impact and the consumer type difference selected by the ad-serving agent. In the absence of an experiment, I may overestimate the ad campaign impact because of the ad-exposure consumer's high conversion tendency.

In this dissertation, I use randomized experimentation and individual level data to understand the causal impacts of an individually-targeted display advertising campaign on consumer choices. Retargeted display advertising can only be implemented through a cookie, which is a small piece of file embedded on the user's browser that enables the firm to identify online visitors. Therefore, the field experiment was conducted using cookies in which first-time-visit cookies were randomly assigned to the control or treatment group. Control and treatment cookie users were from the same population without difference in past online activities, so their response difference represents the effectiveness of a retargeted display ad campaign. Moreover, the focal firm leveraged omnichannel pixel technology that matches cookie

ID with consumer ID, allowing me to measure the ad campaign's effectiveness at the individual level. In addition, this match enables me to relate consumer online activities to offline purchases and extend the research across digital and traditional channels. The field experiment lasted 7 months, and returned 1.21 million US consumers with more than 50 million unique cookies.

I propose three models to explore the impact of retargeted display advertising campaigns. The first model is cookie-level analysis that assumes no individual level matching exists. This method is consistent with literature that assumes each cookie represents a consumer(Lambrecht and Tucker 2013, Johnson et al. 2017, Bleier and Eisenbeiss 2015). Online visit and purchase are jointly estimated at the daily level. Significant negative online visiting and purchase impact from a retargeted display advertising campaign is measured. However, a consumer may have multiple cookies, so ad impact from one cookie may spill over to another, and cookie-level analysis may thus underestimate the campaign impact. Moreover, cookie-level analysis without individual-level matching cannot attribute offline purchase to online digital advertising impact.

As a solution to this cookie-based problem, I discuss two individual-level models to explore retargeted display advertising campaign impact. I jointly model a sequence of consumer decision as responses to a cumulative retargeted display ad campaign over time. The accumulation and decay effect of a display ad campaign is constructed as a goodwill model, and three types of consumer decisions are examined: website visit, online purchase and offline purchase. Moreover, I use the hierarchical Bayes estimation method to calculate the heterogeneity among consumers. In the first individual daily level model, I define the consumer daily experimental group based on the visit cookie's group assignment: a consumer on a given day is in the treatment group as long as at least one visit cookie has been assigned to the treatment group, which means this consumer has a chance to be exposed to display ads. However, this model is inadequate and flawed for two reasons. First, it does not capture the intensity of retargeted display advertising campaigns where an increased number of treatment cookies brings higher intensity of ad exposures. Secondly, the individual daily group assignment mathematically assigns days with more visit cookies to the treatment group, thereby making the treatment and control days imbalanced. Especially, this method tends to create a treatment group of those who have more visit cookies and who also have high engagement with the firm, thus overestimating the ad campaign impact on consumer response. I therefore propose the individual daily intensity level model that captures the treatment and control cookies a consumer has daily and stay with this focal model for the analysis.

First, I find that display advertising can significantly decrease a consumer's online visiting but increase offline purchasing across the first several treated days. The reactance effect on online visiting is consistent with information substitution in that display advertising shows products the consumer browsed, so this consumer has no need to revisit the firm's website for more information. Overall, display advertising can statistically significantly decrease overall website visiting but increase web purchases and store purchases.

Next, I examine how retargeted display ad campaign effectiveness is moderated by the distance from home to store. The carryover effect is stronger for distant consumers. After being treated by the retargeted display ad campaign, consumers who live close to a brick and mortar store visit the web site more times than distant consumers. In terms of purchasing, a retargeted display ad campaign increases revenue more on the channel where consumers have higher accessibility. Consumers who live close to a store are motivated by a retargeted display ad campaign to spend more on the offline channel; consumers living far away tend to choose the online channel as motivated by the retargeted display ad campaign.

Moreover, I find that the individual online and offline purchase in response to a retargeted display ad campaign are not substitutes for each other. Consumers who are influenced by the retargeted display ad campaign to buy more online will not decrease their brick and mortar store spending, and vice versa.

In sum, using disaggregate data from a randomized field experiment, I study a retargeted display ad campaign's causal impact on customer behavior across digital and traditional channels. Specifically, this dissertation provides a novel approach to examining retargeted display ad campaign effect. I find a retargeted ad campaign significantly decreases website visits but increases online and offline purchases, and these effects not only show up in contemporary treated-day responses but also carry over to days after leaving the treatment group. I also find that consumer distance from home to store can moderate the retargeted display ad campaign's effectiveness.

In this dissertation, I contribute to the field in several ways: Substantively, I highlight the importance of holistic measurement. I find there are strong omnichannel effects in that retargeted display advertising impacts both online and offline channels; as well as a significant carryover effect after the ad campaign has ended. Second, I show that those channels do not tend to act as substitutes: if the campaign increases a consumer's online purchase this consumer will not decrease offline purchases, and vice versa. Methodologically, I conduct a randomized field experiment on the cookie level and aggregate those effects up to the individual level. This presents some challenges but also brings enormous opportunities and allows me to study the carryover impact. Using disaggregate data and a disaggregate model allows me to look at heterogeneity within individuals and correlation in responses. I study those effects across the path to purchase, which allows me to look at both how retargeted display advertising impacts consumers and how those effects manifest in consumers as they move along the purchase funnel.

2 Relationship to Existing Literature

2.1 Display Advertising

2.1.1 Display advertising overview

In the United States, $31.9 billion of which was spent on display ads. This was up from $21.07 billion in 2014 and is expected to grow to $46.69 billion in 2019 (The Statistics Portal 2019). The bulk of academic researchers explore the impact of display advertising on various aspects of consumer shopping patterns, including brand recall and awareness (Drèze and Hussherr 2003), memory (Sahni 2015), click-through rates (Chatterjee et al. 2003), website visits (Rutz and Bucklin 2012, Braun and Moe 2013), purchase duration (Manchanda et al. 2006) and online purchases (Johnson et al. 2017, Braun and Moe 2013, Hoban and Bucklin 2015).

The direct effect of display advertising on click-through rates and click-through purchases has been discussed (Chatterjee et al. 2003, Manchanda et al. 2006, Drèze and Hussherr 2003). Purchases in general are positively correlated with banner ads, but click-through purchases are only a small portion of total purchases (Manchanda et al. 2006). Click-through rates have been found to be negatively related to the number of banner ads within the same session (Chatterjee et al. 2003) and nearly half of participants in one study intentionally avoided looking at banner ads (Drèze and Hussherr 2003). However, the indirect measurement of a display ad's effect on boosting recall, recognition, and awareness is still positively correlated with display ads (Drèze and Hussherr 2003). Researchers have also explored more intermediate outcomes of display ads, such as page view, website visit, effectiveness decay and restoration, and memory (Rutz and Bucklin 2012, Braun and Moe 2013, Sahni 2015). Exposure to display ads can increase website visits, but the visit probability has a diminishing marginal return with an increase in the number of ad exposures (Rutz and Bucklin 2012, Braun and Moe 2013). Memory strength of display advertising is related with ad frequency and temporal spacing (Sahni 2015).

Figure 1: Retargeted display Advertising Process

2.1.2 Retargeting

In the current digital ecosystem, one special strength of digital advertising is individual-level targeting. It allows the ad serving platform to provide an ad designed for a specific consumer based on that consumer's characteristics, browsing behavior, and viewed content. Nearly half of display advertising targets at the individual level, one example being retargeted display advertising. Retargeted display advertising only targets those who have previously visited a company's website. For example, as showed in Figure 1, a consumer visited American Eagle's website, browsed several items and then left the site without purchasing; this consumer visited CNN website later and saw display advertising with the same browsed product. The intent of retargeted display advertising is to draw people back to the firm's website, remind them of the product(s) they looked at, and drive incremental sales. The primary argument against the effectiveness of retargeted display advertising is that those consumers already plan to buy from the firm, rendering the retargeted ads superfluous and therefore a waste of money. In addressing this argument and exploring retargeted display advertising effectiveness, one of the predominant challenges I currently face is that the individual-level targeting induces selection bias in observational data.

2.1.3 Selection bias

Display advertising allows the advertiser to provide impressions to specific groups of consumers. The targeting algorithm is designed by an ad-serving agent to increase response by using consumers' demographics and individual past online activities such as pages viewed, products bought, and previous ad responses. The consumers who are more desirable to select for future display ads are those who have higher levels of online activity as well as a higher propensity to convert and/or respond to display ads. The selection algorithm and consumer information are generally not available to advertisers or researchers, and thus display advertising effect is hard to segregate from a selected consumer's activities. For example, in Figure 2, two consumers visited American Eagle's website, one of whom was exposed to display advertising while the other was not. American Eagle (the advertiser) can only observe that one consumer who sees the ad spends $100 and the other who does not encounter the ad spends only $10. For American Eagle, the $90 difference between the two consumers is the impact of display advertising. However, ad serving agents like Google can easily distinguish the two consumers by using their past browsing history, individual demographic information and purchasing behavior and serve display ads to the higher-response type person. The reason the consumer can see the display ad may be because this consumer has a purchase record with a similar fast fashion retailer while the other does not, and this means consumers who see the ad and those who do not are not the same type of consumer. However, this information is not available to American Eagle, making it impossible for American Eagle to identify the two types of consumer. In this case, the $90 spending difference includes not only the advertising impact, but also the difference between the two consumers' types.

2.1.4 Field experiment

This selection bias creates the difficulty of estimating display ad effect with a correlational method (Johnson et al. 2017), so researchers have started to use randomized

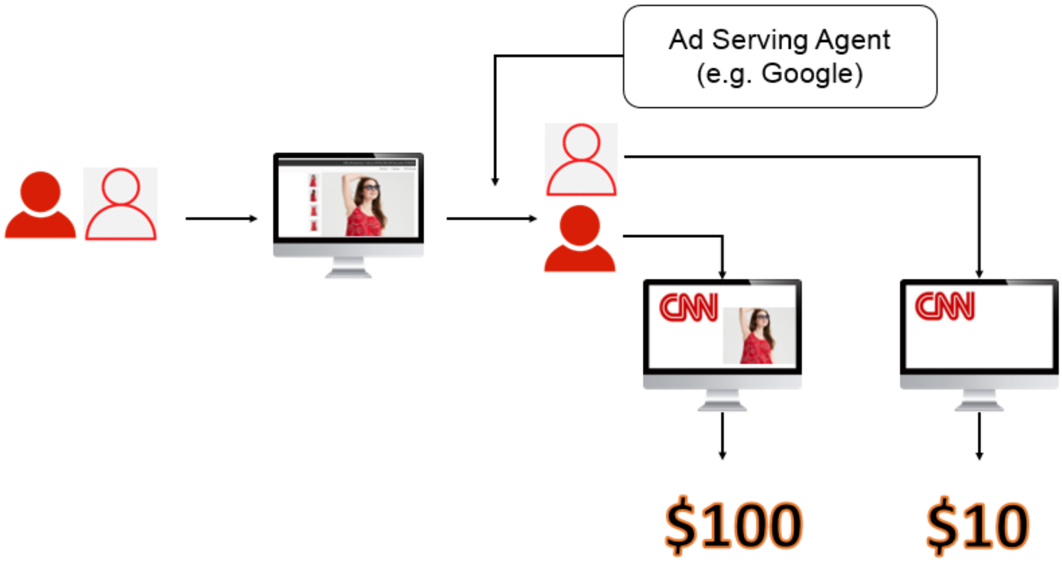


Figure 2: Selection Bias

field experiments to solve this selection bias problem (Lambrecht and Tucker 2013, Hoban and Bucklin 2015, Sahni 2015, 2016, Johnson et al. 2017). Johnson et al. (2017) found significant lift of retargeted display ads on website visits and online sales; Lambrecht and Tucker (2013) found that retargeted ad effectiveness is related with consumer purchase stage and display content; and Bleier and Eisenbeiss (2015) found that the personalized level matters as does the elapsed time since the last visit.

In the field experiments in the literature, consumers were randomly assigned to either treatment or control condition, and the differences in the responses of those two groups indicated the causal effect of the treated ads. The selection algorithm was the same for treatment and control conditions, and the only difference was that when display ads were being presented, people in the treatment condition received the real ads while people in the control condition were either treated with placebo ads (Lambrecht and Tucker 2013, Hoban and Bucklin 2015, Sahni 2015, 2016) or other advertising (Johnson et al. 2017).

In the current digital ecosystem, space at the top and side of most web pages is used by an ad-serving agent such as OpenX, which is owned by Google. Once a web user opens a web page—for example, a CNN news page—OpenX will send a bid request to advertisers with detailed information about the current web browser, such as website, unit size, browser type, and IP address. Each advertiser decides the bidding strategy for this opportunity. OpenX selects the winning bid from various advertisers to display the provided advertising to the web user. This selection algorithm is designed to select advertisers who have a higher click-through rate from the user, and the information used here is not constrained to the advertiser's interaction with the user but includes any of the user's online activities with any firm across different categories.

The two parties involved here, ad-serving agent and advertiser, make different decisions: the ad-serving agent decides which advertiser should be selected and the advertiser decides whether to bid for the web user's position. Even when an advertiser decides to bid on the position at a high price, the ad-serving agent can still select another firm. In contrast to traditional advertising, e.g. TV or newspaper advertising, where the advertiser can choose the number of ad impressions and the platform on which to show the ad, advertisers in the current digital advertising world are not able to control the number of impressions to show or even whether a consumer can see the ad. What advertisers can decide is whether to bid on the current browser's ad position upon request, which is called running a digital advertising campaign. The advertiser cannot pre-determine the number of ads a cookie owner will see but can decide whether to bid on the current cookie's position to run the campaign.

The focal advertiser in this study conducted the experiment by randomly assigning any first time visit cookie to either the treatment or control group. In control group, the visit cookie will not be bid on by our focal firm and thus will not encounter any display ads from us; in treatment group, the visit cookie will be available for bid regularly, but whether the cookie owner will be shown the focal firm's display ads depends on the ad-serving agent's unobserved algorithm. I do not care whether a visit cookie can be shown the retargeted ads; I only count whether that cookie is in the treatment or control group. This is similar to an intent-to-treat design. In the control condition, the advertiser turn off the ad campaign, while in the treatment condition, the advertiser runs the ad campaign. Therefore, consumer response difference between treatment and control cookies is the ad campaign impact. I cannot measure the marginal impact of one digital ad, but I can measure a campaign's impact of retargeted display advertising on a cookie.

Using disaggregate data from a randomized field experiment, I study a retargeted display ad campaign's causal impact on customer behavior. Similar to past research on display advertising, I discuss the digital ad's campaign impact at multiple stages of the purchase funnel, including website browsing and online purchases. Moreover, because I observe both digital activities and offline store purchases, I can extend the literature on display ad campaign effect to both online and offline channels. Finally, I also discuss the contemporary and carryover effect of retargeted display ad campaigns.

2.2 Cross Channel: Online Ads' Effect on Offline Channel

The importance of measuring the offline reaction to online ads has been much discussed. Online ads have been shown to impact offline showroom visits (Naik and Peters 2009). Aggregate offline purchases have been shown to be impacted by online ad spending, with the type of online ads including online banner ads (Naik and Peters 2009, Dinner et al. 2014), and keyword search (Pauwels et al. 2011, Dinner et al. 2014). Moreover, individual level offline purchases can be influenced by the online channel, such as Google search (Chan et al. 2011), online media exposure including display ads, paid search, social media and email (Danaher and Dagger 2013, Lobschat et al. 2017, Zantedeschi et al. 2016), and creating an online information website (Pauwels et al. 2011).

Aggregate cross-channel data can be used to discuss the effect of ad expenditure on search, visit and sales (Naik and Peters 2009, Pauwels et al. 2011, Dinner et al. 2014). Naik and Peters (2009) found a statistically significant cross-channel effect, that online banner ad spending can increase offline showroom visits. Pauwels et al. (2011) found that sales elasticity and profit effect is stronger for online ads (adwords) than offline advertising (faxes and flyers), and they also determined that 73% of online ads' profit is from offline orders. Dinner et al. (2014) used weekly aggregate level data to find that dollars spent on paid search and display ads affect offline sales. More importantly, they show that this cross-channel effect is not ephemeral but has long-term carryover.

The aggregate response model that measures the effect of ad expenditure on total sales or visits is valuable in exploring the overall ad benefit. Compared with disaggregate data, it is difficult to measure accurately consumers' offline responses when each individual is exposed to a unique online schedule. However, disaggregate individual online browsing behavior in one channel is hard to match with offline shopping behavior in another channel. Previous research has used different collection methods in many different areas related to cross-channel effect (Chan et al. 2011, Danaher and Dagger 2013, Pauwels et al. 2011, Zantedeschi et al. 2016, Lobschat et al. 2017).

Chan et al. (2011) used business-to-business data that can match consumers' online business IP addresses with the offline organization names and addresses. They found that customers who visited the firm's website through Google keyword search before their first purchase tended to have higher purchase rates offline. They simulated Consumer-Lifetime-Value through the cross-channel data and found that this value can be underestimated by conventional methods that neglect the offline transactions trigged by online advertisement. Danaher and Dagger (2013) collected media exposure data (online) among consumers in the firm's loyalty program database by sending out an online media survey and then merged this data with the same people's offline purchasing activity. The single-source data provided the insight that online (display, search, social, email) and offline (TV, newspaper, Radio, direct mail) media affect offline sales. Pauwels et al. (2011) examined whether adding an informational website affects offline purchases. In their study, consumers who wanted to get access to the firm's website had to sign in, and this allowed them to track all consumer individual online activities and match them with offline shopping behaviors. They found that website information increased offline revenue in the sensory product category and in all categories for those who lived far from the store. They also found that the website information can decrease store visits for experiential shoppers. Lobschat et al. (2017) used 17-week single-source data from GfK Panel Services Germany. GfK collected offline purchase data through a weekly retrospective survey from households in its Consumer Scope Panel and collected the online media data via a browser extension added to the households' computers. They studied the effect of banner ads on website visits and purchases from the focal retailer firm that predominantly sells offline. They found that current banner ads can only increase a retailer's website visits and indirectly increase offline purchases through website visits for nonrecent online consumers. They also found that being previously exposed to banner ads can increase both nonrecent and recent online consumers' retailer website visits, but only increase recent online consumers' offline purchases.

In summary, I use randomized experimentation and disaggregate level data to understand the causal impacts of individually targeted internet display advertising on website visits and purchases. One of the main advantages of digital advertisement is the ability to tailor appeals based on individual preference, attitude and behavior. Because consumers not only differ in response to advertisements but are also treated with different ad designs, disaggregate level analysis better fits the research purpose.

I extend prior research by examining a retargeted display advertising campaign's impact on traditional channels. I match consumer individual online browsing data with offline purchase data and find significant spillovers in offline purchases with display retargeting advertising. I show that the effects of online advertising on offline sales not only show up in contemporary one-day response but also carry over to days after leaving the treatment group. Moreover, I find this cross-channel effect also depends on the distance form consumer home to store.

2.3 Channel Substitution

Many papers have discussed the effect of adding an additional channel to the existing channel. Either adding a digital channel to the traditional channel (Deleersnyder et al. 2002, Biyalogorsky and Naik 2003, Ansari et al. 2008) or the reverse, adding a brick and mortar store to the online channel (Avery et al. 2012, Bell et al. 2015, Pauwels and Neslin 2015), can bring both advantageous and disadvantageous effects.

The disadvantage of adding a new channel is a decrease in the old channel's revenue, which is also called the substitution or migration effect. The purchase increase on the new channel migrates from the existing channel's revenue, as consumers switch from the old channel to the new one rather than create additional purchases. The existence of the online channel as an addition to the offline channel can lead consumers to switch from one to the other (Biyalogorsky and Naik 2003, Brynjolfsson et al. 2009, Choi and Bell 2011). Similarly, adding an offline store to an existing channel may cause substitution (Pauwels and Neslin 2015, Avery et al. 2007). Avery et al. (2007) and Pauwels and Neslin (2015) report that adding an offline channel can cannibalize purchase frequency, order size, exchange and return frequency, and sales for the existing channel (catalog or internet). Moreover, the satisfaction of one channel increasing will be diminished by the reduced performance of the same retailer's other channel (Montoya-Weiss et al. 2003, Pauwels and Neslin 2015). Montoya-Weiss et al. (2003) find that consumer online channel use is negatively correlated with the perceived service quality for the currently used traditional channel, and Falk et al. (2007) find that consumer offline channel satisfaction reduces the perceived usefulness of the online channel.

On the other hand, adding a new channel can increase the performance of both the new and existing channels, known as the synergy effect. The additional channel increases the number of consumer-firm touch points and thus increases total sales. The multiple touch points may widen consumer awareness of the brand and attract new consumers to the brand (Wang et al. 2017, Avery et al. 2012) and increase retention by strengthening current consumers' relationship with the firm (Ansari et al. 2008, Pauwels and Neslin 2015). Moreover, adding a new channel may increase consumer familiarity with and trust in the brand (Bell et al. 2015). Different channels can be combined to satisfy the consumer's various preferences, which in turn drives both online and offline sales (Avery et al. 2012, Choi and Bell 2011). There is co-existence of migration and synergy between online and offline channels. Many factors can affect the migration or synergy of consumer channel choice: distance to store (Forman et al. 2009, Pauwels et al. 2011), previous exposure (Wang et al. 2017), brand popularity (Choi and Bell 2011), consumer segments (Pauwels et al. 2011), and length of the time measurement (Avery et al. 2012).

Avery et al. (2012) use difference in difference by market panel data to find that adding a physical store to an existing online or catalog channel cannibalizes in the short run but complements in the long run. Pauwels and Neslin (2015) use a VAR model to analyze aggregate time series data and find that adding a physical store cannibalizes the catalog channel but not the online channel. Wang et al. (2017) find that adding an offline store complements the existing online sales in an area without previous brand exposure, but cannibalizes in an area with existing brand presence. Pauwels et al. (2011) use VAR and latent class models to find that adding an online information website complements offline sales in the sensory product category among distant consumers and frequent online visitors, but substitutes offline sales for the opposite product category and consumer segments. Choi and Bell (2011) find that a niche brand underserved on the offline channel has a greater substitution effect than a popular brand.

I contribute to the literature by expanding the extant knowledge on channel substitution. Specifically, I focus on the effects of an online retargeted display advertising campaign on consumer channel choice in purchasing. Instead of discussing the substitution effect of adding a new channel, I discuss how a consumer's response to online display ad campaign influences the choice of online or offline channels. Moreover, I model individual response to online display ads and estimate it by the hierarchical Bayesian method, which allows me to detect the substitution effect on the individual level.

2.4 Distance Effect on Channel Choice

Distance is important to the consumer's offline choice. As discussed in the traditional economic hoteling model (Working and Hotelling 1929) and circular spatial model (Salop 1979), consumer preferences are determined by both product characteristics and geographic location. Tobler (1970) pointed out that in the first law of geography nearby things are more relevant than distant things.

In the digital world, the internet reduces the importance of physical distance by decreasing communication costs (Cairncross 1997). Academic papers theoretically model the impact of distance from consumer home to store on online and offline shopping patterns, and point out that distant consumers tend to choose online channels to avoid the higher travel cost (Balasubramanian 1998, Zhang 2009). Moreover, empirical academic papers show that consumers living far from a brick and mortar store create more value through purchasing online (Forman et al. 2009, Brynjolfsson et al. 2009, Choi et al. 2012, Chintagunta et al. 2012, Anderson et al. 2010). Forman et al. (2009) and Brynjolfsson et al. (2009) show that consumers' online shopping probability increases as the distance to the store increases by using aggregate and disaggregate level data. Anderson et al. (2010) show that a local store opening reduces nearby consumers' online purchasing. Choi et al. (2012) find greater online demand with greater travel distance to a local store. Therefore, the online channel reduces the importance of the role of the distance from home to store and thus creates competition with the offline channel. Chintagunta et al. (2012) show that downtown households are less likely than suburban households to prefer the online channel unless they need to travel longer to the local store.

However, distance may also generate channel synergy. Bell et al. (2017) point out the physical store can play the role of a showroom that allows consumers to gain physical experience through touching and feeling the product and thus increase brand awareness, satisfaction, trust, and feasibility of purchase and reduce uncertainty about the product. Wang et al. (2017) show the billboard effect of an offline store on online sales, especially for those locations where no such brand store existed before. Avery et al. (2012) find an acquisition effect of adding an offline store to attract new consumers.

I contribute to the literature by expanding the extant knowledge of distance's effect on channel substitution. Specifically, I focus on the effect of distance on changing consumers' online ad response in purchasing channel choice and the persistence of ad campaign effects.

2.5 Contribution Tables

Table 1 presents an overall summarization of the related literature. This dissertation uses a randomized field experiment on digital advertising to explore its multichannel impact in terms of online visits, online purchase and offline purchase. Consumer heterogeneity in distance from home to store is discussed by using individual level data and an individual level model.

In contrast with the existing literature on retargeted display advertising(Lambrecht and Tucker 2013, Bleier and Eisenbeiss 2015, Johnson et al. 2017), this dissertation matches consumer cookie IDs with consumer IDs and thus enables the effectiveness measurement on individual level. Moreover, this dissertation explores potential carryover effects and cross-channel impacts of retargeted display advertising.

Table 1: Literature Comparison

Paper	Mult Chan	Indi Data	Field Exp	Vs	Web	Str	Chan Choice	Dist from store
Wang et al. (2017)	x	x	Quasi Exp			x	x	x
Joo et al. (2013)	x			x				
Liaukonyte et al. (2015)	x	x	Quasi Exp	x	x			
Wiesel et al. (2011)	x			x	x	x		x
Naik and Peters (2009)	x	x		x				
Dinner et al. (2014)	x			x	x	x		
Chan et al. (2011)	x	x	x		x	x		
Danaher and Dagger (2013)	x	x				x		
Lobschat et al. (2017)	x	x		x		x		
Pauwels et al. (2011)	x	x				x		
Bellizzi (2000)	x	x	x	x				
Zantedeschi et al. (2016)	x	x	x		x	x		
Naik and Raman (2003)						x		
Naik et al. (2005)		x				x		
Edell and Keller (1989)		x	lab					
Stafford et al. (2003)						x		
Xu et al. (2014)		x		x	x			
Li and Kannan (2014)		x	x	x	x			
Kireyev et al. (2016)				x	x			
Bollinger et al. (2013)	x	x			x			
Zenetti et al. (2014)	x	x	x	x		x		
Reimer et al. (2014)	x	x			x			
Chang and Thorson (2004)	x	x	lab					
Dijkstra et al. (2005)	x	x	lab					
Havlena et al. (2007)	x	x						
Abraham (2008)	x	x		x	x	x		
This Dissertation	x	x	x	x	x	x	x	x

3 Data Collection and Experimental Design

The data stem from a firm's randomized field experiment. The firm leveraged omnichannel pixel technology to collect detailed consumer online browsing behavior; this technology enables matching consumers across online and offline channels. Moreover, in order to measure customer response to online display retargeting advertisement campaign, the firm ran the randomized field experiment on the cookie level. After linking the online cookie data with the CRM data by consumer ID, I was able to explore how display retargeting adverting impacts customer behavior across the digital and traditional channels. In the following section, I describe the details of the data matching and field experiment and how I constructed the individual-level experiment group to fulfill the research purpose.

3.1 Online Tracking Data and Field Experiment Design

The focal firm collected consumer online browsing data by using tracking cookie ID technology. A computer cookie is not a physical object. It is a smallfile embedded on the browser from the firm's website the user visits. The firm's website uses this cookie to track a user's visits and activities. For example, when a user places one or more products in the online shopping cart and leaves the website without purchasing, the next time the cart is opened, the product or products are there instead of there being an empty cart. Tracking cookies creates a long-term record of visits to and activities on the firm's website and helps the firm know who its visitors and customers are. This technology helps firms collect detailed interaction consumer-retailer information, which includes display retargeting exposures, clicks on paid and organic searches, email impressions, website visits, and transactions. The focal firm conducts only retargeted display advertising campaigns for display advertising and thus bids only on ad positions from those who have visited the firm's website. If a consumer visits the firm's website, the cookie information is recorded.

Once an ad-serving agent sends a bid request for this cookie to the focal firm, the firm decides whether to bid on the ad position. If the firm bids and wins this campaign, the consumer is provided a follow-up display retargeting advertisement with the viewed products or similar products from the firm during the visit.

In measuring the effect of a retargeted display advertising campaign, the major concern is selection bias. The firm can bid on all consumers' visited cookie positions, but only the type of consumers with high conversion rate are exposed to display advertising. The response difference between ad exposure and non-exposure consumers includes the ad campaign impact and the consumer type difference. If ad exposure consumers spend more money online, it is difficult to determine whether this is due to the advertising campaign's impact or the purchasing habit that the high potential for conversion type consumer has.

To address this problem, the focal firm ran a randomized field experiment by using the tracking technology the firm adopted to identify cookies which visit the firm's website. The first time a cookie visited the firm's website, the cookie was randomly assigned to the treatment or control group. As shown in Figure 3, if the cookie was in the control group, the focal firm never bid for a retargeted display advertising campaign on this cookie, and the consumer would never encounter any display ads from it; if the cookie was in the treatment group, the focal firm bid for the ad's position as usual, but the consumer may or may not have been exposed to the display ads; this outcome was determined by the ad-serving agent's selection algorithm.

The firm provided me the experimental data from 2016-07-31 to 2017-02-25 and identified the control group cookies. Any first-time visit cookie had a 17% chance to be assigned to the control group and an 83% chance to be assigned to the treatment group. From a managerial perspective, control cookies can be perceived as turning off the retargeted display advertising campaign, and consumer response differences between the treatment and control group represent campaign effectiveness. Thus,

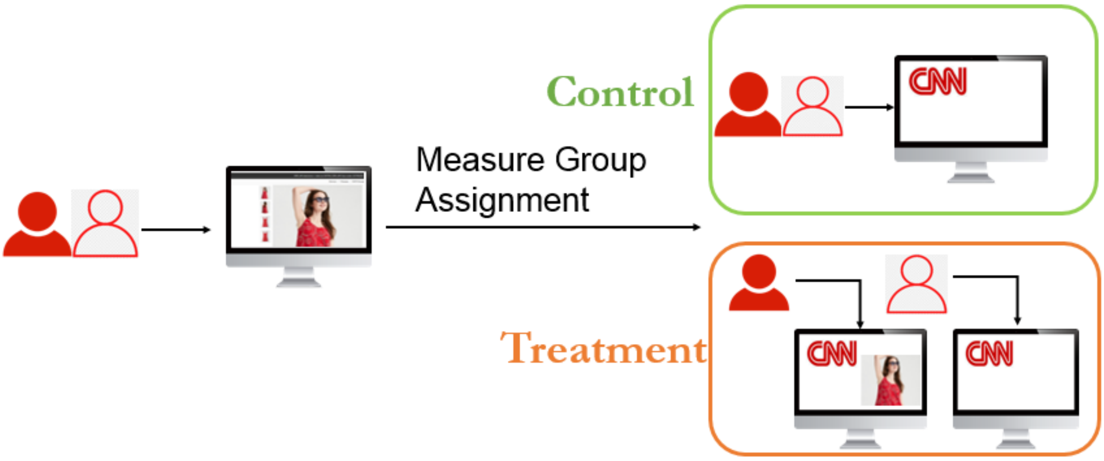


Figure 3: Field Experiment

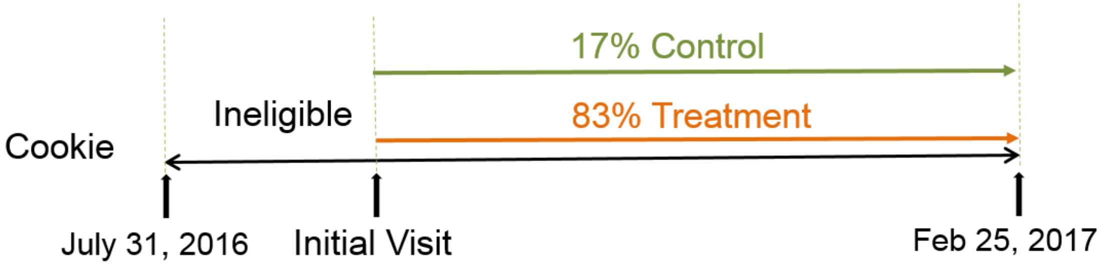


Figure 4: Field Experiment Information

in this study, I measure the digital advertising campaign effectiveness.

3.1.1 Randomization Check

I first performed a randomization check on the data. For sufficiently large samples, randomization produces treatment and control groups are balanced with respect to observed and unobserved characteristics. This probabilistic equivalence is fundamental to identifying the causal impact of any treatment. In advertising experiments, flawed execution can occasionally produce biased samples. Further, targeting algorithms are frequently dynamic and unobserved in digital marketing. It is thus important that I examine the validity of the randomization a posteriori.

Table 2: Randomization Check

DispCondition	Email	Length	Age	Dist From Home
Control	8.274	34.684	43.985	12.091
Treatment	7.999	33.973	43.133	11.819
K-S test P-Value	0.468	0.17	0.379	0.294

In Table 2, I present randomization checks for the display advertising experiment. A randomization check requires group comparison before the start of the experiment, so I look at the cookie-level activity from the first day of cookie observation to the initial visit of the corresponding cookie. The field experiment started on the first day of a cookie's initial visit; I want to check whether the treatment cookie and control cookie have similar activities before the group assignment. Here I only count those visit cookies which have more than one-day length after the first observation and before the initial visit. The two activities are email impressions the cookie received before the initial visit and the length of the cookie I observed before the initial visit on that cookie. On average, treatment cookies received 8.0 email impressions and control cookies 8.3 email impressions. The two means of email impression are very close in a practical sense between the treatment and control group. I also perform a Kolmogorov-Smirnov (KS) test to check whether the samples from the two groups were drawn from the same distribution. For email impressions, the p-value of the KS test is 0.47, so I am unable to reject the null hypothesis that the observations come from a single set of distributions, which means that the number of email impressions between treatment and control groups are distributed from the same distribution before the initial visit. For cookie length, I find that on average, before the cookie's initial visit, treatment cookies have a length of 34.0 days and control cookies have a similar length. The KS test with p-value 0.17 does not allow rejection of the null hypothesis, so I can conclude that the cookie lengths before the initial visit are not different between the treatment and control groups. I also conduct a randomization check with two demographic variables, distance to nearest store and customer age. The owners of control cookies have an average age of 44, while the owners of treatment cookies have an average age of 43; the KS test shows no statistically significant difference between the two groups' age distributions. Similarly, I find that the owners of control cookies live slightly farther from the nearest store than do treatment cookie owners, with the p-value of the KS test showing no statistically significant difference between the two groups. The means are nearly identical, and I find no significant differences in the distributions (Kolmogorov-Smirnov (KS) test; $p>0.1$).

3.1.2 Why Not Count the Number of Impressions or Use Average Treatment Effect (ATE)

In the field experiment setup, I measure whether a visit cookie is in the treatment group or not on a given day and consider that as a binary state because that is the level of randomization I have. This dissertation is going to answer the question whether a retargeted display advertising campaign can impact consumer behavior.

Other than the campaign level randomized field experiment, the online tracking data contain the number of display advertising impressions each cookie received. However, I cannot count the number of display advertising impressions in measur-

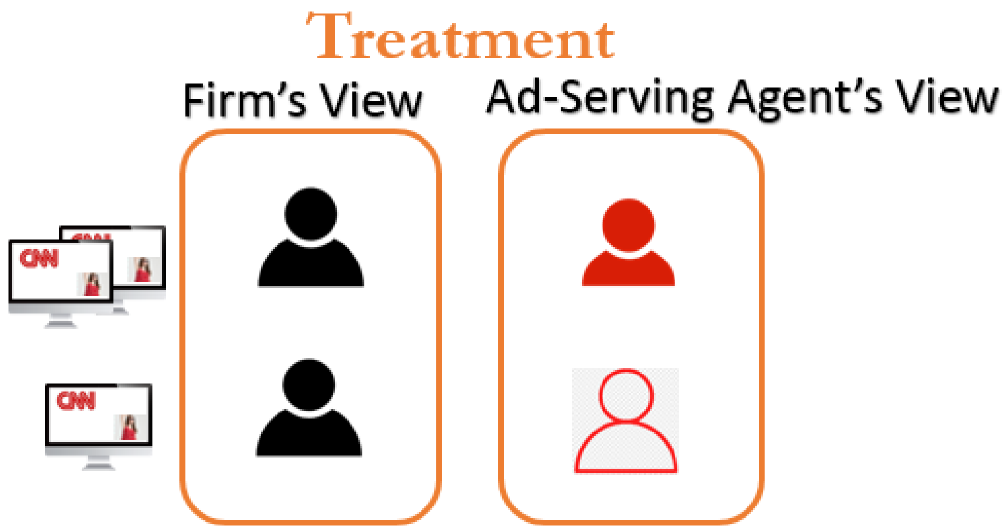


Figure 5: Different Role's Insight

ing an ad's impact. Figure 5 presents two types of people—solid red and hollow red—with solid red more likely to respond to ads than hollow red. Ad-serving agents can infer those two people's types based on their past online behavior and serve more ads to solid red and fewer to hollow red. To the firm or me as researcher, I observe only two similar persons with different numbers of impressions. In the observation, I cannot know who is solid red and who is hollow red or why ad-serving agents serve more ads to one than to the other. I know only that the number of impressions are certainly not random, but I lack the information to infer the criteria the selections were based on. The information the ad-serving agent has is much broader than a single firm's record and includes a web browser's online movement at every second. If I count impressions within the treatment group, I am comparing the impact of number of impressions but confounding that with the individual consumer type (solid red or hollow red). The selection bias shows up again between consumers with different numbers of impressions. In this case, I have to rely on the cookies' experimental condition to measure the digital ad's campaign impact and not rely on the number of impressions.

Based on the intent-to-treat field experiment design, another possible analysis method is average treatment effect (ATE), which purports to capture campaign

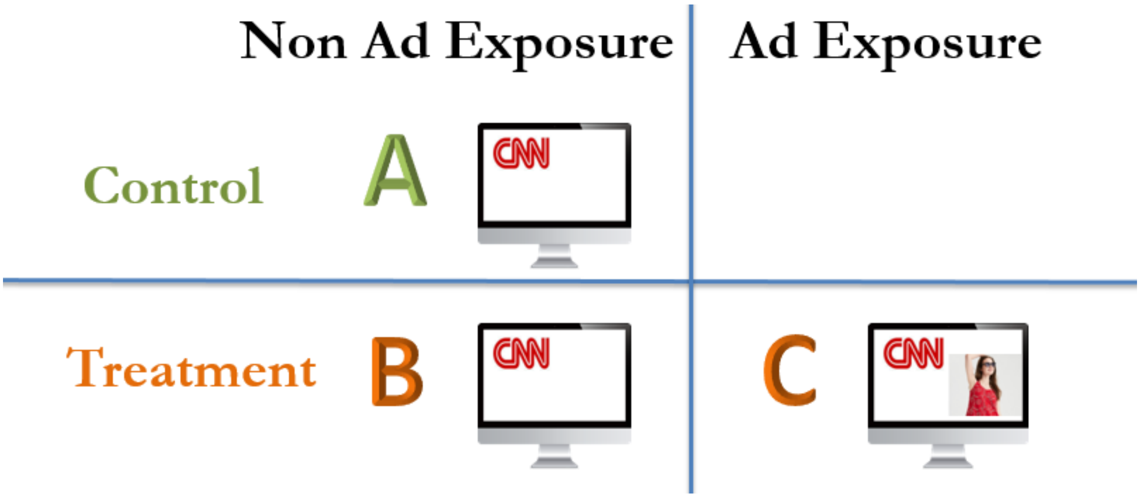


Figure 6: Randomization Check with Different Groups

effectiveness by comparing consumer response from the true treated consumers in the treatment group with the remaining consumers, who never received the ad. In Figure 6, the 2 by 2 matrix represents this consideration. In the intent-to-treat design, consumers in the treatment group may (C) or may not (B) see the display advertising, and I measure the ad's campaign impact as consumer difference between treatment and control (A versus B+C). In ATE analysis, however, the campaign impact should be measured by consumer response difference between non-ad exposure consumers (A+B) and ad exposure consumers (C).

ATE is not a suitable method to capture the impact of a retargeted display advertising campaign. The reason is similar to why I cannot count the number of display advertising impressions. The ad-serving agent has unobserved information to identify treatment group consumers and tends to serve ads to high response consumers. Consumers who have ad exposures in the treatment group are different from the non-ad exposure consumers. Intuitively, consumers in C area should be different from consumers in B area.

I first do a randomization check between the two groups of consumer (B&C) in treatment in Table 3. When it is compared with Table 2, which tests whether the control (A) or treatment (B+C) cookies were randomly assigned, it is clear that ad exposure cookies and non-ad exposure cookies are not randomly assigned. The P-values of the K-S test on email impressions, cookie length before initial visit and cookie owner's age are below .01, which means all three measures between ad exposure and non-ad exposure groups are statistically significantly different. In addition, the difference for the two groups in distance from home to store is marginally significant. To support my contention that ad exposure consumers are different from non-ad exposure consumers in the treatment group, I go back to each cookie owner's purchase history before the cookie's initial visit for those two types (B & C) in Table 4. Both online and offline shopping patterns are checked; this includes purchase incidence, money spent and purchase units. Overall, there is no significant offline purchase history difference between ad exposure and non-ad exposure consumers, but ad exposure consumers a history of significantly more online purchases. On average, ad-serving agents serve display advertising to treatment consumers who spend in the history record an average of $6 more online than the rest of the treatment group consumers.

Table 3: Treatment Group Randomization Check (B Vs C)

Treatment	Email	Length	Age	Dist From Home
Ads	6.937	30.353	43.03	11.708
NoAds	8.835	36.819	44.155	11.145
K-S test P-Value	0	0	0.003	0.087

Table 4: Treatment Group Randomization Check for Purchase (B Vs C)

Treatment>0	Str	Str$	StrUnits	Web	Web$	WebUnits
NoAds	2.127	141.866	6.946	0.75	44.016	1.933
Ads	2.122	144.579	6.932	0.877	51.153	2.221
K-S test PValue	0.535	0.283	0.357	0.029	0.012	0.029

3.2 Matching Online Records with Individual Data

Measuring advertising effectiveness has a long history in marketing. Researchers try to learn how ad exposures influence consumer shopping patterns. Ideally, each consumer's subsequent shopping behavior can be matched with the ad exposure condition.

Traditionally, offline transactions are well recorded at the individual or household level. Some offline advertisements (e.g., TV, radio and print advertising) are hard to link with individual data. Thus, researchers tend to compare aggregate sales before and after launching an advertisement to measure its effect (Joo et al. 2013, Dinner et al. 2014). Some other targeted offline advertisements, like fliers and mailed catalogs, are relatively easier to link with individual data.

In the digital world, customer-firm interactions are more easily tracked at the cookie level, from the early stage when consumers search for product information until the later stage when consumers make a purchase. However, that information is collected by cookie tracking technology that can be applied on a device's web browser. Because an individual may have multiple devices and each device may have installed several different browsers, each cookie ID tracking datum may represent only part of an individual's interaction with the firm. It is possible that a consumer visits the firm's website on a smart phone, receives display retargeting impressions in the following several days, and finally makes a purchase on their desktop. Thus, based on single cookie data, I may underestimate the effect of display retargeting ads on purchases. Moreover, as shown in the literature, online ads can have an effect on offline purchases, so a lack of cross-channel matching could result in biased estimations of the advertisement effect. Therefore, accurately matching individual online and offline data is important in estimating cross-channel advertising response.

Realizing the importance of accurate matching of online records on the individual level, the focal retailer linked digital cookie IDs with consumer IDs. The matching information was collected through two digital touches: regular promotional emails and loyalty program logins. On the online platform, a consumer has to provide an email address for tracking information to place an order, while at the retail store, sales personnel are trained to request a consumer email address for an offline transaction. The firm creates its own cross channel record for each consumer with email address and consumer ID and sends regular promotional emails to consumers. When a consumer opens an email from the firm, the tracking technology links the cookie ID with the corresponding consumer ID. In this study's record, 99.36% of matched data were from email being opened. Secondly, the firm runs a free loyalty program that provides exclusive offers and rewards registered consumers based on past spending. Consumers have a financial incentive to register and maintain membership by providing their email addresses and names. Loyalty program logins helped me to link the remaining 0.64% of matched data. As a result, 73.73% of cookies (106.5M) were matched with 3.72 million consumers in the CRM system.

Once a consumer's online browsing history was matched with a unique consumer ID, a cross-channel data set was created linking consumers' digital actions with the regular consumer relationship management (CRM) database. The CRM system contains consumer demographic, transaction and revenue information. From the digital record, consumers' email opening, display impressions, website visits and online transactions can be obtained. From this combination, cross-channel interactions between individual consumers and the firm can be collected.

During the data collection period, in the CRM transaction data, 3.34 million (81.1%) consumers made at least one offline purchase, and 44.5% of these had an online activity record; all remaining shoppers made both online and offline purchases. For the matched online tracking data, 3.72 million consumers were observed; 17.3% of them made at least one online purchase, 56% of them had at least one visit during the focal period, and 50.0% of them made at least one offline purchase. Without the cross-channel matching, those offline transactions could not be matched with impact from online digital advertisement, and the effect of online advertising would likely be underestimated.

3.3 Individual Experiment Condition

The efficacy of a display retargeting advertising campaign is hard to measure because of selection bias. Consumers who encounter the display advertisement are different from those who do not. Only those consumers who visit a website can be retargeted by display impressions. Exposure to advertisement is the result of the consumer's first visit, which shows the consumer's personal interest in the product. It is hard to say whether any of the consumer's subsequent shopping behavior should be attributed to the consumer's initial visit or the retargeting advertising. Those who are targeted by a display impression are more likely to be those who are more interested in the product, while those who never encounter a display impression are those consumers who never visit the firm's website. I therefore tried to solve the selection bias problem in display retargeting ads by using a field experiment and defined the group assignments based on the experimental design. In this section, I focus on describing the individual daily experiment condition.

In the field experiment, cookies were randomly assigned to the control group the first time they visited the firm's website. Of the first-time visit cookies, 17% were assigned to a control group that would not receive any retargeted display ads in the future. The control group assignment was randomly made on any first-time cookie and not related with the content of the first visit. A cookie in the treatment group meant this cookie visited the website and was not assigned to the control group, making its owner eligible to receive follow-up display retargeting impressions.

First, active duration was defined at cookie level. I follow Hoban and Bucklin (2015)'s setup to define a cookie as active between the first and last tracked behavior that consist of any interaction with the firm such as website visit, email opening, or display impression. Not all cookies were alive during the entire experiment period since people could delete the cookie and even the browser platform, or the owner

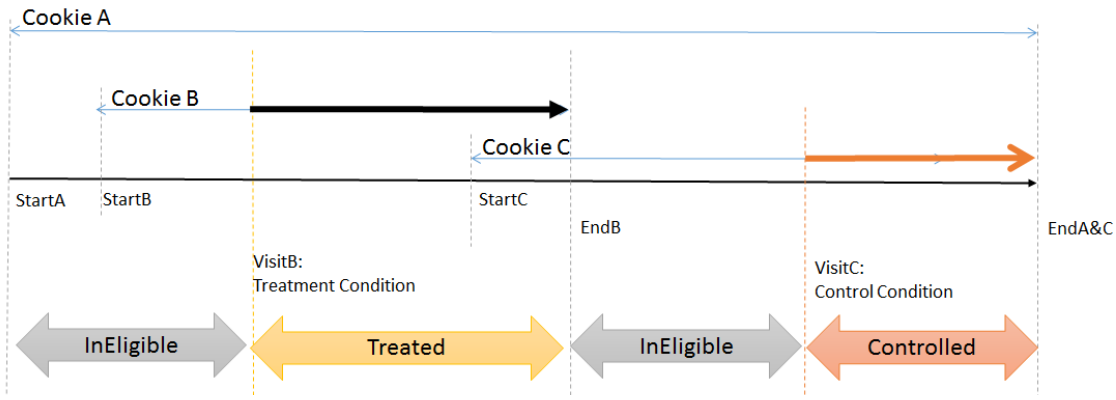


Figure 7: Individual Daily Experiment Group Example

of the cookie ID may simply no longer have interacted with the firm. Either of these conditions meant the cookie was no longer active for the firm. A cookie's active duration was defined as the elapsed time between the first and last tracked behaviors. The tracked behavior included but was not limited to email opening, any website visit, and display impressions. For example, when a shipping confirmation email was opened on a new cookie, this cookie was active and this email opening was recorded as the first active action. An example of the experiment group setup is provided in Figure 7. In this figure, cookies A, B and C were tracked, and only cookie A was alive along the whole timeline. Cookie B was first tracked at StartB and last tracked at EndB, so the active time for cookie B is the length between StartB and End B.

An active cookie could be retargeted only after the first retailer website visit, not at the start of the tracked behavior. For example, if a cookie was first tracked from checking the shipping confirmation email but never visited the website, this cookie never had a chance to encounter a retargeted display impression. A cookie's initial visit point was marked at the first site visit, which represents the possibility of retargeting in the future. In the field experiment, a cookie was randomly assigned to either treatment or control condition at the initial visit point, and this condition lasted until the end of the active cookie. Thus, a visiting cookie had an eligible period starting from the initial visit point and ending with the end of active duration, and during the eligible period, this cookie was treated with display retargeting ads if it had been assigned to the treatment group; otherwise, it was precluded from retargeting impressions. In Figure 7, cookie A never visited the website and thus was never eligible for display ads; cookie B visited the site at visitB and was assigned to treatment condition and received display ads until the end of its active duration at EndB; cookie C visited the website at time VisitC but was assigned to the control group and never received any display ads. Each cookie's active duration is from the start point to the end point, but the eligible duration only starts from the first visit point.

Second, individual observation history and experiment condition were defined as the mixture of this person's multiple cookies. A consumer may have several devices with different types of browsers and thus multiple cookies. An individual's observation history lasted from the beginning of the earliest cookie's active duration until the end of the latest cookie's active duration. A consumer's multiple cookies might be assigned to different experiment conditions, so the individual experiment condition was determined by the combination of active cookies' experiment condition in the eligible period. In Figure 7, the consumer does not have two active cookies that are assigned to different groups at the same time, and the individual daily group definition can be easily seen from the active cookie's group on that day. However, the consumer in Figure 8 has two active cookies in different experiment conditions in the overlap period. The two active cookies' alive durations did not perfectly coincide but had some overlap, as depicted by the active duration of cookie B and cookie C in Figure 8. A consumer may have had group assignment changes due to an old cookie's ending or a new cookie's visit. For example, a consumer could have changed from display-treated to non-treated if the only treated cookie ended, and conversely changed from non-treated to treated if a new cookie visited the firm's website and was assigned to the treatment group. In Figure 7 and Figure 8, the owner of cookies A, B and C changed from being treated to not treated at EndB

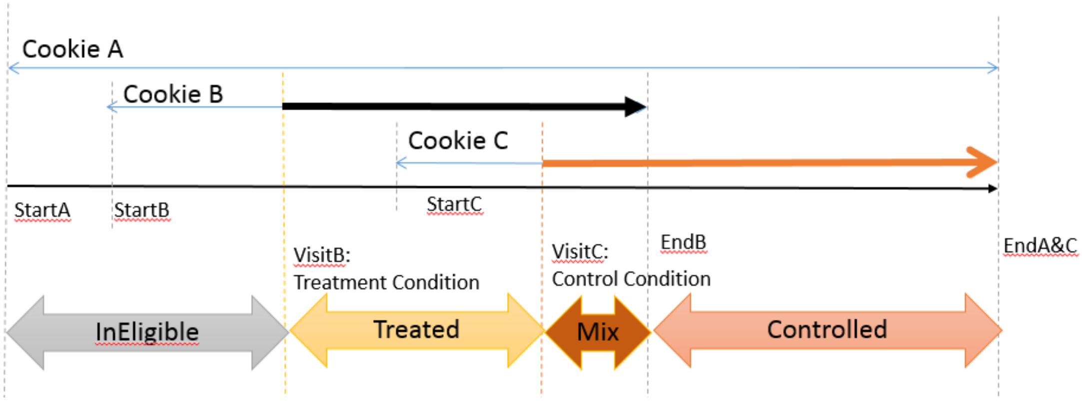


Figure 8: Individual Daily Experiment Group with Overlap Visited Cookies

because of the end of the corresponding treatment cookie B. I define the individual daily experiment condition based on the combination of every active cookie on that day: treated if any active cookie was treated and controlled if all active cookies were controlled. If a day had more than one cookie assigned to different groups, this day is still identified as a treated day since the consumer had a chance to encounter a retargeted display ad.

Thus, there were in general two steps in defining individual experiment condition on the daily level: first, each cookie ID's active duration and eligible period were found; second, each consumer's cookies were combined daily, and the day was classified as treated if any active cookie on that day was eligible and treated, or controlled if all active cookies on that day were eligible but controlled. This individual experiment condition definition enables discussing the effectiveness of display retargeting advertisement as the effect of retargeting possibility, which was randomly assigned at the first-time website visit.

3.3.1 Individual-level Analysis Strength

At the individual level, I can explore carryover impact. A cookie does not last forever. Consumers may delete their cookies in several ways, such as pre-programmed deletion on browsers, or by manually clearing their cookie history. Along the timeline, cookie deletion is exogenous to our field experiment, which brings the opportunity to explore how consumers behave after deleting the treatment cookie. I find that there is no positive correlation between the number of display advertising impressions and cookie duration, which means consumers are not deleting cookies because of more display ad exposures. This evidence supports the assumption that cookie deletion is exogenous to the field experiment. Thus, I can capture consumer response after deleting treatment cookies, and explore the carryover effect of a retargeted display advertising campaign.

At the individual level, I can explore cross-channel impact on both online and offline sales. In current marketing, industries tend to measure online advertising campaign impact on online sales only. Click-through rate remains a popular metric for measuring digital ads' effectiveness and cost-per-click is still used to measure spending in the digital world. Consumers' purchases may be attributed to all possible interactions with a firm's marketing actions; however, last-click attribution assigns all credit to the nearest digital action. Several alternative models have been explored to capture digital marketing impact, such as the linear attribution model, the time decay attribution model, and the position-based attribution model. However, the measurement still captures digital advertising campaign impact on online channels only. The data here contain information from both online and offline channels, which allows me to measure digital advertising campaign impact across channels. I can calculate how much impact spills over from online advertising to offline purchases. The quantified number can reveal whether missing offline channel impact is a big challenge in measuring digital advertising campaign effectiveness. If there is only a small impact from online to offline, there is no huge underestimation. But if the missing number from the impact on offline sales is large, we need to consider holistic measurement across channels.

At the individual level, I can measure heterogeneity based on demographic information such as gender, age, and home address. Since individual IDs have been matched with cookie IDs, such individual information is available on the consumer database. Current IT technology may enable cookie address detection, and consumer location address and geo-information can be inferred from such an algorithm. However, geo-information may not accurately capture consumer home addresses, which is an important measurement for capturing offline shopping costs. Other individual-level demographic information (e.g., age, gender) is available only through the cookie-individual matching algorithm.

In summary, I explore data from a randomized field experiment which is conducted at the cookie level, but I aggregate those effects up to the individual level. This presents opportunities such as allowing me to study carryover impact and spillover impact from the online ad campaign to offline. I use disaggregated data and the disaggregated model to disentangle those effects. That allows me to look at heterogeneity within individuals and correlations in responses.

4 Model Development

In this section, I use modeling methods to explore consumer response to a retargeted display advertising campaign. First, I assume there is no matching algorithm linking cookies with individual IDs and use cookie information to model consumer response to the digital advertising campaign. This cookie-level model is designated as M1, and the available data is consumer online behavior that includes online visits and purchases. I then adopt the matching algorithm and construct models at the individual level. The individual-level data allows me to use consumer online and offline behavior as well as individual demographic information. To construct the individual-level model, I use individual experiment condition to define the daily group assignment (M2) and also incorporate the number of eligible cookie group assignments to add intensity measurement (M3).

4.1 Cookie-level Model Development (M1)

In the cookie-level model (M1), a sequence of online visit and purchase events have been modeled for each cookie. I construct a cookie-level advertising response model for online visiting and conversion. The display advertising campaign impact has been discussed on two consumer shopping behaviors: website visits and online purchases. In line with the literature on measuring the effect of digital marketing ads, website browsing behavior is an intermediate measure of whether the consumer has considered this brand. Following consideration measurement, purchase is the down-funnel activity that directly measures the profit effect of the advertisement. Display advertising can influence consumers' online purchase stages from website browsing to shopping cart decision and final purchase. Moreover, a display retargeting ad campaign can also have an effect on the quantity (how many visits and how much is purchased) of each decision. This model enables me to quantify the effectiveness of the retargeted display advertising campaign in terms of visit frequency and revenue dollars and thus straightforwardly demonstrates the value of the retargeted display advertising campaign.

Cookie-level online visits and purchases are modeled jointly: 1) online visit is characterized by whether a visit occurs and how many times the website is visited; 2) the online purchase can happen only during a website visit, so it is characterized, conditional on a visit, by whether a purchase occurs and how much is bought. In general, each event is characterized in incidence (whether it happens) and quantity (how many times/how much), and the quantity is modeled conditional on the event's occurrence. Especially, an online purchase event is associated with the website visit event and thus modeled as a later stage after the incidence of the online visit. The multiple outcomes of consumer purchase patterns are jointly constructed as a multi-stage model that enables me to examine the display retargeting advertising campaign effect on multiple events together.

The online visit incidence is binary; I use standard logistic regression to model day t's choice of visiting (v_t) as:

$$P(1_{v_t>0}) = \frac{1}{1 + e^{-U(1_{v_t>0})}} \tag{1}$$

where $U(1_{v_t>0})$ is a linear function of display retargeting ad stock:

$$U(1_{v_t>0}) = \alpha_0 + \alpha_1 T_t \tag{2}$$

where α_0 represents a baseline visit probability, and α_1 represents the response to the display retargeting in terms of visiting behavior. $T_t = 1$ if this cookie has been assigned to the treatment group.

The incidence of visiting provides one measure of consumer shopping pattern but does not capture the frequency and depth of the shopping journey. Therefore, I discuss the visit quantity conditional on the corresponding behavior's incidence. I apply a negative binomial model to measure the effect of the display retargeting campaign on visit quantity. Following the standard NBD distribution with mean λ_t, a cookie visiting the website k_v times on day t is

$$Pr(V_t = k_v - 1 \mid \lambda_t) = \frac{\Gamma(\alpha + k_v)}{\Gamma(\alpha)\Gamma(k_v + 1)} \left(\frac{\alpha}{\alpha + \lambda}\right)^{\alpha} \left(\frac{\lambda_t}{\alpha + \lambda_t}\right)^{k_v}, \tag{3}$$

and I adopt the log-link function, such that

$$\ln(\lambda_t) = \alpha_2 + \alpha_3 T_t. \tag{4}$$

where α is the shape parameter, α_2 represents the cookie's baseline visits quantity conditional on a visit, and α_3 captures the cookie's sensitivity to display retargeting campaign in terms of visit quantity.

Consumers can make a purchase only during their visit to the firm's website, so the online purchase can be modeled conditional on the visit behavior. Purchase amount is recorded as dollars spent, so I model the online purchase incidence as a logit model and model the dollar spending as a log normal regression model:

$$P(1_{Web_t>0}|1_{v_t>0}) = \frac{1}{1+e^{-U(1_{Web_t>0})}} = \frac{1}{1+e^{-(\rho_0+\rho_1 A_t)}} \tag{5}$$

$$\log(WebR_t = k_{web} \mid 1_{Web_t>0}, 1_{v_t>0}) = \rho_2 + \rho_3 T_t + \varepsilon_i \tag{6}$$

where ρ_0 captures the baseline online purchase probability and ρ_1 represents the sensitivity to the display retargeting campaign in terms of purchase incidence. ρ_2 captures the baseline online purchase amount, and ρ_3 represents the sensitivity to day t's display ad campaign in terms of purchase quantity.

Similar to visit quantities being conditional on the day's visiting choice, the purchase choice and amount spent are affected by the treatment condition.

The online platform visiting and purchasing behavior can be factored as a joint likelihood l_{online}:

$$\begin{aligned} l_{online} = \prod_t \Big\{ & Pr(1_{v_t>0}) Pr(v_t = k_v | 1_{v_t>0}) \\ & \big[Pr(1_{Web_t>0}|1_{v_t>0}) Pr(WebR_t = k_{web}|1_{Web_t>0}, 1_{v_t>0})\big]^{1_{Web_t>0}} \\ & [1 - Pr(1_{Web_t>0})]^{1-1_{Web_t>0}} \\ & \Big\}^{1_{v_t>0}} \Big[1 - Pr(1_{v_t>0})\Big]^{1-1_{v_t>0}} \end{aligned} \tag{7}$$

I do not incorporate heterogeneity analysis at the cookie level since a cookie observation starts the day after the initial visit when the field experiment is implemented. A treatment or control cookie will stay in the same experiment group until the cookie dies, so there is no variation at cookie level for T_t daily. For each cookie, the independent variable is fixed, so I do not have any variation within a cookie to estimate heterogeneity.

4.2 Individual Daily Level Model Development (M2)

At the individual level, the daily experiment group may change with the corresponding visit cookies. In addition, offline purchase record can be linked with individual IDs. In this section, in consideration of the model on the individual level, a sequence of online visit, online purchase and offline purchase events have been modeled for each consumer while the cumulative display retargeting effect over time is taken into account. I use an ad stock model to capture the accumulation and decay effects of staying in the display retargeting treatment group. I construct an individual-level advertising response model for visiting, offline conversion and online conversion. Moreover, I use the hierarchical Bayes estimation method to assess the heterogeneity among consumers.

4.2.1 Ad Stock

I use the discrete-time exponentially decaying ad-stock model to capture the accumulated retargeted display advertising campaign effect:

$$A_{it} = \gamma_i A_{it-1} + T_{it}. \tag{8}$$

where T_{it} is the display retargeting status for individual i at time t. It is an indicator variable which represents consumer i's previous display retargeting group assignment at the beginning of day t. $T_{it} = 1$ if any visit cookie ID of consumer i was assigned to the treatment group. γ_i is the carryover rate of display retargeting ad stock for consumer i. The carryover rate allows a decay effect of display retargeting from the current period to the next period with a geometric rate between 0 and 1. In this model, ad stock captures the cumulative effect of days in the treatment group at the beginning of each day, in contrast to other papers (Braun and Moe 2013, Zantedeschi et al. 2016) that count the cumulative effect of number of exposures. The number of exposures in the data here was determined by a third party (like

Google) which serves different types of people with different numbers of ads. I lack sufficient information to identify population type from the ad campaign impact, so I construct the ad-stock model based on the possibility of exposure to advertising, which was randomly determined by the field experiment.

4.2.2 Behavioral Outcomes

I construct an individual-level advertising response model for the multi-outcomes of visiting, offline and online conversion. For each day, an individual's correlated decisions are each characterized as one of three events: 1) a visiting event is characterized by whether a visit occurs and how many times the website is visited; 2) the online shopping event can happen only during a website visit, so it is characterized conditional on a visit by whether a purchase occurs and how much is bought; and 3) the offline shopping is also characterized by whether a purchase occurs and how much is bought. Similarly, an online purchase event is modeled as a later stage after the incidence of an online visit.

4.2.3 Online Platform: Visit and Website Purchase

The first determination is whether a consumer's visit choice was affected by being assigned to the display treated group. Individual treatment assignment was defined at the daily level. Here I discuss how the ad stock at time t affects the current day's visit. Because the experiment group assignment was defined on each cookie's initial site visit, if a consumer decided to visit the website with a new cookie during the day, it is highly likely that the current day's experiment group assignment would change. It was not easy to identify the order of an observed visit and the current day's experiment condition, so at the beginning of the day, visiting or not visiting the site is influenced by the accumulation of past potential treated history; and an initial visit can be impacted only by existing ad-stock. After a day's first visit, the treatment assignment can change. Because the outcome of interest is binary, I use standard logistic regression to model consumer i on day t's choice to visit (v_{it}) as:

$$P(1_{v_{it}>0}) = \frac{1}{1+e^{-U(1_{v_{it}>0})}} \tag{9}$$

where $U(1_{v_{it}>0})$ is a linear function of display retargeting ad stock:

$$U(1_{v_{it}>0}) = \alpha_{0i} + \alpha_{1i} A_{it} \tag{10}$$

where α_{0i} represents consumer i's baseline visit probability, and α_{1i} represents consumer i's response to the ad stock of display retargeting in terms of visiting behavior. A_{it} is the ad stock at the beginning of day t, which is the accumulation of the past treated history.

The incidence of a consumer visit provides one measure of consumer shopping pattern but does not capture the frequency and depth of this shopping journey. Therefore, I discuss the visit quantity conditional on the corresponding behavior's daily incidence. Since the duration of observation was defined at the daily level, the binary choice of visiting or not is affected by the ad stock at the beginning of the day, and this visiting decision may change the current day's group assignment. The daily sequential visit quantity is highly related with the current day's group assignment. I therefore analyze the number of visits as the result of yesterday's ad stock and the current day's treatment condition.

I apply a negative binomial model to measure the effect of display retargeting ad stock on visit quantity. Following the standard NBD distribution with mean λ_{it}, consumer i visits the website k_v times on day t is

$$Pr(V_{it} = k_v - 1 \mid \lambda_{it}) = \frac{\Gamma(\alpha + k_v)}{\Gamma(\alpha)\Gamma(k_v + 1)} \left(\frac{\alpha}{\alpha + \lambda}\right)^{\alpha} \left(\frac{\lambda_{it}}{\alpha + \lambda_{it}}\right)^{k_v}, \tag{11}$$

and I adopt the log-link function, such that

$$\ln(\lambda_{it}) = \alpha_{2i} + \alpha_{3i} A_{it} + \alpha_{4i} C_{it}. \tag{12}$$

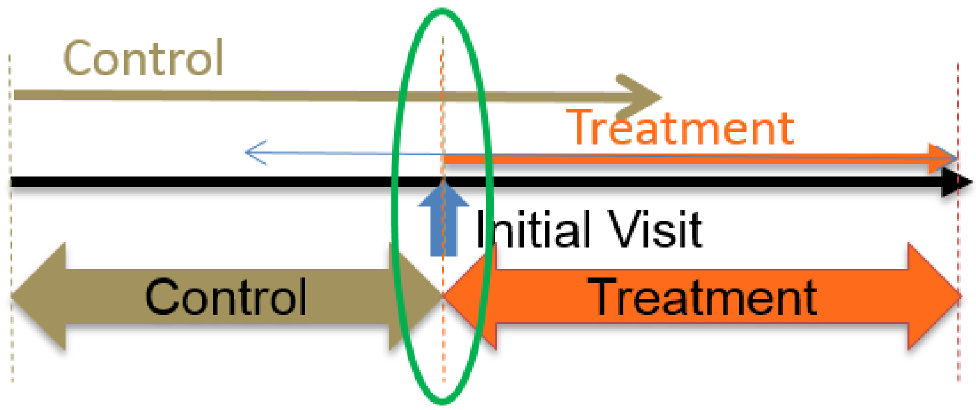


Figure 9: Group Change due to Initial Visit

where α is the shape parameter. α_{2i} represents consumer i's baseline visit quantity conditional on a visit. α_{3i} captures consumer i's sensitivity to ad stock of display retargeting at the beginning of a day in terms of visit quantity. After a control day's initial visit from a new cookie and if this cookie has been assigned to the treatment group, as shown in Figure 9, the group assignment at daily level will change from control to treatment, so I use C_{it} to capture the possible group change. $C_{it} = 1$ if consumer i changes from control to treatment on day t. α_{4i} represents consumer i's response to the current day's change to treatment condition.

Consumers can make a purchase only during their visit to the firm's website, so the online purchase can be modeled conditional on the visit behavior. Purchase amount is recorded as dollars spent, so I model the online purchase incidence as a logit model and model the dollar spending as a log normal regression model:

$$P(1_{Web_{it}>0}|1_{v_{it}>0}) = \frac{1}{1+e^{-U(1_{Web_{it}>0})}} = \frac{1}{1+e^{-(\rho_{0i}+\rho_{1i}A_{it}+\rho_{2i}C_{it})}} \tag{13}$$

$$\log(WebR_{it} = k_{web} \mid 1_{Web_{it}>0}, 1_{v_{it}>0}) = \rho_{3i} + \rho_{4i}A_{it} + \rho_{5i}C_{it} + \varepsilon_i \tag{14}$$

where ρ_{0i} captures consumer i's baseline online purchase probability, ρ_{1i} represents consumer i's sensitivity to the ad stock of display retargeting at the beginning of day t in terms of purchase incidence, and ρ_{2i} captures consumer i's sensitivity to being treated on the current day. ρ_{3i} captures consumer i's baseline online purchase amount, ρ_{4i} represents the sensitivity to the start day's ad stock of display retargeting in terms of purchase quantity, and ρ_{5i} represents the sensitivity to current day being treated in terms of online purchase quantity.

Similar to visit quantities being conditional on the day's visit choice, the purchase choice and amount spent are affected by the beginning of a day's ad stock and the current day's treatment condition.

The online platform visiting and purchasing behavior can be factored as a joint likelihood $l_{i_{online}}$:

$$\begin{aligned} l_{i_{online}} = \prod_t \Big\{ & Pr(1_{v_{it}>0}) Pr(v_{it} = k_v | 1_{v_{it}>0}) \\ & \left[Pr(1_{Web_{it}>0} | 1_{v_{it}>0}) Pr(WebR_{it} = k_{web} | 1_{Web_{it}>0}, 1_{v_{it}>0)} \right]^{1_{Web_{it}>0}} \\ & [1 - Pr(1_{Web_{it}>0})]^{1 - 1_{Web_{it}>0}} \\ \Big\}^{1_{v_{it}>0}} & \left[1 - Pr(1_{v_{it}>0}) \right]^{1 - 1_{v_{it}>0}} \end{aligned} \tag{15}$$

4.2.4 Offline Purchasing

A consumer's offline purchases could be influenced by the online display advertisement. I model the purchase incidence as a logit model and the purchase amount as a log-normal regression:

$$P(1_{Str_{it}>0}) = \frac{1}{1 + e^{-(\eta_{0i} + \eta_{1i} A_{it})}} \tag{16}$$

$$\log(StrR_{it} = k_{str} \mid 1_{Str_{it}>0}) = \eta_{2i} + \eta_{3i} A_{it} + \epsilon_i \tag{17}$$

where η_{0i} captures consumer i's baseline offline purchase probability and η_{1i} represents consumer i's sensitivity to the ad stock of display retargeting at the beginning in terms of purchase incidence. η_{2i} captures consumer i's baseline offline purchase amount, and η_{3i} represents the sensitivity to the ad stock of display retargeting in terms of purchase quantity.

The offline purchasing behavior can be factored as a joint likelihood $l_{i_{offline}}$:

$$l_{i_{offline}} = \prod_t [P(1_{Str_{it}>0})Pr(StrR_{it} = k_{str}|1_{Str_{it}>0})]^{1_{Str_{it}>0}}[1 - P(1_{Str_{it}>0})]^{(1-1_{Str_{it}>0})} \tag{18}$$

4.2.5 Likelihood Function

The joint likelihood function of choice and quantity decision for the three outcomes for each individual can be written as:

$$\begin{aligned} l_i &= l_{i_{online}} * l_{i_{offline}} \\ &= \prod_t \Big\{ Pr(1_{v_{it}>0})Pr(v_{it} = k_v|1_{v_{it}>0}) \\ &\qquad [Pr(1_{Web_{it}>0}|1_{v_{it}>0})Pr(WebR_{it} = k_{web}|1_{Web_{it}>0}, 1_{v_{it}>0})]^{1_{Web_{it}>0}} \\ &\qquad [1 - Pr(1_{Web_{it}>0})]^{1-1_{Web_{it}>0}} \\ &\quad \Big\}^{1_{v_{it}>0}} \Big[1 - Pr(1_{v_{it}>0})\Big]^{1-1_{v_{it}>0}} \\ &\quad \Big[Pr(1_{Str_{it}>0})Pr(StrR_{it} = k_{str}|1_{Str_{it}>0})\Big]^{1_{Str_{it}>0}} \Big[1 - Pr(1_{Str_{it}>0})\Big]^{1-1_{Str_{it}>0}} \end{aligned} \tag{19}$$

And the overall likelihood function is the product over the entire population:

$$L = \prod_i (l_i) \tag{20}$$

4.2.6 Heterogeneity

I estimate the model by using the standard hierarchical Bayes estimation procedure. I define $\theta_i = \{\gamma_i, \alpha_i, \rho_i, \eta_i\}$, and θ_i is the vector of heterogeneity parameters that include the carryover parameter γ_i (1×1), visit parameters α_i (5×1), online purchase parameters ρ_i (6×1) and offline purchase parameters η_i (4×1). This heterogeneity parameter can be written as a function of observed and unobserved individual characteristics:

$$\theta_i = \delta Z_i + \epsilon_{\theta i} \tag{21}$$

where Z_i is a set of individual characteristics for individual i and $\epsilon_{\theta i} \sim N(0, \Sigma_\theta)$. I define Y_i as individual i's observed shopping pattern, including visiting and purchase incidence and amount; T_i is a vector of dummy variables representing whether individual i is in the treatment group of each day during the data collection period. The conditional distribution of the model's parameters are

$$\begin{aligned} \{\theta_i\} &\mid Y_i, T_i, Z_i, \delta, \Sigma_\theta \\ \delta &\mid \{\theta_i\}, Z_i, \Sigma_\theta \\ \Sigma_\theta &\mid \{\theta_i\}, Z_i, \delta \end{aligned} \tag{22}$$

Across each outcome variable, the response to the display retargeting ads could be correlated with each other. The hierarchical Bayesian Model provides parameter estimation within an individual, which enables the discovery of advertising response across events. I can explore whether the display retargeting ads that drive a consumer to visit the website more frequently also drive this person to place more orders online or offline.

The heterogeneity setup allows the parameters to be different across individuals. The correlation of baseline parameters enables me to learn individual shopping patterns by controlling for the ad campaign's effect. And I can discover population differences in response to the retargeted display advertising campaign.

4.3 Individual Intensity Model Development (M3)

In the individual daily level model, a daily experiment condition has been defined as whether having a visited cookie in treatment group. A consumer on day t is treated with the digital ad campaign if any visited cookie is assigned to the treatment group; this consumer is not treated if there is no treatment cookie alive on day t. This definition and setup is intuitive and straightforward for defining the digital advertising campaign on the individual daily level.

However, there are several situations in which this method is flawed. First, this method tends to assign more eligible cookies' days to the treatment group, biasing our ad campaign measurements. The current method defines a consumer's daily group assignment based on there is at least one treatment visited cookie. In Table 5, the probability of defining a treatment day is the sum of the probabilities with all visit cookies in the treatment or a mixed group. On a day when there is only one visit cookie, the chance to be assigned to the daily treatment group is .83. But if the number of visit cookies increases to 2, the current method will assign this day to the treatment group by a probability of .97 (at least one cookie in treatment); and this number will increase to .995 if the day has three visit cookies. In this case, a day with more visit cookies has a higher chance to be defined as a treatment day. Treatment days and control days have different numbers of visit cookies and thus are not balanced. Treatment days have more visit cookies which have more initial visits and thus the treatment effect will be overestimated by the number of visits. This may be the reason I find that the retargeted display advertising campaign has a significant positive impact on online visits by the individual daily model (M2) but a negative impact on online visits by the cookie-level model (M1). Moreover, consumers with more visit cookies are those consumers who have a higher bond with the firm's website and thus a higher chance to purchase, so I can also overestimate the purchase behavior. One simple example is that if ads induce visits on other devices, ad responsive individuals are more likely to be assigned to the treatment group.

Second, this method also defines individual ineligible days as control days or non-treated days. In fact, a consumer's days with no eligible cookie and one control cookie are different. Especially, a consumer who stays ineligible forever versus a consumer who stays ineligible first but revisits later to have a control cookie will have the same daily group assignment by the current method. The former chooses never to revisit the firm's website while the latter chooses to revisit from a new cookie. The decision to remain ineligible and the decision to visit again are not exogenous. Simply placing the two consumers' conditions in the same group is not a proper method and may bias the estimation result.

Table 5: Individual Daily Group Assignment Probability

N of Visited Cookies	All in Treatment	Mix	All in Control
1	.83	0	.17
2	.69	.25	.03
3	.57	.43	.005

Therefore, I propose the individual daily intensity level model (M3), and instead of defining an individual day as treated or not, I count the number of treatment and control cookies on that day. This method clearly counts three types of cookie a consumer may have: treatment, control and ineligible, and counting the number of eligible cookies rules out the daily group definition bias. Moreover, the more treatment cookies a consumer has, the higher their chance of encountering display advertising. Although I cannot discuss advertising intensity through the number of ads, I can still explore advertising campaign intensity impact at the cookie level: the possibility of exposure to retargeted display advertising increases with the number of treatment cookies. The ad response can be captured by comparing individual response between one treatment and one control cookie, and I measure the difference in expected outcomes between individuals with identical cookie assignments. Thus, I stay with this individual daily intensity model and use it as the main model.

4.3.1 Ad Stock

The discrete-time exponentially decaying ad-stock model has been used to capture the accumulated retargeted display advertising campaign effect:

$$A_{it} = \gamma_i A_{it-1} + NT_{it}. \tag{23}$$

where, NT_{it} is the display retargeting status for individual i at time t. It is a discrete variable which represents the number of treatment cookies consumer i has at the beginning of day t. $NT_{it} = 0$ if none of the visit cookie IDs of consumer i were assigned to the treatment group. NT_{it} can also be any positive number, which means the number of treated cookies this consumer has on that day. Intuitively, the higher number of NT_{it}, the greater the advertisement exposure opportunity. γ_i is the carryover rate of display retargeting ad stock for consumer i. The carryover rate allows a decay effect of display retargeting from the current period to the next period with a geometric rate between 0 and 1.

In contrast to other papers (Braun and Moe 2013, Zantedeschi et al. 2016) that count the cumulative effect of the number of exposures, ad stock captures the cumulative effect of days in the treatment group at the beginning of each day and NT_{it} measures the intensity of the possible ad campaign. I cannot count the impact of one retargeted display ad, but I can measure the impact of one ad campaign on each cookie.

4.3.2 Online Platform: Visit and Website Purchase

I use standard logistic regression to model consumer i at day t's choice of visiting (v_{it}) as:

$$P(1_{v_{it}>0}) = \frac{1}{1 + e^{-U(1_{v_{it}>0})}} \tag{24}$$

where $U(1_{v_{it}>0})$ is a linear function of display retargeting ad stock:

$$U(1_{v_{it}>0}) = \alpha_{0i} + \alpha_{1i}A_{it} + \alpha_{v2i}NC_{it} \tag{25}$$

A_{it} is the ad stock at the beginning of day t, which is the accumulation of the past treated history. NC_{it} is the number of control cookies consumer i has at the beginning of day t, and it enables the response comparison between one treatment cookie with one control cookie.

Visit quantity has been modeled as a negative binomial distribution. Following the standard NBD distribution with mean λ_{it}, consumer i visits the website k_v times on day t is

$$Pr(V_{it} = k_v - 1 \mid \lambda_{it}) = \frac{\Gamma(\alpha + k_v)}{\Gamma(\alpha)\Gamma(k_v + 1)} \left(\frac{\alpha}{\alpha + \lambda}\right)^{\alpha} \left(\frac{\lambda_{it}}{\alpha + \lambda_{it}}\right)^{k_v}, \tag{26}$$

and I adopt the log-link function, such that

$$\ln(\lambda_{it}) = \alpha_{3i} + \alpha_{4i}A_{it} + \alpha_{5i}NC_{it} + \alpha_{6i}\Delta T_{it} + \alpha_{7i}\Delta C_{it}. \tag{27}$$

After a day's initial visit, the group assignment might change, so I use dummy variables ΔT_{it} and ΔC_{it} to capture the possible group change. $\Delta T_{it} = 1$ if consumer i had one additional cookie assigned to the treatment group at day t, and $\Delta C_{it} = 1$ if consumer i had one additional cookie assigned to the control group at day t. ΔT_{it} and ΔC_{it} can be larger than 1, which means during that day, there is more than one new cookie that visits the firm's website and has been assigned to experiment conditions. α_{v6i} and α_{v7i} represent consumer i's response to the current day's experiment condition changes.

Consumers can make a purchase only during their visit to the firm's website, so the online purchase can be modeled conditional on the visit behavior. Purchase amount is recorded as dollars spent, so I model the online purchase incidence as a logit model and model the dollar spending as a log normal regression model:

$$P(1_{Web_{it}>0}|1_{v_{it}>0}) = \frac{1}{1+e^{-U(1_{Web_{it}>0})}} = \frac{1}{1+e^{-(\rho_{0i}+\rho_{1i}A_{it}+\rho_{2i}NC_{it}+\rho_{3i}\Delta T_{it}+\rho_{4i}\Delta C_{it})}} \tag{28}$$

$$\log(WebR_{it} = k_{web} \mid 1_{Web_{it}>0}, 1_{v_{it}>0}) = \rho_{5i} + \rho_{6i}A_{it} + \rho_{7i}NC_{it} + \rho_{8i}\Delta T_{it} + \rho_{9i}\Delta C_{it} + \varepsilon_i \tag{29}$$

Similar to visit quantities being conditional on the day's visiting choice, the purchase choice and amount spent are affected by the ad stock and the number of controlled cookies at the beginning of a day and potential changes in the current day's experiment condition.

4.3.3 Offline Purchasing

Consumers' offline purchases could be influenced by the online display advertisement. I model the purchase incidence as a logit model and the purchase amount as a log-normal regression:

$$P(1_{Str_{it}>0}) = \frac{1}{1+e^{-(\eta_{0i}+\eta_{1i}A_{it}+\eta_{2i}NC_{it})}} \tag{30}$$

$$\log(StrR_{it} = k_{str} \mid 1_{Str_{it}>0}) = \eta_{3i} + \eta_{4i}A_{it} + \eta_{5i}NC_{it} + \epsilon_i \tag{31}$$

Similar to M2, M3 has the same likelihood function that consists of online visits, online purchase and offline purchase. I use the hierarchical Bayesian estimation method to calculate the parameter.

5 Data

In this dissertation, I worked with a medium-sized American female fast fashion retailer with more than 1000 retailer stores located in North America. The focal firm sells through online and offline channels. The firm provided cookie level online tracking data and individual offline transaction data and matched cookie IDs with consumer ID. I screened data on the individual level such that each individual had visited the website and was eligible for the retargeted display advertising campaign.

5.1 Data Sampling

There are 3.71 million consumers in the online tracking data with 106.5 million unique cookies. Display advertisements could be targeted only at those who had visited the firm's website, and only consumers who visited the website were relevant to my research purpose. This recalls the earlier point about what makes someone eligible for display advertising. Consumers with no website visit during the seven-month experiment period were excluded. They had no chance to be treated with display ads and thus are not my focus population. Moreover, the display retargeting algorithm only starts from a visit, so each individual's observation starts after their first website visit, and only subsequent consumer actions can be attributed to the display ad campaign. There were 2.08 million consumers who had at least one visit during the focal period, but 504,665 consumers had no tracked behavior or no observation after the initial visit and thus were eliminated since there could be no retargeted display effect. The remaining 1.59 million consumers with 65.3 million unique cookies had at least one day's observation after the initial site visit.

I then excluded the 385,165 customers with no distance to store record. In the CRM system, consumers who placed an order online had their home address recorded, and the firm calculated their distance to the closest store based on geographical information. This also means I restricted the focal sample to those consumers who had likely made a previous purchase. I have 1.21 million such consumers.

I also removed those consumers who had visit cookies in the control group but received retargeted display advertising. This is due to a technical issue that is common to digital advertising and nearly impossible to eliminate. Finally, there are 1.15 million consumers with 51.8 million unique cookies in the sample. Of the 3.71

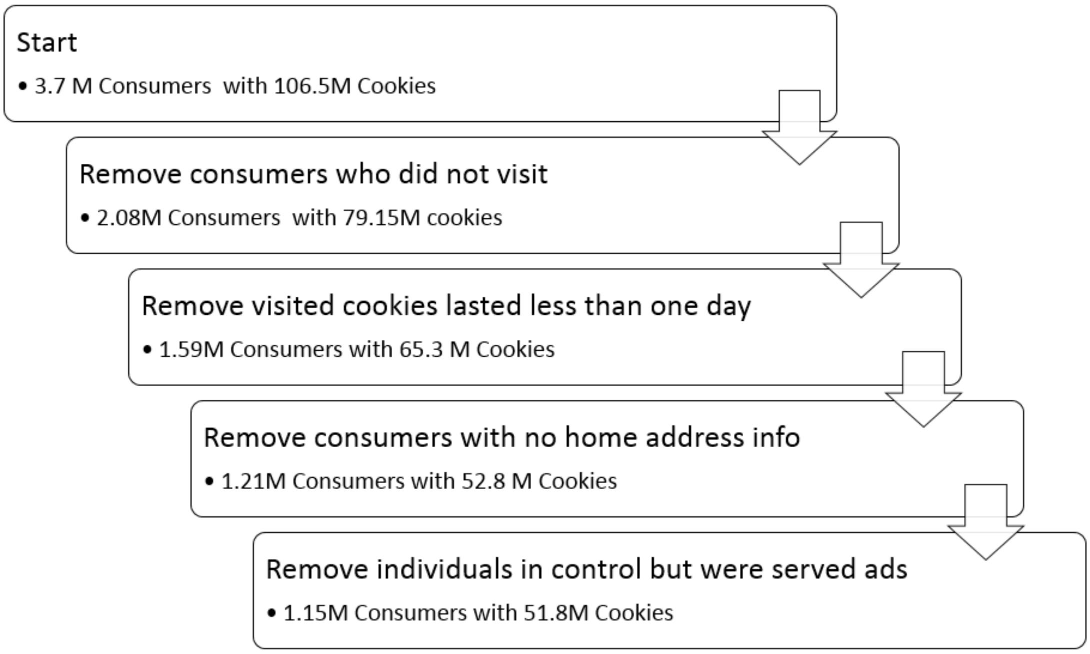


Figure 10: Data Sampling Process

million original population, 43.98% were excluded for having no site visits, 13.1% were excluded for having no observation after the initial visit, 10.36% were excluded for lacking distance to store information, and 1.62% were excluded for having bad control cookies due to the technical issue.

5.2 Cookie-level Summary Statistics

For the dissertation, I randomly selected 10% of the remaining 1.15 million people to simplify the estimation process; this 10% population can represent all targeted consumers and not all data needed (Varian 2014). I also randomly selected another 10% individual observations to run my analysis and all findings were similar. All of the following discussions and results are based on observations of the original 10% population.

Table 6 presents a cookie description of the data. 5.18 million unique cookies were observed during the experiment period, 4.94 million of which were not eligible for treatment. 95.2% of the unique cookies were used to check email without visiting the website. 245,385 unique cookies visited the firms' website and thus became eligible. Among the display eligible cookies, 207,451 were treated cookies that had a chance to encounter display ads while the rest were assigned to the control group with no display exposure. On average, those non-eligible cookies had an active length of 1.298 days while eligible cookies typically lasted more than 50 days. The ineligible cookies were short-lived and existed in all matched and non-matched data sets. Treated cookies had an average active length of 53.25 days and an average eligible length of 50.46 days, while for the control group cookies the two lengths were slightly shorter, 52.59 and 49.09 days, respectively.

Table 6: Cookie Data Description

		N	ActiveLength	EligibleLength
Cookie Level	Cookies	5,182,909	3.897	
	-NotEligible	4,937,524	1.297	
	-Eligible	245,385	53.138	50.225
	– Treat	207,451	53.248	50.464
	– Control	37,934	52.593	49.092

5.3 Individual-level Summary Statistics

A consumer may have multiple devices associated with multiple browsers. Each browser has its own cookie ID, and a consumer may own several cookies at the same time. Because of the inability to match cookies with individuals, past researchers assumed that one cookie represented one individual and used a cookie's activities as a proxy for consumer behavior. This assumption could bias the effectiveness estimation. For example, a consumer could visit a firm's website from their phone and receive retargeted display advertising on the phone; if this consumer were motivated by the retargeted advertising and placed an order on a desktop computer, this advertising campaign impact would not be captured without matching cookies across multiple devices for this consumer. In this case, the effectiveness of retargeted display advertising would be underestimated. As discussed in Coey and Bailey (2016), cookie-level analysis significantly underestimates individual-level impact.

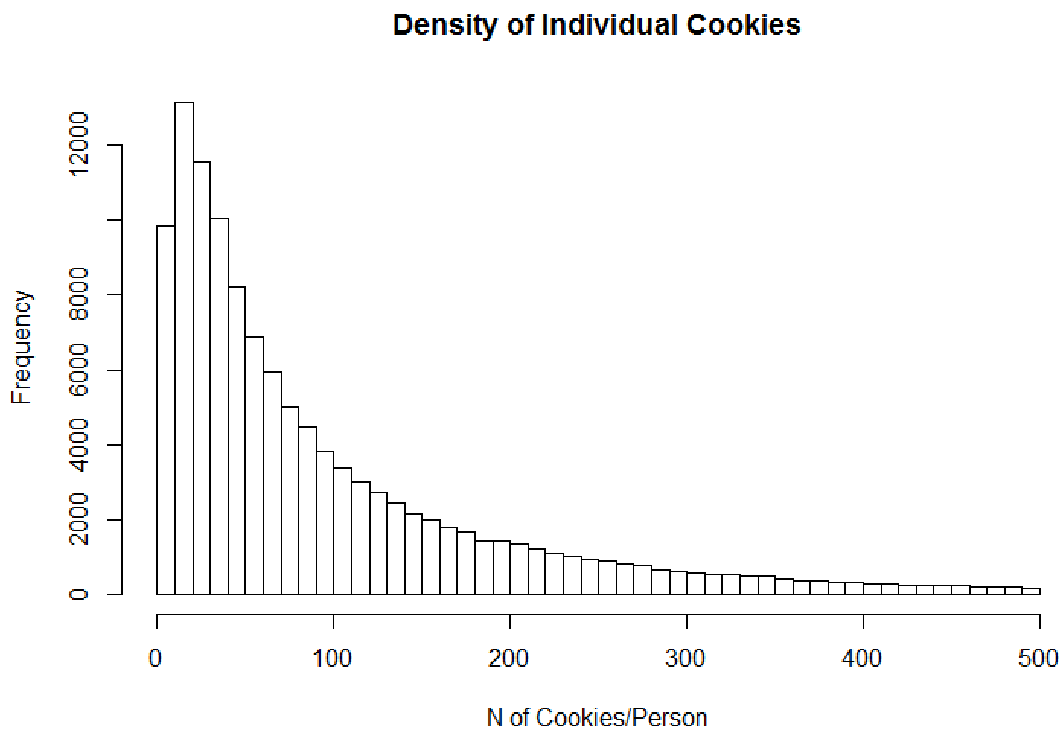


Figure 11: Individual cookie number

A cookie does not make decisions, but consumers do. If I assume each cookie represents a consumer, I can bias the measurement of ad campaign impact. The focal firm links cookies with consumer IDs by using the available rich digital data. This creates the chance to analyze the field experiment data at the individual level. During the 7-month experiment period, the number of cookies each individual had ranged from 2 to 7,575 with a median 18 and mean 43.7. 99.7% of individuals had fewer than 500 cookies. Figure 11 shows the density plot of the number of cookies each individual had, and the distribution is heavily right-skewed. Figure 12 shows the number of visit cookies a consumer had during the experiment period. More than 48.3% of consumers had more than one visit cookie.

The median 18 cookies per person during the field experiment period forms the individual level daily group experiment. Individual observation starts from the first visit to the firm's website during the field experiment period, and after this first visit, the consumer becomes an eligible person for the retargeting advertising campaign.

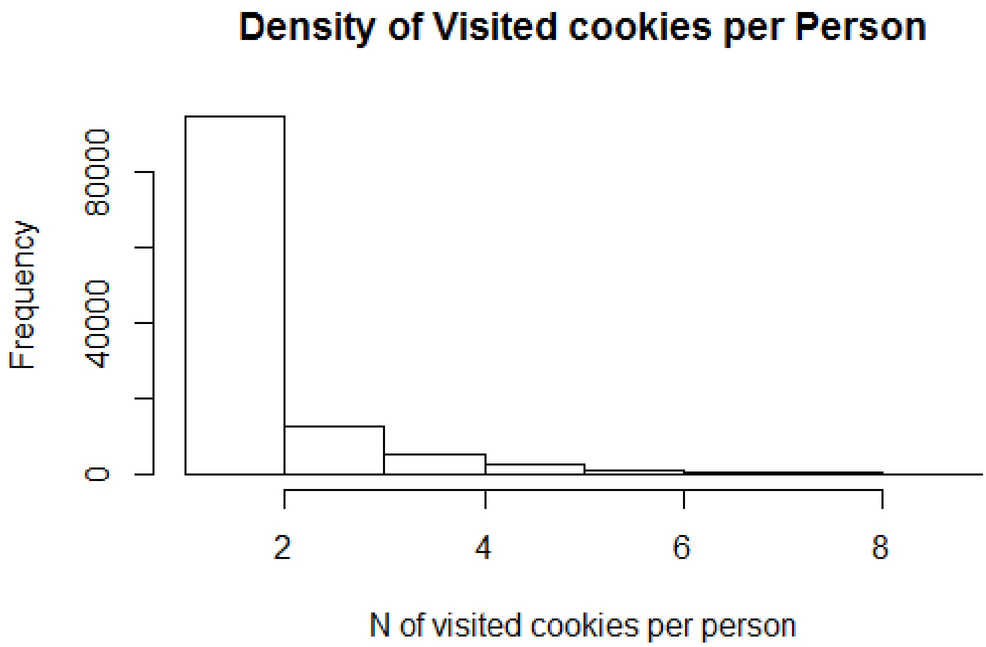


Figure 12: Individual Visited Cookie Number

Table 7: Per Individual Group Transition

	Ineligible	Treat	Control
Ineligible	31.790	1.022	0.207
Treat	0.611	76.753	0.037
Control	0.130	0.037	13.397

As shown in Figure 7, a consumer's daily group assignment is defined based on the treatment cookies the consumer had on each day. If a day contains at least one visit treatment cookie, the day is a treatment day for the consumer. Otherwise, the day is non-treated. Table 8 also provides a summary of the experimental group assignments on a daily level. During the experiment period, there were 15 million days observed with a mean of 123.98 days per person. Of the total 11 million eligible days, 60.6% have only one eligible cookie, 4.2% have more than one cookie assigned to different groups, and the remaining 35.2% have more than one eligible cookie assigned to the same group.

On average, each consumer has 123.98 days of observation. I can observe the group transition among ineligible, treatment and control days. Table 7 shows the average group transition days of each individual. Of the 123.98 days, on average an individual stayed in the same group for 121.94 days (31.8 in ineligible group, 76.75 in treated group and 13.4 in control group) and changed in the remaining 2.04 days.

Table 8: Eligible Cookie Distribution in Eligible Days

N of Elig Cookie	1	>1TreatOnly	>1ControlOnly	>1Mixed
Fraction	0.606	0.298	0.054	0.042

Table 9 shows observations of the focal variables: visits, online purchases and offline purchases. In the 7-month experiment period, consumers in the data visited the website 1.47 million times and generated sales of $14.5 million, half of which came from website purchases. On average, each consumer visited the website on 8.79 days with a total of 12.19 visits and made 0.713 online orders for $59.63, and 0.85 offline orders for $60.06. During the experiment period, I observed 6.7 million email impressions and 5.86 million display impressions. That is, consumers received one email every two days and slightly less than one display impression every two days. In the CRM system, consumer home location was recorded and the distance from home to store was calculated by geographical information. This feature has been incorporated in the hierarchical Bayesian estimation to control for heterogeneity. On average, consumers lived 12 miles from a retail store. This distribution was heavily right-skewed with a range from 0 to 100 miles and a standard deviation of 13.38.

Table 9: Observation Counts

	Total	PerPerson	Min	Max	Std.Err.
VisitDays	1,064,451	8.797	0	208	13.357
Visits	1,474,885	12.189	0	1,729	24.058
WebOrders	86,296	0.713	0	59	1.554
WebRevenue	7,215,663.000	59.632	0	6,792.780	154.525
StrOrders	102,282	0.845	0	66	1.961
StrRevenue	7,266,915.000	60.055	0	6,693.630	146.921
Distance To Store	1,453,107	12.009	0	100	13.376
Impressions					
- Email	6,717,533	55.515	0	47,836	220.488
- Display	5,855,524	48.391	0	4,394	140.982

6 Results

In this section, I first explore the parameter estimation from the three models I proposed and discuss the limitations of the first two. Then I focus on the individual daily intensity model (M3) to explore the digital advertising campaign impact.

6.1 Parameter Estimates

6.1.1 M1 Cookie-level Analysis Parameter Estimates

A cookie is randomly assigned to treatment or control condition after the initial visit. The cookie level observation counts whether the cookie owner revisits the firm's website and places orders online. Each cookie observation includes the number of visits and dollar spending during the experiment period. Therefore, the cookie-level model captures the total impact of the ad campaign on the cookie level.

I estimate the cookie-level model by using the Bayesian method. Proper but diffuse priors have been used for all parameters. The parameter results in Table

10 are based on the 20,000 MCMC draws; only the last 10,000 draws have been kept. Table 10 contains the posterior means, standard deviations and the 95% posterior intervals for the parameters of the cookie-level model. Baseline estimators of incidence (α_0,ρ_0) represent the propensity of a consumer's shopping behavior without the display ad campaign. Without being display retargeted, the average visit probability is 60%, and conditional on the visit, the chance to make a purchase online is 6.3%. Baseline estimators of quantity (α_2,ρ_2) capture the average shopping quantity in the absence of display retargeting treatment. On average, upon deciding to visit, a consumer visits the website 1.11 times, and once they decide to purchase online during the experiment period, the average spending is 54.5 dollars.

If the consumer chose to visit the website, the visit quantity and web purchase decision are modeled as the result of the cookie's experiment condition. The effect of advertising on visiting incidence is captured by α_1, which is significantly negative with a value of -2.153, while the ad campaign effect on visiting frequency is 1.506, which increases the visit quantity per visit incidence decision. Conditional on a visit decision, the effect of treatment cookie ($\rho_1 = -.061$) on web purchase incidence is negative. Conditional on a web purchase decision, the money spent increases (ρ_3=.003), but this value is not statistically significant.

Table 10: Cookie Level Model (M1) Parameter Estimation

	Event	Parameter	Mean	Std.dev.	2.5%	97.5%
Incidence	Visit	Constant(α_0)	0.414	0.004	0.405	0.421
		Treatment(α_1)	-2.153	0.004	-2.16	-2.143
	WebPurchase	Constant(ρ_0)	-2.694	0.01	-2.711	-2.675
		Treatment(ρ_1)	-0.061	0.011	-0.08	-0.042
Quantity	Visit	Constant(α_2)	-2.213	0.03	-2.269	-2.16
		Treatment(α_3)	1.506	0.02	1.467	1.547
	WebPurchase	Constant(ρ_2)	3.992	0.008	3.977	4.008
		Treatment(ρ_3)	0.003	0.009	-0.016	0.019

However, cookie level data cannot represent individual-level decisions. A consumer may have several cookies at the same time and also be impacted by marketing campaigns on different cookies. Cookie-level analysis can underestimate the impact of a display advertising campaign if the effect of a digital ad on one cookie carries over to the other cookies. For example, if a consumer has been exposed to retargeted display advertising on cookie A and places an order on cookie B later, I am unable to link this spillover impact without using individual level matching data. The reactance impact I find on the cookie-level model may be due to this inability to match cookies to individual IDs.

Secondly, cookie-level analysis is unable to capture the digital advertising campaign impact from online to offline. The offline sales cannot be matched to treated consumers without consumer IDs being matched with cookie IDs, causing underestimation of the digital advertising campaign effect.

Finally, cookies have been randomly assigned to treatment or control group. Each cookie's experiment group is fixed after the initial visit on that cookie, and the independent dummy variable for group assignment has no variation on each cookie level. I cannot conduct heterogeneity analysis for the cookie-based model due to lack of variation in the cookie's experiment group.

Therefore, individual-level model analysis is required to further explore digital advertising campaign effectiveness.

6.1.2 M2 Individual Daily Level Analysis Parameter Estimates

M2 captures the daily impact of retargeted display advertising campaign. The individual daily level model has been estimated by the hierarchical Bayesian method. The result in Table 11 is based upon the last 50,000 draws from 100,000 draws overall.

Table 11 contains the posterior means, standard deviations and the 95% posterior intervals for the parameters of the full model. All heterogeneity parameters are mean centered, so the result here represents the population mean of reactions to the retargeted display advertising campaign.

Table 11: M2 Parameter Estimation

	Event	Parameter	Mean	Std.dev.	2.5%	97.5%
		Ad Discount(γ)	-0.153	0.002	-0.157	-0.149
Incidence	Visit	Constant(α_0)	-3.784	0.006	-3.795	-3.772
		Treatment(α_1)	0.618	0.003	0.612	0.624
	WebPurchase	Constant(ρ_0)	-2.938	0.017	-2.965	-2.911
		TreatmentAdStock(ρ_1)	-0.103	0.006	-0.113	-0.09
		C(ρ_2)	0.513	0.013	0.489	0.538
	StrPurchase	Constant(η_0)	-5.958	0.008	-5.973	-5.944
		TreatmentAdStock(η_1)	0.238	0.004	0.231	0.246
Quantity	Visit	Constant(α_2)	-1.895	0.007	-1.907	-1.882
		TreatmentAdStock(α_3)	0.008	0.004	0.001	0.016
		C(α_4)	0.386	0.007	0.375	0.401
	WebPurchase	Constant(ρ_3)	3.987	0.011	3.972	4.012
		TreatmentAdStock(ρ_4)	0.006	0.005	-0.004	0.014
		C(ρ_5)	0.096	0.005	0.087	0.105
	StrPurchase	Constant(η_2)	4.019	0.006	4.009	4.031
		TreatmentAdStock(η_3)	0.004	0.004	-0.002	0.011

The ad stock model captures the accumulation and decay of the advertising campaign over time. In our setup, the goodwill structure captures the over-time effect of staying in the display retargeting treated group. The first line shows the carryover rate (γ) of being display treated, and it indicates that about 53.8% of the effect of staying in the display treatment group on the previous day was lost on the current day.

Baseline estimators of incidence (α_0,ρ_0,η_0) represent the propensity of a consumer's shopping behavior by controlling for display ad campaigns. Without being display retargeted, the average visit probability is 2.2% per day, and conditional on this visit, the chance to make a purchase online is 5.5%. In terms of offline purchases, a consumer's shopping chance is 0.25% per day after controlling for the retargeted display ads campaign. Baseline estimators of quantity (α_2,ρ_3,η_2) capture the average shopping quantity in the absence of display retargeting treatment. On average, on a visiting day, a consumer visits the website 1.15 times, and once they decide to make an online purchase, the average spending is 57.80 dollars. The average offline spending per order is 56.15 dollars without being display treated.

The way I define the experimental group relies heavily on the initial site visit of a new cookie. Starting a new day, a consumer's visiting choice is affected by past individual group assignment, so I model individual visit incidence as a function of the ad stock. If the consumer chooses to visit on that day, the following visit quantity and web purchase decision are modeled as the result of both previous display treated history and the current day's experiment condition. The effect of advertising on visiting incidence is captured by α_1, which is significantly positive with a value of 0.623, while the ad campaign effect on visiting frequency is .008 but not statistically significant. However, the current day being treated ($\alpha_3 = 0.388$) has a statistically positive effect that increases the visit quantity per visit day. Conditional on a visiting day, the effect of past ad stock ($\rho_1 = -.123$) on web purchase incidence is negative, but the current day being treated ($\rho_2 = .459$) is strongly positive, offsetting the ad stock's negative effect. Conditional on a web purchase decision, the money spent decreases (ρ_4) as the length of stay in the treated group increases, and again, the current day being treated ($\rho_5 = .05$) mitigates this effect. In terms of offline shopping, the ad stock has a statistically positive effect on purchase incidence ($\eta_1 = .27$) but no statistically significant effect on the amount of spending (η_3).

6.1.3 M3 Individual Daily Intensity Analysis Parameter Estimates

At the individual level, instead of defining each day's group assignment, I measure intensity of display advertising based on the number of visited cookies. I develop the model on the number of experiment cookies each individual owned and discuss the advertising campaign intensity at the cookie level.

I use the hierarchical Bayesian estimation method to estimate the individual daily intensity model. Proper and diffuse priors for all parameters have been applied. I keep the last 128,000 draws from a total of 158,000 draws to obtain the result in Table 12. Convergence plots are provided in the Appendix (Figure 21 and Figure 22 for key parameters).

Table 12: M3 Parameter Estimation

	Event	Parameter	Mean	Std.dev.	2.5%	97.5%
		Ad Discount(γ)	-0.381	0.001	-0.382	-0.38
Incidence	Visit	Constant(α_0)	-4.063	0.004	-4.071	-4.056
		TreatmentAdStock(α_1)	0.697	0.002	0.694	0.7
		NofControlCookies(α_2)	1.516	0.003	1.509	1.523
	WebPurchase	Constant(ρ_0)	-2.927	0.005	-2.937	-2.917
		TreatmentAdStock(ρ_1)	0.085	0.002	0.081	0.089
		NofControlCookies(ρ_2)	-0.292	0.005	-0.302	-0.281
		$\Delta T(\rho_3)$	-1.313	0.01	-1.333	-1.294
		$\Delta C(\rho_4)$	-5.676	0.022	-5.72	-5.633
	StrPurchase	Constant(η_0)	-6.081	0.004	-6.089	-6.073
		TreatmentAdStock(η_1)	0.259	0.002	0.256	0.262
		NofControlCookies(η_2)	-0.141	0.005	-0.151	-0.131
Quantity	Visit	Constant(α_3)	-2.029	0.003	-2.036	-2.023
		TreatmentAdStock(α_4)	0.238	0.001	0.236	0.24
		NofControlCookies(α_5)	0.365	0.003	0.359	0.371
		$\Delta T(\alpha_6)$	0.237	0.003	0.23	0.243
		$\Delta C(\alpha_7)$	-1.541	0.009	-1.558	-1.524
	WebPurchase	Constant(ρ_5)	3.903	0.003	3.898	3.908
		TreatmentAdStock(ρ_6)	0.087	0.001	0.086	0.089
		NofControlCookies(ρ_7)	-0.01	0.003	-0.015	-0.004
		$\Delta T(\rho_8)$	-0.297	0.003	-0.302	-0.292
		$\Delta C(\rho_9)$	-0.107	0.017	-0.14	-0.074
	StrPurchase	Constant(η_3)	3.86	0.002	3.856	3.863
		TreatmentAdStock(η_4)	0.08	0.001	0.079	0.082
		NofControlCookies(η_5)	-0.027	0.003	-0.033	-0.022

Table 12 contains the posterior means, standard deviations and the 95% posterior intervals for the parameters of the full model. All heterogeneity variables are mean centered, so the result here represents the population mean of reactions to the retargeted display advertising campaign.

The ad stock model captures the accumulation and decay of the advertising campaign over time. In our setup, the goodwill structure captures the over-time effect of staying in the display retargeting campaign treated group. The first line shows the carryover rate (γ) of being display treated, and it indicates that about 59.4% of the effect of having one treatment cookie in the previous day was lost on the current day.

Baseline estimators of incidence (α_0,ρ_0,η_0) represent the propensity of a consumer's shopping behavior by controlling for the display ad campaign. Without being assigned to treatment or control condition, in other words, and without having previously visited the firm's website, the average visit probability is 1.7% per day, and conditional on this visit, the chance to make a purchase online is 5.1%. In terms of offline purchases, a consumer's shopping chance is 0.23% per day. Baseline estimators of quantity (α_3,ρ_5,η_3) capture the average shopping quantity in the absence of a website visit. On average, on a visiting day, a consumer visits the website 1.13 times, and once they decide to make an online purchase, the average spending is 49.40 dollars. The average offline spending per order is 47.47 dollars without being display treated.

I measure the advertising campaign impact based on the number of treatment cookies a consumer had on each day. The longer the consumer stayed in the treatment group, the higher the chance for the consumer to see a display ad; and the more treatment cookies a consumer had, the stronger the advertising campaign impact. I measure the intent to treat impact of the display advertising campaign, not the number of advertising exposures. I also count the number of control cookies to reflect the consumer's browsing habits and match them with the treatment condition; the modeling method helps to prevent confounding advertising campaign effectiveness with the number of visit cookies a consumer has. Controlling for this improves the accuracy of measuring the advertising campaign impact.

On a subsequent day, a consumer's visiting choice is affected by past browsing behavior and the advertising campaign. Past visiting can cause the consumer to have a treatment or control cookie. The number of treatment or control cookies reflects a consumer's online browsing habit: frequent online shoppers were more likely to have more experiment visit cookies. The ad stock structure captures the cumulative advertising campaign impact based on the number of treatment cookies a consumer had. I therefore model individual visit incidence as a function of the ad stock and number of control cookies. If the consumer chose to visit on that day, the following visit quantity and web purchase decision are modeled as the result of both previously display treated and controlled history and the current day's new visit cookies' experiment condition $(\Delta T, \Delta C)$.

The effect of advertising on visiting incidence is captured by α_1, which is significantly positive with a value of 0.697, while the ad campaign effect on visiting frequency is statistically significant with a value of .238. However, the number of control cookies also increases a consumer's online visiting incidence($\alpha_2 = 1.516$) and quantity($\alpha_5 = 0.365$). This is because the baseline compared with treatment and control cookies is ineligible cookies. Compared to ineligible cookie owners, treatment and control cookie owners initiate visiting the firm's website, which shows their interest in the brand. Assuming a consumer visited the firm's website from a new cookie, if this cookie is assigned to the treatment group, the number of current day visits increases ($\alpha_6 = 0.237$), but if this cookie has been assigned to the control group, the number of current day visits decreases ($\alpha_7 = -1.541$). This may be because the display advertising campaign may have a higher intensity of exposures immediately after the treatment cookie's initial visit and thus attract consumers back to the firm's website, while with new control cookies, the consumer receives only the information they need and do not visit again without the display advertising campaign. The overall difference between treatment and control conditions will be discussed later.

Conditional on a day being a visiting day, the effect of ad stock ($\rho_1 = 0.085$) on web purchase incidence is statistically significantly positive, but the number of control cookies has a negative impact ($\rho_2 = -0.292$). If this visit is an initial visit that causes a new cookie's experiment assignment, the current day's online purchase probability decreases ($\rho_3 = -1.313$, $\rho_4 = -5.676$), which is intuitive in that an initial visit from a new cookie causes window shopping. Conditional on a web purchase decision, the money spent increases ($\rho_6 = 0.087$) with the length of having a treatment cookie and decreases ($\rho_7 = -0.010$) if the consumer has a control cookie. If this purchase decision occurs on an initial website visit from a new cookie, the dollar spending decreases in both experiment conditions ($\rho_8 = -0.297$, $\rho_9 = -0.107$). In terms of offline shopping, the ad stock has a statistically positive effect on purchase incidence ($\eta_1 = .259$) and quantity ($\eta_4 = .080$); a higher number of control cookies decreases the offline purchase incidence ($\eta_2 = -.121$) and quantity ($\eta_5 = -.027$).

In the following section, I discuss the advertising campaign effectiveness along the consumer's purchase funnel for M3. I first analyze the immediate effect of display advertising on the consumer's daily response. Then I explore the carryover impact when consumers' treatment cookies end and determine how long the impact of digital advertising campaign can last. I also explore the individual level correlation between online and offline shopping in response to digital advertising. Finally, how the distance from home to store can moderate digital advertising campaign impact is analyzed.

6.2 Contemporaneous effect

Our model adopts an advertising goodwill structure and constructs a multiple-outcomes estimation that allows me to accurately calculate the benefit of being treated in terms of both contemporary effect and carryover effect. The benefits include consumer shopping patterns from website visit and online and offline purchases. I first discuss the contemporary effect of being treated on T days with a single experiment cookie. The kth day contemporary effect is measured as consumer immediate response difference between a treatment cookie and a control cookie on the same kth day. The advertising contemporary effect is the incremental difference of the consumer's each-day response between a treatment cookie and a control cookie.

Table 13: Contemporary lift with a single cookie

		Day 0	Day 1	Day 2	...	Day T
Treatment	Ad Stock	0	1	1+γ^1	...	1+γ^1+...$\gamma^(T-1)$
	NC	0	0	0	...	0
	ΔT	1	0	0	...	0
	ΔC	0	0	0	...	0
Control	Ad Stock	0	0	0	...	0
	NC	0	1	1	...	1
	ΔT	0	0	0	...	0
	ΔC	1	0	0	...	0

As shown in Table 13, assuming a consumer visited the firm's website on day 0 from a new cookie, I keep this cookie for the subsequent K days. In treatment condition, the consumer's visit cookie was assigned to treatment condition on day 0; $\Delta T = 1$ captures this group change. On the next day (day 1), the consumer stayed in the treatment group for one day and thus the ad stock value is 1, and this effect is discounted by γ on the following day (day 2). On the subsequent kth day, $adstock = 1 + \gamma^1 + ...\gamma^(k-1)$, $NC = 0$, $\Delta T = 0$ and $\Delta C = 0$. In the control condition, the consumer's visited cookie is assigned to the control group on day 0 and thus $\Delta C = 1$. On the subsequent days (day 1 to day T), $NC = 1$, $adstock = 0$, $\Delta T = 0$ and $\Delta C = 0$.

6.2.1 Online Contemporaneous Effect

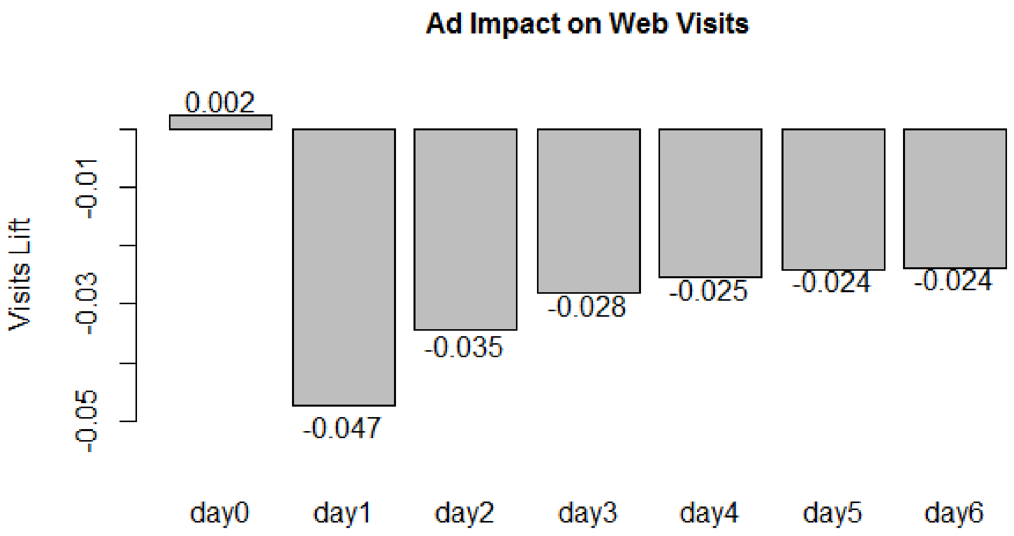
I model consumer response in two steps: the first step is a binary choice and the second step is a quantity decision based on that choice. Consumer online responses include website visit and purchase, and a consumer only can place an order online during a website visit. In our model, I construct web purchase behavior conditional on a website visit and calculate the unconditional choice from the model. The unconditional equation is used for visit numbers, online purchase incidence and quantity:

$$\begin{aligned} Pr(v_{it} = k_v) &= P(1_{v_{it}>0})Pr(v_{it}|1_{v_{it}>0}) \\ P(WebR_{it} = k_{web}|1_{v_{it}>0}) &= P(1_{Web_{it}>0}|1_{v_{it}>0})Pr(WebR_{it} = k_{web}|1_{v_{it}>0}, 1_{Web_{it}>0}) \\ Pr(WebR_{it} = k_{web}) &= P(1_{v_{it}>0})P(1_{Web_{it}>0}|1_{v_{it}>0})Pr(WebR_{it} = k_{web}|1_{v_{it}>0}, 1_{Web_{it}>0}) \end{aligned} \tag{32}$$

Figure 13 shows consumer online visiting contemporaneous response from day 0 to day 6 for treatment and control cookies. On day 0, the display advertising campaign causes consumers to visit the firm's website more often by 0.002 times. But for the following five days, display ads make consumers less likely to visit the firm's website, and the strongest reactance impact occurs on day 1 by 0.047 times. Display advertising only increases consumers' online visiting on the same initial visiting day but reduces the visiting chance for the remaining days.

Conditional on a visit, display advertising can increase a consumer's web purchase behavior as shown in the upper graph in Figure 14. One treatment cookie can increase a consumer's online purchase spending during an online visit by \$.51 on day

Figure 13: Contemporaneous online Visiting response



0, and this number increases to \$1.45 on day 6. The lower graph in Figure 14 shows the unconditional impact of display advertising on online purchasing. On day 0, if an initial website visit results in a new treatment cookie, the consumer purchases more online by \$.01. However, on day 1 this consumer spends less by \$0.38. This reactance effect is caused by the ad campaign's negative influence on online visiting on day 1. However, starting on day 2, the cumulative advertising campaign effect results in a positive unconditional online purchasing response with the consumer spending \$.0025 more with the display advertising condition. On day 6, consumers spend \$.038 more on online purchasing.

6.2.2 Offline Contemporaneous Effect

$$Pr(StrR_{it} = k_{str}) = P(1_{Str_{it}>0})Pr(StrR_{it} = k_{str}|1_{Str_{it}>0}) \tag{33}$$

Consumers' offline purchasing is not dependent on online visiting behavior, so I model offline behavior jointly with online activities but not conditional on website visiting. From the two-step model, I can use Equation 33 to calculate the ad

Figure 14: Contemporaneous online Purchase response

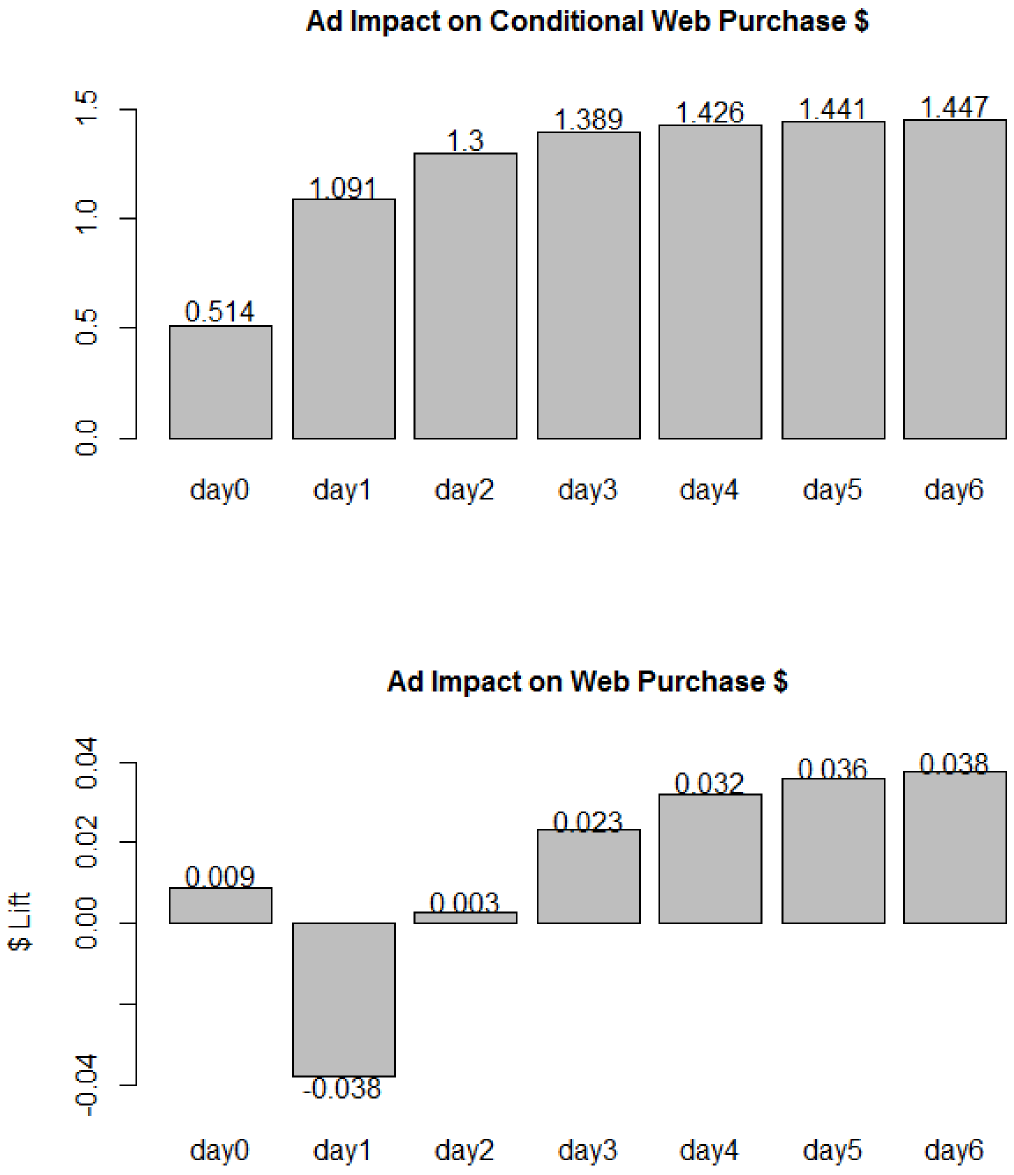
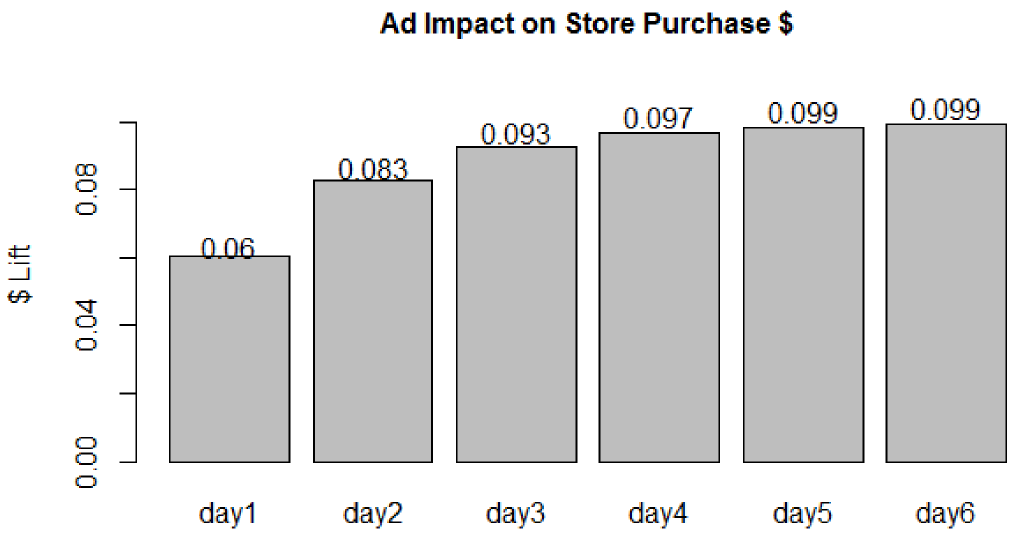


Figure 15: Contemporaneous offline response

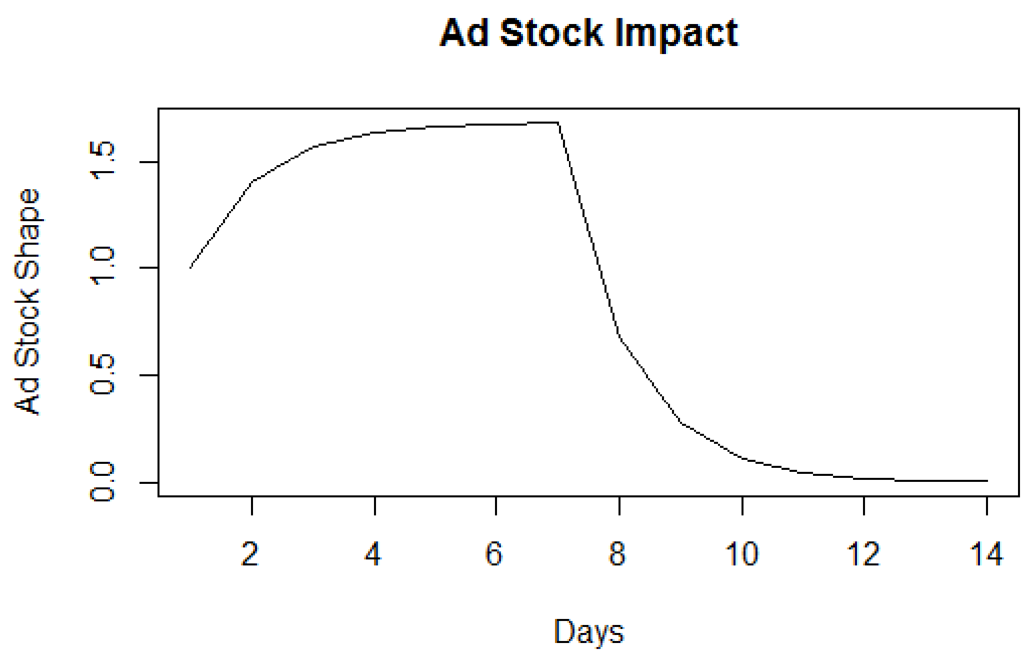


campaign's impact on store purchase quantity. The display advertising campaign impact on store purchases starts from the day after the initial website visit. Overall, display advertising campaign can significantly increase consumers' offline purchasing on day 1 by \$.06 and reach \$.099 by day 6.

6.3 Carryover Effect

The ad stock structure allows me to track the carryover impact from the day a consumer no longer receives the advertising campaign, and the carryover effect is counted as the benefit after deleting the treatment cookie. I first explore the ad stock structure to determine the cumulative effect of display advertising. I then compare the carryover effect to the contemporaneous effect at the static point. The ad stock structure reaches its static point when the additional day's incremental lift is less than 1%. As shown in Figure 16, on average, ad stock reaches its static point when a consumer owns a treatment cookie for seven days, which means the eighth day's incremental lift is less than 1% if the treatment cookie is still alive

Figure 16: Ad Stock Structure



after the seventh day. Assuming this treatment cookie dies on the seventh day after reaching its static point (from Figure 16's day 7), I can observe the carryover effect of display advertising campaign. Even on the twelfth day, five days of no longer being treated with display advertising campaign, there remains a more than 1% advertising campaign effect.

I define contemporaneous effect as the seventh day consumer response to a treatment cookie, which is also the static point of the ad stock structure. The carryover effect starts on the eighth day when the treatment cookie has been deleted and no display advertising campaign exists. However, the ad campaign still impacts consumer behavior through the previous days' cumulative advertising campaign effect, which has been captured by ad stock. The carryover effect lasts until the kth day, when the additional day adds less than 1% to the total impact. I measure contemporaneous effect as the effect on day 7 and carryover effect as the subsequent cumulative effect (>day 7).

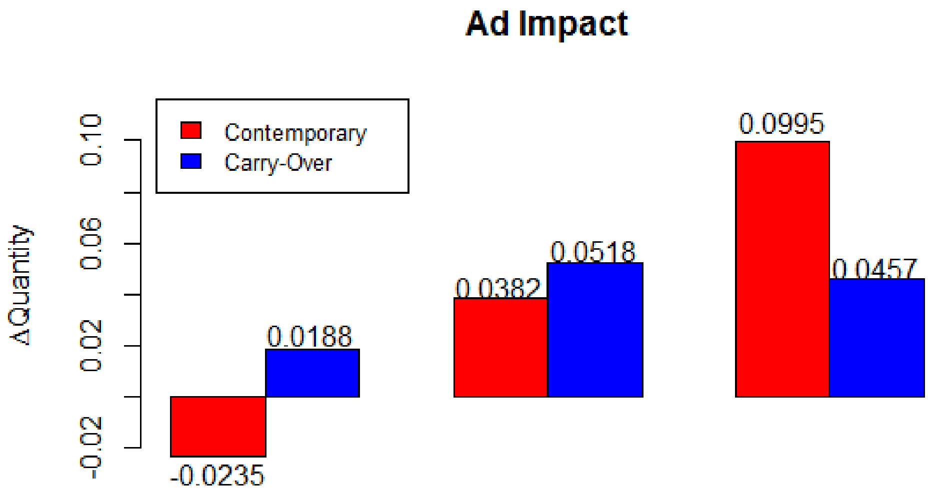
Figure 17 shows the contemporaneous and carryover incremental quantity effects of visit, online purchase and offline purchase at the static point. Overall, the display advertising campaign decreases visit quantity by 0.005 times but increases web purchase amount by \$0.09 and store purchase amount by \$0.14. The lift of store revenue could not be captured without matching the online and offline data. The comparison between the total lift of store revenue and web revenue shows that without matching cross-channel data, the estimation of the return of display retargeting investment would be underestimated by more than half.

Surprisingly, I find display advertising campaign can decrease consumer's online visit numbers on the seventh day by 0.024 times, which means providing display advertising to a consumer may reduce the chance of a website visit. This may be because the display advertising provides the information the consumer needs, so they do not visit the firm's website to seek information. But on the carryover days when display advertising campaign is no longer served, this consumer visits the firm's website 0.019 times more. Once the consumer is no longer targeted with ads, they browse the focal website more often.

The purchase amount is counted on a single day when ad stock reaches its static point, so a small increase can also bring a large money benefit. It is not surprising to see the web revenue statistically significantly increase from being treated by the retargeted display ad campaign seven days later. Of the overall online spending lift, 42.4% is attributable to the contemporaneous effect and 57.6% to the carryover effect. I also find that display advertising significantly increases offline revenue, with 68.5% attributed to the contemporaneous effect and 31.5% to the carryover effect.

Overall, deleting the treatment cookie at the static day, 44.4% of visiting lift, 57.6% of web purchase lift and 31.5% of offline purchasing are attributed to the carryover days when the consumer is no longer being targeted. Without measuring the carryover effect and counting the contemporary effect only, as is common in most online channel measurements, more than 30% of the total lift would be omitted.

Figure 17: Static contemporaneous and carryover effect

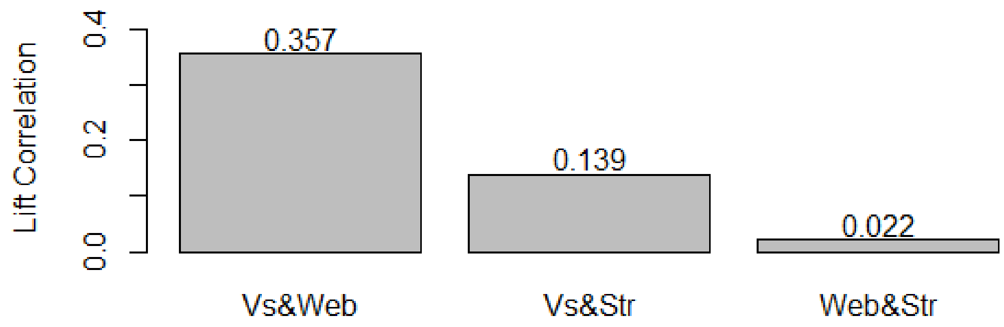


6.4 Correlation of Ad Response Among All Events

The hierarchical Bayes estimation allows me to estimate individual parameter distributions that provide more details of consumer shopping patterns. In terms of campaign response, I can determine the correlation among different outcome lifts of consumer behavior. For example, the static day treated display ad campaign can increase both store and web purchases, but the result is an average across people, and I do not know if the ad campaign just shifts a consumer's purchase from one channel to another. The heterogeneity estimation allows me to measure the correlation of individual online and offline purchase response to retargeted display ad campaigns. A positive correlation shows a consumer's purchase response to the display ad campaign increases both online and offline, while a negative correlation represents a cannibalization effect of the display ad campaign. Specifically, I use individual posterior estimation to calculate the unconditional ad campaign lift on each event.

Figure 18 shows that the correlation of visit lift with purchase lift is statistically

Figure 18: Lift Correlation between Events



significantly positive. The retargeted display ad campaign drives more website visits as well as online and offline purchases. The correlation between online and offline purchases is statistically significantly positive, which means consumers who are influenced by the retargeted display ad campaign to buy more online do not decrease their spending in the brick-and-mortar store.

6.5 Distance from Store Effect

Table 14 is the distance parameter estimated from the joint model. The distance variable is standardized, so the parameter in this table represents how people who live 1 standardized unit farther than the mean distance from the store react to the display retargeting ad campaign differently from people who lived at the mean.

The first row in Table 14 shows the carryover rate (γ) of being display campaign treated, and it captures the over-time effect of staying in the display retargeting treated group. For people who live farther away, the positive sign (0.008) means that the ad campaign effect tends to last longer. Baseline estimators of incidence ($\alpha_0 = 0.059$, $\rho_0 = 0.164$, $\eta_0 = -0.210$) represent that people who live farther away have a greater chance than nearby persons to visit the website and purchase online and a lower chance to purchase in the offline store. Baseline estimators of quantity ($\alpha_3 = 0.059$, $\rho_5 = 0.51$, $\eta_3 = 0.002$) capture the average shopping quantity in the absence of the display retargeting ad campaign. The parameters here show that people living farther away tend to visit more times per visit day, spending more dollars both online and offline.

The incidence parameters (α_1, ρ_1, η_1) capture the distance effect on ad response. People living farther away who are also treated tend to have lower visiting (-.030), online purchasing (-.040), and offline purchasing rates (-.034). The quantity parameters (α_4, ρ_6, η_4) capture the ad campaign effect on visit quantity and online and offline purchase amounts conditional on the event taking place. Compared with people living nearby, people living farther away tend to visit fewer times per visit day and spend less money per online order but more money per offline purchase.

If a distant consumer visits the focal website from a new cookie and this cookie has been assigned to a treatment group, this consumer visits less frequently than the nearby consumer on the current day (α_6), has a lower online purchase probability (ρ_3) and spends less money online (ρ_8); if the new cookie has been assigned to a control group, this consumer visits less frequently on the current day (α_7) but has higher online purchase probability (ρ_4) and spends more money online (ρ_9)

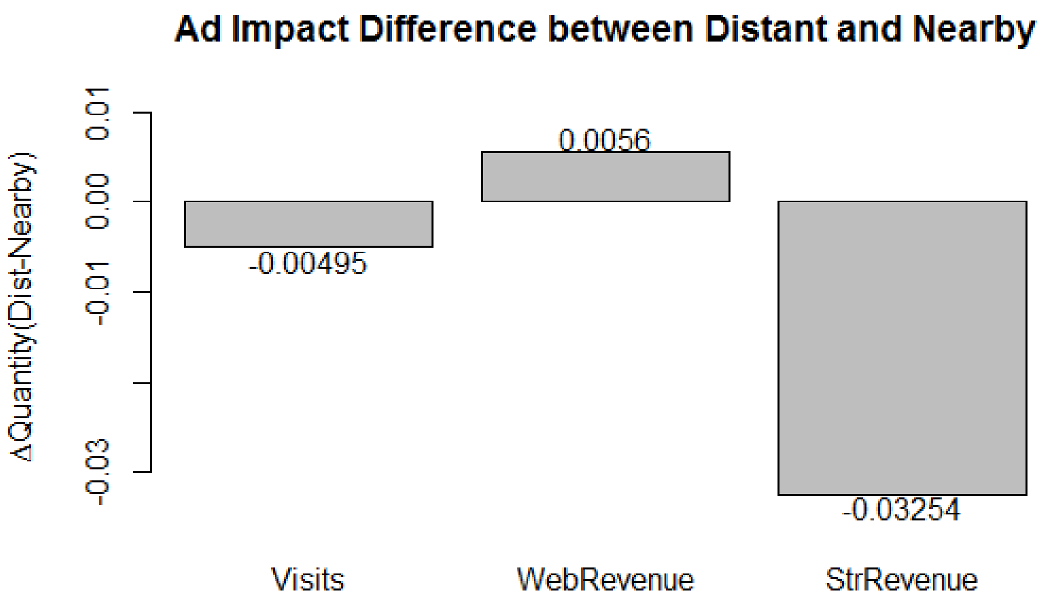
Figure 19 shows the ad response difference between distant and nearby consumers. The overall ad campaign impact on website visiting is slightly stronger for nearby consumers than for distant consumers. The retargeted display ad campaign increases revenue more on the channel where consumers have a relatively lower cost. Consumers who live close to a store have high store accessibility and low offline search cost, so a retargeted display ad campaign motivates them to spend more on the offline channel; consumers living far away have high offline store search cost and thus tend to choose the online channel as motivated by the retargeted display ad.

I also explore the contemporaneous and carryover impacts when the re-targeting ad stock reaches the static point and compare the ad campaign's impact on distant

Table 14: Heterogeneity Parameter Estimation

	Event	Parameter	Baseline	Distant	Std.dev.	2.5%	97.5%
Incidence	Visit	Ad Discount(γ)	-0.381	0.008	0.001	0.006	0.009
		Constant(α_0)	-4.063	0.059	0.004	0.052	0.066
		TreatmentAd Stock (α_1)	0.697	-0.03	0.002	-0.034	-0.027
		NofControl Cookies (α_2)	1.516	-0.02	0.004	-0.027	-0.013
	Web Purchase	Constant(ρ_0)	-2.927	0.164	0.005	0.153	0.174
		TreatmentAd Stock(ρ_1)	0.085	-0.04	0.002	-0.044	-0.036
		NofControl Cookies(ρ_2)	-0.292	-0.021	0.005	-0.031	-0.011
		$\Delta T(\rho_3)$	-1.313	-0.036	0.01	-0.055	-0.017
		$\Delta C(\rho_4)$	-5.676	0.269	0.022	0.226	0.312
	Str Purchase	Constant(η_0)	-6.081	-0.21	0.004	-0.218	-0.203
		TreatmentAd Stock(η_1)	0.259	-0.034	0.001	-0.036	-0.031
		NofControl Cookies(η_2)	-0.141	-0.15	0.005	-0.16	-0.14
Quantity	Visit	Constant(α_3)	-2.029	0.059	0.003	0.053	0.065
		TreatmentAd Stock(α_4)	0.238	-0.019	0.001	-0.021	-0.017
		NofControl Cookies(α_5)	0.365	-0.004	0.003	-0.01	0.002
		$\Delta T(\alpha_6)$	0.237	-0.015	0.003	-0.022	-0.009
		$\Delta C(\alpha_7)$	-1.541	-0.019	0.009	-0.036	-0.002
	Web Purchase	Constant(ρ_5)	3.903	0.051	0.003	0.046	0.056
		TreatmentAd Stock(ρ_6)	0.087	-0.003	0.001	-0.005	-0.001
		NofControl Cookies(ρ_7)	-0.01	0.008	0.003	0.003	0.013
		$\Delta T(\rho_8)$	-0.297	-0.006	0.003	-0.011	0
		$\Delta C(\rho_9)$	-0.107	0.046	0.017	0.013	0.079
	Str Purchase	Constant(η_3)	3.86	0.002	0.002	-0.001	0.005
		TreatmentAd Stock(η_4)	0.08	0.026	0.001	0.024	0.028
		NofControl Cookies(η_5)	-0.027	-0.025	0.003	-0.03	-0.019

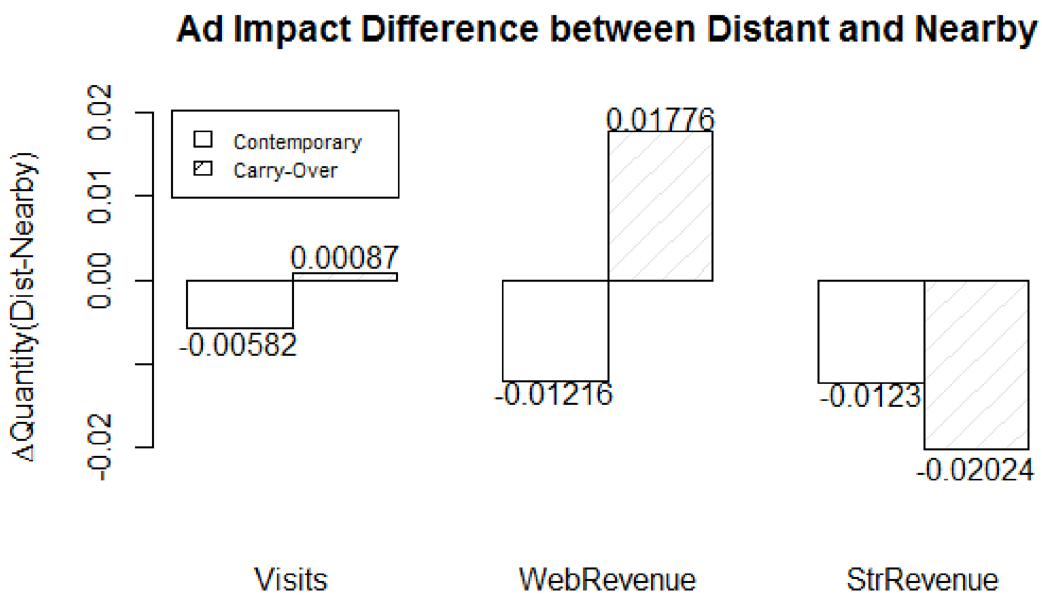
Figure 19: Ads' Overall impact from Distance To Store



and nearby consumers. In Figure 20, I find that people who live farther away have less contemporary visit lift but more carryover visit lift. That is, people who live far from the store respond less immediately to the display retargeting ads, but once they leave the treatment condition, they visit the firm's website more often. The difference in the lift between the two groups is statistically significant. In terms of purchasing, in Figure 20, compared to consumers who live close to the offline store, people who live far from the offline store tend to spend \$0.012 less online as the contemporary effect of a single cookie with the retargeted display ad, and \$0.018 more online as the carryover effect after leaving the treatment condition. Conversely, compared with nearby people, being treated with a retargeted display ad campaign in a single cookie drives the distant consumer to spend \$0.012 less offline as the contemporaneous effect and \$0.020 less offline as the carryover effect.

Nearby consumers visit the firm's website more frequently during the treated days and choose the offline platform to buy more products, while people living far

Figure 20: Ads' Contemporary and carryover impact from Distance To Store



away visit the firm more on the following days after leaving the treatment group and choose the online platform to buy more on carryover days. Consumers who live close to a brick-and-mortar store have higher brand awareness for the product and purchase more often during ad exposure days. The nearby store gives them high accessibility and relatively lower offline-search cost, so they tend to shop in offline stores more often instead of visiting online on carryover days. For distant consumers, the low accessibility to a brick-and-mortar store increases the offline-search cost and makes the online-search cost relatively lower, so they tend to visit the website more often on the days no longer being treated as well as make online purchases.

My findings of distance from store's effect on retargeted display ad campaign response has meaningful implications for the value of brick-and-mortar stores. Without an offline store, the effectiveness of retargeted display advertising campaign would be underestimated.

7 Conclusion and Discussion

To address the research questions, I leverage a randomized field experiment to explore the contemporary and carryover effects of a retargeted display advertising campaign across traditional and digital channels. I propose one cookie-level model and two individual-level models in this dissertation. Cookie-level analysis cannot capture digital advertising spillover effects from online to offline or the spillover effect of one cookie's digital ad campaign to the same owner's purchase on other cookies. Individual daily level analysis defines the daily experiment group by counting treatment cookies. This method overestimates the treatment effect by assigning more visit cookies' days to treatment. This method also defines both days with no eligible cookies and days with control cookies as identical non-treated days.

To address those concerns, I propose the individual daily intensity model that counts a consumer's number of visit cookies on each day and use the modeling method to adjust for the potential bias. The number of treatment and control cookies on each day has been incorporated and all three situations (treat, control and ineligible) are counted.

The results show significant decrease in website browsing but increase in multichannel consumer purchasing from a retargeted display advertising campaign. First, I find that just being treated on a single cookie can decrease overall website visiting but increase both web purchases and store purchases. The positive increases in online purchasing are as expected as the online ad campaign effect on online shopping patterns, while the positive effect of online display ad campaigns on offline purchasing highlights the importance of measuring advertising response across channels. The decrease in online visiting but increase in overall purchasing highlights the importance of using multiple metrics to assess digital ads' impact. Moreover, the multichannel impact not only appears immediately but also lasts several days after the ad campaign ends. More than 30% of the total retargeted display ad campaign effect occurs on days after leaving the treatment group.

As individual purchase response to a retargeted display ad campaign, I find online and offline purchases are not interchangeable, which means consumers who respond positively to a retargeted display ad campaign with web purchases do not decrease their offline purchases. I also find that distance from home to retail store can moderate the contemporaneous and carryover effects of a retargeted display advertising campaign on different shopping patterns. Nearby consumers tend to respond to retargeted display ads immediately by visiting the website several times during the day, while consumers living farther away tend to visit the website more often after leaving the display treated condition. In terms of purchasing, consumers living nearby have a higher propensity to purchase offline as a response to the retargeted ad campaign and consumers living far away tend to choose online purchasing as a response to the display ad campaign. Taken together, a retargeted display ad campaign increases consumer online and offline purchases but decreases website visits, and the effect carries over to days when not being treated. Individual ad response lift among those three choices are not substitutes for each other. Consumer distance from home to store varies website visits in contemporaneous and carryover ad responses, with nearby consumers visiting more times immediately and distant consumers visiting more times later. For purchases, consumers tend to choose the channel with higher accessibility as the response to the ad campaign.

These findings highlight the need to study advertising campaign effect across channels, allowing for potential carryovers. In both industry and academic practice, advertising effectiveness tends to be measured on its own channel at the immediate response time. This can result from the difficulty of matching digital activities with traditional activities, or from traditional structures that never merge online and offline data. This dissertation shows that measuring retargeted display advertising campaign solely on the online channel or in the short term can underestimate its effect.

The data here were constrained to consumers who met three criteria: they shared their email address with the retailer, shared their home address with the retailer and visited the firm's website at least once during the seven-month experiment period. The first constraint enables the matching across online and offline records; the second constraint enables measurement of the distance impact on ad response; and the third constraint helps to sample consumers who are eligible for the retargeted display ad. It is possible that customers who provide a home address are those who purchased before, and thus my analysis is likely restricted to loyal consumers. It is also possible that consumers who were matched by email in the data have unique systematic shopping patterns, meaning my findings only fit one segment of consumers in general. I leave more generalized findings to future research.

8 Potential Future Research

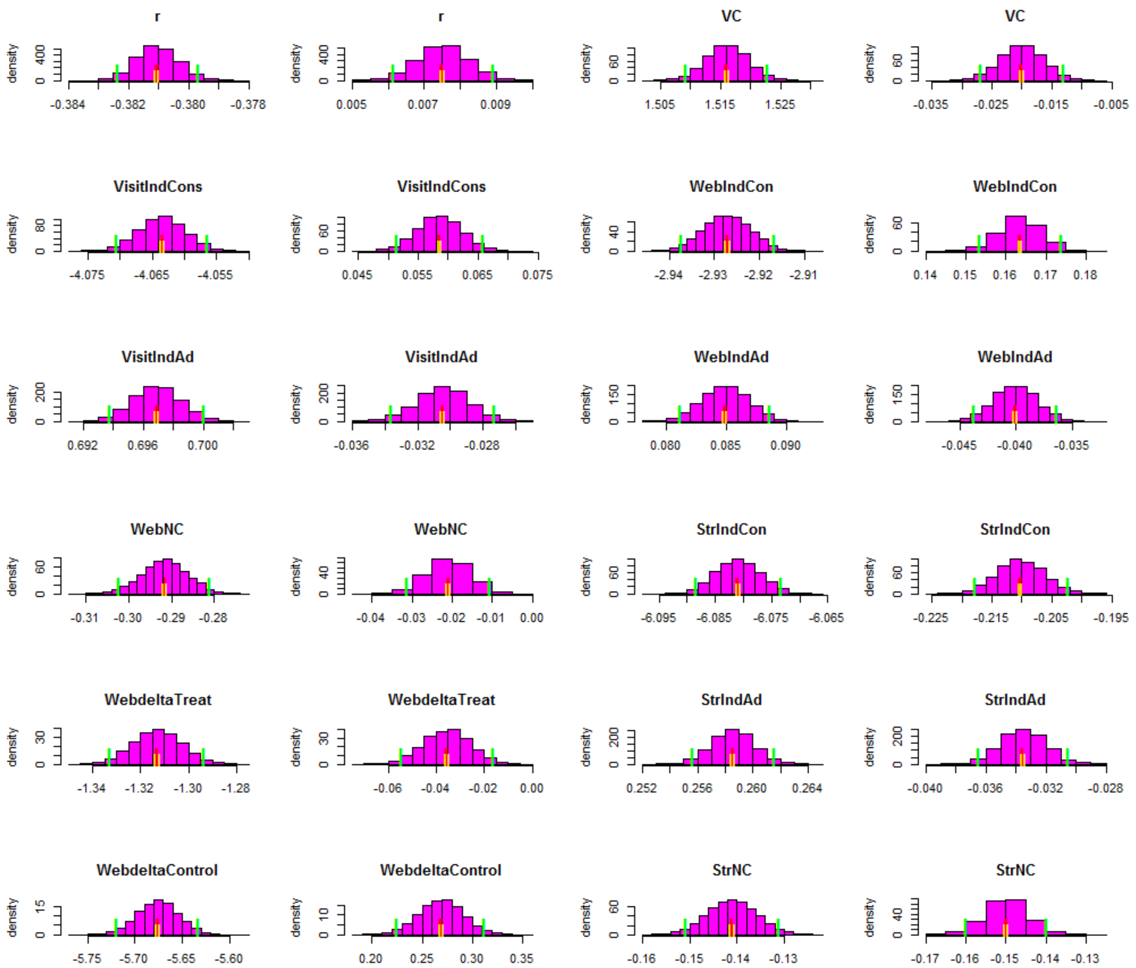
Based on the current data set and research trends, there are several possible research topics that I could pursue.

First, I could add return data into the analysis. The current data include information related to consumer purchases both online and in stores, as well as return behavior. I limited the model to purchasing behavior only, but I could add the return layer to the model in order to investigate how consumers' return patterns change as they respond to a digital advertising campaign. It is possible that a digital advertising campaign causes consumers to purchase more online but also instigates more returns. If I explore overall revenue, it is likely that there is no significant impact of a digital advertising campaign on the firm's profit. If a consumer chooses to return offline, it is also highly likely that this consumer spends more in the brick-and-mortar store, resulting in higher overall profits. I could incorporate all purchase and return information together along a consumer's timeline and then possibly determine the digital ads' impact holistically. In particular, I could discuss the effect of a digital advertising campaign on consumers' online visiting and purchasing behavior as well as consumer response to the ad in terms of product return both online and offline, and the profit impact of a digital advertising campaign.

Secondly, I could plumb the online log file to explore consumer web-browsing history, which includes the initial site visit and subsequent online browsing history, with and without a retargeted display advertising campaign. The initial site visit would result in the experiment group assignment and the useful information it contains: which product the consumer initially browses, how a consumer moves from one page to the other, and whether the consumer either puts a product in the cart or buys a product during the visit. Based on the group assignment, consumers may or may not encounter display advertising, and subsequent visits can yield more interesting data. On the cookie level, I could measure the behavioral difference between treatment and control cookies on subsequent visits. For example, I could check whether consumers in the treatment group tend to browse similar product categories or extend their searches across categories. In this way, I could learn whether a display advertising campaign helps consumers narrow or expand their choice set. On the individual level, I could compare the impact of a display advertising campaign individually, especially among those participants who have group change experience (treatment cookie deletion) during the experimental period.

Finally, another potentially fruitful investigation would be a consideration of timeframe, i.e., weekday versus weekend, on consumer shopping patterns. Unlike brick-and-mortar stores, online retailers are available regardless of the day of the week, and consumers can respond to digital advertising immediately if they have been impacted. However, if there is an offline store nearby, consumers may delay their intended purchases of big-ticket items until the weekend. Therefore, when a consumer encounters a digital ad might also be an important consideration, especially for a retargeted display advertising campaign that shows consumers a product that they have previously seen. The timing of the display ad campaign in conjunction with the time that the consumer visits the firm's website, as well as the consumer's channel response to the ad, may be dependent upon the day of the week. A consumer who views an ad on a Monday may not be in a shopping mood, whereas, if the ad is seen on a Friday, he/she may plan an offline shopping trip. Therefore, the timing of display advertising is another potentially interesting question for me to examine.

A Appendices



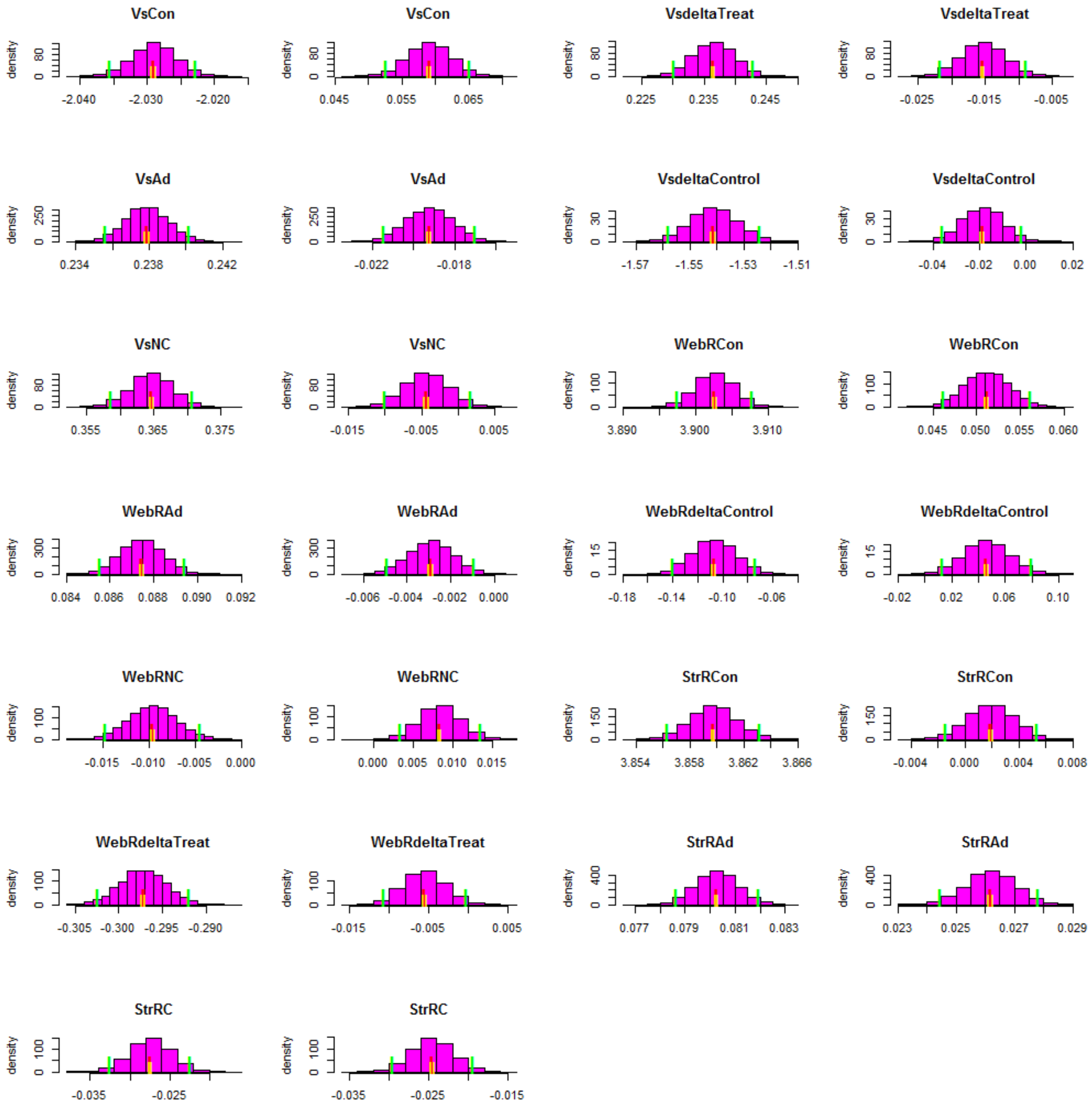

VsCon
density
0
80
-2.040 -2.030 -2.020
VsCon
0.045 0.055 0.065
VsdeltaTreat
0.225 0.235 0.245
VsdeltaTreat
-0.025 -0.015 -0.005
VsAd
0
250
0.234 0.238 0.242
VsAd
-0.022 -0.018
VsdeltaControl
0
30
-1.57 -1.55 -1.53 -1.51
VsdeltaControl
-0.04 -0.02 0.00 0.02
VsNC
0.355 0.365 0.375
VsNC
-0.015 -0.005 0.005
WebRCon
0
100
3.890 3.900 3.910
WebRCon
0.045 0.050 0.055 0.060
WebRAd
0
300
0.084 0.086 0.088 0.090 0.092
WebRAd
-0.006 -0.004 -0.002 0.000
WebRdeltaControl
0
15
-0.18 -0.14 -0.10 -0.06
WebRdeltaControl
-0.02 0.02 0.06 0.10
WebRNC
-0.015 -0.010 -0.005 0.000
WebRNC
0.000 0.005 0.010 0.015
StrRCon
0
150
3.854 3.858 3.862 3.866
StrRCon
-0.004 0.000 0.004 0.008
WebRdeltaTreat
-0.305 -0.300 -0.295 -0.290
WebRdeltaTreat
-0.015 -0.005 0.005
StrRAd
0
400
0.077 0.079 0.081 0.083
StrRAd
0.023 0.025 0.027 0.029
StrRC
-0.035 -0.025
StrRC
-0.035 -0.025 -0.015

Figure 21: Heterogeneity Distribution of Individual Parameter (Constant)

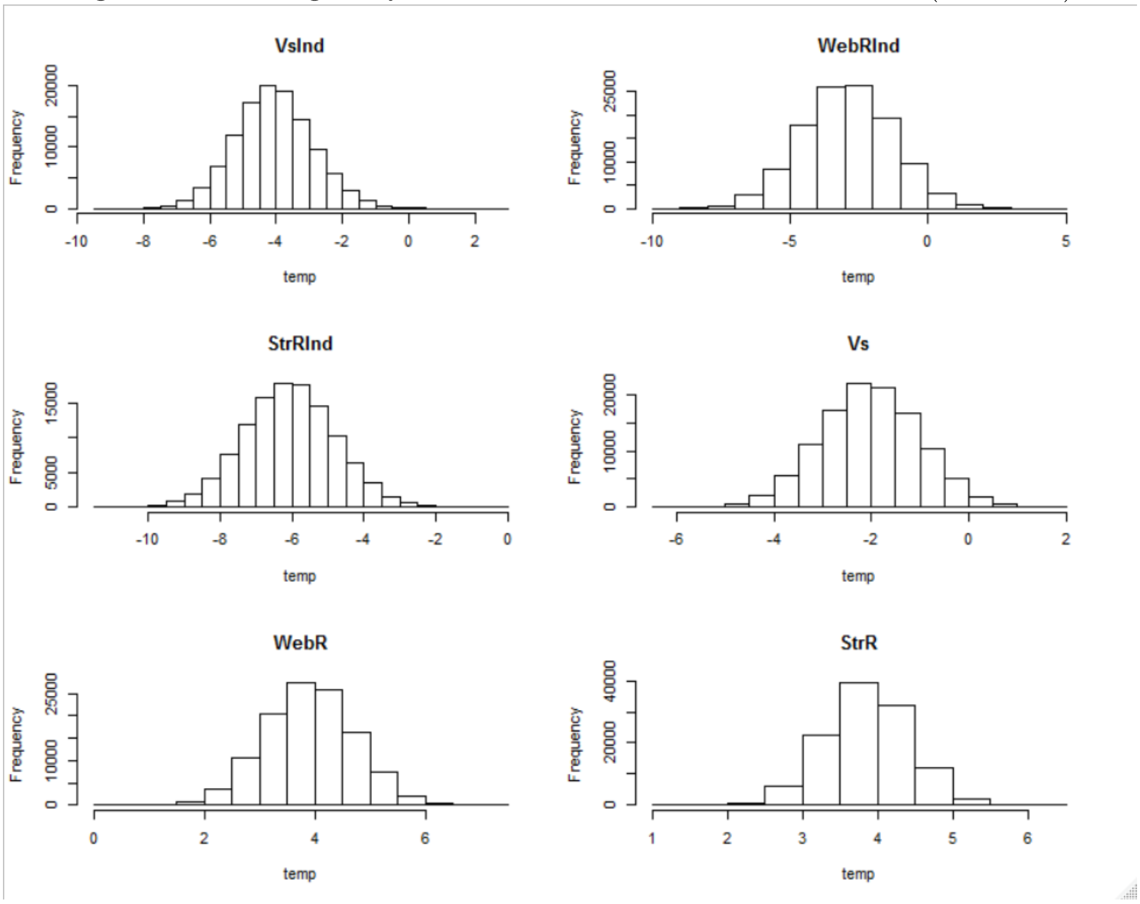
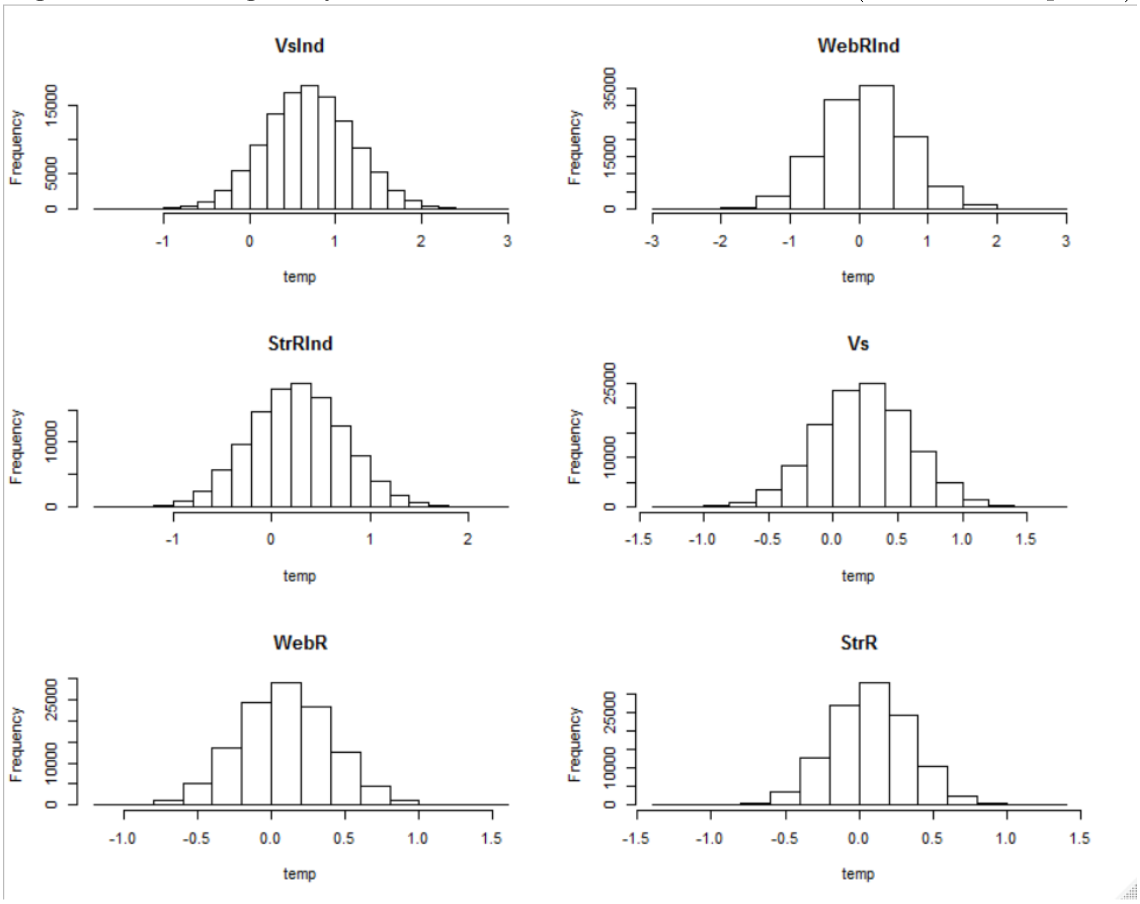


Figure 22: Heterogeneity Distribution of Individual Parameter (Ad Stock Response)



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