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Using Mobile Location Data to Assess Sponsorship Effectiveness

1. Introduction

Out-of-home (OOH) advertising is a form of marketing communication that reaches consumers while they are outside their homes. Stadium advertising, billboards, bus wraps, kiosks and transit furniture exemplify the range of formats OOH advertising can adopt. This outdoor medium is rapidly evolving as digital screens replace static signage in urban environments and public venues, extending digital ad campaigns to the physical world. As part of the digital evolution of OOH advertising, marketers can more easily update the content, offering the potential to increase the performance of OOH advertising. Consumers are also paying more attention and engaging with outdoor media. 90% of consumers noticed OOH advertising within the past month and 66% of consumers have taken action on their smartphones after seeing an outdoor ad, according to a recent report (Nielsen 2019). As consumers pass 70% of their waking hours away from their homes, spend on OOH advertising is expected to grow faster than spend on other traditional ad platforms and to exceed $78 billion worldwide by 2023 (eMarketer 2019, Rosen 2019).

Historically, quantifying the effect of OOH advertising has been a challenge. Identifying consumers who were exposed to OOH media has typically relied on coarse data. Marketers have used commuting statistics and circulation counts to estimate audience size (Quercia et al. 2011). This method of inferring exposure poses attribution problems when attempting to link exposure to sales, as this requires differentiating between the individuals who were exposed to advertising and those who were not. To do so, marketers have used different mechanisms such as the inclusion of QR codes, URLs and hashtags as part of OOH advertising and mined data from online search queries associated with their campaigns (Queiroz 2018). Such tactics, however, capture the immediate engagement that individuals have with campaigns (Fossen and Schweidel 2017, 2019) and may miss longer term outcomes that arise from OOH media exposure. The limited research conducted on OOH advertising has focused on cognition (recall) and conation (purchase intent) effects (Donthu et al. 1993, Goldfarb and Tucker 2011, Wilson et al. 2015). Whether these connections translate to an increase in overall purchases remains unanswered.

In this research, we use location data gathered from mobile devices to measure the impact of OOH advertising. Our data come from a location data provider that collects granular, timestamped location data from millions of individual mobile devices. We identify the devices that are detected at a professional sports stadium during the time that a large healthcare provider began its sponsorship of the team. Combining the data from the CRM system of the healthcare provider with the data from the location data provider, we identify the households who are detected at the stadium during at least one of the team's home games and distinguish these households from those who are not detected at the stadium during one of these games. Using a difference-in-differences analysis, coupled with coarsened exact matching (CEM; Iacus et al. 2012) to alleviate concerns of self-selection, enables us to determine the extent to which OOH advertising (in our empirical analysis, the sponsorship of the team) affects expenditures at the healthcare provider by comparing expenditures before the sponsorship activities and expenditures after the sponsorship concluded.

Our analysis reveals that the sponsorship has a positive effect on patients' expenditures at the focal provider. Average medical expenditures increased for patients who were exposed to the in-stadium advertising compared with patients who were not exposed. This advertising effect is moderated by the breadth of patients' relationships with the healthcare provider. We find that the sponsorship is more effective for patients with weaker relationships with the healthcare provider. In contrast, patients who have a stronger relationship with the healthcare provider are less affected by the sponsorship advertising. This suggests that the sponsorship plays both an awareness and a reinforcement role, creating awareness for new patients and reinforcing the medical expense decisions of current patients through the team sponsorship. Our results are robust to alternative models and estimation strategies.

Our research presents a novel way to measure the effectiveness of sponsorships and other OOH advertising methods by merging data from a mobile location data provider with data from an organization's CRM system. While the marketing literature has used mobile location data for targeting (Fong et al. 2015, Ghose et al. 2019, Luo et al. 2014), to the best of our knowledge our research provides the first use of location data to measuring advertising effectiveness. This location-based method creates new opportunities for the use of location data as an identification tool in a broad class of applications. For instance, our approach can inform studies of offline-to-online and cross-channel advertising (Dinner et al. 2014, Wiesel et al. 2011) by proposing a means to link consumer exposure to marketing activity in one channel with consumer responses in another channel. With the increasing use of digital signage in both enclosed environments (e.g., shopping malls, event venues, trade shows) and outdoor environments (e.g., festivals), our approach offers a means by which marketers can more precisely evaluate the impact of such marketing tactics by generating another consumer touchpoint. Whereas research has examined advertising effectiveness when marketing is delivered to individuals on personal devices that typically command consumer attention (smartphones, tablets, desktops) (Bart et al. 2014, Johnson et al. 2017), we investigate advertising effectiveness when delivered on signage that does not necessarily garner the same level of consumer attention as personal devices (Melumad and Meyer 2020).

Beyond demonstrating how location data can be used to support the evaluation of marketing effectiveness, our research also shows that sponsorships can directly impact actual sales. Focusing on longer-term behavioral outcomes, as opposed to process-related measures such as cognition and conation, contributes to the extant literature on marketing attribution that has demonstrated an immediate impact on pre-purchase engagement (Goldfarb and Tucker 2011, Wilson et al. 2015). Our finding that the sponsorship can create awareness in consumers that affects their purchase decisions confirms studies documenting awareness effects. Our findings also highlight the reinforcement role of sponsorships on the purchase decisions of existing customers because the effects are nuanced. We find that OOH advertising exerts a stronger impact on the expenditures of customers who had a weaker customer-firm relationship, suggesting that sponsorships can serve as a reminder that reinforces previous decisions. Underscoring the role of sponsorships as a form of OOH advertising throughout the customer journey extends the awareness effects the literature has identified. Our research also contributes to recent marketing studies of healthcare decision making (Aizawa and Kim 2018, Kim and KC 2020) by showing how exposure to OOH advertising can influence patients' healthcare decisions and by documenting that the effect is moderated by patients' relationship breadth.

A location-based approach to identify the individuals in a target audience who are exposed to sponsorships can reveal the percent of those who are reached by the advertising and the percent of those who act in response to exposure to the sponsorship, thereby enabling marketers to modify their advertising messages based on the audience present at the location of OOH advertising during a particular time of the day. Just as we have seen experimentation used to support digital advertising (Schwartz et al. 2017), media planners can use granular audience data to assess return on investment in sponsorships and other forms of OOH advertising. Optimizing budgets across types of media can in turn help them design more effective omni-channel communications. While sponsorships can function as an effective acquisition tool by increasing awareness, our findings show that it is also an instrument through which firms can strengthen their relationships with existing customers.

The remainder of this research proceeds as follows. We next describe related research on the use of location data, OOH advertising and sponsorships, and healthcare advertising. We then describe the nature of the in-stadium advertising conducted by our data provider and the process by which we use location data to determine patient exposure to the advertising. We present our estimation strategy and discuss our results. We conclude with a discussion of the opportunities afforded by location data for marketing attribution and the potential limitations, identifying a robust set of research opportunities that such data can support.

2. Section

Our work relates to several research streams. We first discuss the use of mobile location data in marketing. We then review the relevant literature pertaining to OOH advertising. Lastly, given the context of our empirical investigation, we also review recent research that has been conducted in healthcare advertising.

2.1. Location Data in Marketing

Recent research has investigated the use of location data that is collected from smartphones and associated devices (e.g., Bluetooth beacons, Wi-Fi networks) by marketers to understand how contexts affect consumer behavior. Several studies examine how location affects consumer response to mobile promotions. For instance, consumers' proximity to a firm increases mobile promotion response (Danaher et al. 2015, Luo et al. 2014). Additionally, proximity to competitor firms can increase response to mobile promotions from focal firms (Fong et al. 2015). The effects of mobile promotions have also been found to be mitigated when competitors deploy similar promotions (Dubé et al. 2017).

In addition to informing the impact of mobile promotions, mobile location data has also been used to investigate other contextual factors. The crowdedness of the environment and sunny weather, for example, have each been found to boost consumer responses to mobile promotions (Andrews et al. 2016, Li et al. 2017). Mobile location data has also been used to identify consumer trajectories in shopping malls, which in turn affect the likelihood with which promotions are redeemed (Ghose et al. 2019). Such data can even identify consumers who are similar to each other based on their location-visitation patterns (Provost et al. 2015, Zubcsek et al. 2017), with only four spatio-temporal locations needed to identify most individuals (de Montjoye et al. 2013).

Beyond supporting the delivery of targeted mobile promotions, location data can inform decision making. Wang et al. (2019) investigate decision making by taxis drivers and find that the introduction of taxi hailing mobile apps shifts driver behavior toward selecting longer trips and consequently higher hourly wages. Location data and financial transactions from cell phone subscribers have shown that consumers are more likely to use mobile money accounts the farther they travel in a developing country to reduce the risk of robbery (Economides and Jeziorski 2017).

While the use of mobile devices allows for the collection of location data in both enclosed environments (e.g., stores, malls and stadiums) and unenclosed environments (e.g., cities, college campuses), location data can be collected from other devices. For instance, location data from shopping carts can reveal behavioral insights (Hui et al. 2009a). Such data has shown that increasing in-store travel distances increases unplanned purchases, while search duration decreases prices paid (Hui et al. 2013, Seiler and Pinna 2017). These data further show that increased shopping time increases purchase likelihoods, purchasing virtue products increases the purchase of vice products, and populated store areas decrease purchase likelihoods even though consumers are attracted to them (Hui et al. 2009b). Sensor data can also provide information about consumers' movement patterns outdoors. For example, the use of sensors that connect to automobiles reveal that usage-based insurance can improve driving safety (Soleymanian et al. 2019). Our research contributes to the marketing literature that uses location data by showing how it can be used to identify consumers who are exposed to OOH marketing efforts, which enables the effectiveness of OOH advertising to be assessed.

2.2. OOH Advertising

Extant marketing research on OOH advertising has focused largely on the cognitive impacts of billboard media. Billboards can positively influence learning and recall of advertised information (Bhargava et al. 1994, Donthu et al. 1993, Wilson et al. 2015), but this recall decays with time (King and Tinkham 1990). Consumer responses to OOH advertising also differ depending on whether they are new or current customers (Bhargava and Donthu 1999). In addition, factors within OOH advertising can affect the speed and rate at which consumers recognize advertised brands and products (Van Meurs and Aristoff 2009). A key insight from these studies is that OOH advertising generates awareness. We contribute to this understanding by investigating whether awareness may influence consumer spending. Evidence to this effect comes from studies on conation effects. For instance, bans on outdoor advertising of alcoholic beverages can reduce purchase intent, but less so when online alcohol advertising continues (Goldfarb and Tucker 2011). This substitutive effect of online advertising is higher when consumer product awareness is low. Our research builds on these findings by suggesting that OOH advertising effects are also related to the breadth of existing customer-firm relationships. Moreover, the way in which we determine consumers' opportunity to be exposed to OOH media using location data is a scalable approach that does not require consumers' direct involvement.

Due to difficulties in assessing individuals' exposures to OOH advertising, findings on the behavioral impact of OOH advertising on business outcomes are few. When a soup company shifted a portion of its television advertising budget to outdoor advertising, sales increased in test markets compared with a control market (Eastlack and Rao 1989). This increase was likely attributable to a top-of-mind effect since the billboards were located near grocery stores. Billboards advertising a museum increased attendance, especially from areas that typically did not visit the museum (Bhargava and Donthu 1999). Ambient advertising –temporarily placing advertising in unusual locations within the target group environment– corresponded with an increase in shoe store sales (Hutter and Hoffmann 2014). In addition, self-reported soda consumption linked with OOH advertising suggests such advertising can affect purchases (Lesser et al. 2013). While these studies demonstrate that OOH advertising is associated with a lift in performance at the aggregate level, they fall short of conclusively demonstrating that those individuals who were exposed increased their expenditures more so than those who were not exposed. Additionally, we contribute to the literature by investigating the impact of OOH marketing on a high involvement service such as healthcare.

A related strand of literature explores the effects of sponsorships on consumers (Meenaghan 2000). Sponsorships involve firms paying fees to be associated with an organization, such as a sports team, or an event, such as the Olympics. Research has investigated the impact of sponsorships on brand awareness, attitudes, and recall (Cornwell et al. 2006, Johar and Pham 1999, Pham and Johar 1997, Speed and Thompson 2000), largely for nonprofit organizations (Simmons and Becker-Olsen 2006). In terms of financial outcomes, studies find stock prices increase for sponsoring firms (Cornwell et al. 2005) but the value of sponsorship declines with the distance between the team and sponsor headquarters (Yang and Goldfarb 2015). To the best of our knowledge, our research is among the first to use location data to evaluate the impact of sponsorships, a form of OOH advertising. By connecting exposure to the marketing activity with household-level expenditures, we provide a means by which the return on sponsorships can be more accurately evaluated.

2.3. Healthcare Advertising

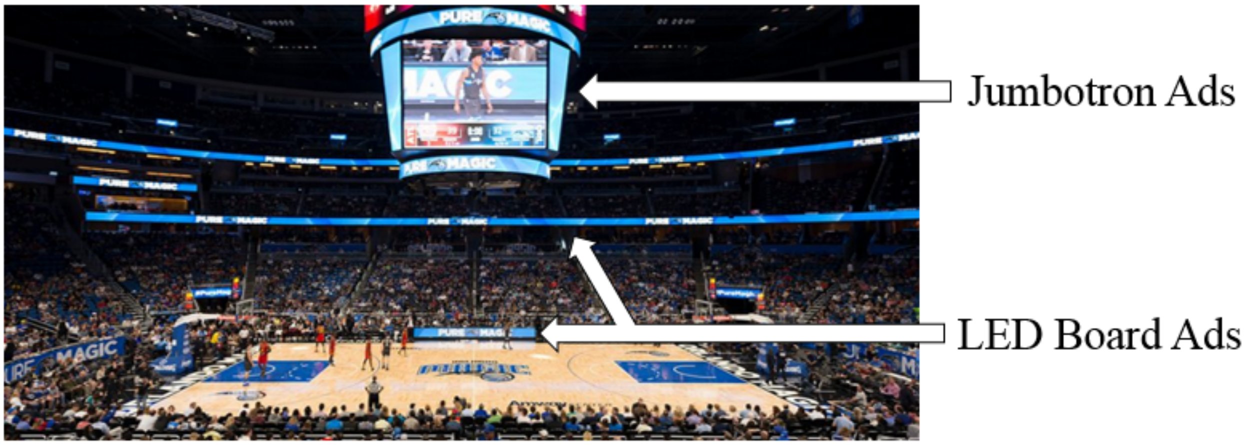
Our research also contributes to the literature on hospital and healthcare advertising. The research in this space continues to grow due in part to advertising by healthcare providers recently becoming legal in the U.S. (the American Medical Association banned hospital advertising until 1980). Studies have examined competitive effects, finding that quality of care, travel distance, and price can affect hospital choice (Luft et al. 1990, Tay 2003). Recent studies demonstrate how medical advertising can influence healthcare decisions. For example, Medicare Advantage advertising can attract newly eligible consumers (Aizawa and Kim 2018), and television advertising can affect patients' hospital choice (Kim and KC 2020). Narayanan et al. (2004) investigate the components of the marketing mix on the pharmaceutical manufacturer's ROI, finding that detailing has a higher ROI than direct-to-consumer advertising. Other studies examining the effect of advertising for prescription drugs have found that such advertising can increase the number of patients (Rosenthal et al. 2003), patient visits (Iizuka and Jin 2005), and compliance with drug regimens by serving as a reminder (Wosinska 2005). Our research extends these studies by quantifying how verified exposure to OOH advertising can affect medical decisions and documenting heterogeneity in these effects by the breadth of consumer relationship.

3. Data

3.1. In-Stadium Advertising

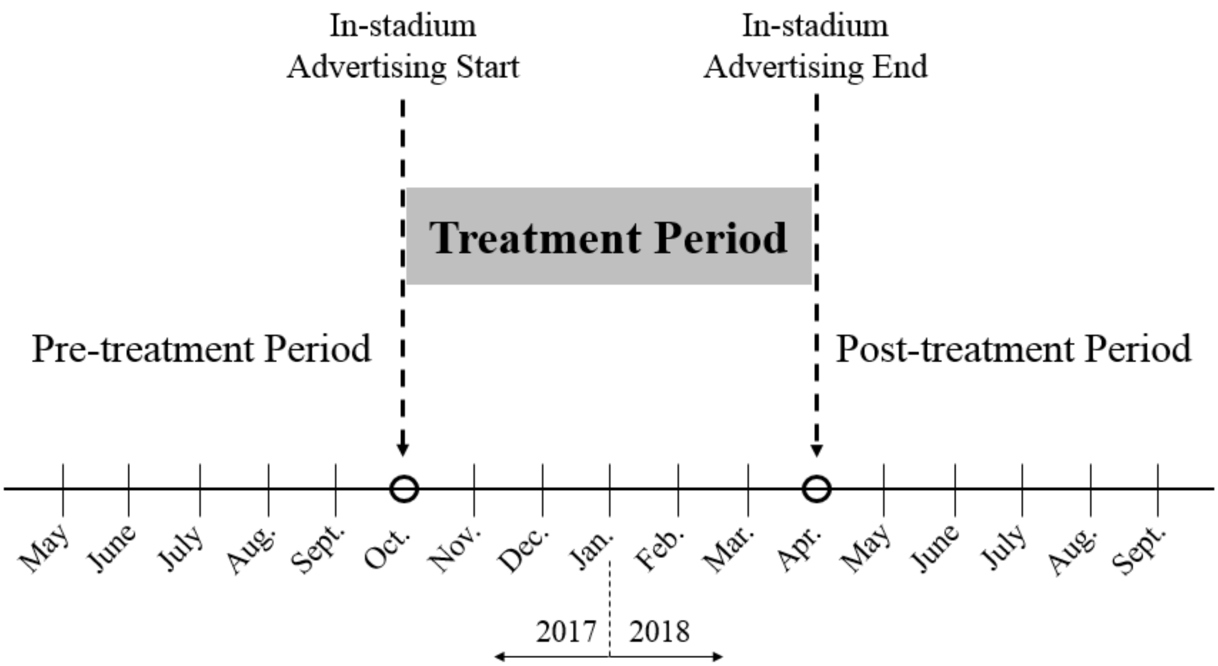
Our data come from a large U.S. healthcare system that began advertising in a professional sports stadium. The stadium is the home venue of a National Basketball Association (NBA) team that seats 20,000 people on average. The in-stadium advertising ran during each home game and consisted of several media types. Ads ran on 42 LED perimeter screens for one minute per quarter. These digital ads showed the healthcare system logo, which dissolved into the words "Official Healthcare Provider of the [Team Name]" and then "Go Where the Players Go" before returning to the healthcare logo. Four, 60-second video ads aired during home games on the jumbotron that hung above the court. These ads featured the team's training facility at the healthcare system's sports medicine complex and the team's access to physicians from the healthcare system. Figure 1 provides an example of in-stadium digital advertising. Full-page printed ads were included in programs available for free at each stadium entrance. A 30-second television commercial also ran during each game that aired on the sports station in the team's home region, and two 30-second commercials ran on the regional radio station during game broadcasts. While the visibility of outdoor advertising may be confounded by weather (sunshine, precipitation; McShane et al. 2012), this is not a concern in our context since the stadium is an indoor arena.

Figure 1: Example of In-stadium Digital Advertising



The in-stadium advertising began at the start of the regular NBA season in October 2017 and continued until the end of the regular season in April 2018. The healthcare provider did not previously advertise in the NBA team arena. We use patient data from the healthcare system from May 2017 (five months before the start of the in-stadium advertising) through September 2018 (five months after the end of the in-stadium advertising). We provide a timeline of the in-stadium advertising and data periods in Figure 2.

Figure 2: Timeline of In-stadium Advertising



Based on the average amount of time between consultation and surgery, a five-month time period is sufficient to measure the effects of the in-stadium advertising on medical expense decisions. Comparing the difference in pre- and post-period medical expenditures between patients who were exposed to the in-stadium advertising (the treatment group) and patients who were not exposed to the in-stadium advertising (the control group) enables us to make causal inferences about the effects of in-stadium advertising. Besides the introduction of in-stadium advertising, all other marketing activities and media spend of the healthcare provider remained constant during this time.

3.2. Data Description

We obtain household-level healthcare expenditure data from a large healthcare provider. While two other healthcare systems operate in the home city of the NBA team, the healthcare provider from whom we obtained data is the largest. The healthcare provider accepts most major insurance plans, as well as state and federal government programs. This provider operates ten hospitals, a university clinic, a sports medicine complex, and more than 250 provider locations throughout the metro area. These multiple locations reduce the role of travel distance in choice of healthcare facility and help rule out the possibility that healthcare provider choice is driven by location or commute time.

The healthcare provider data include the billing address of 726,643 U.S. households who received a medical procedure from the healthcare provider at any point in time between January 2015 and September 2018. We focus only on households in single-unit structures, as we identify treated households based on mobile device location data which cannot be uniquely matched to households in multi-unit housing (e.g., apartment buildings and condominiums). We also focus only on households for whom we observe expenditures on medical procedures during the pre-treatment or post-treatment periods. Thus, the data we conducted our analysis on consist of 582,527 households.

Because OOH advertising can play a reinforcement role for existing consumers, with a greater impact on consumers who have a weaker relationship with the firm, we distinguish households by the relationship they had with the healthcare provider. We do so by constructing a variable for the breadth of a household's relationship with the healthcare provider prior to the pre-treatment window (i.e., January 2015 to April 2017). This variable captures the number of different types of medical procedures a household received from the healthcare provider (Mende et al. 2013).

Table 1 provides summary statistics. From January 2015 to September 2018, the average household had 7.4 medical procedures, with a median of 3. Each household made an expenditure on one or more medical procedures from 40 different procedure types. While households typically had one procedure per admittance to the healthcare system, more than a quarter of households had multiple procedures during a single admission. The average procedure expenditure varies with the type of procedure, ranging from $276 to $30,702. 141,906 households began a relationship with the healthcare provider after April 2017, based on the first date on which the household appears in the data. Some of the 440,621 households who had a relationship with the healthcare provider prior to May 2017 visited the healthcare provider during the post-treatment period, so the expenditures we observe during the pre- and post-treatment windows come from 255,310 households. Combining expenditures during the pre- and post-treatment periods, households spent an average of $6,268 with a standard deviation of $33,330. Interestingly, households who did not have a prior relationship with the healthcare provider had larger average expenditures than households who did, suggesting the in-stadium advertising had a bigger impact on newer patients.

Table 1: Summary Statistics of Household Medical Expenditures

Variable	Description	All Patients		Prior Patients		Newer Patients	
		Mean	Std. Dev.	Mean	Std. Dev.	Mean	Std. Dev.
Medical expenditures	Cost of all medical procedures in USD	6,267.83	33,329.59	5,141.78	28,913.72	9,764.22	44,137.87
Relationship breadth	Number of different types of surgeries prior to pre-treatment period	2.049	2.461	2.709	2.494	0	0
Observations		582,527		440,621		141,906	

3.3. Identifying Consumers who were Exposed to the In-Stadium Advertising

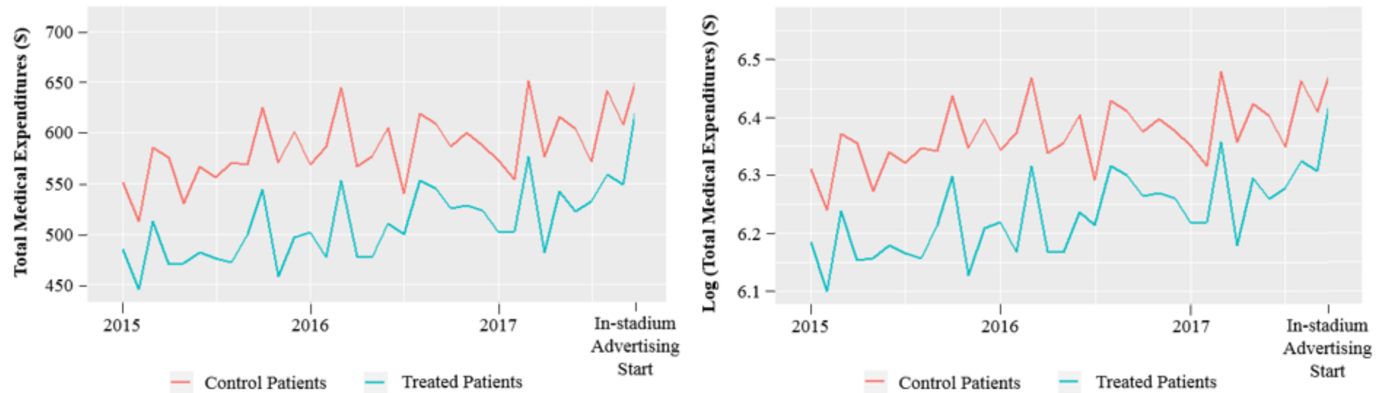
To identify households who were exposed to the in-stadium advertising, we purchased data from a mobile location data provider. The data provider's software development kit (SDK) is built into a number of mobile apps. Permissions granted by app users allow the app developer and the mobile location data provider to passively collect observations from the mobile device that include a device-specific identifier, timestamp, and latitude and longitude. We match the geolocation data from 213,727 mobile devices that were identified as being at the stadium during one of the team's home games with the latitude and longitude corresponding to the billing addresses of the healthcare patients. We acquire the geographic coordinates of the three most frequently observed locations associated with each mobile device from the mobile location data provider, which we assume correspond with home or work locations. The billing addresses of patients of the healthcare system were converted to latitude and longitude coordinates using the SAS GEOCODE procedure. To calculate the distance between the device locations from the mobile location data provider and the billing addresses of healthcare patients, we measure the shortest distance over the earth's surface using the haversine formula. We identify households for which a mobile device was detected at the stadium and at least one of the three frequent locations at which a device was detected that correspond with the billing address of a household in the healthcare provider's billing system. While the location data are at the level of the device, it is possible that the device owner is not a healthcare patient and that a different member of the household was exposed to the in-stadium advertising. Given this limitation of our data, we conduct our analysis at the household-level rather than the individual-level.

3.4. Model-free Evidence

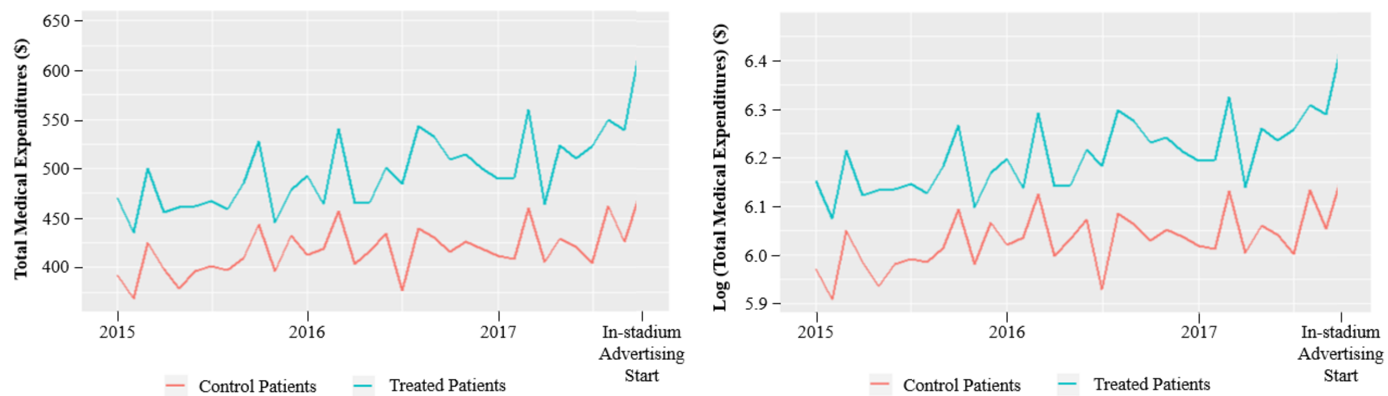
We first visually inspect our data to see whether spending on medical procedures was similar between treated and control groups prior to the start of the in-stadium advertising. Figure 3 plots the pre-treatment spending between each group over time. In the first row, the left figure shows the parallel trends for the absolute value of medical expenditures and the right figure shows them for the logarithm of medical expenditures for the full sample. The second row shows these trends for the matched sample. As shown, pre-treatment spending is highly parallel between the treatment and control groups.

Figure 3: Pre-treatment Trends of Control and Treated Patients

Full Sample

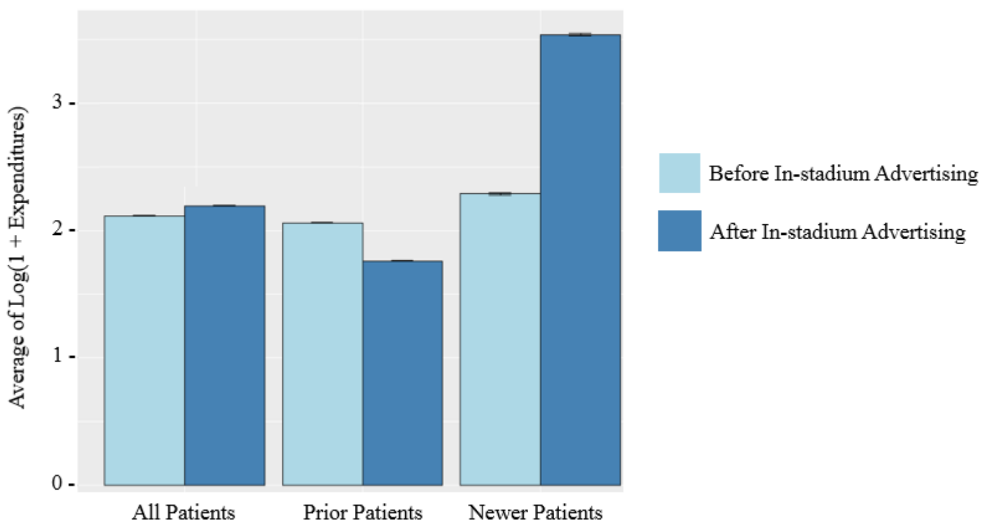


Matched Sample



In Figure 4, we present preliminary evidence that in-stadium advertising affects patients' medical expense decisions. Figure 4 shows average medical expenditures before and after the in-stadium advertising, by type of healthcare patient. Average spending on medical procedures is slightly higher during the period following the in-stadium advertising than during the period preceding it. This effect appears to differ by whether patients had an existing relationship with the healthcare provider or not. Newer patients spent an average of $2,000 more on medical procedures after being exposed to the in-stadium advertising while prior patients reduced their average spend on medical procedures after exposure. This suggests OOH advertising has an effect, but that this effect is driven by patients who are newer to the healthcare provider.

Figure 4: Model-free Evidence of Average Medical Expenditures by Patient Type



Note. Error bars represent standard errors.

We next consider whether the in-stadium advertising effect on expenditures may be driven by the breadth of relationship patients had with the healthcare provider. We do so by examining the average medical spend after advertising exposure of patients who had more different types of procedures with the healthcare provider prior to the advertising. Table 2 shows that patients with greater relationship breadths spend slightly more on medical procedures after exposure to the in-stadium advertising, suggesting that advertising may lead them to continue considering medical procedures they had not previously considered, postponed consultation on, or postponed undergoing. These results proffer model-free evidence that OOH advertising affects expenditures after exposure to the marketing intervention, but do not account for other factors that may impact medical expense decisions. We therefore empirically investigate the significance of this relationship in our analysis.

Table 2: Model-free Evidence of Expenditures by Relationship Breadth

	Log(1 + Expenditures)	
	Treatment Group	**Control Group**
Relationship breadth	0.159***	0.137***
	(0.004)	(0.002)
Constant	1.901***	1.908***
	(0.014)	(0.007)
Observations	105,969	476,558

Note. ****p* < 0.01.

4. Estimation Approach

4.1 Overview

To identify the causal impact of OOH advertising on medical spending at the healthcare provider, we employ a difference-in-differences (DID) approach. Our source of identification is that for each treated household (a household that was exposed to the advertising), our DID analysis constructs a counterfactual outcome by using a set of control households (households that were not exposed to the advertising). We examine the change in the treated households' expenditures relative to the expenditures by control households before and after exposure to in-stadium advertising. Recognizing that advertising exposure may not be random, resulting in treated and control households potentially differing in unobservable ways, our analysis enables us to investigate the causal effect of OOH advertising on healthcare expenditures for exposed households by controlling for unobserved sources of heterogeneity across both groups.

A precondition of exposure to the in-stadium advertising is game attendance. Household propensities to attend a game affect selection into the treatment group, presenting selection bias concerns. Households located closer to the stadium and/or affluent households may be more likely to attend a game. The propensity to attend a game and be exposed to the in-stadium advertising may be similar among households within a given zip code, but different among households across zip codes. We therefore use zip codes to account for variation in distance from the stadium and income level that may affect attendance decisions and match treated households with control households within the same zip code to ensure comparability between groups. Combining DID with matching for our identification strategy limits unobserved confounds that may bias our estimates.

4.2 DID Analysis

We first estimate a DID model of consumers' healthcare expenditures in each period as follows:

$$Log(1 + Spend_{it}) = \beta_1 Exposure_i + \beta_2 Period_t + \beta_3 Exposure_i Period_t + zip_i + \epsilon_{it}. \quad (1)$$

The dependent variable is the log of household i's total medical expenditures in dollars during five months before (t = 0) and after (t = 1) the in-stadium advertising. We model a log-linear form to account for nonnegativity and right-skewness of spending amount. $Exposure_i$ is a binary treatment indicator of whether household i was exposed to advertising or not. $Period_t$ is a binary indicator of whether procedures occurred before (the pre-treatment period) or after (the post-treatment period) the advertising. In this analysis, the parameter of interest is β_3 which estimates the change in log transformed expenditures from treated households after exposure to the advertising compared with changes in log transformed expenditures from control households over the same period.

We then investigate whether patients' prior relationship with the healthcare provider affects the link between advertising and expenditures. $Breadth_i$ denotes the number of different types of medical procedures household i received prior to the pre-treatment window. β_7 captures the moderating effect of relationship breadth. Our parameters of interest are therefore β_3 and β_7. Our model includes zip code fixed effects zip_i to control for zip code-level heterogeneity and we cluster standard errors at the zip code level.

$$Log(1 + Spend_{it}) = \beta_1 Ad\ Exposure_i + \beta_2 Period_t + \beta_3 AdExposure_i Period_t + \beta_4 Breadth_i +$$

$$\beta_5 AdExposure_i Breadth_i + \beta_6 Period_t Breadth_i + \beta_7 AdExposure_i Period_t Breadth_i + zip_i + \epsilon_{it}.$$

(2)

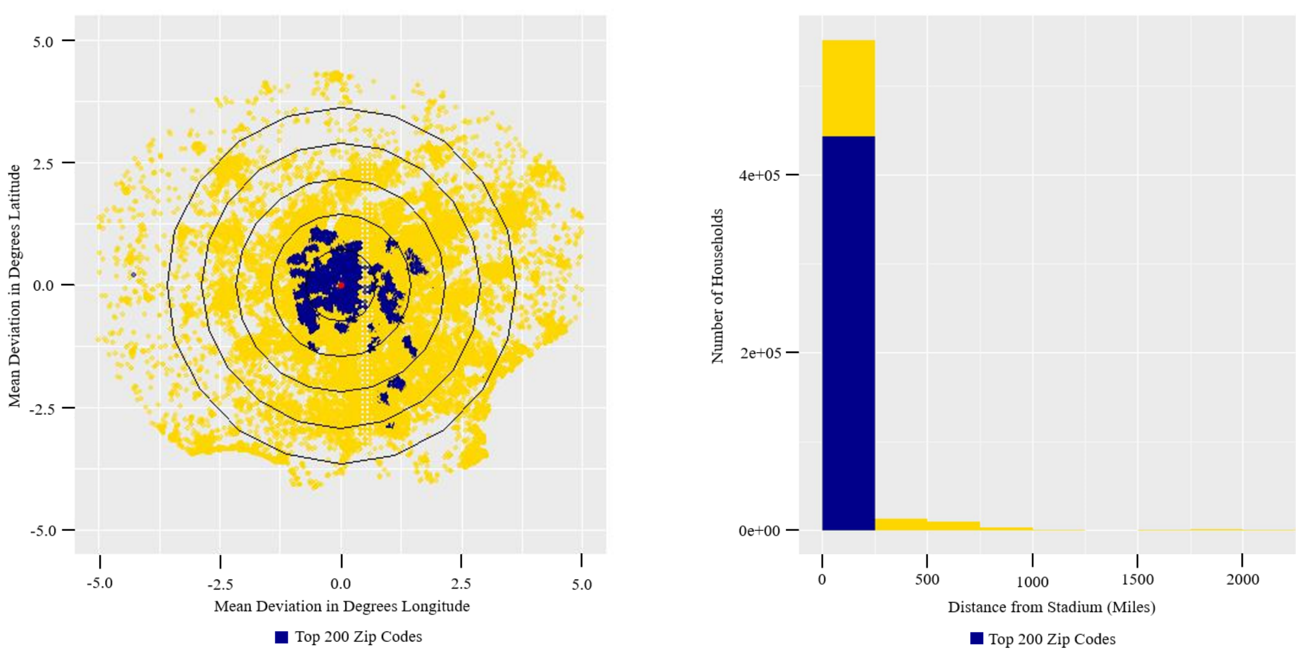
4.3 Coarsened Exact Matching

To render treated and control groups more similar based on observed characteristics, we matched each treated household who was exposed to the advertising with a control household who was not exposed to the advertising, and discarded the remaining unmatched households. Matching is often employed in conjunction with DID analyses to prune observations and reduce model dependence (Datta et al. 2018, Ho et al. 2007, Ransbotham et al. 2019). In our empirical investigation, a source of model dependence is the imbalance between the treated and control groups over the characteristics represented in zip codes. We therefore remove this imbalance and produce a matched dataset. We use CEM to approximate a fully blocked experimental design that performs better with categorical variables compared with matching that approximates a completely randomized experiment such as propensity score matching (Iacus et al. 2012). CEM involves two steps. First, we stratify households by zip code. Second, we drop strata that contain only treated or control households and renormalize the observation weights in the remaining strata to place equal weight on treated and control households in each stratum.

We focus our analysis on the top 200 zip codes with regards to the total expenditures by zip code during the period prior to the pre-treatment window. Based on the healthcare provider's billing data, there are 11,240 zip codes in which households had a relationship with the healthcare provider. Three quarters of these zip codes have no more than five households in the healthcare provider's billing data and most have only control households who were not exposed to the advertising. Since hospital advertising likely does not affect the medical expense decisions of consumers from out-of-state, following Kim and KC (2020) we restrict our attention to in-state consumers from the top 200 zip codes. We depict the geographic distribution of households who had a relationship with the healthcare provider in Figure 5. Figure 5a maps the location of households from the top 200 zip codes (purple dots) and all other zip codes (yellow dots) relative to the location of the stadium (red dot), in degrees (1° is approximately 69 miles). Each concentric circle in Figure 5 represents a distance of 50 miles from the stadium. Figure 5b is a histogram of households' distance from the sports stadium.

Figure 5: Household Distance from Sports Stadium

a) Distance from Stadium **b) Histogram**



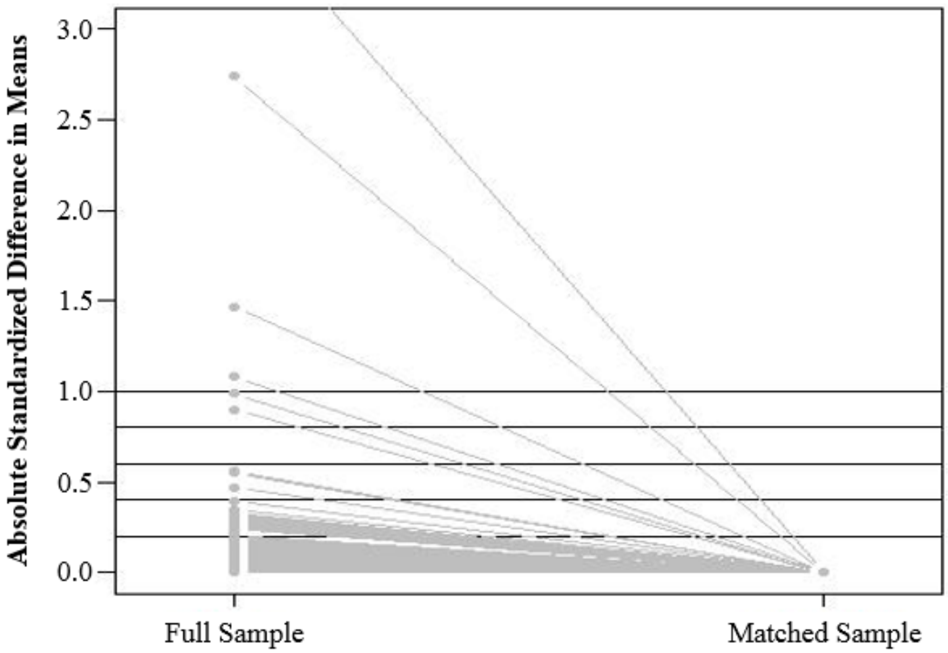
As Figure 5 reveals, households located in the top 200 zip codes are concentrated in closer proximity to the stadium compared with households from the remaining zip codes. For computational efficiency, we applied CEM to households located in these 200 zip codes. We thus estimate the OOH advertising impact using DID with both an unmatched data set and a CEM-matched subset of households.

After applying CEM, our matched data include 443,637 households in 183 zips. Table 3 shows the matching result of 10 sample zip codes. For each anonymized zip code identifier, the mean (share) of corresponding zip codes in control households are adjusted to be the same as the mean of zip codes in treated households after matching. Standardized mean differences, which are the difference between the mean of each covariate in the treated group and the mean of each covariate in the control group divided by the standard deviation in the treated group are thus reduced to zero after matching. Figure 6 shows that treated and control data are successfully matched in terms of the covariates.

Table 3: Coarsened Exact Matching

Treated Group		Control Group			
		Before Matching		After Matching	
ZIP	Means	Means	(Std. Mean Diff.)	Means	(Std. Mean Diff.)
3661	0.0063	0.0105	-0.0535	0.0063	0
3662	0.0036	0.0061	-0.0419	0.0036	0
3666	0.0034	0.0024	0.0168	0.0034	0
3667	0.0002	0.0025	-0.1841	0.0002	0
3668	0.0000	0.0011	-0.1861	0.0000	0
3669	0.0001	0.0015	-0.1133	0.0001	0
3673	0.0019	0.0068	-0.1121	0.0019	0
3674	0.0020	0.0070	-0.1134	0.0020	0
3675	0.0005	0.0032	-0.1245	0.0005	0
3676	0.0009	0.0040	-0.1079	0.0009	0

Figure 6: Mean Differences Before and After Matching



5. Results

We first discuss our results for the effect of advertising exposure on medical expenditures using the full sample. Table 4 shows these results. Model 1 of Table 4 includes the main effect of advertising exposure on healthcare expenditures. Consistent with the model free evidence, this effect is positive and significant, indicating that exposure to in-stadium advertising increases household healthcare expenditures at the healthcare provider. This suggests OOH advertising creates awareness in consumers about the existence of the healthcare provider for new patients, and reminds existing patients of medical consultations they may need or medical procedures they postponed scheduling. To assess whether OOH advertising affects these two groups of consumers differently, we include the moderating effect of relationship breadth in Model 2 of Table 4.

Table 4: Ad Exposure Increases Total Medical Expenditures

	Full Sample log(1 + Expenditures)		Matched Sample log(1 + Expenditures)	
	Model 1	Model 2	Model 1	Model 2
Ad Exposure	-0.203***	-0.242***	-0.194***	-0.157***
	(0.023)	(0.021)	(0.023)	(0.020)
Period	0.074***	0.479***	0.085***	0.475***
	(0.008)	(0.010)	(0.009)	(0.013)
Relationship Breadth		0.325***		0.356***
		(0.006)		(0.007)
Ad Exposure × Period	0.024*	0.058***	0.012	0.065***
	(0.014)	(0.017)	(0.015)	(0.019)
Ad Exposure × Relationship Breadth		0.027***		-0.002
		(0.007)		(0.008)
Period × Relationship Breadth		-0.200***		-0.184***
		(0.004)		(0.004)
Ad Exposure × Period × Relationship Breadth		-0.001		-0.018***
		(0.007)		(0.007)
Zip Code Fixed Effects	Yes	Yes	Yes	Yes
Observations	1,165,054	1,165,054	877,297	877,297

Notes. Standard errors are clustered at the zip code level. *$p < 0.10$; ***$p < 0.01$.

A likelihood ratio test ($\chi2$ = 36097, $p < 0.01$) and comparison of BIC between Model 1 and Model 2 (ΔBIC=36041) indicate the inclusion of breadth significantly improves model fit. When we include the relationship breadth moderator (Model 2), we find that in-stadium advertising can increase healthcare expenditures for those who are exposed to it. While the main effect of ad exposure on medical expenditures remains positive and significant, the effects do not appear to differ by the breadth of relationship patients had with the healthcare provider prior to the in-stadium advertising. One limitation of the analyses conducted on the full sample is that they do not account for potential self-selection concerns. Consumer decisions to attend a regular season game, and consequently be exposed to the in-stadium advertising, may also be related to their healthcare expenditure decisions at the focal healthcare provider. To control for concerns of self-selection into game attendance, we further analyze the effect of in-stadium advertising using CEM. On the right side of Table 4, we present the results of our analysis using a matched sample. While Model 1 omits the relationship breadth moderator, we include this effect in Model 2.

Analyzing the matched sample, we similarly find that a likelihood ratio test ($\chi2$ = 34847, $p < 0.01$) and comparison of BIC between Model 1 and Model 2 (ΔBIC=34792) support the inclusion of relationship breadth in the analysis. While the two-way interaction between Period and Exposure is positive and significant, the three-way interaction between Period, Breadth and Exposure is negative and significant. This suggests that expenditures at the healthcare provider are expected to increase for those households who are exposed to the in-stadium advertising, but the extent of this effect depends on the household's relationship breadth with the healthcare provider. Households who had more procedure types performed by the healthcare provider prior to advertising were subsequently less affected by the advertising. That is, the reminder effect of advertising is weaker for patients who previously had more types of surgeries. Conversations with the healthcare provider revealed a potential explanation for this result: patients who had more procedure types performed by the healthcare provider in the past are less likely to require as many procedures in the near future as those who had fewer procedures performed previously, rendering the role of in-stadium advertising as a reminder less effective for them.

6. Discussion

This research uses location data that is passively collected from mobile devices to measure the impact of sponsorships, a form of OOH advertising. By matching the home address of mobile devices that were detected at a sports arena with that of healthcare patients, we identify households that were exposed to the in-stadium advertising of the healthcare provider. We then compare differences in medical expenditures before and after exposure to the in-stadium advertising between households in which a member was exposed to the advertising and households that were not exposed to the advertising. We find that the sponsorship has a positive effect on healthcare expenditures, especially for patients who do not have a broad relationship with the healthcare provider.

Based on the expected increase in healthcare expenditures among households that were exposed to the in-stadium advertising compared with the counterfactual in which they were not exposed to the advertising, the advertising contributed an increase in expenditures at the focal healthcare system of $126,146 during the 5-month post-exposure period. If the per-month increase in expenditures remains constant through the remainder of the year, this corresponds to an increase in revenue for the healthcare system of $302,750. This offers a conservative estimate of the incremental revenue attributable to OOH advertising. Weighing this incremental revenue against the cost of the sponsorship, the healthcare provider can assess the ROI of the sponsorship and compare its impact with other marketing efforts at its disposal.

Location data offers unprecedented opportunities to understand how consumers behave in the offline world. Digital footprints from stationary devices such as desktop computers and smart TVs enable marketers to investigate consumer search behaviors, interests, and consumption as revealed from their online activities, while data collected from mobile devices have the potential to reveal offline activities. Among the insights that mobile location data can inform are social interactions (Zubcsek et al. 2017), individual movements (Ghose et al. 2019) in both enclosed and unenclosed environments, and environmental influences (Andrews et al. 2016).

The availability of location data is nascent but growing as more developers embed location-based functionality into their apps. A key issue associated with the use of location-based data is the way in which the data are collected. One way in which location data can be collected is directly from the mobile telecommunication providers. The Federal Communications Commission recently proposed fines in excess of $200 million against the four largest wireless carriers "for selling customers' real-time location data" (Valentino-DeVries 2020).

While the sale of mobile location data by telecommunication providers is being regulated, location data can still be collected through mobile apps. In this case, consumers consent to data collection that is necessary for them to use the full capabilities of the app. Without location data, for example, a weather or ride hailing app would not be capable of delivering the benefits sought by consumers. The SDKs built into these apps enable the collection of location data from multiple apps, which can then be aggregated to obtain sufficient coverage of a population of interest.

In using mobile location data, it is important to bear in mind the way in which the data is collected. In contrast to data collected by mobile carriers, the data collected through mobile apps is not collected continuously. Rather, data collection through mobile apps is sporadic, depending on the permissions granted by the user. While some apps will collect location data while running in the background, others may only collect location data while they are in use. This aspect of the data requires careful consideration. In our empirical analysis, more than half of the devices detected at the stadium are only detected once. This does not imply these devices only attended one game, but that the location of the device was only shared once while the device was at the stadium. It is also possible that devices that were at the game were not detected at the stadium. In addition, we do not account for the possibility that consumers in the control group were exposed to the TV or radio commercials that aired on the sports station and radio during game broadcasts. The nature of how the location data we employ in our analysis is collected and the possibility of control group exposure outside the stadium therefore provides a conservative estimate of the impact of sports sponsorships on healthcare expenditures.

Deriving meaningful insight from location data requires marketers to combine location data with other datasets, such as transaction data. Doing so also requires processing geolocation information and matching device identifiers. This may involve tracing device signals over time or converting information from outcome datasets into geographic coordinates to connect the places that consumers have visited to downstream behaviors.

Our research demonstrates one application of location data: identifying exposure to a marketing intervention in which the outcome is decoupled from the location of exposure. While research has used location data for targeting (Danaher et al. 2015, Luo et al. 2014), other approaches have the potential to significantly and rapidly shape public policy and marketing offerings. These include understanding how consumers respond to incentives or changes in policies (Soleymanian et al. 2019, Wang et al. 2019), and whether consumers comply with government mandates such as shelter-in-place or social distancing (Haselton 2020). Location data can also be used to identify areas, populations, or individuals that are more vulnerable to crime (Economides and Jeziorski 2017) or disease transmission (contact tracing, disease tracking) (Romm 2020). More emerging topics that correspond with the novel use of location data involve comprehending how consumer environments influence their lifestyles. For instance, researchers link more fast food restaurants along consumer work commutes to higher body mass indexes (Dornelles 2019). Location data use can also help spot key trends or complete partial pictures, such as merging online and offline journeys across channels for better attribution.

The future use of location data in research may help identify exposure to, and the effectiveness of, marketing, political, and social interventions. However, issues involving privacy, transparency, and consent can affect access to and the use of location data. If not properly anonymized, location data can compromise the privacy of individuals. Moreover, some developers may not request consent from users to be tracked or have location data collected, or may bury notification of updates to data use policies during routine upgrades, obfuscating how they are used. Government agencies, mobile ad networks, location data providers, academics and researchers consequently play critical gatekeeping roles in ensuring the appropriate collection, storage, sale, and use of location data. OOH advertising is unique because points of contact can occur on anything (building facades, elevators), anywhere (stadiums, airports), at any time (24 hours a day). Our findings confirm that OOH advertising can influence purchasing and spending decisions, especially for those who have not purchased as broadly from the advertiser. This implies that OOH advertising can not only serve as a customer acquisition tool but can also be a customer development tool. Marketers should therefore tailor their ad messages to the composition of the exposed audience, as the effectiveness of call to actions may differ depending on whether those exposed are new versus existing consumers. Our research also extends the concept of digital marketing as digital signage is replacing static signage in outdoor environments and consequently consumer exposure to digital marketing campaigns also occurs out-of-home. As marketers obtain more fine-grained data on consumer movements, the personal and public touchpoints through which they can reach consumers may further blend digital and physical spaces.

For marketers, our research provides a means to measure return on investment in OOH advertising. By attributing sales that arise from exposure to outdoor media, marketers can determine whether their OOH advertising works and the extent to which it is a worthy investment. This enables more effective budget allocation across the various types of advertising media that marketers deploy. Our research also suggests a way to determine whether the time and location of outdoor media provides adequate exposure to target audiences, which is important as advertising costs depend on the type and location of outdoor media. OOH advertising may also be effective when consumer exposure to advertising occurs at home. Many sports stadiums surround basketball courts, soccer pitches, and football fields with LED perimeter boards for advertising purposes. Augmented reality technology allows sponsors to modify the virtual ads on these boards according to the viewing audience. Television feeds can consequently expose audiences in one region to perimeter ads that differ from the ads that audiences in another region or in the stadium are exposed to, all during the same live event (Kidd 2018). This hybrid approach to targeted courtside advertising suggests OOH advertising will become more efficient by segmenting offerings to on-site and at-home audiences effectively.

Our research suggests several avenues of future inquiry. One path concerns the use of location data to determine message timing and content. Similar to using consumer trajectories to optimize promotion redemption, consumer location visits and durations may help marketers develop profiles and reach consumers when they are most receptive to marketing messages. Another avenue involves the role of OOH advertising in the consumer journey. Whether outdoor media is more effective at instigating consumer journeys or ushering embarked consumers further down the purchase funnel remains unanswered and has implications for message design and call to actions. Yet another avenue focuses on consumers. For example, since OOH advertising does not involve targeting consumers on their personal devices, consumers may perceive it as less intrusive and may be more receptive to it. And, since digital signage in public environments may not attract the attention that personal devices do, the optimal length of time for outdoor media to generate downstream behaviors merits investigation. These questions aside, we believe our research is a useful first step in demonstrating the potential of location data to reveal how OOH advertising in consumer environments influences consumer behaviors.

In addition to exploring applications for the use of location data, much remains to be done by marketers seeking to derive insights from them. Given the privacy concerns that arise from location, it is important to identify ways to alleviate these concerns. One option is to obscure the granularity of the location data to which marketers have access. Doing so, however, comes at the cost of precision. Research that helps determine the extent to which location data can be obscured without resulting in a precipitous degradation of precision would be relevant as we seek to balance these competing objectives. Another fundamental issue involves combining location data with online data from the same consumer while recognizing the intermittent nature with which they may be collected. This can help marketers investigate how consumers move between online and offline activities. Doing so can reveal a richer understanding of how consumers respond to marketing efforts throughout the customer journey, as well as how online and offline activities complement or substitute for each other.

References

[1] Aizawa N, Kim YS (2018) Advertising and risk selection in health insurance markets. *Amer. Econom. Rev*. 108(3):828-867.

[2] Andrews M, Luo X, Fang Z, Ghose A (2016) Mobile ad effectiveness: Hyper-contextual targeting with crowdedness. *Marketing Sci*. 35(2):218-233.

[3] Bart Y, Stephen AT, Sarvary M (2014) Which products are best suited to mobile advertising? A field study of mobile display advertising effects on consumer attitudes and intentions. *J. Marketing Res*. 51(3):270-285.

[4] Bhargava M, Donthu N (1999) Sales response to outdoor advertising. *J. Advertising Res*. 39(4):7-18.

[5] Bhargava M, Donthu N, Caron R (1994) Improving the effectiveness of outdoor advertising: Lessons from a study of 282 campaigns. *J. Advertising Res*. 34(2):46-55.

[6] Cornwell TB, Humphreys MS, Maguire AM, Weeks CS, Tellegen CL (2006) Sponsorship-linked marketing: The role of articulation in memory. *J. Consumer Res*. 33(3):312-321.

[7] Cornwell TB, Pruitt SW, Clark JM (2005) The relationship between major-league sports' official sponsorship announcements and the stock prices of sponsoring firms. *J. Academy Marketing Sci*. 33(4):401-412.

[8] Danaher PJ, Smith MS, Ranasinghe K, Danaher TS (2015) Where, when, and how long: Factors that influence the redemption of mobile phone coupons. *J. Marketing Res*. 52(5):710-725.

[9] Datta H, Knox G, Bronnenberg BJ (2018) Changing their tune: How consumers' adoption of online streaming affects music consumption and discovery. *Marketing Sci*. 37(1):5-21.

[10] de Montjoye YA, Hidalgo CA, Verleysen M, Blondel VD (2013) Unique in the crowd: The privacy bounds of human mobility. *Sci. Rep*. 3:1-5.

[11] Dinner I, Van Heerde HJ, Neslin S (2014) Driving online and offline sales: The cross-channel effects of traditional, online display, and paid search advertising. *J. Marketing Res*. 51(5):527-545.

[12] Donthu N, Cherian J, Bhargava M (1993) Factors influencing recall of outdoor advertising. *J. Advertising Res*. 33(3):64-72.

[13] Dornelles A (2019) Impact of multiple food environments on body mass index. *PLOS One*. 14(8):e0219365.

[14] Dubé JP, Fang Z, Fong N, Luo X (2017) Competitive price targeting with smartphone coupons. *Marketing Sci*. 36(6):944-975.

[15] Eastlack JO Jr., Rao AG (1989) Advertising experiments at the Campbell soup company. *Marketing Sci*. 8(1):57-71.

[16] Economides N, Jeziorski P (2017) Mobile money in Tanzania. *Marketing Sci*. 36(6):815-837.

[17] eMarketer (2019) Out-of-home ad spending worldwide, 2013-2023. https://chart-na1.emarketer.com/231022/out-of-home-ad-spending-worldwide-2013-2023-billions).

[18] Fong NM, Fang Z, Luo X (2015) Geo-conquesting: Competitive locational targeting of mobile promotions. *J. Marketing Res*. 52(5):726-735.

[19] Fossen BL, Schweidel DA (2017) Television advertising and online word-of-mouth: An empirical investigation of social TV activity. *Marketing Sci.* 36(1):105-123.

[20] Fossen BL, Schweidel DA (2019) Social TV, advertising, and sales: Are social shows good for advertisers? *Marketing Sci*. 38(2):274-295.

[21] Ghose A, Li B, Lui S (2019) Mobile targeting using customer trajectory patterns. *Management Sci*. 65(11):5027-5049.

[22] Goldfarb A, Tucker C (2011) Advertising bans and the substitutability of online and offline advertising. *J. Marketing Res*. 48(2):207-227.

[23] Haselton T (2020) Apple and Google team up to track spread of coronavirus using iPhone and Android apps. *CNBC* (April 10), https://www.cnbc.com/2020/04/10/apple-google-team-up-to-track-coronavirus-spread-using-iphone-android.html.

[24] Ho DE, Imai K, King G, Stuart EA (2007) Matching as nonparametric preprocessing for reducing model dependence in parametric causal inference. *Political Analysis* 15(3):199-236.

[25] Hui SK, Bradlow ET, Fader PS (2009a) Path data in marketing: an integrative framework and prospectus for model building. *Marketing Sci*. 28(2):320-335.

[26] Hui SK, Bradlow ET, Fader PS (2009b) Testing behavioral hypotheses using an integrated model of grocery store shopping path and purchase behavior. *J. Consumer Res*. 36(3):478-493.

[27] Hui SK, Inman JJ, Huang Y, Suher J (2013) The effect of in-store travel distance on unplanned spending: Applications to mobile promotion strategies. *J. Marketing* 77(2):1-16.

[28] Hutter K, Hoffmann S (2014) Surprise, surprise. Ambient media as promotion tool for retailers. *J. Retailing* 90(1):93-110.

[29] Iacus SM, King G, Porro G (2012) Causal inference without balance checking: Coarsened exact matching. *Political Analysis* 20(1):1-24.

[30] Iizuka T, Jin GZ (2005) The effects of direct-to-consumer advertising on doctor visits. *J. Econom. Management Strat.* 14(3):701-727.

[31] Johar GV, Pham MT (1999) Relatedness, prominence, and constructive sponsor identification. *J. Marketing Res.* 36(3):299-312.

[32] Johnson GA, Lewis RA, Nubbemeyer EI (2017) Ghost ads: Improving the economics of measuring online ad effectiveness. *J. Marketing Res.* 54(6):867-884.

[33] Kidd R (2018) How 'virtual' advertising is helping brands reach international soccer fans. *Forbes* (August 24), https://www.forbes.com/sites/robertkidd/2018/08/24/how-virtual-advertising-is-helping-brands-reach-international-soccer-fans/#19b149bc6b7f.

[34] Kim TI, KC D (2020) The impact of hospital advertising on patient demand and health outcomes. *Marketing Sci.* Forthcoming.

[35] King KW, Tinkham SF (1990) The learning and retention of outdoor advertising. *J. Advertising Res.* 29(6):47-51.

[36] Lesser LI, Zimmerman FJ, Cohen DA (2013) Outdoor advertising, obesity, and soda consumption: A cross-sectional study. *BMC Public Health* 13(20):1-7.

[37] Li C, Luo X, Zhang C, Wang X (2017) Sunny, rainy, and cloudy with a chance of mobile promotion effectiveness. *Marketing Sci.* 36(5):762-779.

[38] Luft HS, Garnick DW, Mark DH, Peltzman DJ, Phibbs CS, Lichtenberg E, McPhee SJ (1990) Does quality influence choice of hospital? *J. Amer. Medical Assoc.* 263(21):2899-2906.

[39] Luo X, Andrews M, Fang Z, Phang CW (2014) Mobile targeting. *Management Sci.* 60(7):1738-1756.

[40] McShane BB, Bradlow ET, Berger J (2012) Visual influence and social groups. *J. Marketing Res.* 49(6):854-871.

[41] Meenaghan T (2001) Understanding sponsorship effects. *Psychology & Marketing* 18(2):95-122.

[42] Melumad S, Meyer R (2020) Full disclosure: How smartphones enhance consumer self-disclosure. *J. Marketing*, forthcoming.

[43] Mende M, Bolton RN, Bitner MJ (2013) Decoding customer-firm relationships: How attachment styles help explain customers' preferences for closeness, repurchase intentions, and change in relationship breadth. *J. Marketing Res.* 50(1):125-142.

[44] Narayanan S, Desiraju R, Chintagunta PK (2004) Return on investment implications for pharmaceutical promotional expenditures: The role of marketing-mix interactions. *J. Marketing Res*. 68(4):90-105.

[45] Nielsen (2019) Out-of-home advertising study. https://oaaa.org/ProofOOHWorks/MarketingResearch.aspx.

[46] Pham MT, Johar GV (1997) Contingent processes of source identification. *J. Consumer Res*. 24(3):249-265.

[47] Provost F, Martens D, Murray A (2015) Finding similar mobile consumers with a privacy-friendly geosocial design. *Info. Sys. Res*. 26(2):243-265.

[48] Queiroz R (2018) Measuring outdoor advertising performance. *Dash Two* (January 18), https://dashtwo.com/blog/how-to-measure-outdoor-advertising/.

[49] Quercia D, Di Lorenzo G, Calabrese F, Ratti C (2011) Mobile phones and outdoor advertising: Measurable advertising. *IEEE* 10:28-36.

[50] Ransbotham S, Lurie NH, Liu H (2019) Creation and consumption of mobile word of mouth: How are mobile reviews different? *Marketing Sci*. 38(5):773-792.

[51] Romm T (2020) Google taps vast trove of location data to aid global effort to combat coronavirus. *Washington Post* (April 3), https://www.washingtonpost.com/technology/2020/04/03/google-data-distancing-coronavirus/.

[52] Rosen M (2019) Why out-of-home is the future of video advertising. *AdAge* (December 6), https://adage.com/article/intersection/why-public-space-next-frontier-video-storytelling/2220831.

[53] Rosenthal MB, Berndt ER, Donohue JM, Epstein AM, Frank RG (2003) Demand effects of recent changes in prescription drug promotion. *Forum for Health Econom. Policy* 6(1):1-26.

[54] Schwartz EM, Bradlow ET, Fader PS (2017) Customer acquisition via display advertising using multi-armed bandit experiments. *Marketing Sci.* 36(4):500-522.

[55] Seiler S, Pinna F (2017) Estimating search benefits from path-tracking data: Measurement and determinants. *Marketing Sci*. 36(4):565-589.

[56] Simmons CJ, Becker-Olsen KL (2006) Achieving marketing objectives through social sponsorships. *J. Marketing* 70(4):154-169.

[57] Soleymanian M, Weinberg CB, Zhu T (2019) Sensor data and behavioral tracking: Does usage-based auto insurance benefit drivers? *Marketing Sci*. 38(1):21-43.

[58] Speed R, Thompson P (2000) Determinants of sports sponsorship response. *J. Academy Marketing Sci*. 28(2):226-238.

[59] Tay A (2003) Assessing competition in hospital care markets: The importance of accounting for quality differentiation. *RAND J. Econom*. 34(4):786-814.

[60] Valentino-DeVries, J (2020) F.C.C. to fine cellphone carriers for selling customers' locations. *New York Times* (February 27), https://www.nytimes.com/2020/02/27/technology/fcc-location-data.html.

[61] Van Meurs L, Aristoff M (2009) Split-second recognition: What makes outdoor advertising work? *J. Advertising Res*. 49(1):82-92.

[62] Wang Y, Wu C, Zhu T (2019) Mobile hailing technology and taxi driving behaviors. *Marketing Sci*. 38(5):734-755.

[63] Wiesel T, Pauwels K, Arts J (2011) Marketing's profit impact: Quantifying online and off-line funnel progression. *Marketing Sci*. 30(4):604-611.

[64] Wilson RT, Baack DW, Till BD (2015) Creativity, attention, and the memorability for brands: An outdoor advertising field study. *Internat. J. Advertising* 34(2):232-261.

[65] Wosinska M (2005) Direct-to-consumer advertising and drug therapy compliance. *J. Marketing Res*. 42(3):323-332.

[66] Yang Y, Goldfarb A (2015) Banning controversial sponsors: Understanding equilibrium outcomes when sports sponsorships are viewed as two-sided matches. *J. Marketing Res*. 52(5):593-615.

[67] Zubcsek PP, Katona Z, Sarvary M (2017) Predicting mobile advertising response using consumer colocation networks. *J. Marketing* 81(4):109-126.