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Mobile Ad Effectiveness: Hyper-Contextual Targeting with Crowdedness

Michelle Andrews
Goizueta Business School, Emory University, Atlanta, Georgia 30322; and Fox School of Business, Temple University, Philadelphia, Pennsylvania 19122, andrews@temple.edu

Xueming Luo
Fox School of Business, Temple University, Philadelphia, Pennsylvania 19122, luoxm@temple.edu

Zheng Fang
Sichuan University, Sichuan 610064, China, 149281891@qq.com

Anindya Ghose
Stern School of Business, New York University, New York, New York 10012, aghose@stern.nyu.edu

This research examines the effects of hyper-contextual targeting with physical crowdedness on consumer responses to mobile ads. It relies on rich field data from one of the world's largest telecom providers who can gauge physical crowdedness in real-time in terms of the number of active mobile users in subway trains. The telecom provider randomly sent targeted mobile ads to individual users, measured purchase rates, and surveyed purchasers and nonpurchasers. Based on a sample of 14,972 mobile phone users, the results suggest that, counterintuitively, commuters in crowded subway trains are about twice as likely to respond to a mobile offer by making a purchase vis-à-vis those in noncrowded trains. On average, the purchase rates measured 2.1% with fewer than two people per square meter, and increased to 4.3% with five people per square meter, after controlling for peak and off-peak times, weekdays and weekends, mobile use behaviors, and randomly sending mobile ads to users. The effects are robust to exploiting sudden variations in crowdedness induced by unanticipated train delays underground and street closures aboveground. Follow-up surveys provide insights into the causal mechanism driving this result. A plausible explanation is mobile immersion: As increased crowding invades one's physical space, people adaptively turn inwards and become more susceptible to mobile ads. Because crowding is often associated with negative emotions such as anxiety and risk-avoidance, the findings reveal an intriguing, positive aspect of crowding: Mobile ads can be a welcome relief in a crowded subway environment. The findings have economic significance because people living in cities commute 48 minutes each way on average, and global mobile ad spending is projected to exceed $100 billion. Marketers may consider the crowdedness of a consumer's environment as a new way to boost the effectiveness of hyper-contextual mobile advertising.

Data, as supplemental material, are available at http://dx.doi.org/10.1287/mksc.2015.0905.

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1. Introduction

As mobile advertising rapidly evolves, marketers are using contexts such as location to target consumers. Examples of such contextual targeting include geofencing (i.e., sending mobile coupons to people within the virtual perimeter of a store) and Bluetooth-based beacons (i.e., sending deals to devices within venues) (Luo et al. 2014). Interestingly, hyper-contextual targeting may even allow marketers to engage with other environmental contexts such as weather to dynamically influence behavior (Marshall 2014).

This research investigates how another hyper-context, physical crowdedness, may affect consumer response to mobile ads. We define physical crowdedness as the degree of population density or number of people per unit area (Stokols 1972). The unique environment of subway trains is used to test the effects of physical crowdedness because of the natural setting of trains with different levels of crowd density. In the city of this study, the underground subway is equipped with mobile signal receivers and allows passengers to use their mobiles throughout their commute. Cellular technology can record in real-time the number of users in each mobile-equipped subway train. Traditionally, crowding has been difficult to measure in conventional retail environments. Today, mobile technologies allow researchers to more precisely determine people's spatial proximity to one another and to gauge crowd density as the number of passengers per square meter.

A large mobile telecom company provided field data for our study. The experiment design and the unique attributes of this data can causally identify the effects of crowding. The company sent targeted mobile ads via short message services (SMS) to consumers in subway trains who could purchase the mobile ads by responding to the SMS. The company randomly sampled commuters from the targeted subway population using an instant computational and randomization procedure. Because crowding is naturally confounded with the time of day and the day of the week, the field data can isolate the effect of crowdedness on mobile purchases by controlling for self-selection and user heterogeneity across (i) peak versus non-peak hours, and (ii) weekdays versus weekends. To further address endogenous selection concerns and rule out alternative explanations, our identification strategy exploits sudden variations in crowdedness that are induced by unanticipated train delays underground and street closures aboveground. Based on 14,972 mobile phone users, the results show that commuters in crowded subway trains are about twice as likely to respond by making a purchase vis-à-vis those in noncrowded trains. On average, the purchase rates measured 2.1% with fewer than two people per square meter, and increased to 4.3% with five people per square meter. However, the effect of crowdedness on response to mobile ads is neither simple nor linear, but rather nonlinear and positive after a lower threshold.

Why would people welcome targeted ads on their mobile phones in crowded trains, more so than in noncrowded trains? Behavioral constraint theory provides a possible answer (Sommer 2009, Stokols 1972). Specifically, crowding in subway trains can invade people's physical space and restrict their behaviors, giving rise to adaptive strategies. Commuters adaptively turn inwards, i.e., focus less on the physical crowding but more on their personal mobile phones. This mobile immersion may thus lead to greater susceptibility to mobile ads in crowded trains.

This research offers several contributions. Our finding of the positive effect of crowding is counterintuitive given prior studies that largely note negative effects. Specifically, in crowded retail stores, people tend to become more anxious, reduce their shopping time, and adopt risk-avoidance behaviors (Harrell et al. 1980, Maeng et al. 2013). Yet, in the context of subway trains, we find that crowding may actually increase purchase likelihood. In this sense, we contribute to the literature on crowding and retail environments by revealing a positive aspect of crowding: Mobile messages can be a welcome relief in a crowded subway environment. Theoretically, this finding is intriguing because crowding may reduce outside options and lead people to adaptively focus their attention inwards. This new insight into how people may behave in crowded environments suggests that crowding makes audiences for ads more attentive and susceptible.

We also extend the mobile ad literature by advancing a new way to think about mobile targeting. Crowding makes people turn inwards which, in today's age, is manifested by immersion in their mobile phones. Spending more time browsing on the phone when idle in subway trains increases the probability of increased susceptibility to mobile ads. This susceptibility is crucial to the literature since extant work notes that there can be "noise" and distractions when people construe mobile ads, regardless of whether such ads are displayed on mobile optimized sites (Bart et al. 2014) or are inserted within apps (Ghose and Han 2014). Paradoxically, we find that when surrounded by others, people may be less influenced by outside noise but rather inwardly more attentive to their private mobile devices and responsive to mobile ad signals. Also, the effect of crowding may not be simply about the pure presence of others, because we do not find a linear effect. Rather, the effect is nonlinear with a lower threshold, confirming that crowding may pose physical constraints that make people turn inward and engage in higher mobile immersion. That is, the effect of crowding kicks in after a certain threshold of crowding, whereby people can no longer move around to preserve personal space. Prior studies on consumers' use of mobile phones and responsiveness to mobile ads have examined contextual factors such as users' geographic mobility (Ghose and Han 2011), location (Molitor et al. 2014), location and time at which they receive a promotion (Luo et al. 2014), weather (Molitor et al. 2013), and product characteristics (Bart et al. 2014). We extend these studies by advancing a novel nonlinear view of mobile ad response in the contextual environment of subway crowding.

Our findings also have meaningful managerial implications. Mobile marketers are excited about harnessing a better understanding of the context that drives consumer response to mobile ads. With mobile ad spending projected to near $100 billion by 2018 (eMarketer 2014), marketers have a vested interest in reaching consumers when and where they are most receptive to mobile ads. Our study suggests that for managers, crowding represents a new setting for gauging the effectiveness of context-sensitive mobile messages. Public transit commutes provide a unique marketing environment and thus a window of opportunity for marketers to target mobile users. In most cities people spend a considerable amount of time commuting, averaging 48 minutes each way, according to Census Bureau reports (McKenzie and Rapino 2011). This commuting time in the subway can be a boon for marketers to deliver ads to mobile users at the right time and location. As more cities facilitate mobile use in underground subways (Flegenheimer 2013), marketing opportunities to target consumers based on ambient factors such as crowding will abound.

2. Background and Hypothesis

2.1. Literature on Mobile Ad Response

Our work builds on two streams of research. First, the mobile ad literature reveals several contexts that influence consumers' likelihood of responding to mobile promotions. In terms of location, Ghose et al. (2013a) find that consumers are more likely to click on links to stores close to them and on higher-ranked links on their mobile screens. Echoing this, Molitor et al. (2014) found that mobile coupon redemption rates increased the closer consumers were to a store and the higher the offer was displayed on the screen, conditional on the discount. Luo et al. (2014) show how the location of consumers relative to a promoted venue and the time at which they receive a promotion affects their mobile purchase likelihood. Researchers have also demonstrated how real-time mobile promotions transmitted within grocery stores can increase shoppers' travel distance and, consequently, boost their unplanned spending (Hui et al. 2013). In addition, scholars have found that for mobile display advertising, products higher on involvement and utilitarian dimensions generate more purchase intentions (Bart et al. 2014). Studies have also found that the interdependence between PC and mobile use creates positive synergistic effects that impact consumer responsiveness to mobile advertising (Ghose et al. 2013b). Market competition and environmental factors may also explain why consumers make mobile purchases (Fong et al. 2015, Molitor et al. 2013).

2.2. Literature on Crowdedness

Our study is also related to the literature on crowdedness. In the sociology and psychology literature, studies have linked crowding to physical and mental diseases and juvenile delinquency (Schmitt 1966). Crowding can increase stress (Collette and Webb 1976), frustration (Sherrod 1974), and hostility (Griffitt and Veitch 1971). Individuals may consider themselves more anonymous in crowds, which can reduce their social interactions and fuel antisocial behavior (Zimbardo 1969). In more crowded areas, for example, crime rates were found to spike due to the higher likelihood that criminals could avoid detection (Jarrell and Howsen 1990). Scholars have demonstrated that in crowded settings, people perceive less control over their situations (Aiello et al. 1977, Hui and Bateson 1991). In consumer behavior research, crowding has been found to induce avoidance behaviors and reduce shopping times (Harrell et al. 1980). Other studies have shown that crowding can threaten consumers' sense of uniqueness, which may lead them to purchase more distinctive products to restore their perceived individuality (Xu et al. 2012). Researchers also found that crowding can boost purchase variety due to consumers' desire to assert freedom through choice (Levav and Zhu 2009). Relatedly, Maeng and colleagues (2013) note that crowded environments can spur shoppers to become more risk-averse and favor safety-oriented options such as visiting a pharmacy rather than a convenience store. Following these research streams, we suggest that the effectiveness of mobile targeting may also depend on another context, i.e., how crowded a consumer's environment is.

2.3. The Effect of Crowdedness on Mobile Ad Response

Mobile ads may elicit higher response rates when people are in crowded subway trains vis-à-vis noncrowded trains. Crowding invades personal space and restricts behavior; people can adapt by turning inwards and becoming more responsive to mobile ads.[1] More specifically, crowding arises from the physical proximity of others in confined subway trains, where "riders are often squeezed into very close proximity" (Milgram and Sabini 1978, p. 32). As more commuters occupy the train, individuals' personal and physical spaces are invaded. This spatial limitation poses a behavioral constraint that can lead people to experience a reduction in the outside options of things to do. For example, people will be less prone to look around because crowding can boost the likelihood of catching unwanted gazes (Aiello et al. 1977, Evans and Wener 2007). Behavioral constraint theory (Stokols 1972) suggests that people use adaption strategies in a crowd to alleviate perceived behavioral restrictions: People may adapt to crowded situations by turning *inwards* to filter out inputs from social and physical surroundings (Milgram 1970). Similarly, scholars have documented that when consumers perceive a threat to their freedom due to spatial confinement, they may react by engaging in actions designed to reassert their freedom (Brehm 1966, Wicklund 1974). For example, consumers may use their purchasing decisions to exert control over their environment (Levav and Zhu 2009). In today's age, people can adapt by turning inwards and paying more attention to their mobile devices. That is, people can immerse themselves in their private mobiles "as a means of *escape*, a way by which a person can avoid unwanted encounters" and gain a sense of control over her space and privacy (Sommer 2009, p. 1227). Crowding can lead people to adaptively respond by escaping into the "technologically mediated private realm" of their mobiles (Bull 2005, p. 354). This mobile immersion allows passengers to psychologically withdraw from the physical crowd and can boost their attention to mobile ads (Maeng and Tanner 2013), thus

[1] We acknowledge an anonymous reviewer for this point.

likely leading to higher purchase responses in more crowded trains.

However, this effect of crowding on purchase likelihood may be neither simple nor linear, but rather nonlinear with a lower threshold. In the closed environment of subway trains, individuals may initially adapt to crowdedness by moving around to preserve personal space. Once this becomes less feasible as the subway train fills up, they may resort to turning inwards via mobile immersion after a certain threshold level of crowding.[2] If so, we test the following:

Hypothesis. *Ceteris paribus, physical crowdedness engenders higher consumer response to mobile ads. Yet the effect of crowdedness is nonlinear and positive after a lower threshold.*

3. Field Data, Identification, and Results

An ideal way to test the effects of crowdedness would be to conduct a randomized field experiment in which the level of crowdedness is varied. Yet this is extremely difficult because it would require randomly assigning commuters to more versus less crowded subway trains. In other words, it is quite hard to manipulate the level of crowdedness in a field setting. Thus, our study relies on field data in which users are randomly targeted with mobile coupons as a function of the level of crowdedness.

In our field data, a total of 10,690 mobile users who rode the subway were randomly selected to be sent a promotion through a text message, and their responses were recorded. The SMS advertised a missed call alert service, which, if purchased, would notify mobile users of the time and number of the calls they missed. The study took place in Asia in September 2013, where cell phone plans are piecemeal rather than all-inclusive. As such, mobile users must purchase a missed call alert service separately to be notified of missed calls. The SMS read "*Missed a call and want to know from whom? Subscribe to* [Wireless Service Provider's] *missed call alert service and be notified by SMS of the calls you missed! Only* ¥9 *for* 3 *months! Get* ¥3 *off if you reply 'Y' to this SMS within the next* 20 *minutes!*" Because the average subway commute is 30 minutes, the reply time was restricted to 20 minutes to ensure that most commuters would respond to the SMS while still in transit. The provider offered a ¥3 rebate to incentivize mobile users to respond. For those who responded, the cost was charged to their phone bills. Thus, we measure response to mobile ads as the purchase rate (1 = purchase, 0 = no purchase), also labeled as mobile ad effectiveness, i.e., our dependent variable. Of the 10,690 mobile users who received an SMS, 334 replied and purchased the promoted service, corresponding to a 3.22% response rate in our data. These response rates seem low, but are fairly high compared with the 0.6% response rate for mobile coupons in Asia (eMarketer 2012) and the 1.65% response rate for the effectiveness of location-based mobile coupons (Molitor et al. 2014).

Crowdedness, our key independent variable, is measured as the number of subway passengers per square meter. We did this in a step-by-step fashion. First, in our study, the subway consisted of articulated trains modeled after accordion-style buses where the absence of doors between cars enables passengers to travel the length of the subway train without restriction. Each subway train is composed of six articulated cars. We measured the volume of mobile users in each subway train as the number of mobile users who are automatically connected to the subway-tunnel cellular lines.[3] Second, we calculated passenger volume. The mobile phone penetration rate in major Asian cities is very high. In the large city we studied, the telecom provider serves 70% of the population. We thus derived passenger volume by dividing the mobile user volume by 0.7. Third, we calculate crowdedness by dividing this passenger volume by the total area of each subway train. Each subway car is 19 meters long and 2.6 meters wide, totaling 296.4 m^2 (6 cars × 19 m length × 2.6 m width).[4] We measure crowdedness at the time the SMS mobile ad is sent. Table 1 presents the measured crowdedness per time cycle per train. As shown in Table 1 for the 14:00–16:00 time cycle, in train 7 the crowdedness (shown in bold) is 1.91 passengers/m^2 on a weekday but is much higher at 3.42 on a weekend, as expected. As depicted in Figure 1, mobile purchase likelihood increases as a function of crowdedness. This pattern gives initial model-free evidence for the effect

[2] In theory, an upper-boundary may exist: Too dense a crowd would negatively affect mobile ad response because congestion would restrict the ability to even use a mobile phone. For example, in Tokyo, subway commutes can be packed to capacity with up to 11 passengers/m^2, and in Hong Kong, transit authorities are considering removing seats from subway trains to give commuters "more room to interact with their devices" (Agence France-Presse 2014). In the city of our study, however, the highest level of crowding we observe is 5 people/m^2, so we cannot test for an upper threshold. Also, as our research aims to make a causal inference of crowdedness on mobile ad sales, we recognize that consumer response to mobile ads while in a crowded environment may be multiply determined.

[3] The telecom provider can identify all mobile users' phone numbers, including those of phones that are off (due to telecommunication company chip-tracking technology). Thus, both phones that are on and those that are off are recognized and recorded. According to the provider, over 99.9% of phones are on during the day.

[4] Because crowdedness differs from city to city and culture to culture (e.g., cities with a high population density such as Hong Kong are different from those with a low population density such as Auckland), tolerance for crowdedness may also vary. Because Asians are more tolerant of crowdedness given their large population, the effects in our field study may be more conservative.

Table 1 **Level of Crowdedness in Subway Trains**

		Weekday sample	Weekend sample
Time of day	Train	Crowdedness	Crowdedness
7:30–8:30	1	4.18	1.80
	2	3.93	1.87
10:00–12:00	3	2.99	3.07
	4	2.93	3.18
	5	2.91	3.20
14:00–16:00	6	2.01	3.09
	7	**1.91**	**3.42**
17:30–18:30	8	5.36	4.67
	9	4.57	4.54
21:00–22:00	10	0.96	1.51
	11	0.94	1.62
	12	0.91	1.64
	13	0.89	1.65
	14	0.83	1.72

Note. Crowdedness is the number of passengers per square meter.

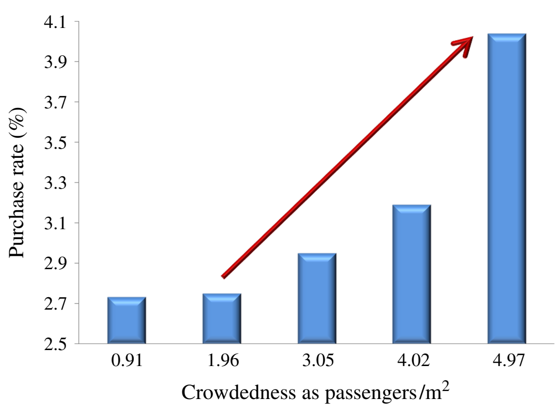
of crowdedness on consumer response to mobile ads. Next, we present model-based evidence.

3.1. Identification and Model-Based Results

Because crowding is naturally confounded with the time of day and day of week, the validity of results based on field data is often threatened by alternative explanations. For greater confidence in the results, our identification strategies are multifaceted to: (1) address selection on observable variables that include peak versus nonpeak crowdedness hours, weekdays versus weekends, mobile use behavior, and randomly sending mobile ads, and (2) exploit sudden variations in crowdedness induced by street closures *aboveground* and unanticipated train delays *belowground* in the subway system.

3.1.1. Identification with Peak-Hour, Weekend, and Mobile Usage Behavior. Self-selection concerns arise when people self-select into more or less crowded trains depending on factors such as the time of day and whether it is a weekday or a weekend. For instance, during morning rush hours, there is likely to be more crowding with a greater proportion of working professionals, whereas at other times, seniors, children, and homemakers may be more likely to use the subway. If this is the case, the observed effects may reflect systematic differences in behavior between people who travel during rush hours versus other times, rather than the effect of crowdedness per se. That is, purchases may be driven by variations in commuter type rather than crowdedness. Thus, to reduce the concern of self-selection we address this threat in several ways.

Figure 1 **(Color online) Crowdedness and Purchase Rates**



First, crowdedness is more likely to occur during peak hours of travel. To isolate the effects of crowdedness from peak hours, we have field data across peak and nonpeak hours of crowdedness. This is because the SMS was sent from morning to evening. For each day of our study, five different times were selected to represent the five cycles people may experience during an average day. Each time cycle represents a peak or nonpeak hour of crowdedness and thereby a potentially different level of crowdedness. The first time cycle was from 7:30–8:30 and represents the morning rush hour. The second was from 10:00–12:00, representing the lull after the morning rush hour traffic. The third was from 14:00–16:00, the afternoon lull before the evening rush hour traffic. The fourth was from 17:30–18:30, the evening rush hour. The fifth was from 21:00–22:00, the after-dinner traffic. Within each time cycle, the provider sent SMS to two or three trains, for a total of 14 trains a day. These five time cycles nested in the 14 subway trains help control for the systematic differences between various types of subway commuters, i.e., business commuters at rush hours versus nonbusiness commuters at nonrush hours.

In addition, crowding may differ across weekdays and weekends. On weekdays, work schedules might force business travelers to self-select into crowded trains during rush hours, while nonbusiness travelers (e.g., retirees and homemakers) might self-select into noncrowded trains during lull hours. Also, on weekends, leisure schedules allow people to self-select into more or less crowded trains. Thus, to isolate the effects of crowdedness from different types of commuters across weekdays and weekends, we have field data from two different days, i.e., a weekday (Wednesday) and a weekend (Saturday). This helps control for the systematic differences between weekday and weekend crowdedness in our model.

Our model estimates the purchase likelihood of each mobile user as $PurchaseLikelihood_i$. We model the unobserved likelihood of making a mobile purchase as a logit function of crowdedness in subway trains. Following Agarwal et al. (2011, p. 1063) and Guadagni and Little (1983), we assume an i.i.d. extreme value distribution of the error term in the logit model:

$$PurchaseLikelihood_i = \frac{\exp(U_i)}{1+\exp(U_i)}$$
$$U_i = \alpha + \beta \times crowdedness_i + \gamma \times weekend_i + \delta \times peak\ hour_i + \tau \times X_i + \varepsilon_{i1}, \tag{1}$$

where U_i denotes the utility of a mobile purchase, and X_i is a vector of control variables with mobile use behaviors. Because weekends and weekdays are expected to have different crowdedness patterns, we control for these effects with a *weekend* dummy (1 = weekend, 0 = weekday). We further identify the effects of crowdedness by controlling for time of day effects. Because peak hours and nonpeak hours are expected to have different crowdedness patterns, we include a *peak hour* dummy (1 = peak hours during 7:30–8:30 and 17:30–18:30, 0 = otherwise). Also, we conducted additional analyses with more time dummies of time-specific effects, beyond the one weekend dummy and peak hour dummy, and found robust effects of crowding on purchase rates of the SMS mobile ads. Also, ε_i is comprised of the idiosyncratic error terms. Of key interest here is the effect (β) of crowdedness on mobile purchase likelihood, after controlling for mobile user behaviors, peak hours, and day effects. Our model controls for mobile use habits based on mobile users' individual monthly bills (average revenue per user (ARPU)), call minutes used (monthly minutes of usage (MOU)), SMS sent and received, and data use (general packet radio service (GPRS)).[5] Appendix A presents a histogram of ARPU.

Also, although we do not have random treatment of crowdedness, the wireless company randomly selected subjects from the targeted subway population to randomize away user heterogeneity. The targeted population had not previously subscribed to a missed call alert plan, nor received a similar SMS from the wireless company. This also helps rule out potential carryover effects of prior marketing campaigns. For example, if passengers have already received a similar mobile promotion, promotion repetition or fatigue may drive the results. For each user from this targeted subway population, a random number was assigned via SAS software's random number generator and RANUNI function, which returns a random value from a uniform distribution (Deng and Graz 2002). The random numbers are then sorted in sequence from which a sample is extracted. Integrated in the wireless provider's IT system, this algorithm can compute and randomize users instantly to accurately gauge the level of crowdedness while sending the SMS in real time. Because the wireless company maintains the purchase records of all of its clients, it knows immediately whether a given mobile user in the subway train had previously subscribed to the promoted service. Such dynamic but instant computation and randomization are difficult to execute if not done by the wireless company, thereby representing a unique feature of our field data.[6]

Table 2, Panel A presents the logit model results. Various models test the effects of crowding with and without the peak hour and weekend covariates, in addition to the mobile use behaviors. As shown in Table 2, the effects of crowdedness on consumer responses to mobile ads (i.e., purchase likelihood) are statistically significant (all $p < 0.05$), after controlling for the effects of observable user heterogeneity due to peak versus nonpeak hours, weekday or weekend variables, and mobile use behaviors. These effects are consistently significant across the models with or without the weekday versus weekend effects and peak versus nonpeak hour effects.

Furthermore, we test the threshold level for the effects of crowding. Because fewer than two passengers per square meter is not truly representative of crowded environments, we should not see effects of crowdedness on mobile purchase likelihood for such a low threshold of crowdedness. We report our results in Table 2, Panel B. As expected, we find no significant effect of crowdedness on mobile purchase when crowdedness is less than two passengers per square meter. This

[5] Government regulations prohibit the wireless provider from revealing customers' private information such as income. However, income is not relevant in our context because the promoted product costs about 50 cents per month. ARPU is the revenue that one customer's cellular device generated. Users with a higher ARPU might be more likely to purchase the missed call alert promotion because they might connect with more people. Individual MOU is how much voice time a user spent on her mobile. MOU can help control for customer heterogeneity, as business travelers may have a higher MOU. Also, SMS is the amount of monthly text messages sent and received, and can also help tease out the effects of consumer age as younger generations are more prone to SMS use. GPRS is a measure of the individual monthly volume of data used with the wireless service provider. GPRS is useful in controlling for traveler habits in using the mobile Web and downloading mobile content. In additional analyses, we also tried to use factor analysis with Principal Component Analysis via VARIMAX rotation and obtained one underlying common factor of ARPU, MOU, SMS, and GPRS. The results are robust to this factor analysis approach to mobile use behavior.

[6] The field data further control for several other factors. First, we rule out station effects by using only one station in the subway system. Compared with stations in suburban areas, those in downtown areas are likely to be more crowded. Also, some subway stations have food stands and newspaper stands, whereas others do not. To control for these differences, the SMS was pushed from only the fourth stop along the subway line. The fourth station was selected to ensure that enough passengers had boarded the train since the first station, but that they also still had a sufficient distance to travel to stations further along the line. Also, we rule out the effect of the subway direction in which passengers travel because the wireless company sent the SMS to trains travelling in a single direction towards the city center.

Table 2 Effect of Crowdedness on Consumer Response to Mobile Ads

Panel A: Effect of crowdedness				
Crowdedness	**0.239**** (**0.067**)	**0.213**** (**0.075**)	**0.178**** (**0.071**)	**0.114**** (**0.042**)
Day effects (weekend dummy)	No	No	Yes	Yes
Time of day effects (peak hour dummy)	No	Yes	No	Yes
Ln(ARPU)	0.415** (0.181)	0.411** (0.173)	0.303** (0.124)	0.305** (0.128)
Ln(MOU)	−0.045 (0.072)	−0.045 (0.066)	−0.043 (0.070)	−0.044 (0.069)
Ln(SMS)	0.004 (0.076)	0.004 (0.075)	0.003 (0.073)	0.006 (0.073)
Ln(GPRS)	−0.002 (0.028)	−0.002 (0.027)	−0.001 (0.025)	−0.001 (0.024)
Observations	10,690	10,690	10,690	10,690

Panel B: Lower threshold with under 2 passengers/m^2		
Crowdedness		−**0.084** (**0.270**)
Day effects (weekend dummy)	Yes	Yes
Time of day effects (peak hour dummy)	Yes	Yes
Ln(ARPU)	0.354 (0.267)	0.352 (0.265)
Ln(MOU)	−0.235 (0.142)	−0.231 (0.142)
Ln(SMS)	0.083 (0.146)	0.074 (0.148)
Ln(GPRS)	−0.028 (0.052)	−0.026 (0.053)
Observations	2,886	2,886

Notes. ARPU, Average revenue per user; MOU, minutes of use; SMS, number of texts sent and received per user; GPRS, data use with the wireless provider. Note also that Panel B restricts the observations to under two passengers/m^2.
$^{*}p < 0.10$; $^{**}p < 0.05$.

suggests a lower boundary threshold of crowdedness effects. Put differently, for crowdedness to have an effect, there must be at least two or more passengers per square meter.

Therefore, these results support our overall hypothesis: Physical crowdedness engenders higher consumer response to mobile ads. Still the effect of crowdedness is nonlinear and positive after a lower threshold.

We also assess the economic significance of crowdedness on mobile ad purchases. As shown in Figure 1, compared with the baseline of a lower level of crowdedness (1.96 passengers/m^2), when crowdedness doubles (4.02 passengers/m^2), the estimated marginal mean likelihood of mobile purchases increases by 16.0% (=(0.0319 − 0.0275)/0.0275). In addition, when crowdedness spikes even more (4.97 passengers/m^2), the likelihood of mobile purchases jumps 46.9% (=(0.0404 − 0.0275)/0.0275). On average, purchase rates measured 2.1% with fewer than two people per square meter, and increased to 4.3% with five people per square meter. As such, commuters in crowded subway trains may welcome targeted ads on their mobile phones and are about twice as likely to respond by making a purchase vis-à-vis those in noncrowded trains.

Note that in our setting, subways were not packed to capacity (such as some commutes in Tokyo, with up to 11 passengers/m^2). In that case, it is logical to speculate an upper boundary effect of crowdedness: Too dense a crowd would negatively affect mobile purchases because congestion would restrict the ability to use a mobile phone. However, we checked the squared and cubed terms of crowdedness, but failed to find either of them significant ($p > 0.10$).

Even after accounting for observables, some unobservables may drive both crowdedness and purchases. That is, because commuters may self-select into different trains, the crowd may be endogenously induced, and some unobserved variable may drive both crowdedness and purchases. In other words, the crowd may be endogenous and, if so, may confound the results.[7] We address this potential endogeneity threat by exploiting sudden variations in crowdedness induced not only by unanticipated street closures aboveground but also by train delays belowground.

3.1.2. Identification to Address Endogeneity via Unanticipated Street Closures. We exploit sudden variations in crowdedness due to a traffic halt aboveground. Via street closures, the local government temporarily halted vehicular traffic for an hour on a weekday. Because the traffic intervention was enforced to provide a high-security police escort to government personnel, passengers were not forewarned. Thus, the temporary traffic intervention changes the level of crowdedness within the subway trains, creating a sudden spike in crowdedness. During this traffic halt intervention, the wireless provider randomly sent SMS to passengers on subway trains. It promoted a different product category with the same purchase price for greater generalizability of the findings. The promoted service enabled users to stream videos on their mobile devices. The SMS read "*To watch the newest videos on your mobile anytime, anywhere, for only ¥3 per month, reply KTV3 now and get ¥3 off of your next month's bill!*" For mobile users who responded with the provided mobile short code, the cost was charged to their phone bill. Crowdedness was measured in the same manner and mobile users who had not previously subscribed to this video service were selected. Thus, we can pool the street closure

[7] We acknowledge the associate editor and two anonymous reviewers for this insight. One common strategy to address endogeneity threats is to use instrument variables (Shriver et al. 2013, Sonnier et al. 2011, Stephen and Toubia 2010). However, a valid instrument variable (correlated with crowding but not correlated with purchase rates) is hard to obtain in our natural setting of crowding in subway trains. Another common strategy is Propensity Score Matching (PSM) as discussed later in §3.2.

sample and add the interaction between the street closure and crowdedness. A significant interaction here would be a stronger test of the impact of crowdedness because this impact is driven by the sudden variations in crowdedness induced by the street closures. To that end, we developed the following model:

$$\begin{aligned} U_i = \alpha + \beta \times crowdedness_i + \phi \times street\ closure_i \\ + \varphi \times crowdedness_i \times street\ closure_i + \gamma \times weekday_i \\ + \delta \times peak\ hour_i + \xi \times location_i + \tau \times X_i + \varepsilon_{i2}, \quad (2) \end{aligned}$$

where *street closure* is a dummy variable (coded as = 1 for users in the street closure sample and = 0 if otherwise). Because the street closures affected two specific subway stations, we added a *location* variable in model 2.

We report the results in Table 3, Panel A. In model 1 we entered the mobile covariates to control for user heterogeneity in terms of observable mobile use behaviors. In model 2 we entered the street closure variable to control for its main effects. In model 3 we entered the crowdedness variable, and in model 4 we entered the interaction between crowdedness and the street closure. As shown in Table 3, model 2, the street closure dummy was negative and insignificant, which makes sense because the street closure itself should not lead to a higher purchase likelihood. As shown in model 4 of Table 3, the interaction between crowdedness and the street closure was positive and significant. This confirms that variations in mobile purchases are indeed significantly driven by sudden variations in crowdedness induced by the street closure shock aboveground.

We also verified that the average crowdedness in this street closure during the same affected hour (14:00–15:00 during the business week on Thursday) was 3.257 passengers/m^2. As expected, this is indeed substantially higher than the counterpart (2.01 passengers/m^2) *not* in this street closure but in the same hour. In addition, there may be a concern that the street closure intervention could bring a systematically different type of commuter population (one that normally uses surface transportation modes) into the subway system, which may confound our results. We checked and confirmed that the observable characteristics of people in the street closure sample are statistically the same as their counterparts not in the street closure sample (see Table 4). Thus, this alleviates the concern that street closures bring a different population into the subway and further supports the effect of crowding on mobile purchases.

Still, we cannot rule out the possibility that this street closure aboveground may involve a different type of commuter population belowground. Thus, we need sudden variations in crowdedness that involve the same subway commuter population. This is achieved by exploiting unanticipated train delays in the subway system.

Table 3 Evidence with Sudden Variations in Crowdedness

Panel A: Sudden street closures effects				
Crowdedness × Sudden street closures				**0.492**** (**0.187**)
Crowdedness			**0.126**** (**0.041**)	**0.114**** (**0.042**)
Sudden street closures		−0.120 (0.117)	−0.142 (0.177)	−1.887 (1.057)
Ln(ARPU)	0.301** (0.118)	0.308** (0.119)	0.308** (0.119)	0.306** (0.119)
Ln(MOU)	−0.043 (0.065)	−0.043 (0.065)	−0.044 (0.065)	−0.044 (0.065)
Ln(SMS)	0.014 (0.069)	0.014 (0.069)	0.015 (0.069)	0.013 (0.069)
Ln(GPRS)	−0.001 (0.024)	−0.001 (0.023)	−0.001 (0.023)	−0.001 (0.023)
Day effects (weekend dummy)	Yes	Yes	Yes	Yes
Time effects (peak hour dummy)	Yes	Yes	Yes	Yes
Observations	11,960	11,960	11,960	11,960
Panel B: Sudden train delays effects				
Crowdedness × Sudden train delays				**0.669***** (**0.148**)
Crowdedness			**0.306***** (**0.108**)	**0.282***** (**0.119**)
Sudden train delays		0.142 (0.161)	0.130 (0.184)	0.162 (0.174)
Ln(ARPU)	−0.0003 (0.0016)	−0.0003 (0.0016)	−0.0003 (0.0016)	−0.0003 (0.0016)
Ln(MOU)	0.0001 (0.0001)	0.0001 (0.0001)	0.0001 (0.0001)	0.0001 (0.0001)
Ln(SMS)	0.0001 (0.0003)	0.0001 (0.0003)	0.0001 (0.0003)	0.0001 (0.0003)
Ln(GPRS)	−0.0000 (0.0000)	−0.0000 (0.0000)	−0.0000 (0.0000)	−0.0000 (0.0000)
Day effects (weekend dummy)	Yes	Yes	Yes	Yes
Time effects (peak hour dummy)	Yes	Yes	Yes	Yes
Observations	13,702	13,702	13,702	13,702

Notes. ARPU, Average revenue per user; MOU, minutes of use; SMS, number of texts sent and received per user; GPRS, data use with the wireless provider.
$^{*}p < 0.10$; $^{**}p < 0.05$.

3.1.3. Identification to Address Endogeneity via Unanticipated Train Delays. On a Friday in the city of our study, the subway trains were delayed for several minutes because a passenger's backpack became accidentally stuck in a train door. As a result, the trains suddenly became more crowded. Because the train delays were unexpected a priori, this natural experiment with sudden variations in crowdedness further addresses the potential endogenous selection bias via the same population of commuters in the subway system. During the unanticipated train delays, the wireless provider randomly sent mobile ads to users to stream videos on their mobile devices. Crowdedness was measured in the same manner. Thus, we can add

Table 4 Summary Statistics of Mobile Users' Wireless Usage Behavior

	Regular passengers ($N = 10{,}690$)		Street closures passengers ($N = 1{,}270$)		Train delays passengers ($N = 3{,}012$)	
	Mean	S.D.	Mean	S.D.	Mean	S.D.
ARPU	59.424	41.144	59.551	41.488	59.118	40.147
MOU	567.024	731.090	561.063	736.778	550.804	719.550
SMS	311.913	222.189	312.346	224.979	315.522	228.972
GPRS	27,856.6	8,867.1	28,445.8	8,944.3	27,336.8	8,506.7

Notes. F–tests of ARPU, MOU, SMS, and GPRS show no statistical differences (all $p > 0.20$) across the three samples, and t-tests of them also show no statistical differences (all $p > 0.20$) across any combination of two samples. ARPU, MOU, SMS, and GPRS comprise key indicators of wireless use behavior. ARPU is the revenue that one customer's cellular device generated. MOU is how much voice time a user spent on her mobile. SMS is the amount of monthly text messages sent and received. GPRS is a measure of the individual monthly volume of data used with the wireless service provider.

the interaction between unanticipated train delays and crowdedness. Significance of this interaction would be a stronger test of the impact of crowdedness because this impact is driven by the sudden variations in crowdedness induced by unanticipated train delays with the same population of subway passengers. Thus we developed the following model:

$$\begin{aligned} U_i = {} & \alpha + \beta \times crowdedness_i + \phi \times train\ delay_i \\ & + \varphi \times crowdedness_i \times train\ delay_i + \gamma \times weekday_i \\ & + \delta \times peak\ hour_i + \tau \times X_i + \varepsilon_{i3}, \end{aligned} \tag{3}$$

where *train delay* is a dummy variable (coded as $= 1$ for users in the delayed trains, and $= 0$ if otherwise). Table 3, Panel B presents the results. In model 1 we entered the mobile covariates to control for user heterogeneity. In model 2 we entered the unanticipated delay shock variable to control for its main effects. In model 3 we entered the crowdedness variable, and in model 4 we entered the interaction between crowdedness and the unanticipated train delay. As shown in Table 3, Panel B, model 2, the unanticipated train delay shock, itself, was insignificant. This makes sense because the unanticipated delay, per se, should not lead to a higher purchase likelihood. As shown in models 3 and 4, crowdedness significantly boosts mobile ad purchase likelihood ($p < 0.05$). Most important, the interaction between crowdedness and the unanticipated train delay was positive and significant. This confirms that variations in mobile purchases are indeed significantly driven by the sudden variations in crowdedness that are exogenously induced by the unanticipated train delays.[8] We also determined that the average crowdedness *with* train delays around 10:00 during the business week on Friday was 3.63 passengers/m^2. As expected, this is indeed higher than the corresponding level (2.91 passengers/m^2) *without* train delays in the same hour. We also verified that the observable characteristics of commuters in the train delay sample are statistically the same as their counterparts not in this sample (see Table 4). This confirms that the same subway population was involved in the train delays. Therefore, these results provide more empirical evidence for the effects of crowding by exploiting an exogenous shock of unanticipated delayed trains in the subway system.

3.2. Robustness Checks with Propensity Score Matching

We adopt PSM to determine consumer responses to crowding after matching passengers via observable covariates. PSM tests whether consumer responses are driven by crowding rather than user heterogeneity; after matching covariates via PSM, users are not heterogeneous but rather homogenous. With PSM, the field data mimics randomized field experiments and becomes a quasi-experiment design with pseudo-treatment and pseudo-control groups (Huang et al. 2012). Then, the pseudo-treatment is exogenous and confounds are randomized away, so that the effects on mobile ad purchases are attributed to crowdedness (Rosenbaum and Rubin 1983, Rubin 2006).[9]

PSM involves two stages. The first is to derive the propensity score to match individuals, and the second is to test the effects of crowding conditional on the matched homogenous individuals. In the first stage, we mirrored randomization by matching the probability of passengers who would experience the sudden variations of crowding with PSM. The propensity score is the probability that passengers would enter trains with sudden variations of crowding (pseudo-treatment group) versus otherwise (pseudo-control group), given their observed covariates of mobile use behavior. We derive propensity scores using a logistic regression in which the dependent variable $= 1$ if a commuter enters trains with sudden variations in crowding, and $= 0$ if otherwise. We then match the propensity scores, and as a

[8] Note that unanticipated delays can lead passengers to use their phones more (e.g., to inform others about the delays), which can systematically change the purchase rates. However, these results provide more evidence that, together with the other analyses, there is a causal effect of crowdedness on purchase rates. We thank an anonymous reviewer for this point.

[9] We acknowledge the associate editor and an anonymous reviewer for this suggestion. Huang et al. (2012, p. 133) note that "PSM and instrumental variables are two common techniques to correct for selection bias" and if instruments are hard to find, PSM is a viable solution. In essence, conditional on covariates, PSM helps ensure that the assignment of commuters to pseudo-treatment or control crowding is independent of crowdedness outcomes (Rosenbaum and Rubin 1983). When the propensity scores of users in the two types of crowdedness are identical, users are equally likely to experience pseudo-treatment of crowding, since the values of the confounding covariates indicate an equal chance. We also analyzed the data with same-train-same-time commuters but without PSM and found consistent support for the significant effects of crowding.

result can compare commuters who are virtually similar to each other in the pseudo-treatment group with those in the control group. Matching these two groups allows us to isolate and test the pseudo-treatment effects of crowdedness in the second stage, after accounting for the effects due to observable covariates.

Table 5 reports the two-stage results of the PSM. Panel A summarizes the results using the sudden variations in crowding from street closures, whereas Panel B does so for sudden variations from train delays. In Panel A, we have 782 matched passengers (391 matches between the pseudo-treatment and control groups) from the passengers who rode the same train in the same affected hour. In Panel B, we have 2,270 matched passengers (1,135 matches). In Table 5 first-stage results in Panels A and B suggest that many linear and squared terms of mobile use behaviors are significant in determining the propensity score.[10] As shown in Figure 2, Panels A and B, the propensity score distributions between the pseudo-treatment and control groups are quite different in the histogram plots before PSM using nearest neighbor matching. However, after matching, the distributions are virtually identical between the two groups. Thus, PSM helps to ensure that the commuters are virtually similar to each other, suggesting that we have established user homogeneity to the extent possible.

In the second stage of PSM, we test our results of crowdedness effects conditional on matched propensity scores. The second-stage results in Table 5, Panels A and B confirm that crowdedness significantly affected mobile purchase likelihood after PSM. Of particular importance, conditional on user homogeneity via PSM, the interaction between crowdedness and street closures (Panel A) and unanticipated train delays (Panel B) were both statistically significant ($p < 0.05$). As such, this confirms that after using PSM to derive virtually similar passengers, consumer response to mobile ads are indeed driven by crowdedness, and that the lifts in mobile ad response are robust to sudden variations in crowdedness induced by both street closures aboveground and train delays belowground.

Table 5 Robustness Checks with Propensity Score Matching

	Estimate	Pr > ChiSq
Panel A: Street closures PSM		
First-stage PSM parameter		
Ln(ARPU)	−1.387	0.015
Ln(MOU)	1.642	0.002
Ln(GPRS)	0.303	0.000
Ln^2(ARPU)	0.458	0.000
Ln^2(MOU)	−0.131	0.001
Ln^2(SMS)	−0.038	0.018
Ln^2(GPRS)	−0.045	0.000
Second-stage PSM parameter		
Crowdedness × Sudden street closures		0.318*** (0.075)
Crowdedness	0.131** (0.052)	0.125** (0.047)
Sudden street closures	−0.082 (0.069)	−0.095 (0.076)
Observations	782	782
Panel B: Train delays PSM		
First-stage PSM parameter		
Intercept	109.6	<0.0001
Ln(ARPU)	3.9236	<0.0001
Ln(MOU)	−0.1596	0.5231
Ln(SMS)	0.2555	0.5131
Ln(GPRS)	−17.5559	<0.0001
Ln^2(ARPU)	−0.4188	<0.0001
Ln^2(MOU)	−0.00349	0.8699
Ln^2(SMS)	−0.0193	0.5941
Ln^2(GPRS)	0.6442	<0.0001
Second-stage PSM parameter		
Crowdedness × Sudden train delays		0.519*** (0.131)
Crowdedness	0.281*** (0.111)	0.236*** (0.131)
Sudden train delays	1.124 (0.190)	1.074 (0.185)
Observations	2,270	2,270

Notes. In the first-stage of PSM, the predicted likelihood in this logit model is the propensity score $P(X)$. After matching $P(X)$ with nearest neighbor scores, the sample t-tests of ARPU, MOU, SMS, and GPRS show no statistical differences ($p > 0.10$) between the pseudo-treatment and pseudo-control groups. ARPU, Average revenue per user; MOU, minutes of use; SMS, number of texts sent and received per user; GPRS, data use with the wireless provider.
$^{*}p < 0.10$; $^{**}p < 0.05$; $^{***}p < 0.01$.

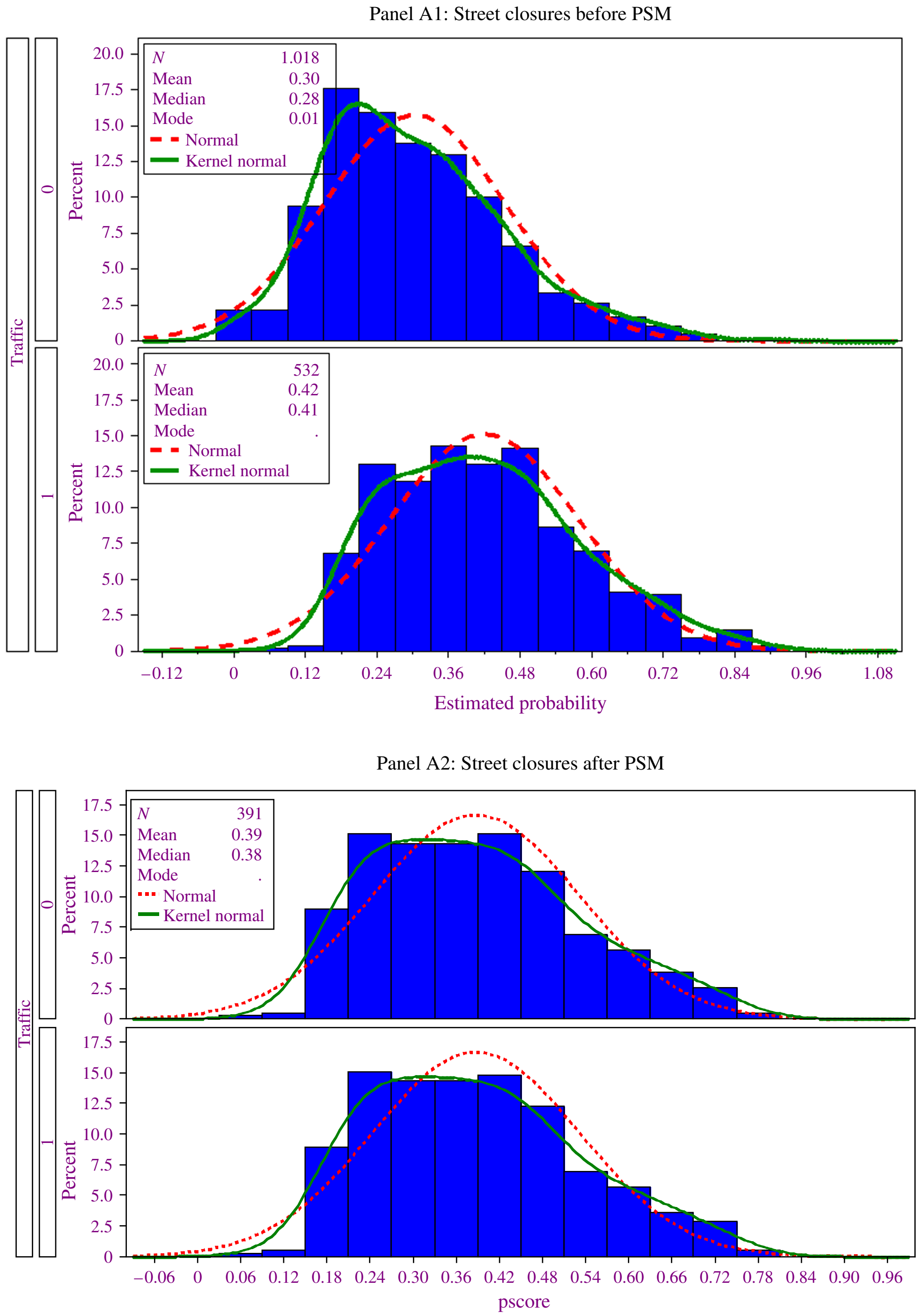
3.3. More Evidence with Survey Data

Further evidence with survey data provides deeper insights into the effects of crowding. With its customer service call-center, the wireless provider surveyed 300 passengers. Among these, 180 had received and purchased the promoted service, and 120 had received but had not purchased it. The surveys can help identify possible reasons that crowdedness affects purchase likelihood, after matching the purchase records and measured crowdedness from the field data.[11] Appendix B shows the survey instrument adopted by our corporate

[10] The PSM literature suggests that use of the squared terms in the first stage is common. For example, Huang et al. (2012, p. 134) used population squared, income per capital squared, Herfindahl index squared, distance in nearest Walmart store squared, and total population within two miles squared. Entering squared terms makes sense when they improve the model fitness in generating the propensity score, i.e., generating a better propensity score for matching observables. Nevertheless, we ran the PSM model without such squared terms and found consistent evidence for the effects of crowding, albeit with worse first stage model fitness in generating the propensity score.

[11] A caveat of surveys is that correlation, rather than causality, is involved. Given the low purchase rate, another caveat is the oversampling of users who made mobile purchases. Yet oversampling also implies a high chance of capturing the true purchase reasons

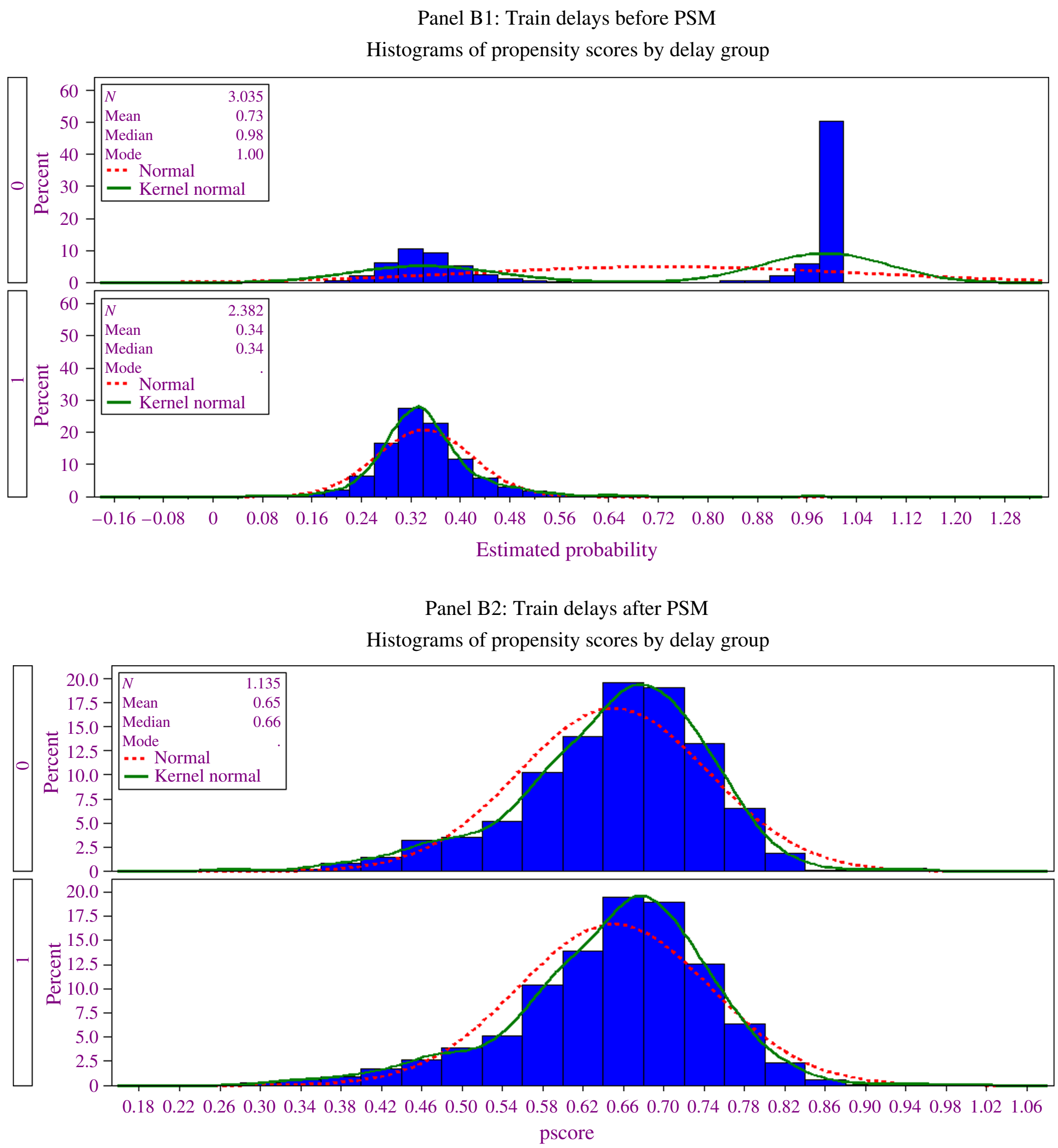
Figure 2 (Color online) Propensity Score Distribution



partner. We report the results in Table 6. In model 1, we entered mobile use behaviors, along with survey responses to questions related to preference for the promotion, perceptions of missed call frequency, a prevention focus, deal proneness, and price consciousness. As expected (and as shown in model 1), preference for the promotion had a significant impact on purchase likelihood ($p < 0.05$). In model 2 we entered the crowdedness variable from our field data. The results confirm that crowdedness had a significant impact on mobile purchase ($p < 0.05$). This corroborates our field data evidence for the effect of crowdedness. Interestingly, as

among all purchasers. Still, we have a representative sample of nonpurchasers similar to the general users in our data in terms of mobile use behavior characteristics. Also, the surveys help rule out several alternative explanations such as social anxiety, prevention mindsets, price consciousness, and deal proneness (see Appendix B for the constructs).

Figure 2 (Color online) Continued



shown in model 3, mobile immersion had a significant impact, while crowdedness remains significant, albeit with a smaller effect size (all $p < 0.05$). As expected, in model 4, mobile involvement is positively related to purchase likelihood ($p < 0.05$). Also, via bootstrap mediation tests (Preacher and Hayes 2004), we find that crowdedness is positively related to mobile immersion (0.465, $p < 0.01$), which is positively related to involvement with SMS and phones (1.375, $p < 0.01$). In both cases, zero is not included in the 95% confidence interval estimates of the bootstrap mediation tests. Together, these findings support a *mobile immersion* explanation: As crowding invades one's physical space, people adaptively turn inwards and become more involved with their personal mobile devices. In turn, the more consumers are involved with their mobile devices, the more likely they are to purchase (Petty et al. 1983).

4. Conclusion

This research tests whether consumers are more likely to respond to mobile ads in the hyper-contextual dimension of a crowded environment. It analyzes the impact of crowdedness in subway trains on users' propensity to respond to targeted mobile ads. An ideal way to gauge the effect of crowdedness would be to randomize consumers into different conditions of crowdedness. Because this is practically impossible to achieve in an actual field setting, we depend on field data (a quasi-field experiment combined with natural experiments) and multiple identification strategies to address potential endogeneity and selection issues.

Table 6 Field Survey Results

Parameter	Model 1	Model 2	Model 3	Model 4
Ln(ARPU)	0.066	0.067	−0.116	0.033
	(0.364)	(0.367)	(0.423)	(0.372)
Ln(MOU)	−0.127	−0.135	−0.124	−0.128
	(0.162)	(0.164)	(0.185)	(0.165)
Ln(SMS)	−0.145	−0.132	0.228	−0.159
	(0.190)	(0.191)	(0.213)	(0.196)
Ln(GPRS)	−0.067	0.060	0.119	0.063
	(0.067)	(0.068)	(0.075)	(0.068)
Missed call preference	0.741**	0.723**	0.766**	0.752**
	(0.122)	(0.122)	(0.134)	(0.129)
Missed call frequency	0.023	0.026	0.125	0.029
	(0.140)	(0.141)	(0.153)	(0.143)
Prevention focus	0.061	−0.029	0.042	0.082
	(0.146)	(0.171)	(0.214)	(0.202)
Price consciousness	−0.041	−0.047	−0.074	−0.016
	(0.145)	(0.146)	(0.162)	(0.148)
Deal proneness	0.080	0.060	0.112	0.116
	(0.141)	(0.143)	(0.159)	(0.148)
Crowdedness		0.238**	0.219**	0.152*
		(0.116)	(0.118)	(0.097)
Mobile immersion			**0.821****	**0.725****
			(**0.352**)	(**0.358**)
Social mimicry			−0.203	−0.165
			(0.245)	(0.231)
Down time			0.144	0.220
			(0.143)	(0.134)
Social anxiety			−0.097	−0.059
			(0.160)	(0.152)
Show off			−0.076	−0.186
			(0.161)	(0.150)
Mobile involvement				0.882**
				(0.218)
Day effects (weekend dummy)	Yes	Yes	Yes	Yes
Time effects (peak hour dummy)	Yes	Yes	Yes	Yes
Observations	235	235	235	235

Notes. The dependent variable here is purchase or not. ARPU, Average revenue per user; MOU, minutes of use; SMS, number of texts sent and received per user; GPRS, data use with the wireless provider.
*$p < 0.10$; **$p < 0.05$.

Mobile technology provides novel measures of physical crowdedness. In the unique marketing environment of our data, the underground subway is equipped with subway-specific cellular lines that run along the tunnel walls. Crowdedness is then gauged as the volume of mobile users in each subway train who automatically connect to this underground line as a function of the size of the train compartment. Our data analyses: (1) control for selection on observables that include peak versus nonpeak traffic hours, weekdays versus weekends, mobile use behaviors, and randomly sending mobile ads, (2) exploit sudden changes in crowdedness induced by street closures aboveground and train delays belowground, and (3) use a PSM estimator to further eliminate selection bias. With over 15,000 mobile users, our data documents that crowdedness has a positive effect on mobile ad purchase likelihood after a lower threshold, and that this crowding effect is quite robust to different modeling techniques. Further analyses with field surveys suggest that a mobile immersion accounts for why crowding affects response to mobile ads: Consumers may be more deeply immersed in their mobile phones when in a crowded environment. That is, consistent with the social psychology literature, as crowding invades one's physical space, people adaptively turn inwards and become more susceptible to mobile ads.

Our results offer several theoretical and managerial implications. Theoretically, we deepen understanding of consumer reactions to crowding. The consumer behavior literature reveals how people react to crowding. Crowding can trigger nervousness and decrease creativity (Maeng et al. 2013). In retail settings it can provoke negative attitudes towards the store (Hui and Bateson 1991). Crowding has also been shown to induce avoidance behaviors and prompt shoppers to rely more on familiar brands, avoid interaction with store employees and others, and reduce shopping time (Harrell et al. 1980). Overall, these studies have largely shown the negative effects of crowding. However, we find that targeting consumers in crowded environments with mobile promotions may serve as a welcome relief. That is, in the context of the consumers' physical environment, our work reveals positive effects of crowding on mobile ads.

We also extend the mobile commerce literature by showing that environmental contexts such as crowding in public transit are significant determinants of mobile ad effectiveness. Physical crowding affects consumer receptivity to mobile messages. We advance prior research on mobile targeting (Danaher and Dagger 2013; Dickinger and Kleijnen 2008; Ghose et al. 2013a, b; Fong et al. 2015; Luo et al. 2014; Molitor et al. 2014) by revealing the new hyper-contextual dimension of crowding, a novel way to target mobile users. For marketers, the ability to reach consumers anytime, anywhere, offers substantial opportunities (Kim et al. 2011). The potency of mobile ads hinges on understanding consumers' real-time experiences and the hyper-contextual environment (Kenny and Marshall 2000). Marketers must not only comprehend "how customers behave with respect to the mobile medium" (Shankar and Balasubramanian 2009, p. 128) but also how they behave with respect to their dynamic environment.

The average public transportation commute time for Americans is 48 minutes each way (McKenzie and Rapino 2011). This considerable amount of consumer down time during daily commutes can be a gold mine for marketers. Grocery retailers in countries such as South Korea have created virtual stores in underground subways by superimposing product images with Quick Response (QR) codes over the platform walls. While waiting for their train, commuters can purchase groceries on their mobiles for convenient delivery (Solon 2011). In the Netherlands, infrared sensors inside trains are used to send mobile alerts to boarding passengers about each car's occupancy to improve commuting efficiency (Wokke 2013). Indeed, marketers are adopting new mobile technologies such as iBeacon (a short-distance pulsing device that operates on the Bluetooth low energy of any iOS7 device). Retailers can send within-store mobile promotions to connect with shoppers in real time. Sports stadiums and entertainment venues have also adopted iBeacon to help spectators find their seats and receive concession-stand offers (Grobart 2013). Understanding consumers' quotidian routines and contextual activities enables marketers to deliver relevant messages that cater to customer needs in the moment. Especially as Apple's iPhone 6 hits the market with bigger screen sizes for more vivid viewing, marketers can deliver more media-rich mobile ads (Sloane 2014). Indeed, consumers are receptive to receiving "messages from particular brands at specific times and under certain conditions" (Johnson 2013). To the extent that consumers have a greater involvement with their mobile phones in relatively more crowded contexts, mobile marketing may see higher effectiveness in crowded settings with in-app advertising and display ads (Bart et al. 2014).

However, there is a catch. Although crowding is an inherent part of everyday life, marketers should acknowledge that personal space preferences and tolerance for crowding may vary by settings (subway, concert hall, and restaurant). For example, crowded restaurants more likely comprise self-selected attendance and can boost people's feelings of excitement or signal quality (Knowles 1980, Tse et al. 2002). In that context, targeting consumers on their personal devices may be construed as an annoying and unwelcome invasion of privacy. By contrast, our subway is less likely to involve self-selecting into desired crowds because public transit often denotes commutes with strangers. Also, in the subway setting, consumers could instantly purchase and activate the promoted service. Future research could investigate different consumption settings to reveal more nuanced effects of crowdedness. Research could also study whether differences in product conspicuousness matter when targeting consumers in crowded versus noncrowded settings. Finally, future research may examine whether consumers can regulate their negative moods such as stress in crowded environments by purchasing hedonic goods or services.

In conclusion, this research serves as an initial step to measure crowdedness with mobile technologies and identify the effects of crowdedness on purchases. Managers may consider gauging the crowdedness of a consumer's physical environment as a new way to boost the effectiveness of mobile ads.

Supplemental Material

Supplemental material to this paper is available at http://dx.doi.org/10.1287/mksc.2015.0905.

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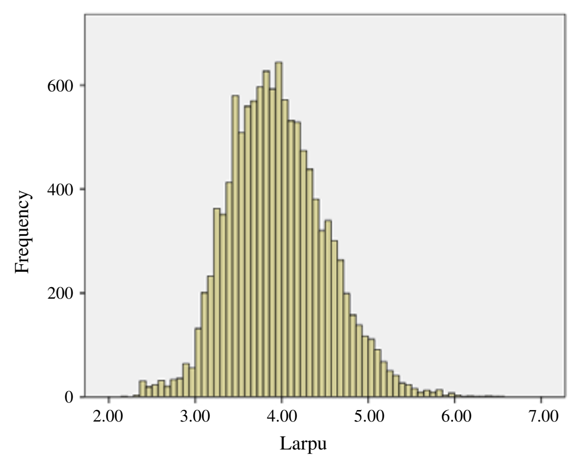
Appendix A. Histogram of ARPU Mobile Usage Behavior



Appendix B. Field Survey Items

The corporate partner's customer service call-center conducted the field surveys. The surveys were conducted the day after the first part of the field study. This day was selected because the first part of the field data was completed after 22:00, thus making it too late to call respondents. To avoid demand effects, the surveys were presented under the guise of a customer satisfaction survey intended to assess satisfaction with the subway wireless signal. Before answering the survey questions, mobile users were asked to recall when they received and purchased the SMS on the subway the preceding day to remind them of the crowdedness they experienced. Respondents were asked to confirm whether they had received the promotional SMS while in the subway and whether they had read and replied (or not) to it while in the subway.

Mobile immersion (adapted from Burger 1995)

When surrounded by a lot of people in the subway, I am usually eager to get away by myself.

During a subway ride, I would like to spend the time quietly.

Social mimicry (Tanner et al. 2008)

When I see others looking at their mobiles, I usually look at my own mobile.

Passing down time

I prefer to pass down time by fiddling with my mobile phone in the subway car.

Social anxiety (Fenigstein et al. 1975)

Large groups in the subway make me nervous.

During the subway ride, it is embarrassing to look at strangers.

Show off (Richins and Dawson 1992)

I like my cellular phone to be noticed by other people.

Mobile involvement (Olsen 2007, Warrington and Shim 2000)

In the subway, I am involved with my cell phone.

I pay attention to incoming SMS during the subway ride.

Several alternative explanations to the results are tested. First, commuters may wish to occupy themselves during the *down time* of their travel. Crowdedness would restrict the activities commuters could engage in to make this down time productive (i.e., it would be harder to use a laptop). Also, due to crowded environments, the invasion of personal space would mean an increased likelihood of catching unwanted gazes, which can heighten social stress and embarrassment. This is tested for with a measure of *social anxiety* (Fenigstein et al. 1975). Also, in crowded environments, there may be a higher number of consumers who use their mobiles, which could visibly and subconsciously prompt others to do likewise. Thus, *social mimicry* (Chartrand and Bargh 1999, Tanner et al. 2008) is tested for. In public environments, some people may wish to flaunt their smartphones to others. This alternative explanation is tested by measuring the desire to *show off* mobile devices (Richins and Dawson 1992). All of these explanations may account for why crowdedness may lead consumers to become more involved with their mobile devices. To rule out additional explanations, several control variables were included in the survey instrument. The covariates included deal proneness (Lichentenstein et al. 1995), price consciousness (Dickerson and Gentry 1983), a prevention-focused mindset (per prior research which finds that crowdedness triggers a prevention-focused mindset (Maeng et al. 2013)), the perceived frequency of missed calls, and the preference for missed call alerts. In addition, we control for mobile use behaviors with the company's customer records.

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