Mobile Targeting

Xueming LUO, Michelle ANDREWS, Zheng FANG, and Chee Wei PHANG

Forthcoming at Management Science

Acknowledgement:

The authors gratefully acknowledge the immense and invaluable support from one of the world's largest mobile service providers to conduct the field experiment. The work described in this paper was supported by a grant from the National Natural Science Foundation of China (Grant No. 71102018).

Xueming Luo is Charles Gilliland Distinguished Professor of Marketing, Department of Marketing and Supply Chain Management, Temple University (luoxm@temple.edu); Michelle Andrews is PhD student at Temple University (michelle.andrews@temple.edu); Zheng Fang is Associate Professor at Sichuan University, China (149281891@qq.com). Chee Wei Phang is Associate Professor of Information Systems at School of Management, Fudan University, Shanghai China (phangcw@fudan.edu.cn).

Mobile Targeting

Abstract

Mobile technologies enable marketers to target consumers by time and location. This study builds on a large-scale randomized experiment of short message service (SMS) sent to 12,265 mobile users. We draw on the contextual marketing theory to hypothesize how different combinations of mobile targeting determine consumer responses to mobile promotions. We identify that temporal targeting and geographical targeting individually increase sales purchases. Surprisingly, the sales effects of employing these two strategies simultaneously are not straightforward. When targeting proximal mobile users, our findings reveal a negative sales-lead time relationship; sending same-day mobile promotions yields an increase in the odds of consumer purchases compared to sending them two-day prior to the promoted event. However, when targeting non-proximal mobile users, there is an inverted-U, curvilinear relationship. Sending one-day prior SMSs yields an increase in the odds of consumer purchases by 9.5 times compared to same-day SMSs, and an increase in the odds of consumer purchases by 71% compared to two-day prior SMSs. These results are robust to unobserved heterogeneity, alternative estimation models, bootstrapped resamples, randomization checks, consumer mobile usage behavior, and segmentation of consumer scenarios. In addition, we conducted follow-up surveys to delve into the psychological mechanisms explaining the findings in our field experiment. In line with consumer construal arguments, consumers who received SMSs close (far) in time and location formed a more (less) concrete mental construal, which, in turn, increased their involvement and purchase intent. These findings suggest that understanding the when, where, and how of mobile targeting strategies is crucial. Marketers can save money by carefully designing their mobile targeting campaigns.

Key words: mobile commerce; mobile targeting; randomized field experiment

1. Introduction

Mobile commerce is projected to exceed $86 billion by 2016 (eMarketer 2013a). This exponential growth is facilitated by mobile technology's distinct capacity for targeting by both location and time (Ghose and Han 2011, Shankar et al. 2010). On one hand, the portability of cell phones allows marketers to communicate with customers through timely messages (Chung, Rust, and Wedel 2009, Hui et al. 2013). Thus, temporal targeting is a prudent strategy for companies who can wield information technology to connect with customers at the right moment.

On the other hand, GPS-enabled smartphones permit managers to target customers by location. Research has demonstrated the significance of proximity in consumers' mobile Internet searches, suggesting that geographical targeting can boost consumer responses (Ghose, Goldfarb, and Han 2013).

Interestingly, the efficacy of simultaneously employing geographical and temporal targeting strategies has yet to be examined. This research gap is rather intriguing because mobiles' commercial advantages are due to their spatial *and* temporal maneuverability: time and space are "among the most fundamental dimensions of all economic activity" (Balasubramanian et al. 2002, p. 350). After all, the effectiveness of mobile promotions is context dependent, i.e., reaching customers at the right place *and* time (Kenny and Marshall 2000).

Therefore, the goal of our research is to analyze how well geographical and temporal targeting strategies work when considered in combination. Specifically, to explore the effectiveness of mobile targeting strategies, we use data derived from a large, randomized field experiment conducted in partnership with a mobile carrier. In our experiment, we created a new application for smartphone devices to offer movie tickets to mobile users, so as to cleanly identify the causal effects of treatment conditions. Customers in proximal and non-proximal locations received SMS messages offering discounted movie tickets on different days prior to the movie's show time. These tickets were purchasable with the download of the accompanying new cinema-ticket-app.

In our experiment, the mobile service provider relied on two principle methods to influence sales purchases. Specifically, the experiment employed *temporal targeting* with three manipulations (by sending messages to mobile users on the same day, one-day prior, or two-day prior to the movie's showing) and *geographical targeting* with three separate manipulations (by sending messages to mobile users located at near, medium, or far distances from the cinema). We examine the joint effects of temporal targeting and geographical targeting in generating mobile sales purchases.

Our results indicate that temporal targeting and geographical targeting individually increase sales. Surprisingly, the sales effects of combining these two mobile targeting strategies are not straightforward. When targeting proximal mobile users, our findings reveal a negative sales-lead time relationship;

sending same-day mobile promotions yields an increase in the odds of consumer purchases by 76% compared to sending them two-day prior to the promoted event. However, when targeting non-proximal mobile users, there is an inverted-U, curvilinear relationship. Sending one-day prior SMSs yields an increase in the odds of consumer purchases by 9.5 times compared to same-day SMSs, and an increase in the odds of consumer purchases by 71% compared to two-day prior SMSs. These results admonish targeting non-proximal distances with either too little or too much promotional lead-time. Additional analyses support that these results are robust to a wide array of alternative explanations (estimation models, bootstrapped resamples, experiment randomization checks, unobserved heterogeneity due to theater effects, consumer mobile usage behavior, and segmentation of consumer scenarios).

To reveal the psychological mechanisms explaining the results of our randomized experiment, we conducted follow-up surveys. We show that consumer construal level explains how consumers differentially evaluate mobile messages under varying contexts of spatial and temporal conditions, thereby leading to variance in the effectiveness of mobile targeting. Consumer purchase intentions are highest when they receive an SMS close to the time and place of the promoted event. This occurs because shorter temporal and geographical distances induce consumers to mentally construe the promotional offer more concretely, which, in turn, increases their involvement and purchase intent. These surveys also eliminate many additional alternative explanations (i.e., price sensitivity, consumer impulsiveness, intrusiveness concerns, age, gender, education, income, mobile experience, movie-watching preferences and frequency), thus lending further support to our field experiment observations.

We offer several contributions to the IS and marketing fields. Substantially, our investigation quantifies the effectiveness of combining temporal and geographical targeting for mobile commerce. While prior mobile literature has examined either promotion lead-time or geographical location individually, the effectiveness of combining them both has not been well studied yet. Specifically, as shown in Table 1, we are the first to apply scientific methods in a realistic business setting in order to address how mobile targeting's effects vary by *both* when and where messages are sent. This is important because "if time is the warp of economics, then space is its woof" (Ohta 1993, p. 1). As space and time are intertwined, simultaneously tapping into these two dimensions to target customers at the right place and at the right time can enhance the performance implications of mobile technologies. Thus, to gain a more holistic understanding of mobile commerce, it is imperative to investigate the effects of mobile targeting with respect to both space and time. Complementing prior studies with secondary mobile usage data (Ghose, Goldfarb, and Han 2013), we leverage a large-scale randomized field experiment to account for endogeneity and causality issues. We show that the effectiveness of time-based targeting is contingent upon user location, and vice versa, providing new insights on how promotion lead-time and geographical location work jointly. In addition, follow-up surveys support a psychological mechanism, i.e., consumer construal level can account for why consumers respond to SMSs under different combinations of spatial and temporal distances. By explicating the combined effects of geographic and temporal targeting via field experiment, as well as the underlying psychological mechanism of consumer construal via survey methods, we contribute to theory for IT-enabled marketing in the mobile space.

<< Insert Table 1 about here >>

Practically, we offer actionable guidelines for marketers to harness the advantages of mobile targeting amidst its growing popularity. As mobile users are demanding localized and timely access to content and services, companies are rushing to acquiesce (Frost and Sullivan 2012). To court over 137 million in the "smartphone surge" (Birkner 2012), industry leaders such as Apple, Google, and Nokia now provide free map and navigation services. Location-based services furnish compelling opportunities for businesses to advertise relevant offers when nearby consumers are searching for services. Concomitantly, faster delivery rates to consumers enhance the virtual prospects of mobile commerce (Chen and Wu 2013). Marketing to mobile users is more economical than traditional mediums, with $2.85 per user a much lower expenditure than the $50 to $100 per user for newspapers (Ovide and Bensinger 2012). Yet, adopting a spray and pray strategy may not be optimal. Targeting mobile users by time inevitably requires the consideration of their location, and vice versa. While marketers should shift resources to targeting either by time or location, when considering both components simultaneously, they should carefully balance the combinations. As consumers increasingly use location-based services and time-sensitive offerings, discerning the effectiveness and mechanism of mobile targeting strategies in terms of *both* location and time is critical for the growth of the mobile commerce industry.

2. Theory and Hypotheses

This section details the importance of timing and location for mobile targeting. We also examine why combining temporal and geographical targeting is complicated. Contextual marketing is the fundamental theory motivating our study.

2.1 Contextual Marketing Theory

The contextual marketing theory (Kenny and Marshall 2000) can account for the importance of temporal and geographical targeting for mobile users. Essentially, this theory holds that marketers' efforts must be context dependent in order to influence consumer purchasing decisions. It is noted that "new [mobile] technologies enable businesses to reach customers whenever and wherever they are ready to buy … the focus will shift from content to *context*" (Kenny and Marshall 2000, p. 119). As mobiles are portable with ubiquitous reach, mobile users can respond to location-based services and time-sensitive offerings (Johnson 2013). As such, marketers may leverage contextual messages to build ubiquitous relationships with mobile customers "24 hours a day, seven days a week, anywhere on the planet – in their cars, at the mall, on an airplane, at a sports arena" (Kenny and Marshall 2000, p. 123). Thus, temporal and/or geographical targeting for mobile users can be effective.

More importantly, contextual marketing theory also suggests that temporal and spatial boundary conditions may have an *interactive* impact on consumer behavior. The interrelationship of different contexts and situational constraints affect consumer decision-making, since consumers' decision to attend an event may vary as a function of the time and place of the event (Cappelli and Sherer 1991, Johns 2006). In the IS literature, Galletta et al. (2006) found that web usage contexts operate in conjunction to affect consumer intentions to revisit the site. Deng and Chi (2012) demonstrated that situational constraints interact to affect consumers' use of the information systems. As such, this stream of research on context-based decisions in both the marketing and IS literature motivates us to expect interactive effects of time and distance, beyond the individual effect of either temporal or geographical targeting.

2.2 Why Does Temporal Targeting Matter?

Prior literature affirms that the timing of promotions impacts their effectiveness (Zhang and Krishnamurthi 2004). For example, Prins and Verhoef (2007) show how marketing communications reduce consumers' adoption time for a new mobile e-service. Acquiring real-time insights into customer needs can endow companies with a competitive advantage when they react with a "speed versus sloth" approach (McKenna 1995, Scott 2012). Indeed, the virtual intimacy resulting from technological advances permits marketers and customers to maintain continuous connections that foster the transition from "real-time insight to real-time action" (Macdonald et al. 2012, p. 108). The benefit of real-time targeting has been demonstrated by in-store promotions, i.e., spending on the fly (Stilley et al. 2010). Recently, Hui et al. (2013) documented that in-store real-time targeting mobile coupons can increase consumers' unplanned purchases. Thus, it is expected that temporal targeting on the same day with less promotional lead-time (versus earlier days with more lead-time) would be an effective strategy in generating mobile sales.

2.3 Why Does Geographical Targeting Matter?

Studies also highlight the importance of location proximity in mobile decisions. Consumers were more willing to act on a promotional offer whose event was located close to them (Banerjee and Dholakia 2008, Spiekermann et al. 2011). Specifically, consumers were more likely to respond to a mobile promotion when they were close to the promoting store than when they were at home (Banerjee and Dholakia 2008). In a field experiment, Spiekermann and colleagues (2011) found that consumers were less likely to redeem restaurant coupons when they received them at farther locations from the restaurant. Similarly, Ghose and colleagues (2013) support consumers' preference for locations that are close to them at the time they conduct their mobile-based internet searches. Consumers also rely on location-based applications to coordinate with friends and acquire local information (Lindqvist et al. 2011, Molitor, Reichart, and Spann 2012). As consumers adopt GPS-enabled technology, more marketers are embracing mobile marketing strategies (Shankar et al. 2010). Thus, consistent with these studies, it is expected that geographical targeting at proximal distances (versus non-proximal distances) would be more effective in garnering mobile sales.

2.4 Why Is Temporal and Geographical Targeting in Combination Complicated?

However, the effects of combining both temporal and geographical strategies simultaneously have been neglected in the literature. Grounded in the contextual marketing theory, we expect that the interactive effects would be rather complicated, and may not always produce synergistic sales outcomes when combining two seemingly beneficial targeting strategies, as the costs and benefits of different combinations may vary for consumer decision-making.[1]

More specifically, for targeting mobile users in proximal distances, we expect that promotion lead-time will have a negative effect on sales purchases. This is because when an event is happening soon and close by, consumers focus on the *contextualized* benefits of the event, i.e., doing it right then and there, according to the contextual marketing theory (Kenny and Marshall 2000). Indeed, consumers often attach greater significance to events whose benefits are experienced immediately (Prelec and Loewenstein 1991) and are easier to visualize (Chandran and Menon 2004) with increased purchases. In contrast, when events occur later in time, the less contextual benefits are perceived for immediate decision-making (Goodman and Malkoc 2013, Liberman and Trope 2008). Given the small screen sizes of mobile devices, consumers tend to use mobiles for immediate activities, so less-timely information would be perceived to be less beneficial to consumers (Molitor, Reichart, and Spann 2012). Thus,

H_1: When targeting mobile users located at proximal distances, promotion lead-time will have a negative effect on the likelihood of consumer purchases as a result of the mobile promotions.

[1] We thank an anonymous reviewer for this insight.

On the other hand, for targeting mobile users at non-proximal distances, mobile promotion lead-time will not have a simple linear, but rather an inverted U-shaped effect on sales purchases. This is because too little lead-time (same-day mobile promotions) will provide low benefits to mobile users located in non-proximal distances, given the rather short notice and little time to plan and act on the mobile promotions (Kenny and Marshall 2000, Thomas and Tsai 2012). Such low perceived benefits thus reduce the likelihood that consumers will purchase the mobile promotions.

However, too much promotional lead-time (two-day prior mobile promotions) will not be effective either. This is because the perceived benefits of receiving promotions for events occurring both in the far future *and* at a farther distance are also low, given that such events are not immediate, contextualized, or concrete (Liberman and Trope 2008). That is, mobile messages containing less-timely information and events at non-proximal distances generate little utility for consumer decision-making (Ghose et al. 2013, Yan and Sengupta 2013). As such, the low perceived benefits of too much promotion lead-time for non-proximal distances would also reduce the purchase likelihood. Thus, the upshot is that when targeting consumers at non-proximal distances, neither too little lead-time nor too much lead-time in mobile promotions would deliver the highest benefits for consumers to make mobile purchases.

H_2: When targeting mobile users located at non-proximal distances, promotion lead-time will have an inverted U-shaped effect (one-day prior mobile promotions are more effective than same-day or two-day prior) on the likelihood of consumer purchases as a result of the mobile promotions.

3. Field Experiment and Data Description

3.1 Experimental Design

To explore the effectiveness of mobile targeting strategies, we conducted a *randomized* field experiment with one of the largest wireless providers in the world. We randomly selected mobile users in our experiment to send an SMS message. The SMS advertised a hedonic experience in a movie-going setting by offering movie tickets at a substantial discount (50% off).

To clearly identify the effectiveness of mobile targeting, we controlled for five factors. First, we selected only one movie to promote in order to decrease the confounding effects of different movies and customer tastes. We also ensured that our selected movie was not a blockbuster to control for bias due to popularity. Second, we targeted mobile users who had not previously purchased movie tickets with their mobiles, which we ascertained because we developed a *new* mobile app specifically for this experiment.

Third, the mobile users in our database were sent SMS messages based on a randomization procedure. Our randomized experiment consisted of nine treatment groups (3 distance manipulations x 3 time manipulations), from which mobile users were randomly selected. Specifically, mobile users were randomly selected using three steps following Deng and Graz (2002). First, we assigned a random number to each user of all mobile customers (of the wireless provider) who were at near, medium, or far distances from the movie theaters at the time we sent the SMSs. We did this by using SAS software's random number generator and running the RANUNI function, which returns a random value from a uniform distribution. Then, we sorted all random numbers in sequence, after which we extracted a sample from the sequence. These three steps were integrated in an algorithm of the wireless provider's IT system, which enabled *instant* computation and randomization in order to avoid mobile users moving from one location to another while the SMSs were being sent in real-time (this instant computation/randomization is difficult to execute and serves as a unique feature of our field experiment design).

In our experiment, distance means a mobile user's physical distance from the movie theater. This definition of location from the promoted event is in line with Spiekermann and colleagues's (2011) use of distance from a restaurant and Ghose and colleagues' (2013) use of distance from retailers in mobile-based internet searches. Drawing a circle with the movie theater located at the circle's center suggests that at a larger radius (a farther distance from the movie theater), there would be more mobile users located within this band. At a smaller radius (a closer distance to the movie theater), there would be fewer people located within this band. That is, the mobile service coverage of locations that are at near, medium, and far distances from the cinema grows larger and larger. Thus, a potential bias would be the *over*-sampling of users at far distances and the *under*-sampling of users at near distances within the concentric circle. To overcome this bias, we sampled an equal number of mobile users located at each of the three distances to the movie theater (near, medium, far). In other words, we have paid a great amount of attention in order to be free from such biases and have achieved a relatively balanced set of cells for the treatments, as discussed subsequently.

The fourth factor we controlled for was cinema-specific. We did so by locating cinemas in four different directions of the city's center (north, south, east, and west) and selecting four movie theaters that were all located along the *same* periphery (on the 2nd ring) of the city.

Fifth, we controlled for users' wireless behavior, based on each user's monthly phone bills, minutes used, SMSs sent and received, and data usage. We use these covariates to control for the alternative explanations of our results due to different user wireless habits. For example, it is possible that users with higher SMS and data usage might be more likely to download a movie app and purchase tickets since they are likely to be more familiar and hence comfortable with such an operation. Because regulation enjoins the wireless provider from releasing customers' private information, we could not identify users by demographic information. However, our data permit us to describe users by their mobile usage behavior.

In the wireless industry, ARPU, MOU, SMS, and GPRS are key indicators of mobile usage behavior. ARPU (the average revenue per user) is a measure of the revenue generated by one customer's cellular device. MOU (individual monthly minutes of usage) is the amount of voice time a user spent on his or her mobile. SMS (short message service) is the number of monthly text messages sent and received. GPRS (general packet radio service) is used to measure the individual monthly volume of data usage with the wireless service provider. Table 2 reports the summary statistics of these variables in our data, and Table A1 in the appendix presents the distributions of the variables.

<< Insert Table 2 about here >>

Our experiment occurred over a three-day period during the last weekend of August 2012. We conducted our experiment in cooperation with an international chain of cinemas (IMAX theaters). The wireless provider sent SMS messages promoting discounted tickets to a movie showing at 4 pm on the last Saturday of August 2012. Recipients purchased movie tickets by downloading the accompanying movie ticket application and ordering from the app. Mobile users could not purchase IMAX movie tickets through other mobile apps from our wireless provider partner at the time of this field experiment. The population of targeted users consisted of mobile users who were geographically within two kilometers of one of the four cinemas when the SMSs were sent (because all cinemas are more than four kilometers away from each other, there were no redundant subjects). Once mobile users downloaded the app, they could then purchase their tickets and reserve their seats. If users bought a ticket, the cost was immediately charged to their monthly phone bill.

In total, we sent SMSs of the promoted movie showing to 12,265 mobile users. Of these users who received an SMS, 901 of them bought movie tickets. This equates to a 7.35% response rate, which initially seems low. But, this rate is high compared to the 0.42% response rate for mobile targeting (measured by click-through rates) (eMarketer 2012). Each of the movie theaters reserved several rooms for the promoted movie's showing in anticipation of mobile sales from our field experiment. Also, because the selected movie was showing at 4 pm, which is a typically slower time for movie sales, we did not have capacity constraints that would contaminate the experiment. This is a between-subjects (not a within-subjects) field experiment design, whereby each mobile user only receives one SMS message promoting the movie. The wireless provider partner can identify all mobile users' phone numbers and made sure no mobile user was sent the message more than once in our field experiment. Because the mobile service provider maintains download and purchase records of every user it sent the SMS to, it provides a good opportunity for testing and measuring the effectiveness of mobile targeting. Also, our dataset permits us to identify what time and where each user was located when he or she received an SMS of the mobile promotion.

3.2 Temporal Targeting Messages

For temporal targeting, we employed three (same-day, one-day prior, and two-day prior) targeting conditions. We manipulated same-day targeting by sending SMSs on Saturday at 2 pm (2 hours prior to the movie's showing), one-day prior by sending SMSs on Friday at 2 pm (26 hours prior), and two-day prior by sending SMSs on Thursday at 2 pm (50 hours prior).[2]

3.3 Geographical Targeting Messages

For geographical targeting, we employed three (near, medium, and far) targeting conditions. We manipulated near distances by sending messages to users located within 200 meters of a theater. We manipulated medium distances by sending SMSs to users located between 200 and 500 meters of a cinema, and far distances by sending SMSs to users located between 500 meters and 2 kilometers of a cinema.[3] The mobile industry distinguished distance by the microcell in which a user's mobile was located at the time of the SMS' transmission. A microcell is a cell in a mobile phone network that is served by a low-power cellular base station and covers a limited area, usually ranging from 50 to 200 meters. Because wireless providers need to forecast mobile usage and configure their service accordingly, they have accurate geographic and population information of every microcell.

4. Econometric Analysis

The randomized nature of our field experiment renders our data analyses straightforward in the traditional treatment-control sense. Randomized field experiments can avoid the endogeneity and causality biases (Goldfarb and Tucker 2011). While users' unobservable differences might confound our results, by dint of the experiment's randomization, differences in user purchase likelihoods can be attributed to the targeting strategies. Our model estimates the unobserved likelihood or probability of sales purchase for each mobile user, which we denote as $Purchase\ Probability_i^{Mobile}$. We model the latent probability of purchasing movie tickets as a logit function of temporal targeting and geographical targeting. Following Agarwal et al. (2011, p. 1063) we assume an i.i.d. extreme value distribution of the error term in the logit model:

---

[2] The SMS message sent to mobile users in our field experiment would read as follows: "To enjoy a movie showing this Saturday at 4:00 pm for a discounted price, download this mobile ticket app to purchase your movie ticket and reserve your seat." This SMS is sent to mobile users with a combination of three time manipulations (2, 26, and 50 hours prior to the movie's showing) and three distance manipulations (< 200 m, between 200 m and 500 m, and between 500 m and 2 km from the movie theater).

[3] We classified near distances as being fewer than 200 m because microcells usually only serve 200 m radii. We classified medium distances as being between 200 m and 500 m since this range is still within walking distance to the theater. We classified far distances as being between 500 m and 2 km since people can take public transport to reach the theater. We limited our targeting to 2 km since distances beyond that render it hard to control experimental manipulations.

$$Purchase\ Probability_i^{Mobile} = \frac{\exp(U_i^{Mobile})}{\exp(U_i^{Mobile})+1},$$

$$U_i^{Mobile} = \alpha^l + \beta^l \times distance_i + \gamma^l \times time_i + \delta^l \times distance_i \times time_i + \tau^l \times X_i + \mu_j{}^l + \varepsilon_i{}^l, \qquad (1)$$

where U_i^{Mobile} denotes the latent utility of a mobile purchase, X_i is a vector of mobile user controls (specifically, each user's average monthly revenue = ARPU, individual monthly minutes of usage = MOU, individual monthly SMSs sent and received = SMS, individual monthly volume of data usage = GPRS), μ_j accounts for the random unobserved heterogeneity in consumer preferences for specific theaters, and ε_i is comprised of the idiosyncratic error terms. Of key interest are the main effects of geographical targeting (distance), temporal targeting (time), and the interactive effects between geographical and temporal targeting (distance × time). We assess the model goodness-of-fit with Pearson Chi-square χ^2 in equation 2, Cox and Snell R^2 in equation 3, and Nagelkerke R^2 as specified in equation 4.

$$\chi^2_{Pearson} = \sum\nolimits_{\text{all cells}} \frac{(\text{observed count} - \text{expected count})^2}{\text{expected count}} \qquad (2)$$

$$\text{Cox and Snell } R^2_{CS} = 1 - \left(\frac{L(\mathbf{B}^{(0)})}{L(\hat{\mathbf{B}})}\right)^{\frac{2}{n}} \qquad (3)$$

$$\text{Nagelkerke's } R^2_N = \frac{R^2_{CS}}{1 - L(B^{(0)})^{2/n}}, \qquad (4)$$

where $L(\hat{\mathbf{B}})$ is the log-likehood function for the model with all estimates, and $L(\mathbf{B}^{(0)})$ is the Kernel of the log-likelihood of the intercept-only model, and n denotes the number of cases. We estimate the models with robust standard errors (sandwich estimators) clustered at the theater level, which can account for the possible bias that observations in one theater may have a common latent trait not observed by researchers (Greene 2007, see also Goldfarb and Tucker 2011, p. 393).

5. Results

In this section, we discuss our results and their economic impact. We also explore some additional analyses to check the robustness of the results.

5.1 Main Results

5.1.1 The Effect of Temporal Targeting

The key empirical results of our model are summarized in Table 3. Column (1) includes only the control variables as the baseline predictions, while column (2) enters the temporal and geographical targeting variables. Column (3) also includes the interaction terms for the targeting combinations.

Because there are three conditions for temporal targeting, we only need two dummy variables (the base is same-day targeting). As shown in column (2), the parameter estimate for the effect of temporal targeting with one-day prior mobile promotions is negative and significant compared to same-day mobile promotions ($\gamma = -0.285$, $p < 0.005$), and the estimate for two-day prior mobile promotions is also negative and significant compared to same-day mobile promotions ($\gamma = -0.330$, $p < 0.001$).[4] As shown in Figure 1, the estimated marginal mean effects results visually support that same-day mobile promotions generate a higher likelihood of consumer purchases than one- or two-day prior mobile promotions. These results are consistent with prior literature on the effect of temporal targeting, supporting that real-time marketing matters in mobile promotions (Hui et al. 2013, Zhang and Krishnamurthi 2004).

<< Insert Table 3 and Figure 1 about here >>

5.1.2 The Effect of Geographical Targeting

Also, consistent with prior literature on the effect of geographical targeting, the results in column (2) show that compared to near-distance mobile promotions (the base), the parameter estimate for geographical targeting with far-distance is negative and significant ($\beta = -0.284$, $p < 0.006$), though negative and insignificant with medium-distance ($p > 0.10$). As shown in Figure 2, the estimated marginal mean effects results visually support that near-distance mobile promotions result in a higher likelihood of consumer purchases than far-distance mobile promotions. These findings largely support the notion that location-based mobile technologies also matter in generating consumer purchases (Ghose et al. 2013, Spiekermann et al. 2011).

<< Insert Figure 2 about here >>

5.1.3 The Effect of Combining Temporal and Geographical Targeting

[4] Note that when testing hypotheses dealing with main effects (not interactions) in logit models, there could be cases where parameter coefficients are significant but marginal effects based on the Delta method are insignificant. In such cases, Greene (2007) explicitly recommends using the raw logit parameter coefficients, rather than the marginal effects, which is echoed in both the IS (Chen and Hitt 2002, p. 267) and the marketing literature (Agarwal et al. 2011, p. 1063).

Our main focus is on the combination of temporal and geographical targeting. Results of the likelihood ratio tests of comparing two models (one full model with all interaction terms and the other a reduced model without them) suggest that the full model with interactions significantly outperformed the reduced model (Chi-square = 38.88, $p < 0.001$), as shown in column 3 of Table 3. In addition, the parameter estimates of the four combinations of temporal and geographical targeting are all statistically significant (all δ estimates are significant, p ranges from 0.000 to 0.033). These results provide initial evidence for the significant effects due to different combinations of geographical and temporal targeting for mobile users.

Because our hypotheses involve interactions in logit models which specify non-linear relationships, it is not straightforward to interpret the coefficient results. Thus, we use the marginal effects of logit model estimates (Forman 2005) and the *pairwise comparison* of the estimated *marginal* means (Greene 2007) to test our hypotheses. We fixed variables in the model at their sample mean values, i.e., ARPU = 4.25; MOU = 5.97; SMS = 3.85; GPRS = 8.96 when obtaining the marginal effects. Specifically, using the sequential Sidak pairwise comparison, we find that the estimated marginal means of the near-distance x same-day are statistically significantly higher than that of near-distance x one-day-prior ($\chi^2 = 24.79$, $p <$ 0.000). In addition, the estimated marginal means of near-distance x same-day are significantly different from those of near-distance x two-day-prior ($\chi^2 = 23.08$, $p < 0.000$). Also, the pairwise comparison test results suggest that the marginal means of near-distance x one-day prior are insignificantly different from those of near-distance x two-day prior ($p > 0.082$). As shown in Figure 3, the estimated marginal mean effects results visually support that when targeting mobile users located in <u>proximal</u> distances, both one-day prior and two-day prior promotions are less effective than same-day, i.e., promotion lead-time has a negative effect on the likelihood of consumer purchases as a result of the mobile promotions, thus supporting H_1.

<< Insert Figure 3 about here >>

Similarly, with regards to targeting *far* distances, the pairwise comparison tests suggest that the marginal means of far-distance x one-day prior are statistically significantly larger than those of far-distance x same-day ($\chi^2 = 19.26$, $p < 0.001$), indicating that too *little* promotion-lead time (same-day targeting) results in a lower purchase likelihood. In addition, the pairwise comparison tests indicate that the marginal means of far-distance x one-day prior are *also* statistically significantly larger than those of far-distance x two-day prior ($\chi^2 = 8.67$, $p < 0.01$), suggesting that too *much* promotion-lead time (two-day prior targeting) also results in a lower purchase likelihood. As shown in Figure 3, the estimated marginal mean effects results visually support that when targeting mobile users located in <u>far</u> distances, neither too little lead-time (same day) nor too much lead-time (two-day prior) in mobile promotions would deliver the highest benefits for consumers to make mobile purchases, i.e., one-day prior is more effective than either same-day or two-day prior in an inverted U-shaped effect, thus supporting H_2.

To further test the significance of the inverted U-shaped effects of far distance, we employed a different method with the restricted and unrestricted models. Specifically, we compare two models via the likelihood-ratio Chi-square test, with one an *unrestricted* full model and the other a *restricted* model in which one interaction coefficient is set as the same as another interaction coefficient via linear restrictions, i.e., $\delta_{far\ distance \times same\ day} = \delta_{far\ distance \times two\text{-}day\ prior}$ (Greene 2007).[5] The likelihood-ratio test results suggest that the estimate parameter of far-distance x one-day prior is indeed statistically significantly different from that of far-distance x two-day prior (rejecting the null hypothesis of $\delta_{far\ distance \times same\ day} = \delta_{far\ distance \times two\text{-}day\ prior}$, $\chi^2 = 9.51$, $p < 0.01$), thus confirming H_2.

5.1.4 Economic Importance of Combining Temporal and Geographical Targeting

Following Ghose et al. (2013, p. 12) and Rutz et al. (2012), we describe the economic impact of combining temporal and geographical targeting strategies using the *odds ratios*. For mobile users located at proximal distances to the promoted movie theater, sending same-day mobile SMSs, compared to sending two-day prior SMSs, produces an increase in the odds of purchasing tickets on the mobile devices by 76% (1.76 = exp(0.570)), holding other variables constant.

For non-proximal targeting, sending *one*-day prior SMSs, compared to same-day SMSs, yields an increase in the odds of purchasing movie tickets by 9.5 times (10.46 = exp(2.348)), holding other variables constant. Also, compared to two-day prior SMSs, sending *one*-day prior mobile promotions exhibits an increase in the odds of purchasing movie tickets by 71% (1.71 = exp(2.348-1.814)), holding other variables constant. Therefore, for marketers targeting mobile customers located at non-proximal distances, sending messages one-day prior is optimal, and if marketers give too much or too little promotion lead-time, the targeting effectiveness tanks substantially.

5.2 Results Robustness and Ruling out Alternative Explanations

We took several additional steps to check the robustness of our results. First, besides the logit model, we conducted more analyses with a Probit model.

Specifically, with respect to the Probit model, the latent mobile purchase likelihood can be defined as:

Probit z = 1 mobile purchase if $z_i^* > 0$, and = 0 if otherwise,

$$z_i^* = \alpha^b + \beta^b \times distance_i + \gamma^b \times time_i + \delta^b \times distance_i \times time_i + \tau^b \times X_i + \mu_j{}^b + \varepsilon_i{}^b. \qquad (5)$$

[5] See a similar approach to tests comparing restricted vs. unrestricted logit models (but in a nested design) in Guadagni and Little (2008) and Kim et al. (2002).

Table 4 reports the Probit model results. As shown in Table 4, the results from the Probit model are qualitatively the same as those in Table 3. Also, the results of pairwise comparisons of models consistently show that for mobile users located at *proximal* distances to the promoted movie theater, sending same-day mobile SMSs significantly outperformed sending one-day-prior or two-day-prior SMSs in generating mobile purchases ($p < 0.001$). Thus, H_1 is supported across this alternative estimation model. Again, with regards to targeting *far* distances, the results of pairwise comparisons of models consistently suggest that the effects of far-distance x one-day-prior promotions are statistically significantly larger than not only those of far-distance x same-day (smallest $\chi^2 = 15.08$, $p < 0.001$) but also those of far-distance x two-day-prior (smallest $\chi^2 = 9.66$, $p < 0.01$) in generating mobile purchases across the Probit model specifications. Thus, these results confirm H_2 that neither too much nor too little promotion-lead time results in a higher likelihood of purchase for consumers located at far distances.

<< Insert Table 4 about here >>

Besides different estimate models, we conducted a battery of additional checks to rule out alternative explanations. First, we find that our results are robust to experiment randomization checks. Specifically, regarding possible imbalances in manipulation allocations and non-randomization bias, we checked our cells. As evidenced in Table 5, the counts in Panel A are fairly evenly distributed. For example, a total of 11.9% of mobile users received SMSs at near distances from the theater on a Thursday (two-day prior), 11.0% received SMSs at medium distances from the theater on a Thursday (two-day prior), and 11.5% received SMSs at far distances from the theater on a Thursday (two-day prior). Also, Panel B shows that the distance conditions are evenly distributed, and Panel C supports that the time conditions are evenly distributed as well.[6] As such, our results appear to pass the randomization check and do not suffer from systematic bias due to imbalances in manipulation allocations.

<< Insert Table 5 about here >>

Second, in our models, we have controlled for the effects of past mobile user behaviors in terms of ARPU, MOU, SMS, and GPRS. Thus, the observed effects of mobile targeting cannot be explained by alternative explanations due to different mobile usage behaviors.[7] Third, our equations have specified the parameter μ_j which accounts for unobserved heterogeneity in consumer preferences of theaters in our field experiment. Fourth, we checked the sub-samples of our data. Our main results included consumers who have non-smartphones (471 cases), who could not download the app to make the mobile purchase.

[6] We acknowledge an anonymous reviewer for this insight.

[7] Per an anonymous reviewer, we conducted more analyses with only the mobile targeting treatment dummies and without mobile user behavior controls. The results are qualitatively the same as those reported in Table 3 column 3. Again, all dummies for temporal targeting and geographical targeting and their interactions are significant ($p < 0.05$), as expected.

Thus, to test for result sensitivity, we excluded these non-smartphone cases and conducted sub-sample analyses. Again, as reported in Table 6, our results are robust to this sub-sample analysis. Moreover, we used the bootstrapping method with 5,000 resampling of the full dataset. The results in Table 6's last column confirm that our results are robust to bootstrap resampling.

<< Insert Table 6 about here >>

Finally, we check whether customer scenarios (as heterogeneous across users located in shopping, residential, and business districts) may drive some of our results, because prior studies on mobile targeting have suggested customer heterogeneity (Ghose and Han 2011, Vodanovich et al. 2010, Xu et al. 2010). Thus, we check customer scenarios to uncover subpopulations of consumers whose latent heterogeneity may be different and hence whose response may differ to the SMS.[8] Specifically, in our experiment, messages sent to different customer scenarios consisted of SMSs transmitted to users who were in one of three specific areas (labeled as segments). These customer scenarios consisted of mobile users in shopping, residential, or business districts at the time that we sent the SMS messages. We distinguished districts by the microcell in which a user's mobile was located at the time of the SMS' transmission. The results are reported in Table 6, and the estimated marginal mean effects results are visualized in Figure 4. Once again, we find that across the shopping and residential districts, targeting mobile users located at proximal distances by sending same-day mobile SMSs consistently significantly outperformed sending one-day prior or two-day prior SMSs (all $p < 0.001$), thus confirming H_1. With regards to targeting *far* distances, the pairwise model comparison results also consistently suggest that the effects of far-distance x one-day prior mobile promotions are statistically significantly larger than not only those of far-distance x same-day (smallest $\chi^2 = 12.69$, $p < 0.001$) but also those of far-distance x two-day prior (smallest $\chi^2 = 8.07$, $p < 0.01$) across the shopping and residential districts. Thus, again, H_2 is confirmed.

Interestingly, the estimates for targeting users located in the shopping district are relatively larger in effect size than in residential districts. This finding can be explained by prior literature on the congruence of consumers' mind-sets, which suggests that consumers' activities can trigger a particular mind-set which, in turn, can increase congruent purchase incidences (Chandran and Morwitz 2005, Xu and Wyer 2007). Because mobile users in shopping districts may engage in the hedonic experience of shopping, they will be more likely to respond to proximal SMSs promoting a congruent hedonic experience (a movie). Thus, the consumer purchase likelihood in shopping districts is higher than that in residential

[8] We thank an anonymous reviewer for pointing this out. Also, compared with traditional field experiments in which the messages vary while the targeted population is kept fixed, our field experiment is a targeting experiment in which the targeted sub-group populations vary in our field experiment (and thus may require various mobile targeting strategies).

districts. In addition, the results in Table 6 suggest most of the interaction effects were insignificant in the case of business districts. This is expected because SMS recipients located in business districts are more likely to have full-time jobs (relative to shopping or residential districts) and are thus less likely to purchase the tickets for the promoted movie.[9] Thus, these findings serve to not only pass falsification checks but also suggest that customer scenarios (as heterogeneous across users located in shopping, residential, and business districts) may indeed drive some variations in the potency of the effectiveness of mobile targeting.

<< Insert Figure 4 about here >>

6. Follow-up Survey and Psychological Theory

6.1 Psychological Theory-based Underlying Mechanism

To gain a better understanding of the psychological mechanism explaining the results of our field experiment, we conduct follow-up surveys. Grounded in the construal level theory (Trope and Liberman 2010), we expect that geographical distances (i.e., how far away from a promotional event in location) and temporal distances (i.e., how long away from a promotional event in time) can induce different consumer mental construals, which, in turn, can account for variances in mobile purchases. In a nut shell, this theory posits that individuals form a concrete or abstract mental construal, which, in turn, guides their decisions and behaviors.

Specifically, when individuals are close (far) to an event, they form more (less) *concrete* mental construals of the event's contextual details. In the psychology literature, with regards to time, when individuals were asked how likely they would attend a lecture that was happening in the near future, a concrete mental construal (i.e., the time of the lecture) was formed and more influential in their decisions (Liberman and Trope 1998). Similarly, with regards to location, when participants were informed that a video was filmed domestically (near), they described it more concretely than participants who were told it was filmed abroad (far). More importantly, consistent with contextual marketing's emphasis on the interactive effects of time and location (Kenny and Marshall 2000), construal level theory suggests that in contexts of close distance and near time, consumers focus on the *contextualized* benefits and form more concrete mental construals, which then induce more purchases. In other words, when consumers receive SMSs close to the place and time of the mobile offer, they form more concrete mental construals and, through this concrete construal, experience higher involvement in considering the offer and higher purchase intentions. Based on this discussion we designed our follow-up surveys to empirically test the underlying mechanism of consumer construal level.

[9] We thank an anonymous reviewer for this insight.

6.2 Survey Design

We measure the following constructs in our follow-up survey: *purchase intention*, *involvement*, *concrete construal level*, and *perceived intrusiveness of the message*. We also examine whether the relationships hold when considering consumer purchase *impulsiveness* that may be triggered upon receiving the SMS message (Rook and Fisher 1995) and *price consciousness* that may increase consumer interest in the discount offer (Dickerson and Gentry 1983). Additionally, we control for user *demographics* (age, gender, income, and education), whether a user had previously installed a similar mobile app for buying movie tickets, mobile usage experience, preference of when to watch movies (as some consumers may prefer watching movies on particular days of the week), and movie watching frequency. Figure 5 depicts the conceptual model tested in our survey.

<< Insert Figure 5 about here >>

The measurements of the main constructs are shown in Table A2 in the Appendix. To determine whether participants prefer watching movies on certain days of the week, we asked participants to respond to the following statement (framed in a reverse manner), “It does not matter to me what day of the week I watch a movie,” along a seven-point Likert scale from “Strongly disagree” to “Strongly agree.” To determine how often participants watch movies, we asked participants to select from amongst five options that ranged from “several times a week” to “less than once a month.”

Based on this set of items, we created four versions of the survey questionnaire to manipulate the different geographic and temporal distances: 1) low geographic distance, low temporal distance; 2) low geographic distance, high temporal distance; 3) high geographic distance, low temporal distance; and 4) high geographic distance, high temporal distance. Each questionnaire began with a description of a scenario corresponding to one of the four conditions as follows: “Imagine you are hanging out near a shopping mall located [200 meters, for the low geographic distance scenario, or 2 kilometers, for the high geographic distance scenario] away, at 2:00 pm on a [Saturday, for the low temporal distance scenario, or Thursday, for the high temporal distance scenario] afternoon, when you receive the following SMS message from the [wireless provider] (a picture of the message in a mobile phone screen is shown; the message promotes discounted tickets to a select movie showing at 4 pm on Saturday, consistent with the field experiment).”

We conducted our survey with the cooperation of a market research firm. The firm emailed subjects who use smartphones and randomly assigned a link to one of the four versions of survey questionnaires. We obtained 414 complete responses, with each survey version having approximately the same number of respondents. Table A3 in the appendix provides the descriptive statistics of the samples. The samples for the four scenarios are comparable since the mean comparison tests of their demographics are insignificant.

6.3 Survey Results

The descriptive statistics from Table A3 in the Appendix reveal insights that are largely consistent with our discussion. Across the scenarios, consumers in Scenario 1 (low spatial distance, low temporal distance) demonstrated the greatest tendency to construe the offer in concrete terms (as manifested by the amount of attention paid to concrete, incidental details such as the constraints and resources associated with installing the app to purchase movie tickets). Consumers in Scenario 1 also demonstrated the highest level of purchase intention and involvement in the SMS offer. These purchase intentions and involvement levels are noticeably lower in Scenario 3, which is characterized by low spatial distance but high temporal distance, compared with Scenario 1. This shows that for geographically proximate consumers, providing more time would decrease their involvement in considering the offer and purchase intention. It is also noted that concrete construal level, involvement, and purchase intention are lowest in Scenario 4, which is characterized by both high spatial and temporal distances.

Additionally, we observe a higher level of perceived intrusiveness of the SMS message in Scenarios 2 and 4 than in Scenarios 1 and 3. This supports that when consumers located farther away receive a message with little lead-time, the greater difficulty of reaching the event on time can induce consumers to perceive the message to be highly intrusive. In contrast, consumer perceived intrusiveness of the SMS message is lowest in Scenario 1. This indicates that consumers are more tolerant of unsolicited SMS messages when they are received at the right place and right time, and vice versa.

To obtain deeper insights into the relationships among the constructs, we proceeded to test the structural model using SmartPLS v2.0.M3, given that the analysis of the measurement model indicates satisfactory reliability and convergent and discriminant validity levels of the constructs (refer to Tables A4 and A5 in the Appendix). Table 7 presents the results of our analyses, organized according to the four samples. Specifically, we find that for consumers in Scenario 1 (low in both spatial and temporal distances), their more concrete construal level indeed led to their higher purchase intention. Thus, a concrete mental construal can directly prompt intention to install the app to purchase the discounted movie ticket. Also, a concrete construal level can operate indirectly by increasing the involvement of consumers in considering the offer, which subsequently leads to higher purchase intentions. Furthermore, a more concrete mental construal may reduce the degree to which consumers perceive the SMS message to be intrusive.

Compared to Scenario 1, the results from the other scenarios suggest a less prominent role of the proximity-inducing concrete construal level. Specifically, a concrete construal level appears to only weakly influence purchase intention in Scenario 2, and to only weakly influence involvement level in Scenario 4 ($p < 0.10$). The only significant effect ($p < 0.05$) observed for this measure is its link to involvement level in Scenario 3, which is characterized by low spatial distance. It is also important to note that in Scenario 2, the high perceived intrusiveness of the SMS message undermines consumer involvement in considering the offer. Such an effect is not observed in Scenario 4, although the perceived intrusiveness level is also high, which suggests that consumers in this scenario may be indifferent towards this type of targeted SMS message. While in Scenarios 1 and 3 perceived intrusiveness also poses a negative effect on involvement, a concrete construal level plays a role by directly reducing the perceived intrusiveness (Scenario 1) or by promoting involvement (Scenarios 1 and 3); both of which are absent in Scenario 2. Again, these results support that the heightened perceived intrusiveness of the SMS message in situations characterized by high spatial distance but low temporal distance has a detrimental impact on consumer involvement and purchase intentions.

Overall, the findings from the follow-up surveys not only corroborate our hypotheses, but also proffer a consumer construal level-based psychological process explaining the results of our field experiment.

6.4 Ruling out Additional Alternative Explanations

Our follow-up surveys also serve to rule out more alternative explanations. For example, one may question whether consumers who bought movie tickets in our field experiment were prone to impulse buying or were more price-conscious. Our survey findings disconfirm these notions, indicating no effect of possible confounds with impulsiveness or price consciousness on purchase intent. Our survey also enables us to control for the effects of education, age, and income on buying intentions. In addition, the results counter the preconception that consumers will feel intruded upon when they receive unsolicited mobile messages by revealing that consumers who were close to the movie temporally and geographically were more receptive to the SMSs.

7. Discussion

Our research adds to the strategy rulebook of the mobile marketing industry by showing the importance of temporal and geographical targeting. We draw on the contextual marketing perspective to hypothesize how different combinations of mobile targeting determine consumer responses to mobile promotions. To execute a large-scale randomized experiment, we undertook laborious efforts including striking collaborations with one of the world’s largest wireless providers, negotiating the mobile promotion discount, engaging real-world mobile users, and convincing our collaborating partners of the worth of testing combinations of mobile targeting strategies. In addition, we conducted follow-up surveys to delve into the psychological mechanisms underlying the different consumer responses to mobile targeting. Our findings offer important implications to both theory and practice, as discussed below.

7.1 Theoretical Implications

Despite its importance, mobile targeting is underexplored in the literature. Past research investigated geographical targeting (Ghose et al. 2013) and temporal targeting (Hui et al. 2013), but has not brought the two together to understand what combination defines the "right place and right time." Since space and time are inter-related and should be considered holistically through a contextual perspective, simply adding up their individual effects may not suffice. In this sense, we pioneer the exploration of the joint effects of geographical and temporal targeting for mobile users.

In analyzing the effects of SMS-based mobile targeting by time and location simultaneously, we affirm the localization- and time-criticality of mobile value propositions. We not only confirm that location-based services can influence consumer purchasing decisions, but also suggest that the success of location-based mobile targeting depends on time, and vice versa. By informing promotions in the mobile space, we respond to calls to investigate "the optimal strategies to adopt once GPS-enabled mobile devices become commonplace" (Forman et al. 2009, Shugan 2004, p. 473). For proximal locations, same-day targeting is more effective. For farther distances, giving enough time (to provide higher contextual benefits to mobile users) is more effective than giving too little or too much time. The inter-dependence of time- and location-based targeting highlights how employing both strategies in combination is more complicated than marketers would initially surmise.

This work contributes to the contextual marketing perspective (Kenny and Marshall 2000) in three key ways. (1) Our findings echo the alert that "simply multiplying the points of contact" is not the recipe for winning in the age of digital ubiquity. Marketers should shift their focus from multi-point contacts to a timely contact at the right place. (2) We also caution firms against employing targeting strategies that give too short or too long of an advanced notice when catering to customer needs. And (3) our finding underlines the importance of understanding customer scenarios. By knowing who the customer is and what they are currently doing, firms can achieve even greater mobile targeting effectiveness.

Also, we elucidate a psychological mechanism for why consumers behave differently under varying contexts of spatial and temporal distances through follow-up surveys. As prior research (Trope and Liberman 2010) shows that consumer mental construal can be contextually stimulated, our survey results suggest that the right combination of temporal and geographical targeting induces consumers to mentally construe the promotions more concretely, which, in turn, increases their involvement and purchase intent.

Thus, to the extent that consumer construal level is the process underlying mobile targeting effectiveness, marketers can employ messages designed to trigger concrete construals in order to increase mobile sales.

7.2 Practical Implications

Consumers are driving the need for a contextual mobile experience (Johnson 2013). Effective mobile targeting lies in the ability to deliver information that is both current and relevant. For example, stores like H&M and Central Market experienced 2.3% and 4.1% click-through rates respectively when they sent geoaware messages to nearby mobile users (Tode 2013). Recognizing this, 30% of the travel industry's mobile ad campaigns in 2012 employed geoaware targeting presumably to reach travelers who make in-destination bookings (eMarketer 2013b). Even the consumer packaged goods industry has begun to capitalize on limited-time offers and in-store promotions (eMarketer 2013c, Hui et al. 2013). Empowered by geo-fencing technologies, more and more marketers can more precisely target mobile customers when and where they are ready to buy.

Yet, there is a catch. When managers wish to reach consumers located at non-proximal distances, they should give just the right amount of advanced notice (not too much or too little lead-time). Our non-linear findings can help give their mobile strategies a makeover (eMarketer 2013d).

In light of the rapid increase in volume and diversity of mobile content (Niculescu and Whang 2012), we suggest an effective customer targeting strategy entails connecting customers whose mentality aligns well with mobile promotions. For example, our results show that mobile users located in shopping (versus non-shopping) districts were more responsive to hedonic mobile promotions and potentially can generate more positive word-of-mouth and brand advocacy (Luo 2009, Luo, Raithel, and Wiles 2013).

Mobile marketers must devise a "new corporate agenda" that centers on the consumer context in order to prevent their campaigns from slipping into irrelevance. Our findings show managers that contextualized marketing is more complicated due to the interaction of time and location. In other words, treating time and location separately in a 1+1 fashion will not work. Contextual marketing has huge potential, but managers should heed the inverted-U effect of targeting non-proximal distances. Thus, IS and marketing executives must carefully design mobile campaigns that balance the goals of timely information against the risks of alienating customers through a shotgun approach.

Our findings are also relevant for current and *future* executives to appreciate mobile commerce.[10] In keeping pace with the "hot" topic of mobile commerce in the industry, business schools are scrambling to

[10] We thank the AE for this insight.

offer MBA courses. The crux of these courses is creating mobile campaigns to enhance sales (Dushinksi 2013, Hopkins and Turner 2012). Complementing these textbooks, our real-world, large-scale field experiment enriches the training of MBAs and future executives by demonstrating how contextual dependence determines the effectiveness of mobile campaigns.

7.3 Limitations and Future Research Directions

The limitations of our study suggest potential avenues for future research. First, consumer decisions of whether to purchase mobile promotions may be associated with many factors, such as income level and occupation status. For instance, those with a higher income level may have a higher propensity to pay for a movie ticket. Also, messages sent at 2 pm on a work day may engender different responses between those who are tied at work and those who are not.[11] Due to regulations, we were unable to obtain personal information such as income levels and occupations in our field experiment. While our follow-up survey shows that demographic variables such as income do not have a significant influence, future research could explore these issues (Ghose and Han 2011). Second, the generalizability of our conclusions is limited by the fact that the promotions were fixed at a substantial discount (50%). For elastic goods and services, changes in discount percentages may have a disproportional impact on purchases among customers.[12] Future research may investigate these effects. Finally, consumer privacy concerns are relevant issues for mobile commerce. Future research may investigate how privacy concerns and personalization can be integrated in mobile targeting and social media to reap its benefits while avoiding its pitfalls (Goldfarb and Tucker 2011; Luo, Zhang, and Duan 2013).

7.4 Conclusion

In conclusion, this study aims to provide a better understanding of balancing temporal and geographical mobile targeting strategies. We hope future research will build on this study to shed further light on how mobile targeting can be effective for consumer purchases.

---

[11] We thank an anonymous reviewer for pointing this out.

[12] An anonymous reviewer brought this to our attention.

References

Agarwal A, Hosanagar K, Smith MD (2011) Location, location, location: an analysis of profitability of position in online advertising markets. *J. Marketing Res.* 48(6):1057-1073.

Balasubramanian S, Peterson RA, Jarvenpaa SL (2002) Exploring the implications of m-commerce for markets and marketing. *J. Academy of Marketing Sci.* 30(4):348-361.

Banerjee S, Dholakia RR (2008) Does location-based advertising work? *Internat. J. Mobile Marketing* 3(2):68-74.

Birkner, C (2012) Small business, big mobile tactics. *Marketing News* 46(16):8.

Bloch, PH, Richins, ML (1983) A theoretical model for the study of product importance perceptions. *J. of Marketing* 47(Summer): 69-81.

Cappelli P, Sherer PD (1991) The missing role of context in OB. *Res. Org. Behavior* 13:55-110.

Chandran S, Menon G (2004) When a day means more than a year: effects of temporal framing on judgments of health risk. J. Consumer Res. 31(2):375-89.

Chandran S, Morwitz VG (2005) Effects of participative pricing on consumers' cognitions and actions: A goal theoretic perspective. *J. Consumer Res.* 32(2):249-259.

Chen P-Y, Hitt LM (2002) Measuring switching costs and the determinants of customer retention in internet-enabled businesses: a study of the online brokerage industry. Info. Sys. Res. 13(3):255-274.

Chen P-Y, Wu S-Y (2013) The impact and implications of on-demand services on market structure. *Inform. Systems Res.* Forthcoming.

Chung TSS, Rust RT, Wedel M (2009) My mobile music: An adaptive personalization system for digital audio players. *Marketing Sci*. 28(1):52-68.

Deng C, Graz J (2002) Generating randomization schedules using SAS programming. *Proc. 27th Annual SAS Users Group Internat. Conf*. 267-270.

Deng X, Chi L (2012) Understanding postadoptive behaviors in information systems use: a longitudinal analysis of system use problems in the business intelligence context. *J. Management Info. Sys.* 29(3):291-326.

Dickerson MD and Gentry JW (1983) Characteristics of adopters and non-adopters of home computers. *J. of Consumer Res.* 10(9):225-235.

Dushinksi K (2013) *The Mobile Marketing Handbook: A Step by Step Guide to Creating Dynamic Mobile Marketing Campaigns* (2nd ed.). New Jersey: Information Today.

Edell, JE, Burke, MC (1987) The power of feelings in understanding advertising effects. *J. of Consumer Research* 14(December): 421-33.

eMarketer (2012) Mobile banners continue to boast high click rates. *Emarketer.com.*

eMarketer (2013a) Tablets, smartphones drive mobile commerce to record heights. *Emarketer.com.*

eMarketer (2013b) Real-time location data gets a bigger slice of mobile targeting. *Emarketer.com.*

eMarketer (2013c) CPG brands up the mobile app ante. Emarketer.com.

eMarketer (2013d) Search gets a mobile makeover. *Emarketer.com.*

Forman C (2005) The corporate digital divide: determinants of internet adoption. *Management Sci.* 51(4):641-654.

Forman C, Ghose A, Goldfarb A (2009) Competition between local and electronic markets: How the benefit of buying online depends on where you live. *Management Sci.* 55(1):47-57.

Frost and Sullivan (2012) Research and markets: U.S. location-based services market. *The Wall St. J.* http://online.wsj.com/article/PR-CO-20121218-908397.html?mod=crnews.

Galletta DF, Henry RM, McCoy S, Polak P (2006) When the wait isn't so bad: the interacting effects of website delay, familiarity and breadth. *Info. Sys. Res.* 17(1):20-37.

Ghose A, Goldfarb A, Han S (2013) How is the mobile internet different? *Inform. Systems Res*. Forthcoming.

Ghose A, Han S (2011) An empirical analysis of user content generation and usage behavior on the mobile internet. *Management Sci.* 57(9):1671-1691.

Goldfarb A, Tucker C (2011) Online display advertising: Targeting and obtrusiveness. *Marketing Sci*. 30(3):389-404.

Goodman JK, Malkoc SA (2013) Choosing here and now versus there and later: The moderating role of psychological distance on assortment size preferences. *J. of Consumer Res.* Forthcoming.

Greene W (2007) *Functional Form and Heterogeneity in Models for Count Data* (Boston: Now Publishers).

Guadagni PM, Little JDC (2008) A logit model of brand choice calibrated on scanner data. *Marketing Sci.* 27(1):29-48.

Heilman CM, Nakamoto K, Roa AG (2002) Pleasant surprises: Consumer response to unexpected in-store coupons. J. Marketing Res. 39(2):242-252.

Hopkins J, Turner J (2012) *Go Mobile: Location-Based Marketing, Apps, Mobile Optimized Ad Campaigns, 2D Codes and Other Mobile Strategies to Grow Your Business* (New Jersey: Wiley).

Hui S, Inman J, Huang Y, Suher J (2013) Estimating the effect of travel distance on unplanned spending: applications to mobile promotion strategies. *J. Marketing* 77(2):1-16.

Johns G (2006) The essential impact of context on organizational behavior. *Academy of Management Rev.* 31:396–408.

Johnson L (2013) Consumers are driving need for contextual mobile experiences: token exec. *Mobile Commerce Daily*.

Kenny D, Marshall JF (2000) Contextual marketing: The real business of the internet. *Harvard Bus. Rev.* (November-December) 119-125.

Kim N, Han NK, Srivastava RK (2002) A dynamic IT adoption model for the SOHO market: PC generational decisions with technological expectations. *Management Sci*. 48(2):222-240.

Li, H, Edwards, SM, Lee, J-H (2002) Measuring the intrusiveness of advertisements: scale development and validation. *J. of Advertising* 31(2): 37–47.

Liberman N, Trope Y (1998) The role of feasibility and desirability considerations in near and distant future decisions: a test of temporal construal theory. J. Personality and Social Psych. 75(1):5-18.

Liberman N, Trope Y (2008) The psychology of transcending the here and now. *Sci.* 21(322):1201–1205.

Lindqvist J, Cranshaw J, Wiese J, Hong J, Zimmerman J (2011) I'm the mayor of my house: Examining why people use Foursquare – a social-driven location sharing application. *CHI 2011*, May 7-12, Vancouver, BC, Canada.

Luo, X (2009) Quantifying the long-term impact of negative word of mouth on cash flows and stock prices. *Marketing Sci.* 28(1): 148-65.

Luo, X, Raithel S, and Wiles M (2013),The impact of brand dispersion on firm value. *J. Marketing Res.* 50(3):399-415**.**

Luo, X, Zhang J, and Duan W (2013) Social media and firm equity value. *Information Systems Res*. 24(1):146-163.

Macdonald EK, Wilson HN, Konus U (2012) Better customer insight – in real time. *Harvard Bus. Rev.* (September) 102-108.

MacKenzie, SB, Podsakoff, PM, Podsakoff, NP (2011) Construct measurement and validation procedures in MIS and behavioral research: Integrating new and existing techniques. *MIS Quarterly* 35(2): 293-334.

McKenna R (1995) Real-time marketing. *Harvard Bus. Rev.* (July-August) 87-95.

Mitchell, A (1979) Involvement: A potentially important mediator of consumer behavior. *Advances in Consumer Research* 6: 191-196.

Molitor, D., P. Reichart, M. Spann. (2012) Location-based advertising: What is the value of physical distance on the mobile internet? Working Paper, Ludwig-Maximilians Universitat.

Niculescu MF, Whang S (2012) Codiffusion of wireless voice and data services: An empirical analysis of the Japanese mobile telecommunications market. *Inform. Systems Res.* 23(1):260-279.

Ohta H (1993) Introduction: in honour of Melvin L. Greenhut. In *Does Economic Space Matter: Essays in Honour of Melvin L. Greenhut.* H Ohta and JF Thisse (Eds.) (St. Martin's, New York):1-18.

Ovide S, Bensinger G (2012) Mobile ads: Here's what works and what doesn't. *The Wall St. J.*, September 27. http://online.wsj.com/article/SB10000872396390444083304578016373342878556.html.

Prelec D, Loewenstein G (1991) Decision making over time and under uncertainty: a common approach. *Management Sci.* 37(7):770-786.

Prins R, Verhoef PC (2007) Marketing communication drivers of adoption timing of a new e-service among existing customers. *J. Marketing* 71(4):169-183.

Rook DW, Fisher RJ (1995) Normative influences on impulsive buying behavior. *J. of Consumer Res.* 22:305-313.

Rutz OJ, Bucklin RE, Sonnier GP (2012) A latent instrumental variables approach to modeling keyword conversion in paid search advertising. *J. Marketing Res.* 49(3):306-319.

Scott DM (2012) *Real-time marketing and PR* (Willey, New Jersey).

Shankar V, Venkatesh A, Hofacker C, Naik P (2010) Mobile marketing in the retailing environment: Current insights and future research avenues. *J. Interactive Marketing* 24(2):111-120.

Shugan SM (2004) The impact of advancing technology on marketing and academic research. *Marketing Sci*. 23(4):469-476.

Spiekermann S, Rothensee M, Klafft M (2011) Street marketing: How proximity and context drive coupon redemption. *J. of Consumer Marketing* 28(4):280-289.

Stilley KM, Inman JJ, Wakefield KL (2010) Spending on the fly: Mental budgets, promotions, and spending behavior. *J. Marketing* 74(5):34-47.

Taylor, S, Todd, PA (1995) Understanding information technology usage: A test of competing models. *Inform. Systems Res.* 6(2): 144-176.

Thomas M, Tsai CI (2012) Psychological distance and subjective experience: how distancing reduces the feeling of difficulty. *J. Consumer Res.* 39(2):324–340.

Tode C (2013) Location targeting more than doubles performance of mobile ads: report. *Mobile Marketer*. http://www.mobilemarketer.com/cms/news/research/14731.html.

Trope Y, Liberman N (2010) Construal-level theory of psychological distance. *Psychological Rev.* 117(2):440-463.
Vodanovich S, Sundaram D, Myers M (2010) Digital natives and ubiquitous information systems. *Inform. Systems Res.* 21(4):711-723.
Xu AJ, Wyer RS Jr. (2007) The effects of mind-sets on consumer decisions strategies. *J. Consumer Res.* 34(4):556-566.
Xu X, Venkatesh V, Tam KY, Hong S-J (2010) Model of migration and use of platforms: Role of hierarchy, current generation, and complementarities in consumer settings. *Management Sci*. 56(8):1304-1323.
Yan D, Sengupta J (2013) The influence of base rate and case information on health-risk perceptions: a unified model of self-positivity and self-negativity. *J. Consumer Res.* 39(1):931-946.
Zhang J, Krishnamurthi L (2004) Customizing promotions in online stores. *Marketing Sci.* 23(4):561-578.

Table 1: Overview of Previous Research

Studies	Temporal Targeting	Geographical Targeting	Sales Impact	Segmenting by Customer Scenario	Sample Size	Relevant Findings
Heilman et al. (2002)	✓		✓		192	Coupons that target customers in real-time (at point-of-purchase) increase purchase amounts.
Prins and Verhoef (2007)	✓				6,000	Direct marketing communications (such as advertising) shorten consumers' adoption time of new technological services.
Banerjee and Dholakia (2008)		✓	✓		351	Consumers are more willing to respond to a proximally-located promotional offer.
Spiekermann et al. (2011)		✓	✓		171	The proximity of a promoted restaurant increases consumers' coupon redemption likelihood.
Ghose et al. (2013)		✓	✓	✓	260	Proximally-located stores are more likely to garner clicks in mobile-based Internet searches.
Hui et al. (2013)	✓		✓		300	Within a grocery store, a real-time coupon resulted in more unplanned spending.
The Present Study	✓	✓	✓	✓	12,265	Promoting to close distances is more effective with same-day targeting; it is more effective for far distances when targeting one-day prior.

Table 2: Summary Statistics

Panel A: Definitions and Basic Summary Statistics of Variables

Variable	Definition	Mean	Median	Std. dev.	Min	Max	Observations Valid	Observations Missing
Time	The time condition during which SMS was sent (3 conditions total)	2.03	2.00	0.811	1	3	12265	0
Distance	The distance condition to which SMS was sent from the movie theater (3 conditions total)	2.02	2.00	0.824	1	3	12265	0
Customer Scenario	The customer scenario condition in which SMS was sent (3 conditions total)	1.96	2.00	0.822	1	3	12265	0
ARPU	Average revenue per mobile user generated by her cellular device in month prior	4.2503	4.2850	0.86597	0.00	7.52	12265	0
MOU	Minutes of usage in voice time per user in month prior	5.9685	6.2710	1.51144	0.00	8.72	12265	0
SMS	Number of short message service texts sent and received per user in month prior	3.8508	4.1744	1.75977	0.00	7.94	12239	26
GPRS	Data usage volume per user in month prior measured by the general packet radio service	8.9565	9.8546	2.88166	0.00	16.04	12238	27

Panel B: Additional Summary Statistics

	Variance	Skeweness	Kurtosis	Percentile *10%*	*20%*	*25%*	*30%*	*40%*	*50%*	*60%*	*70%*	*75%*	*80%*	*90%*
Time	0.658	-0.055	-1.478	1.00	1.00	1.00	1.00	2.00	2.00	2.00	3.00	3.00	3.00	3.00
Distance	0.680	-0.031	-1.528	1.00	1.00	1.00	1.00	2.00	2.00	2.00	3.00	3.00	3.00	3.00
Customer Scenario	0.675	0.079	-1.514	1.00	1.00	1.00	1.00	2.00	2.00	2.00	3.00	3.00	3.00	3.00
ARPU	0.750	-0.706	2.294	3.2268	3.5771	3.7200	3.8486	4.0737	4.2850	4.5163	4.7214	4.8598	4.9752	5.2769
MOU	2.284	-1.947	5.097	4.4308	5.1930	5.4467	5.6490	5.9965	6.2710	6.5280	6.7869	6.9202	7.0579	7.3877
SMS	3.097	-0.645	-0.423	1.0986	2.3026	2.7726	3.0910	3.6636	4.1744	4.6347	5.0689	5.3033	5.4972	5.8051
GPRS	8.304	-1.725	2.780	5.1358	7.6436	8.2011	8.6512	9.3116	9.8546	10.2560	10.5261	10.7282	10.9639	11.4334

Table 3: Effects of Geographic and Temporal Targeting on Mobile Purchases

	Column (1)					Column (2)					Column (3)				
Variable	**B**	***p*-value**	**Wald**	**df**	**Exp(B)**	**B**	***p*-value**	**Wald**	**df**	**Exp(B)**	**B**	***p*-value**	**Wald**	**df**	**Exp(B)**
Constant	-12.972***	0.000	689.702	1	0.000	-13.287***	0.000	696.946	1	0.000	-13.265***	0.000	669.504	1	0.000
	(0.494)					(0.503)					(0.153)				
ARPU	0.603***	0.000	62.593	1	1.827	0.624***	0.000	66.206	1	1.866	0.668***	0.000	74.429	1	1.951
	(0.076)					(0.077)					(0.077)				
MOU	-0.815***	0.000	296.689	1	0.433	-0.813***	0.000	294.065	1	0.444	-0.814***	0.000	294.073	1	0.443
	(0.047)					(0.047)					(0.047)				
SMS	1.785***	0.000	680.308	1	5.960	1.780***	0.000	669.184	1	5.931	1.759***	0.000	648.120	1	5.806
	(0.068)					(0.069)					(0.069)				
GPRS	0.358***	0.000	149.359	1	1.430	0.353***	0.000	145.957	1	1.423	0.348***	0.000	142.088	1	1.416
	(0.029)					(0.029)					(0.029)				
Theater		0.927	0.464	3			0.914	0.523	3			0.862	0.746	3	
Theater (E)	0.067	0.657	0.197	1	1.069	0.077	0.608	0.263	1	1.081	0.076	0.615	0.253	1	1.079
	(0.151)					(0.151)					(0.152)				
Theater (W)	0.007	0.960	0.003	1	1.007	0.011	0.934	0.007	1	1.011	-0.004	0.978	0.001	1	0.996
	(0.133)					(0.133)					(0.134)				
Theater (N)	-0.015	0.913	0.012	1	0.985	-0.008	0.953	0.003	1	0.992	-0.029	0.836	0.043	1	0.971
	(0.141)					(0.141)					(0.142)				
Time							0.002	12.189	2	0.752		0.000	35.949	2	
Time (1)						-0.285**	0.005	7.735	1		-0.748***	0.000	22.339	1	0.473
						(0.102)					(0.158)				
Time (2)						-0.330***	0.001	10.278	1	0.719	-0.849***	0.000	27.299	1	0.428
						(0.103)					(0.162)				
Distance							0.023	5.512	2	0.869		0.000	38.590	2	
Distance (1)						-0.140	0.154	2.035	1		-0.456**	0.003	8.887	1	0.634
						(0.098)					(0.153)				
Distance (2)						-0.284**	0.006	7.413	1	0.752	-1.509***	0.000	36.407	1	0.221
						(0.105)					(0.250)				
Distance x Time												0.000	38.880	4	
Distance (1) x Time (1)											0.516**	0.033	4.557	1	1.675
											(0.242)				
Distance (1) x Time (2)											0.570**	0.015	5.862	1	1.767
											(0.235)				
Distance (2) x Time (1)											2.348***	0.000	25.390	1	10.464
											(0.311)				
Distance (2) x Time (2)											1.814***	0.000	35.799	1	6.133
											(0.303)				
Chi-Square	2492.354					2545.281					2688.186				
-2 Log likelihood	3979.916					3886.989					3744.084				
Cox & Snell R-square	0.182					0.188					0.194				
Nagelkerke R-square	0.448					0.459					0.487				
Observations	12,220					12,220					12,220				

Note: ***$p < 0.001$, **$p < 0.05$, *$p < 0.01$. ARPU = average revenue per user, MOU = minutes of usage, SMS = number of texts sent and received per user, GPRS = data usage with wireless provider; Theater = the cinema in the south of the city, Theater (E) = in the east of the city, Theater (W) = in the west, Theater (N) = in the north, and base is the cinema in the south; Distance = < 200m from the cinema; Distance (1) = 200m < x < 500m; Distance (2) = 500m < x < 2km, base is < 200m; Time = SMS sent same-day, Time (1) = one-day prior, Time (2) = two-day prior, and base is the same day. We estimate the models clustered at the theater level and with robust standard errors.

Table 4: Robustness to an Alternative Estimation Model

Probit Model Parameter Estimates						
	Model (1)		*Model (2)*		*Model (3)*	
	Coefficient (std. error)	*p*-value	Coefficient (std. error)	*p*-value	Coefficient (std. error)	*p*-value
(Intercept)	5.924*** (0.4023)	0.000	-5.783*** (0.4053)	0.000	-5.619*** (0.4085)	0.000
ARPU	-0.355*** (0.0402)	0.000	0.369*** (0.0408)	0.000	0.388*** (0.0412)	0.000
MOU	-0.429*** (0.0258)	0.000	-0.429*** (0.0258)	0.000	-0.430*** (0.0258)	0.000
SMS	-0.809*** (0.0621)	0.000	0.815*** (0.0615)	0.000	0.802*** (0.0611)	0.000
GPRS	-0.145*** (0.0198)	0.000	0.144*** (0.0197)	0.000	0.142*** (0.0196)	0.000
Theater (E)	-0.053 (0.0754)	0.483	0.062 (0.0758)	0.416	0.062 (0.0755)	0.412
Theater (W)	-0.054 (0.0668)	0.421	-0.059 (0.0669)	0.380	-0.057 (0.0669)	0.395
Theater (N)	-0.013 (0.0704)	0.856	-0.019 (0.0706)	0.792	-0.011 (0.0705)	0.879
Time (1)			-0.192*** (0.0512)	0.000	-0.537*** (0.0843)	0.000
Time (2)			-0.231*** (0.0526)	0.000	-0.945*** (0.0853)	0.000
Distance (1)			-0.096* (0.0516)	0.064	-0.290** (0.0853)	0.001
Distance (2)			-0.161** (0.0554)	0.004	-0.657*** (0.1473)	0.000
Distance (1)*Time (1)					0.331** (0.1254)	0.008
Distance (1)*Time (2)					0.334** (0.1240)	0.007
Distance (2)*Time (1)					0.982*** (0.1701)	0.000
Distance (2)*Time (2)					0.560*** (0.1731)	0.001

Note: ***$p < 0.001$, **$p < 0.05$, *$p < 0.10$; ARPU = average revenue per user, MOU = minutes of usage, SMS = number of texts sent and received per user, GPRS = data usage with wireless provider; Theater = the cinema in the south of the city, Theater (E) = in the east of the city, Theater (W) = in the west, Theater (N) = in the north, and base is the cinema in the south; Distance = < 200m from the cinema, Distance (1) = 200m < x < 500m, Distance (2) = 500m < x < 2km, base is < 200m; Time = SMS sent same-day, Time (1) = one-day prior, Time (2) = two-day prior, and base is the same day. We estimate the model clustered at the theater level and with robust standard errors.

Table 5: Cell Counts of Randomization Checks

Panel A: Distance x Time

Distance	Time	Observed Count	Observed %
Near	Same-day	1209.000	9.9%
	One-day Prior	1389.000	11.4%
	Two-day Prior	1459.000	11.9%
Medium	Same-day	1333.000	10.9%
	One-day Prior	1245.000	10.2%
	Two-day Prior	1350.000	11.0%
Far	Same-day	1313.000	10.7%
	One-day Prior	1542.000	12.6%
	Two-day Prior	1416.000	11.5%

Panel B: Distance

		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	Far	4271	34.8	34.8	34.8
	Medium	3928	32.0	32.0	66.8
	Near	4066	33.2	33.2	100.0
	Total	12265	100.0	100.0	

Panel C: Time

		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	Two-day Prior	4225	34.4	34.4	34.4
	One-day Prior	4185	34.1	34.1	68.6
	Same-day	3855	31.4	31.4	100.0
	Total	12265	100.0	100.0	

Table 6: Additional Robustness Tests

	Customer scenario (Shopping)		Customer scenario (Residential)		Customer scenario (Business districts)		Sub-sample without non-smartphones		Boot-strapping resamples	
Variable	**B**	***p*-value**	**B**	***p*-value**	**B**	***p*-value**	**B**	***p*-value**	**B**	***p*-value**
Constant	-14.033*** (0.157)	0.000	-12.865*** (0.156)	0.000	-13.039*** (0.158)	0.000	-15.511*** (0.161)	0.000	-13.508*** (0.161)	0.000
ARPU	0.671*** (0.075)	0.000	0.672*** (0.072)	0.000	0.665*** (0.069)	0.000	0.681*** (0.072)	0.000	0.673*** (0.081)	0.000
MOU	-0.822*** (0.045)	0.000	-0.808*** (0.043)	0.000	-0.811*** (0.041)	0.000	-0.835*** (0.038)	0.000	-0.816*** (0.033)	0.000
SMS	1.763*** (0.066)	0.000	1.758*** (0.065)	0.000	1.771*** (0.073)	0.000	1.793*** (0.062)	0.000	1.766*** (0.061)	0.000
GPRS	0.351*** (0.026)	0.000	0.352*** (0.028)	0.000	0.356*** (0.025)	0.000	0.342*** (0.021)	0.000	0.346*** (0.024)	0.000
Theater		0.871		0.859		0.861		0.866		0.861
Theater (E)	0.078 (0.151)	0.615	0.077 (0.155)	0.614	0.081 (0.154)	0.615	0.072 (0.152)	0.615	0.074 (0.150)	0.615
Theater (W)	-0.006 (0.133)	0.961	-0.004 (0.136)	0.975	-0.003 (0.139)	0.973	-0.004 (0.137)	0.977	-0.005 (0.136)	0.977
Theater (N)	-0.031 (0.145)	0.842	-0.027 (0.141)	0.843	-0.026 (0.146)	0.839	-0.028 (0.148)	0.846	-0.032 (0.147)	0.846
Time		0.000		0.000		0.000		0.000		0.000
Time (1)	-0.919*** (0.157)	0.000	-0.746*** (0.155)	0.000	-0.445** (0.113)	0.003	-0.916*** (0.153)	0.000	-0.746*** (0.158)	0.000
Time (2)	-0.861*** (0.163)	0.000	-0.846*** (0.160)	0.000	-0.252 (0.539)	0.638	-0.865*** (0.158)	0.000	-0.845*** (0.161)	0.000
Distance		0.000		0.000		0.000		0.000		0.000
Distance (1)	-0.458** (0.151)	0.003	-0.455** (0.154)	0.003	-0.423 (0.859)	0.613	-0.459** (0.148)	0.002	-0.457** (0.156)	0.003
Distance (2)	-1.511*** (0.243)	0.000	-1.506*** (0.252)	0.000	-0.515 (1.24)	0.637	-1.517*** (0.251)	0.000	-1.508*** (0.255)	0.000
Distance x Time		0.000		0.000		0.000		0.000		0.000
Distance (1) x Time (1)	0.568** (0.233)	0.029	0.519** (0.243)	0.035	-0.426 (0.855)	0.614	0.572** (0.242)	0.032	0.519** (0.240)	0.032
Distance (1) x Time (2)	0.575** (0.233)	0.011	0.568** (0.234)	0.014	-0.510 (1.19)	0.634	0.572** (0.231)	0.013	0.573** (0.236)	0.013
Distance (2) x Time (1)	2.359*** (0.309)	0.000	2.347*** (0.310)	0.000	-0.456 (0.912)	0.631	2.362*** (0.309)	0.000	2.332*** (0.309)	0.000
Distance (2) x Time (2)	1.856*** (0.306)	0.000	1.818*** (0.305)	0.000	-0.503 (1.27)	0.645	1.896*** (0.301)	0.000	1.839*** (0.308)	0.000

Note: *** $p < 0.001$, ** $p < 0.05$, * $p < 0.10$; ARPU = average revenue per user, MOU = minutes of usage, SMS = number of texts sent and received per user, GPRS = data usage with wireless provider; Theater = the cinema in the south of the city, Theater (E) = in the east of the city, Theater (W) = in the west, Theater (N) = in the north, and base is the cinema in the south; Distance = < 200m from the cinema; Distance (1) = 200m < x < 500m; Distance (2) = 500m < x < 2km, base is < 200m; Time = SMS sent same-day, Time (1) = one-day prior, Time (2) = two-day prior, and base is the same day. We estimate the models clustered at the theater level and with robust standard errors.

Figure 1: Effect of Mobile Promotions via Temporal Targeting

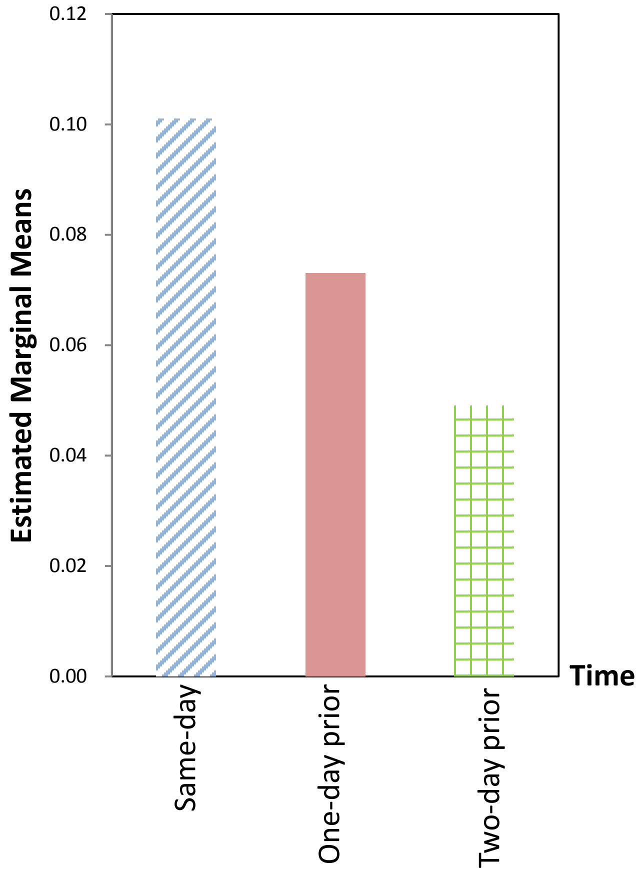


Figure 2: Effect of Mobile Promotions via Geographical Targeting

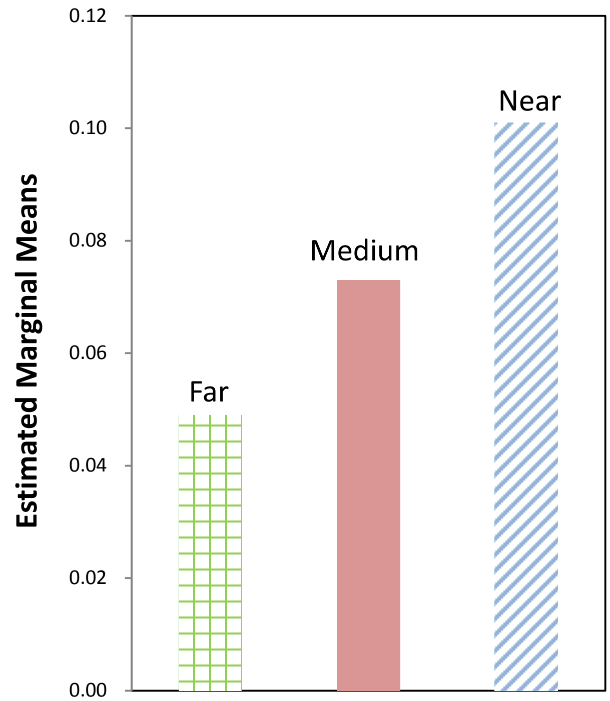


Figure 3: Effect of Mobile Promotions via Combining Temporal and Geographical Targeting

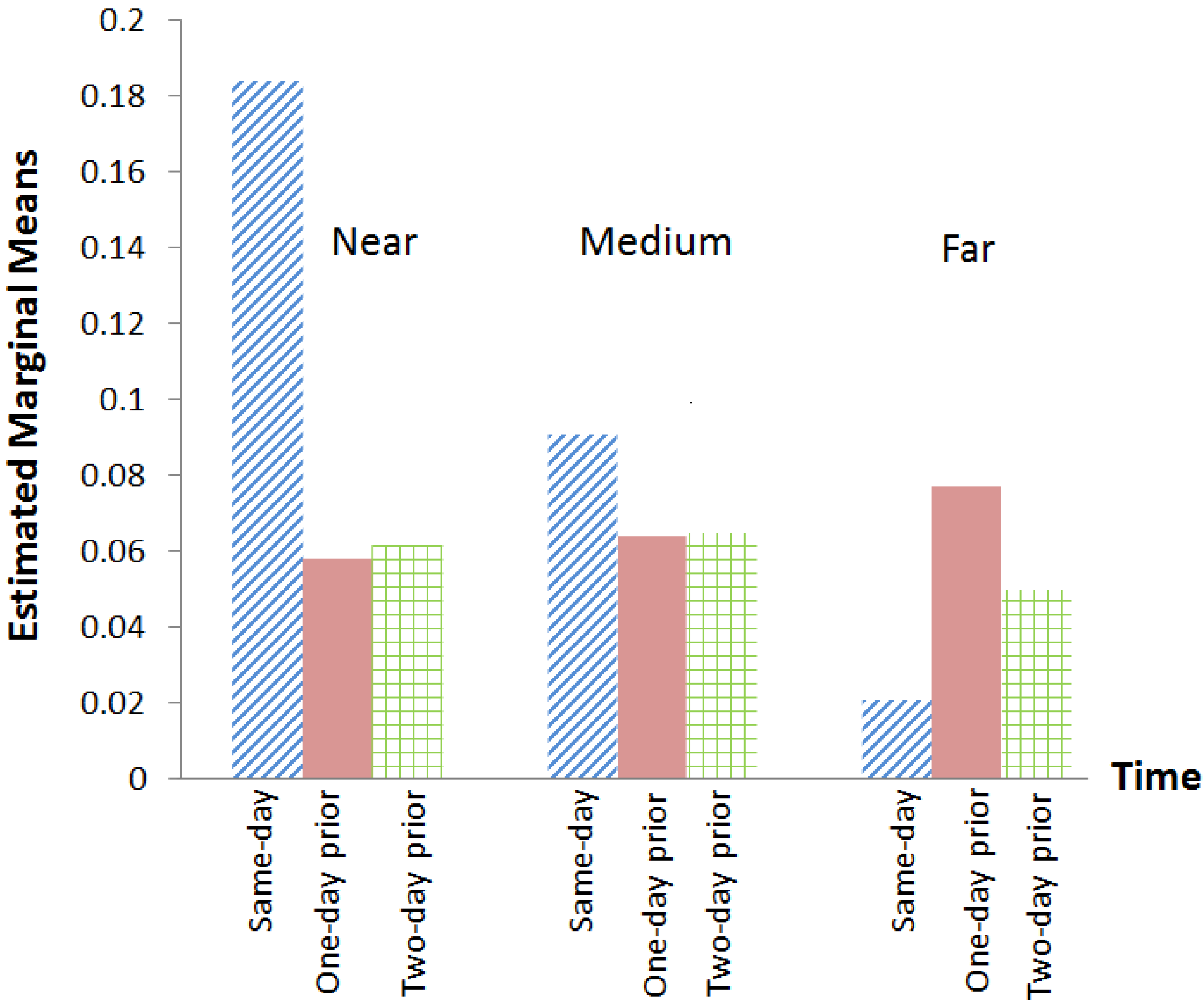


Figure 4: Effect of Mobile Promotions via Combining Temporal Targeting and Geographical Targeting by Customer Scenario

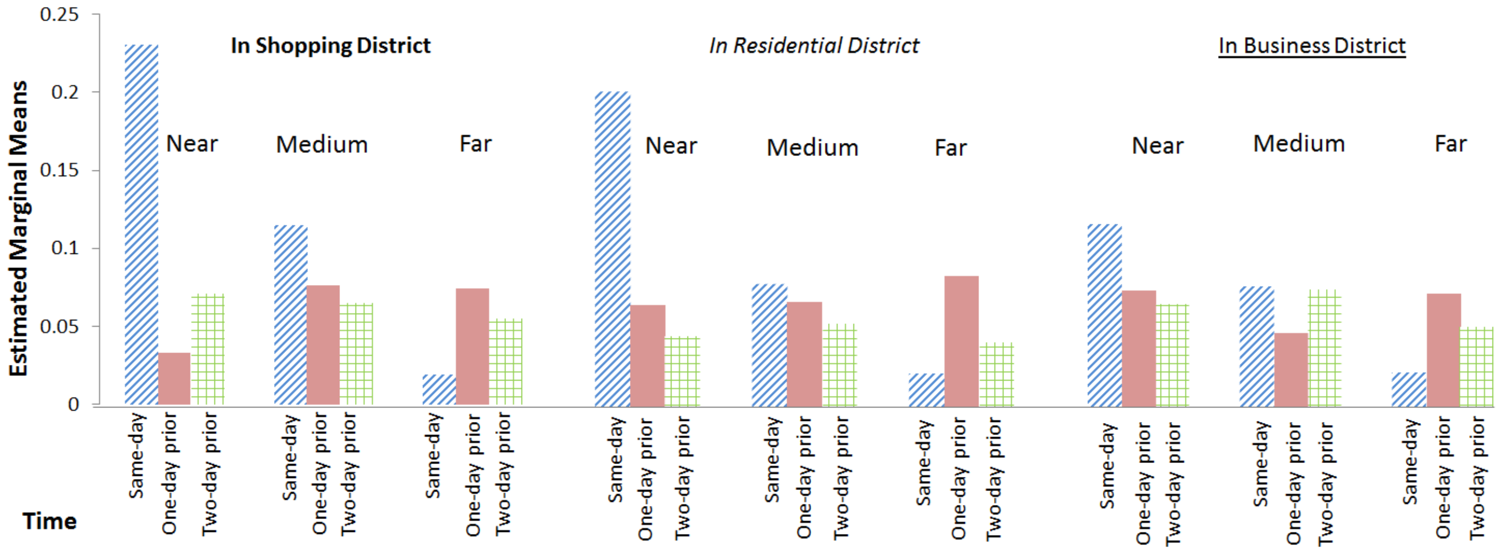
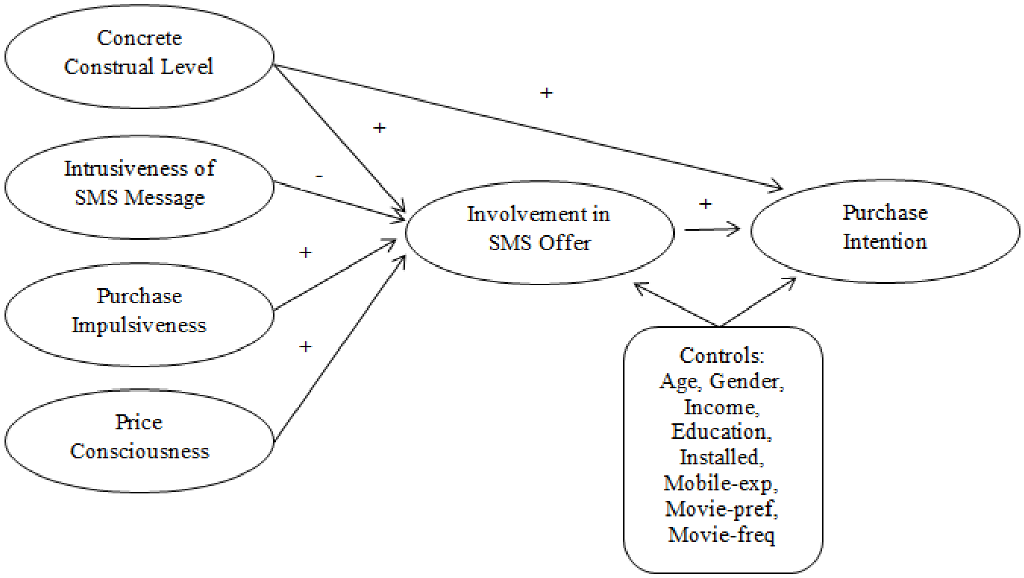


Figure 5: Conceptual Model of Follow-up Surveys



*Note: Installed = whether users had previously installed a similar mobile application; Mobile-exp = users' mobile usage experience; Movie-pref = user preference of when to watch a movie; Movie-freq = user movie-watching frequency

Table 7: Results of Follow-up Surveys

Results of Analyzing the Relationships				
	Scenario 1 (low g, low t) N=104	**Scenario 2** (high g, low t) N=101	**Scenario 3** (low g, high t) N=108	**Scenario 4** (high g, high t) N=101
	coefficient, t-value			
Intention as the DV				
Involvement → Intention	**0.43, 4.66*** **	**0.63, 9.29*** **	**0.58, 6.35*** **	**0.65, 8.24*** **
Construal → Intention	**0.30, 3.00** **	0.19, 1.71^{+}	0.14, 1.37	0.08, 0.75
Control: Age	0.13, 1.30	0.06, 0.43	-0.15, 1.06	0.00, 0.00
Control: Gender	0.07, 1.00	-0.09, 1.33	-0.03, 0.30	0.14, 1.44
Control: Income	0.11, 0.51	-0.02, 0.16	0.09, 0.93	-0.01, 0.13
Control: Education	0.02, 0.21	0.01, 0.05	0.03, 0.39	-0.06, 0.57
Control: Movie_freq	-0.09, 1.19	-0.07, 0.83	-0.08, 1.05	-0.02, 0.22
Control: Movie_pref	0.01, 0.14	-0.02, 0.23	0.11, 1.51	0.02, 0.30
Control: Installed	**-0.19, 2.87** **	-0.05, 0.71	**-0.22, 2.89** **	-0.08, 0.84
Control: Mobile_exp	-0.01, 0.14	-0.05, 0.37	-0.11, 0.82	0.05, 0.56
Involvement as the DV				
Construal → Involvement	**0.24, 2.18***	0.13, 1.26	**0.33, 2.84** **	0.22, 1.64^{+}
Construal → Intrusiveness	**-0.27, 2.36***	-0.04, 0.32	-0.13, 0.95	-0.07, 0.37
Intrusiveness → Involvement	**-0.24, 2.31***	**-0.36, 3.38*** **	**-0.26, 2.80** **	-0.17, 1.07
Impulse → Involvement	0.13, 1.27	**0.31, 3.32*** **	-0.09, 0.70	0.09, 0.62
Price → Involvement	0.20, 1.67^{+}	0.14, 1.26	0.17, 1.29	**0.31, 2.67** **
Control: Age	0.11, 0.86	-0.02, 0.16	0.26, 1.69^{+}	0.05, 0.38
Control: Gender	0.07, 1.30	-0.05, 0.76	0.11, 1.40	-0.06, 0.56
Control: Income	-0.09, 0.78	0.01, 0.12	0.04, 0.28	0.08, 0.79
Control: Education	0.05, 0.63	0.11, 1.01	-0.14, 1.30	-0.01, 0.07
Control: Movie_freq	**-0.20, 2.04***	-0.13, 1.27	-0.02, 0.19	0.12, 1.05
Control: Movie_pref	-0.10, 0.95	-0.06, 0.54	0.02, 0.19	-0.13, 1.22
Control: Installed	-0.13, 1.55	0.03, 0.26	-0.02, 0.19	-0.03, 0.25
Control: Mobile_exp	0.01, 0.04	0.04, 0.25	-0.15, 1.02	-0.03, 0.24

$^{+}p < 0.10$, $*p < 0.05$, $**p < 0.01$, $***p < 0.001$, Significant relationships are in bold