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Seizing the Commuting Moment: Contextual Targeting Based on Mobile Transportation Apps¹

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Abstract

Despite the average daily commuting time of commuters increasing by the day, the way marketers can benefit from our commuting behaviors has not yet been thoroughly examined. In collaboration with one of the largest global mobile service platform providers, this study investigates how contextual targeting with commuting is associated with responses to mobile coupons. The analysis is based on a field study in which 14,741 mobile coupons were sent to 9,928 public transit app users on commuting routes or routes other than commuting routes (i.e. commuters or non-commuters). The key findings indicate that commuters are about three times as likely to redeem their first mobile coupon compared to non-commuters. Further analyses allowing users to receive multiple coupons provide useful insight into an effective distribution strategy for mobile coupons. The findings suggest that enhanced receptiveness to mobile coupons is more perceivable when users obtain multiple coupons. Additionally, multiple-coupon distribution strategy increases response rates more effectively among non-commuters than commuters. Moreover, coupons with short expiration dates more successfully improve the response rates of commuters than do coupons with long expiration dates. For non-commuters, however, the reverse holds true; their response rates are higher for coupons with long expiration. Finally, commuters redeem coupons not only more frequently but also at a faster rate. Both dynamic and static matching methods are adopted to address possible selection biases. By carefully exploiting commuting, which is easily identifiable and occurs throughout the world, managers may improve their mobile marketing effectiveness.

Keywords: Commuting, contextual targeting, field study, mobile coupon, mobile marketing

¹ The authors are listed in alphabetical order.

1. Introduction

The mobile revolution has fundamentally changed the manner by which marketers reach and engage with consumers. This development has provided an unprecedented opportunity for researchers and practitioners to gain insight into the dynamic behaviors and preferences of customers. The advent of mobile-enabled promotional coupons that are characterized by geographical and temporal features has enabled retailers to track and target consumers in real time on the basis of location, shopping trajectory, and “meaningful” moments (e.g., purchase). Recognizing the immense potential upside of disruptive advertising innovations in the emerging “mobile-only” era, marketers are poised to increase their investments in mobile promotions. One industry forecast projects that in 2019 spending on mobile advertisements in the U.S. will exponentially grow to arrive at over US\$65 billion—a figure that accounts for 72% of all digital ad investments². Another survey reveals that 87% of retailers intend to invest more heavily in mobile marketing to target on-the-go shoppers³. Mobile-based promotion has become integral to mobile marketing initiatives, driving sales in online, offline and omni channels. A study shows that more than 90% of all mobile users who are on the lookout for great shopping deals actively search for mobile coupons⁴. The same study indicates that nearly 50% of mobile consumers want sellers to send location-based coupons to them when they are near a store.

Despite the strong promise of mobile coupons, however, they have yet to live up to their much vaunted potential. Mobile coupon redemption accounts for merely 2% of all coupon redemptions (MMA 2013), and only 16% of mobile users regularly use and redeem mobile vouchers (eMarketer 2013). Although the rate of mobile coupon redemption is substantially higher than that of paper-based promotional incentives, this level remains at around only 10%⁵. Moreover, the privacy and security concerns of mobile consumers prevent marketers from vigorously capitalizing on geolocation-based tracking and targeting.

² <https://www.emarketer.com/Chart/US-Mobile-Ad-Spending-2013-2019/167656>

³ <http://www.prnewswire.com/news-releases/survey-the-vast-majority-87-of-retail-marketers-plan-to-invest-more-in-mobile-marketing-in-2016-300230162.html>

⁴ <http://www.trueship.com/blog/2015/03/24/one-click-savings-a-quick-look-at-2015-mobile-coupon-statistics>

⁵ <http://www.mirror.co.uk/lifestyle/family/paper-vs-mobile-how-growth-4052583>

Confronted with these challenges, marketers seek more accurate, context-relevant mobile-based targeting approaches that seamlessly integrate geographical features with temporal elements. Such challenges are exacerbated by the infancy of research on context-based targeting in mobile environments (e.g., Andrews et al. 2016) and the minimal effort devoted to systematic inquiries into mobile applications (apps) that may accurately capture users' behaviors, preferences, and contexts. Given that many mobile apps are routinely used by consumers, they offer marketers authentic information on the specific contexts that inspire customer engagement with mobile innovations. A number of scenarios can illustrate the value of data on mobile engagement. For example, a game user may feel happy when he or she earns the highest rank or defeats friends in a close match. Similarly, a user feels accomplished when he or she creates a new music playlist or downloads a new album that was released only two hours ago. A mobile user who relies on navigation apps is likely to feel exhausted upon arriving at a rest stop after hours of driving. The patterns and tendencies that are captured by mobile apps with geographical and temporal features can serve as important vantage points from which marketers can infer consumer emotion, context, and purchase intent.

This study is motivated by the desire to expand current works on context-based mobile coupon targeting through the examination of a popular public transportation (i.e., bus and subway) app that tracks commuting behaviors. Commuting refers to the repetitive and routine travel between home and the workplace. Commuters spend an average of 52 minutes every day traveling between home and work, and some workers spend three or more hours on their daily commute⁶. Given that individuals are exposed to various stressors including time pressure and traffic congestion while commuting (Novaco et al. 1990), commuting is well recognized in psychology as a source of stress (Novaco et al. 1990, Schaeffer et al. 1988). Accordingly, commuting has been extensively studied in diverse academic disciplines as an important socio-economic factor that influences public health [e.g., obesity (Lee et al. 2008), stress (Stutzer and Frey 2008), cardiovascular risk (Hamer and Chida 2008)] and urban planning [e.g., residential location (Cervero

⁶ <https://www.washingtonpost.com/news/wonk/wp/2016/02/25/how-much-of-your-life-youre-wasting-on-your-commute/>

and Wu 1997), commuting duration (Gordon et al. 1991), worker mobility and unemployment (Simpson 1992), jobs–housing balance (Peng 1997)]. Marketers have been equally interested in how they can reach and engage with consumers during the long daily commute. The traditional approach to reach and engagement is advertising in subway stations, subway cars, or free newspapers distributed at stations. However, because people have become more engaged with mobile phones than with newspapers, books, or display advertisements during their commute⁷, a number of companies have attempted to take advantage of mobile-centric commuting. Two large grocers (Tesco and Peapod) are among the first to target mobile-connected commuters and achieve success^{8,9}. The two companies superimposed virtual grocery stores on subway stations' walls in South Korea and the U.S., respectively, thereby enabling commuters to shop for groceries using their smartphones and have their purchases delivered by the time they reach home. Despite these benefits, the potential of mobile-centric commuting as a marketing opportunity has yet to be fully exploited.

Commuting can serve as one of the most attractive contexts that mobile marketers can target not only because of commuters' high level of mobile engagement during long daily commutes, but also because of its effortless and accurate identifiability and potential for strong marketing effectiveness. Mobile marketers can simply use open APIs provided by map applications (e.g. Google Maps) to access and use information related to users' residential and workplace addresses. Google Maps and Apple Maps, for example, have been collecting such information (See Figure 1) to provide effective navigation services on users' commuting routes (i.e. between home and workplace) (See Figure 2). Alternatively, mobile app developers can easily adopt software development kits (SDKs) for this purpose. For instance, a free SDK for iOS and Android called Neura identifies critical locations (e.g. home and workplace) within a few days of learning phase and notify the focal app when users arrive and leave.

⁷ <http://www.thedrum.com/news/2013/12/04/89-browse-or-buy-using-smartphones-and-tablets-during-their-commute>

⁸ <http://www.businessday.in/magazine/lbs-case-study/case-study-tesco-virtually-created-new-market-based-on-country-lifestyle/story/214998.html>

⁹ <http://techland.time.com/2012/05/07/smartphone-friendly-grocery-store-adorns-walls-of-chicago-l-station/>

Figure 1. Home and Workplace Addresses in Google Maps App

Figure 2. 3D Touch Functions of Google Maps and Apple Maps¹⁰

The specific interest of the current research is whether targeting a commuting context is associated with purchase-related behavioral patterns that are induced by mobile coupon offers. In collaboration with one of the largest mobile service platform providers in Korea, we conduct a field study on how contextual targeting with commuting is associated with responsiveness to mobile coupons. We first define commuting routes as routes between home and the workplace and non-commuting routes as those other than commuting routes. We then send 14,741 mobile coupons to 9,928 public transit app users who travel over commuting or non-commuting routes (i.e., commuters or non-commuters). We analyze the relationship between targeting methods (i.e. targeting commuters vs. targeting non-commuters) and response to mobile coupons

¹⁰ iPhone users can instantly start the navigation process of Google Maps and Apple Maps on their commuting routes right from the Home screen by using iPhone's 3D Touch technology.

and how this relationship is moderated by user attributes (e.g., demographics, previous redemption experience, and exposure to multiple coupons) and coupon characteristics (e.g., expiration dates). Dynamic and static matching mechanisms are adopted to corroborate the causal relationship and address potential endogeneity. Finally, we conduct additional econometric analyses to confirm that potential confounding factors do not drive the obtained results.

The key findings indicate that, compared to targeting non-commuters, targeting commuters increases the rate of mobile coupon redemption even after we control for the potential effects of users, coupons, and products. Enhanced receptiveness to mobile coupons is more perceivable when users obtain multiple coupons. Further analysis reveals that the multiple-coupon distribution strategy (i.e. repeated targeting) increases response rates of non-commuter targeting more effectively than commuter targeting. After controlling for unobserved heterogeneity, we find that coupons with short expiration dates more successfully improve the response rates of commuter targeting than do coupons with long expiration dates. For non-commuter targeting, however, the reverse holds true; response rates of non-commuter targeting are higher for coupons with long expiration. For example, offering discount coupons for which a day or a few hours remain before expiration is an effective strategy for commuter targeting. By contrast, coupons with relatively longer expiration dates (i.e., one week) should be utilized for non-commuter targeting to enhance its redemption rates. Finally, commuter targeting exerts a significantly positive effect on redemption speed as well as the rate of mobile coupon redemption.

The contribution of our study to the growing body of literature on moment-based marketing lies in its examination of whether targeting commuting context stimulates high receptiveness to mobile coupons. Consumers may have unstable preferences for the same product over different time periods and contexts (Bettman et al. 1998). Although perceived as a negative socio-economic component, commuting offers marketers opportunities that advance marketing success. The findings serve as useful guidance on who to target, when to send mobile coupons, how many coupons to distribute, which coupons are more attractive, and what products should be advertised on mobile coupons. Contextual targeting that is underlain by

analyses of mobile apps with geographical and temporal components substantially increases users' reception to mobile coupons. Our results provide managers with several fruitful directions in formulating effective distribution strategies for mobile coupons, implementing precise consumer segmentation, and achieving context-specific product positioning.

2. Research Background

2.1. Mobile Coupon Redemption

Given the portability and ability of mobile devices to locate and track themselves using global positioning systems (GPS), mobile coupons have a distinctive capacity for targeting users using both location and time (Ghose and Han 2011). Accordingly, managers have utilized the geographical and temporal features of mobile coupons to increase their redemption rates. Surprisingly, only a few researchers have examined mobile coupons, as summarized in Table 1. Luo et al. (2014) are among the first to identify the geographical and temporal aspects of mobile coupons and examine their individual and interaction effects on redemption behaviors. By conducting a field study in which users at different locations (i.e., geographical aspects) are targeted at different periods (i.e., temporal aspects), Luo et al. (2014) find that targeting proximal users using a product with a short promotion lead time can lead to higher coupon redemption rates than targeting distant users and using a product with a long lead time. They also identify the interaction effect between the geographical and temporal aspects; that is, the effects of promotion lead time show an inverted U-shape when targeting distant users, but become negative when targeting proximal users. Other studies suggest diverse aspects of geographical and temporal targeting and examine their effects on mobile coupon redemption rates. For example, Danaher et al. (2015) employ the vertical and horizontal distances between customers and stores in a large shopping mall as an aspect of geographical targeting and find that not only horizontal distance but also vertical distance has a significantly negative effect on mobile coupon redemptions. Fang et al. (2015) and Fong et al. (2015) develop and examine the effectiveness of two geographical targeting concepts, namely geo-fencing and geo-conquesting, which target focal and

competitive locations, respectively.

Table 1. Summary of Prior Mobile Coupon Literature

Authors	Coupon Type	Method	Geographical Aspect	Temporal Aspect
Luo et al. (2014)	Movie theater	Field experiment	Three treatments of distance from theaters (i.e., near, medium, and far)	Three treatments of timings (i.e., same day, one day prior, and two days prior)
Danaher et al. (2015)	Shopping mall	Panel set in the field	Horizontal and vertical distance to stores	Time of day and day of week
Fang et al. (2015)	Movie theater	Field experiment	Three treatments of location (i.e., geo-fenced treatment, non-geo-fenced control, and geo-fenced control)	
Fong et al. (2015)	Movie theater	Field experiment	Three treatments of shopping area (i.e., competitive, focal, and benchmark location)	
Ghose et al. (2016)	Multiple product categories in a shopping mall	Field experiment	Treatments based on users spatial trajectory	Temporal aspects of user shopping times
Andrews et al. (2016)	Missed call alert and video streaming service	Panel set in the field	Crowdedness in subway	
Present study	Food and beverage	Field study	Commuting	

While earlier studies have focused mostly on the individual or interaction effects of geographical and temporal targeting, recent studies have focused on contextual targeting, which integrates both aspects of mobile coupon targeting. For example, Andrews et al. (2016) investigate how a context (i.e., physical crowdedness) affects consumer responses to the mobile coupons of a missed call alert service by using panel sets in the fields of subway trains. Using free food and beverage coupons, our study offers an extension of the studies that investigate the contextual targeting of commuters.

2.2. Commuting and Mobile Coupon Redemption

Among daily life experiences, commuting is associated with the lowest level of positive mean affect (e.g., happiness, warmth/friendliness, and enjoying oneself) and a relatively high level of negative mean affect (e.g., frustration/annoyance, depression, and anger/hostility) (Kahneman et al. 2004). In other words,

commuting between the home and the workplace is a source of stress (Novaco et al. 1990, Schaeffer et al. 1988). This problem has driven researchers from diverse disciplines to examine the determinants and consequences of commuting stress (See summaries by Koslowsky et al. 1995). First, researchers have reported that stress during commuting is induced by various factors, such as noise, time pressure, traffic congestion, and air pollution. Commuting stress also stems from repeated exposure to the same stimuli—a situation engendered by travel over the same route at the same time of day. Prolonged exposure of this kind exacerbates stress from commuting, pushing it to levels that exceed that experienced on other trips or journeys (Baron 1986). Commuting becomes even more stressful when individuals are unable to manage environmental factors (Stutzer and Frey 2008), which are often beyond their control (Koslowsky et al. 1995). Second, scholars have indicated that diverse stress-related outcomes are significantly related to commuting. After a commute, individuals demonstrate not only lowered moods and reduced tolerance for frustration but also increased anxiety, heart rate, and hostility (Koslowsky et al. 1995).

Stress arising from commuting is an equally important issue with respect to consumer targeting, exerting different effects on, for instance, the redemption of mobile coupons. Stress occurs when an individual is unable to cope with the demands of an environment (Lazarus 1966, Lazarus and Folkman 1984, Cohen et al. 1995). People who suffer from stress therefore tend to believe that they have no control over their surroundings and the outcomes of their actions (Cutright and Samper 2014). Several empirical studies (e.g., Cutright et al. 2013) have demonstrated, however, that humans naturally crave the restoration of control (Fiske et al. 1996). For example, Durante and Laran (2016) argue that people under stress are willing to save money and spend only on necessities to recover control over themselves and their environments. Levav and Zhu (2009) reveal that customers are inclined to buy various products that will help them take charge of their environments. Regardless of the disagreement between research findings on how control is acquired, what is clear is the fact that the coping strategies typically implemented by people (e.g., exercise, buying) involve simple actions that are designed to re-establish self-restraint or environmental regulation (Koslowsky et al. 1995). Notwithstanding this aim for control, however,

individuals are reluctant to follow through with their attempts for fear of wasting effort (Cutright and Samper 2014). They thus often exhibit limited initiative even if this means loss of the control that they desire (Glass et al. 1969, Lefcourt 1973). Put differently, the greater the predictability and producibility of the outcomes of actions, the stronger the propensity of individuals under stress to endeavor restoring control (Cutright and Samper 2014). In accordance with the clear outcomes of redemption behavior (i.e., acquisition of a product), we expect commuter targeting to stimulate a higher mobile coupon redemption rate than non-commuter targeting given that redemption behavior poses no risk and allows people to control environments.

In physiology, stressors, which represent agents that induce stress, are usually classified into two categories, namely, acute and chronic stress. Acute stress is caused by a specific, unpredictable event and is short-lived in nature, whereas chronic stress occurs on a daily basis (i.e., long-term stress). In other words, chronic stress is driven by a prolonged stressful situation (Koslowsky et al. 1995). Thus, commuting stress can be classified as a type of chronic stress given that commuting is not a one-day event but a daily routine. Chronic stressors bring forth physiological reactions and induce a desire to eat. In the physiology literature, the link among stress, food choice, and food intake is well established. Researchers (e.g., Takeda et al. 2004) have revealed that the cortisol (a glucocorticoid class of steroid hormone) produced by chronic stress induce appetite. More specifically, chronic stress is highly associated with cortisol exposure, which poses a considerable effect on the brain's reward system. When greatly sensitized, this reward system drives individuals to consume highly palatable foods, such as those containing sugar (Adam and Epel 2007). Given that commuting stress can be classified as a type of chronic stress and that we use food and beverage coupons in our study, we expect commuter targeting to result in high redemption rates of mobile coupons that enable individuals to satisfy the appetite and desire to eat induced by chronic commuting stress.

Despite the positive effects of chronic stress and cortisol on appetite, these may also pose adverse consequences on the normal functioning of the dopaminergic system, thereby increasing individuals' impulsivity and unplanned behaviors. Impulsivity represents a multidimensional attribute wherein

individuals attach more weight to immediate gain than to long-term future benefits (Moustafa et al. 2017). This natural human trait is known to moderate the relationship between chronic stress and coping actions (i.e., redemption behaviors). Previous studies (e.g., Inman and McAlister 1994, Krishina and Zhang 1999) have demonstrated that coupon duration is significantly associated with redemption likelihood, which in turn, affects coupon profitability. Promotional coupons with short duration restrictions inspire a higher sense of urgency and a greater feeling of anticipatory regret (if economic savings are missed because coupons are left to expire) in consumers than do coupons with long duration restrictions (Inman and McAlister 1994). Regret theory (Bell 1982, Inman and McAlister 1994) is often adopted as a frame of reference for delving into the effects of time pressure on coupon redemption and purchase behaviors; the theory indicates that consumer regret increases as an expiration date approaches.

Scholarly interest has been directed primarily toward across-time redemption patterns for coupons that come with and without time restrictions and toward anticipated regret. By contrast, limited attention has been paid to the effects of time pressure on redemption in a context where consumers may exhibit impulsivity due to chronic stress. Because the redemption of mobile coupons with short (or long) durations until expiration may stimulate less (or more) planned and more (or less) impulsive behaviors, people experiencing chronic commuting stress are expected to be more responsive to coupons with short expiration durations. That is, given that highly impulsive consumers exhibit a greater sense of urgency and anticipatory regret than do consumers with low proclivity for impulsivity, promotions with short duration restrictions are more effective for the former than the latter. Conversely, because non-commuters are less likely to exhibit impulsivity and anticipatory regret, they are more responsive to coupons when sufficient time is available until expiration to exchange their coupons and obtain economic benefits.

3. Research Setting

3.1. Promotions via Mobile App

To test whether commuter targeting can increase the rate of mobile coupon redemption, we conducted a

field study using a mobile app operated by one of the largest mobile service platform providers in South Korea. This mobile app, which has attracted more than a million active users, is developed for people who use public transportation, such as buses or subways. Its key feature is a public transit guidance function that provides users with several optimal routes (i.e., faster routes) and estimated times of arrival at their destinations based on real-time traffic conditions. After a user chooses a route from the available options, the app provides step-by-step guidance in real time during travel, accurately identifies the location of the user (i.e., on a bus, subway, or street), and alerts him/her about when and where to board, exit, and change public transportation modes.

The installation and use of the mobile app requires registration of users' home and work addresses. As each user can register only one pair of home and work address, he/she is recorded as having two *commuting routes*, that is, from home to workplace and vice versa. To use the app function for commuting routes, users can simply tap the “*guide me to workplace*” or “*guide me home*” button. The app then guides the users from their homes to offices or vice versa. When users wish to be guided on routes other than those through which they commute, they must add a *temporal route* by registering points of departure and destination. They can then activate the guidance function for the temporal route by tapping “*guide me on the route*.” These temporal routes are called *non-commuting routes*. Note, however, that the manner by which the user interface was designed ensures that users (commuters) have no incentive to add a temporal route and favor the respective function over those for commuting routes. The app provides exactly the same guidance function to commuters and non-commuters. In this study, *commuters* and *non-commuters* refer to users on commuting routes and non-commuting routes, respectively.

3.2. Field Study and Empirical Design

To validate the effectiveness of targeting commuters versus non-commuters with respect to redemption rate, we conducted a field study using the data provided by our partner company. We randomly selected subjects who use the guidance function of the app, either for commuting or non-commuting routes, and sent them mobile coupons. When a user activates the guidance function for commuting or non-commuting routes,

a popup window with the message “*check the gift in your gallery*” randomly opens, and a mobile coupon is automatically downloaded to the gallery application of the user’s mobile phone (Figure 3, left side). Immediately after the mobile coupon is downloaded, the user is requested to answer a short follow-up survey on his/her age group and gender on the popup window with no compensation offer. The survey is optional (i.e. A user can close the popup window that directs him/her to the survey) because requests for private information can negatively affect the redemption behaviors of users. The mobile coupon is an image file that contains the picture, name, expiration date, and unique barcode of a product (Figure 3, right side). Using this barcode, users can exchange their coupon for the product at no extra charge (i.e., free coupon) and at any selected store before its expiration. The barcode can also be used to identify whether, when, and where users exchange their mobile coupons. Five food and beverage products were provided by two national chain stores for the promotional campaign, and these products were allocated randomly to selected users (Table 2). Specifically, we chose the largest donut-selling (Dunkin’ Donuts) and convenience store (CU) chains in South Korea on the basis of their store count and availability across the nation. The selection was also based on the consideration that users should easily find stores where they can redeem their coupons.

Figure 3. Description of Mobile Coupons

Our 21-day field study was conducted in South Korea on weekdays from August 24, 2015 to September 21, 2015. A total of 71,828 mobile coupons were distributed to 44,622 randomly selected users of the transit mobile app. Note that every user can receive one coupon a day. We identified the effectiveness of targeting people on commuting routes clearly by excluding users who received mobile coupons on both commuting and non-commuting routes, and limiting our sample to users who received one or more coupons on either commuting or non-commuting routes *only*. The filtering left us with 9,928 users, who received a total of 14,741 mobile coupons (i.e., 14,741 observations). We categorized 1,107 and 8,821 users into treatment and control groups, respectively, corresponding to those who received mobile coupons on commuting and non-commuting routes, respectively. In other words, treatment and control groups represent users' reception of mobile coupons through two targeting methods, namely, *commuter targeting* and *non-commuter targeting*, respectively.

Table 2. Five Products of Mobile Coupons

Products	Stores	Price	Expiration Date
Two Donuts	Dunkin Donuts	\$2.30	September 30, 2015
Muffin and Coffee	Dunkin Donuts	\$5.00	
Korean Rice Roll (Gimbap)	CU	\$1.00	
Candy Bar	CU	\$1.10	
Strawberry Juice ^a	CU	\$1.30	

^a The strawberry juice coupon was distributed from September 7, 2015.

A sensible approach to identifying the increase in incremental purchases driven by promotions (i.e. mobile coupons) may be to recruit another control group to which no promotions are provided and track their purchase histories. As with other studies that inquired into the effectiveness of mobile coupons (e.g. Luo et al. 2014, Danaher et al. 2015, Fong et al. 2015, Andrews et al. 2016), however, this study did not cover investigating the effects of promotions (i.e., promotions vs. no promotions). Instead, we concentrated on two promotional treatments and ascertained which one more effectively elicit higher redemption rates.

The control group is about eight times larger than the treatment group because the reminder function

is used more frequently on non-commuting routes. We adopted both dynamic and static matchings to alleviate the concern that the size difference between the groups and their varying traits could have influenced our results. Among the 14,741 mobile coupons distributed to users, 5,123 were redeemed, corresponding to a 34.8% redemption rate. The value is relatively higher than those derived of other studies (e.g., 3.22% by Andrews et al. (2016), 7.35% by Luo et al. (2014), and 2.6% by Fong et al. (2015)). This difference may have stemmed from the fact that our mobile coupons are *free* coupons (with a full 100 % discount), whereas those offered in other studies are *discount* coupons (with small or very low discounts). Our findings are consistent with those of Ghose et al. (2016), who reached a redemption rate greater than 30% when they offered a 50 % discount on coupons.

4. Econometric Analysis and Results

To directly identify the treatment effects on redemption rate, we initially focused on users who received only one coupon on either commuting or non-commuting routes throughout the study (*one coupon users*); that is, we excluded users who received multiple coupons. We then included users who received multiple coupons (*one or more coupon users*) and examined the treatment effects over the multiple coupon approach to determine which mobile coupon distribution strategy is more effective.

In addition, the users in the treatment and control groups may differ in terms of traits and observability. Such differences, instead of the treatment, can lead to the different redemption behaviors of mobile coupons. To mitigate the concern that the results are driven by user heterogeneity instead of the treatment effect, we adopt the propensity score matching (PSM) method. PSM helps to address selection biases and establishes a causal link between commuter targeting and redemption behaviors by generating a matched control group that best resembles the observed characteristics of the treatment group (Rosenbaum and Rubin 1983, Rubin 2006).

4.1. One Coupon Users

4.1.1. Model Specifications. In this section, we discuss the users who received only one coupon throughout

the study period. Our model was designed to estimate the unobserved probability or likelihood of redemption for each mobile application user. This variable is called *RedemptionLikelihood_i* and was modeled as a logistic function of whether a user is on commuting routes (i.e., belongs to the treatment group). Other control variables were also included as follows:

$$RedemptionLikelihood_i = \frac{\exp(U_i)}{1 + \exp(U_i)}, \quad (1)$$

$$U_i = \alpha + \beta * Treatment_i + \tau * X_i + \varepsilon_i,$$

where i represents each user, U_i denotes the latent utility of mobile coupon redemption, $Treatment_i$ indicates whether user i is travelling on his/her commuting routes when he/she receives the coupon (i.e., belongs to the treatment group). X_i is a vector of control variables with user behaviors, and ε_i comprises idiosyncratic error terms. We carefully identified the commuting effect by controlling for time of day and day of week effects. We incorporated three *part of day* dummies (i.e., *Morning*, *Afternoon*, and *Evening*) and four *day of week* dummies (i.e., *Monday*, *Tuesday*, *Wednesday*, and *Thursday*) because commuters are expected to exhibit varying commuting patterns at different parts of the day and days of the week. *Nighttime* and *Friday* are employed as bases in the model, and *Morning*, *Afternoon*, *Evening*, and *Nighttime* represent 5:00–12:00, 12:00–17:00, 17:00–22:00, and 22:00–5:00, respectively. We also conducted robustness checks by replacing the three *part of day* dummies with 23 *hour of day* dummies, and the results remained robust under the alternative specification. We also included four *product* dummies to control for product effects given that redemption rates may differ systematically across the five products. As redemption behavior can be affected by the number of days that are left before expiration (Inman and McAlister 1994), we controlled for the corresponding effects by incorporating the *Days to Expiration* variable, which refers to the number of days between the receipt and expiration of a coupon. Our model controls for the mobile App Usage Behavior of each user by incorporating three variables, namely, *Usage Amount*, *Usage Frequency*, and *Avg Usage Amount*. *Usage Amount* and *Usage Frequency* represent the number of times that each user has activated the application in the previous week, and the number of days during which each user has used the

app in the previous week, respectively. The variable *Avg Usage Amount* indicates the ratio of *Usage Amount* to *Usage Frequency*.

We estimate the propensity scores or probabilities for the *one coupon users* to be assigned to the treatment group. Using a logistic regression, we model the likelihood of receiving a coupon on commuting routes as a function of the covariates, such as *Days to Expiration* and the *part of day*, *day of week*, and *product* dummies. These variables are included to control the factors that may affect commuting patterns and redemption behaviors. We also include *Usage Amount*, *Usage Frequency*, and *Avg Usage Amount* to account for the mobile application usage patterns of users. Using the estimated propensity scores, we match a control group user with a treatment group user to enable each treatment group user to have a corresponding unique control group user. In this way, we considered the biases that may arise from the different sample sizes of the treatment and control groups. After the matching procedure, 353 out of the 478 treatment group users are matched to control group users.

Figure 4. Distribution of Propensity Score before and after Matching

We identified the statistical differences of the covariates between the treatment and control groups before and after matching via a t-test to ensure the quality of the matching procedure (see Table A1 in Appendix). The results show that although the differences among several covariates are statistically significant before matching, all covariates are balanced and statistically similar after matching ($p > 0.1$).

Figure 4 plots and compares the propensity score distribution of these covariates before and after matching. The gray solid line represents the matched treatment group, while the dotted and dashed lines represent the control group before and after the matching, respectively. Figure 4 shows that the propensity score distribution of the matched treatment group is more similar to that of the matched control group than to that of the unmatched control group. We conduct the Kolmogorov-Smirnov test to examine the equality of the distribution statistically, and to determine whether the distributions of the matched treatment and control groups are statistically similar. These results validate the quality of the matching procedure.

4.1.2. Results. We estimated various models with and without the control variables to test the rigorousness of our results. Table 3 presents the results. The treatment effects on redemption rates are significantly positive across all the model specifications, suggesting that targeting commuters increases the rate of mobile coupon redemption even after controlling for the selection biases (i.e., PSM) as well as the effects of products, App Usage Behaviors (i.e., *Usage Amount*, *Usage Frequency*, and *Avg Usage Amount*), coupon characteristics (i.e., *Days to Expiration*), and time (i.e., *part of day* and *day of week* dummies).

Table 3. Results for Users Who Receive Only One Coupon

Variables	Model 1	Model 2	Model 3	Model 4	Model 5
Treatment	0.808*** (0.175)	0.818*** (0.175)	0.854*** (0.179)	0.895*** (0.182)	0.923*** (0.185)
Constant	-1.188*** (0.159)	-1.527*** (0.280)	-0.907** (0.380)	-1.031*** (0.348)	-0.651 (0.423)
App Usage Behavior (3 Var.)	Y	Y	Y	Y	Y
Days to Expiration	N	Y	Y	Y	Y
Parts of Day, Day of Week	N	N	Y	N	Y
Product	N	N	N	Y	Y
Observations	706	706	706	665	665
LL	-401.6	-400.7	-392.8	-378.7	-374.2

Significance levels: *p < 0.1, **p < 0.05, ***p < 0.01. Robust standard errors are enclosed in parentheses.

Base on the results of Model 5, Figure 5 illustrates the estimated marginal mean likelihood of coupon redemption for the treatment and control groups. The two vertical lines in the figure represent the 95% confidence intervals. The estimated marginal mean likelihood of coupon redemption for the treatment group is 37.8%, which is 1.94 times greater than that for the control group (19.5%).

Figure 5. Effects of Commuting on Redemption Rate

4.2. One or More Coupon Users

4.2.1. Model Specification. For this analysis, we included users who have received multiple coupons during study period. We estimate the latent probability of redemption of user i 's c -th coupon as $RedemptionLikelihood_{ic}$, which was modeled as a logistic function of the variables described in the previous section. Given that the number of products that each user redeems upon receiving a coupon can affect redemption rates, we controlled for such effects by incorporating the variable *Number of Prior Redemptions*. The variable *Number of Coupons*, which represents how many coupons a user has received, was also included. We likewise incorporated the interaction terms of $Treatment_i$ with *Number of Coupons* and *Days to Expiration* to identify the treatment effects over the multiple coupon strategy and derived the findings from the optimal strategies for mobile coupon distributions¹¹. The mean and maximum VIF for the model with all the control variables are 2.06 and 4.82, respectively, indicating inconsequential collinearity. We adopted random effects logistic regression to capture both within- and across-individual unobserved heterogeneities and identified the time-invariant treatment effects as follows:

¹¹ We also incorporated the nonlinear (i.e., quadratic) terms of *Number of Coupons* and *Number of Prior Redemptions*, and their interaction terms with $Treatment_i$. The effects are insignificant across different model specifications.

$$RedemptionLikelihood_{ic} = \frac{\exp(U_{ic})}{1 + \exp(U_{ic})}, \quad (2)$$

$$U_{ic} = \alpha + \beta * Treatment_i + \tau * X_{ic} + \nu_i + \varepsilon_{ic},$$

where i and c represent the users and the coupons that each user received, respectively; ν_i is a user-specific random effect; and ε_{ic} is a reminder disturbance. The random effects model is preferred when unobserved individual heterogeneity ν_i can be assumed uncorrelated with model variables. Given that every user in our sample was *randomly* selected, we assume that the variables in our model are free of unobserved individual heterogeneity. Furthermore, following an approach analogous to that of De et al. (2013), we estimated ν_i and found that all the correlations of the estimated ν_i with the model variables are less than 0.3, indicating negligible correlation (Hinkle et al. 2003). We first adopt the matching procedure described in the previous section for the *one or more coupon users*. We estimated the overall propensity score of each user for multiple observations (i.e., multiple coupons) using the covariates and then match those treatment and control group users that are most similar to each other in terms of estimated propensity scores. Since a matched control group user for a treatment group user remains the same across multiple observations (i.e., one to one matching) of the treatment group user, we call it a *static matching* (Xu et al. 2016). Given the nature of time-variant covariates, we also adopt a *dynamic matching* procedure in which we calculated the propensity scores of a treatment group user for each observation and then assign different matched control group users to the treatment group for each observation (i.e., one to many matching) (Xu et al. 2016). In both matching procedures, we additionally included *Number of Prior Redemptions* as a covariate for estimating the propensity scores.

A total of 637 and 913 out of the 1,107 treatment group users are matched with control group users after the static and dynamic matching procedures, respectively. Given the time-varying nature of covariates, dynamic matching generates more accurate matches by using user-coupon-level covariates, while static matching merely uses user-level covariates that are collapsed across observations. Following Haviland et al. (2007), we calculated the standardized bias before and after the matching procedures to check the

covariate balance and compare the qualities of the static and dynamic matching procedures. Specifically, for a covariate X , the standardized biases before and after matching (i.e., d_X and d_{Xm} respectively) are calculated as follows:

$$d_X = \frac{|M_{X_t} - M_{X_p}|}{\sqrt{\frac{S_{X_t}^2 + S_{X_p}^2}{2}}} \text{ and } d_{Xm} = \frac{|M_{X_t} - M_{X_C}|}{\sqrt{\frac{S_{X_t}^2 + S_{X_C}^2}{2}}}, \quad (3)$$

where M_{X_t} is the mean X for treatment group users, while M_{X_p} and M_{X_C} are the mean X for the unmatched and matched control groups, respectively. The denominators represent the overall standard deviations, where S_{X_t} is the standard deviation of X for treatment group users, and S_{X_p} and S_{X_C} are the standard deviations of X for the unmatched and matched control group users, respectively. Therefore, the standardized bias represents the absolute mean difference of a covariate between two groups standardized by the overall standard deviation, which is calculated using the standard deviations of the covariate for the two groups.

We found that both the static and dynamic matching procedures greatly reduce the standardized biases (see Table A2 in Appendix). On average, these methods improve the standardized biases by 58.9% and 68.3%, respectively. Moreover, whereas dynamic matching shows a consistent percentage improvement in the standardized biases, a bias for the covariate *Two Donuts* is worsened after the static matching procedure, even if the bias after the matching remains sufficiently low. Therefore, as expected, dynamic matching exhibits greater efficiency than static matching. We also evaluated the covariate balance and conducted the Kolmogorov-Smirnov test to ensure the quality of the matching procedures. The results confirm the statistical similarity between the treatment and control groups after the matching procedures.

4.2.2. Results. Table 4 summarizes the results of the models with and without the interaction terms after adopting either static or dynamic matching method. The estimated coefficients are qualitatively consistent across the models, but Model 8 is the most desirable, as indicated by the greater efficiency of dynamic

matching compared to static matching as well as both Akaike's information criterion (AIC) and the Bayesian information criterion (BIC). Hence, we focused on the results of Model 8. The treatment effect on redemption rate is significantly positive, indicating that targeting commuters increases the rate of mobile coupon redemption even after consideration for multiple-coupon users. The results show that the effect of *Number of Coupons* on redemption rate is significantly positive, whereas its interaction term with *Treatment_i* is significantly negative. The magnitude of the negative interaction effect is less than that of the positive main effect. To identify treatment effects on the basis of *Number of Coupons*, we plotted the estimated marginal mean likelihood of coupon redemption in the treatment and control groups using this variable (Figure 6). The vertical lines in Figure 6 represent the 95% confidence intervals. The estimated marginal mean probability of first coupon redemption (i.e., *Number of Coupon* = 1) in the control group is 19.5%, whereas that in the treatment group is 57.1%, which is 2.93 times greater than that in the former. Promotions become more effective as they are repeated, but the distribution of multiple coupons is especially effective for non-commuter targeting. To illustrate, the estimated marginal mean probability of fourth coupon redemption (i.e., *Number of Coupon* = 4) in the treatment group is 67.4%, which is only 10.3% points higher than that of first coupon redemption. By contrast, the estimated marginal mean probability of fourth coupon redemption in the control group is 62.3%, which is 42.8% points higher than that of first coupon redemption (19.5%). This figure is also similar to the estimated marginal mean probability of the first coupon redemption in the treatment group (i.e., 57.7%). However, although targeting non-commuters using four coupons is as effective as targeting commuters using one coupon in terms of increasing redemption rate, this strategy incurs a significant cost. In our setting, at least \$3 is required for each user to send three additional mobile coupons.

Table 4. Results for Users Who Receive One or More Coupons after Static and Dynamic Matching

Variables	Static Matching					Dynamic Matching		
	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6	Model 7	Model 8
Treatment	0.985*** (0.196)	1.136*** (0.266)	2.156*** (0.495)	4.316*** (0.803)	1.511*** (0.146)	2.092*** (0.258)	2.300*** (0.410)	4.449*** (0.619)
Number of Coupons	0.171* (0.0893)	0.216** (0.107)	0.175** (0.0885)	0.428*** (0.121)	0.438*** (0.0815)	0.608*** (0.105)	0.435*** (0.0812)	0.750*** (0.113)
Days to Expiration	0.0200* (0.0121)	0.0204* (0.0121)	0.0439*** (0.0153)	0.0742*** (0.0184)	0.0104 (0.00918)	0.0109 (0.00931)	0.0261** (0.0119)	0.0488*** (0.0133)
Number of Prior Redemptions	-0.468*** (0.146)	-0.477*** (0.148)	-0.437*** (0.149)	-0.470*** (0.149)	0.125 (0.154)	0.109 (0.153)	0.139 (0.155)	0.117 (0.154)
Number of Coupons*Treatment		-0.0839 (0.102)		-0.451*** (0.132)		-0.306*** (0.110)		-0.566*** (0.126)
Days to Expiration*Treatment			-0.0467*** (0.0180)	-0.0994*** (0.0236)			-0.0322** (0.0154)	-0.0752*** (0.0177)
Constant	-1.274*** (0.484)	-1.360*** (0.493)	-1.921*** (0.550)	-3.172*** (0.684)	-0.947** (0.370)	-1.257*** (0.388)	-1.361*** (0.421)	-2.522*** (0.507)
App Usage Behavior	Y	Y	Y	Y	Y	Y	Y	Y
Parts of Day, Day of Week	Y	Y	Y	Y	Y	Y	Y	Y
Product	Y	Y	Y	Y	Y	Y	Y	Y
Observations	2,782	2,782	2,782	2,782	3,564	3,564	3,564	3,564
Number of Users	1,274	1,274	1,274	1,274	2,244	2,244	2,244	2,244
LL	-1,593	-1,592	-1,589	-1,583	-2,068	-2,063	-2,066	-2,054

Significance levels: *p < 0.1, **p < 0.05, ***p < 0.01. Robust standard errors are enclosed in parentheses.

Figure 6. Effects of Commuting on Redemption Rate by Number of Coupons

The findings also indicated that the effect of *Days to Expiration* is significantly positive, whereas its interaction term with *Treatment_i* is significantly negative. The magnitude of the negative interaction effect is greater than that of the positive main effect; thus, *Days to Expiration* differentially influence the treatment and control groups. Specifically, the estimated coefficient of *Days to Expiration* for the treatment group is -0.0264 ($p < 0.05$), whereas that for the control group is 0.0488 ($p < 0.01$)¹². These values reflect that responsiveness to commuter targeting is not significantly affected by the number of days to expiration but that such responsiveness with respect to non-commuter targeting increases as expiry length grows longer. These results provide additional insight into the effects of mobile coupons' expiry lengths on redemption rates. In the case of movie coupons, Luo et al. (2014) found a negative inverted U-shaped relationship (i.e., positive and then negative) between expiry lengths and redemption rate for proximal and non-proximal users, respectively. With regard to shopping mall coupons, Danaher et al. (2015) identified a negative relationship between expiry lengths and redemption rates.

¹² The point estimate and the p-value represent the results of the following null hypothesis:

$$H_0: \hat{\beta}_{Days\ to\ Expiration} + \hat{\beta}_{Days\ to\ Expiration * Treatment} = 0$$

5. Robustness Check

5.1. Inclusion of Demographic Control Variables

Given that our user demographic information was collected voluntarily, we have demographic information of only 34.52% of all users. Considering the limited amount of information, we included all users in our analyses regardless of whether we have their demographic information or not and then excluded the demographic variables. To test whether the results remain robust even after controlling for the demographic information of users, we employed missing information groups as bases in the model and included demographic dummy variables (Xu et al. 2016), such as age group and gender. We included two *gender dummies* and five *age dummies* (i.e., under 17 years, 18 years to 25 years, 26 to 33 years, 34 to 39 years, and over 40 years) and replicated all previous estimations. Table 5 reports the results after controlling for demographic information. Our results remain robust against the alternative model specifications after accounting for the available demographic information.

Table 5. Results after Controlling for Demographic Variables

Variables	One Coupon Users		One or More Coupon Users		
	Full Sample	After Matching	Full Sample	After Static Matching	After Dynamic Matching
	Model 1	Model 2	Model 3	Model 4	Model 5
Treatment	0.757*** (0.122)	0.945*** (0.186)	4.599*** (0.422)	4.292*** (0.805)	4.472*** (0.620)
Number of Coupons			0.536*** (0.0554)	0.420*** (0.120)	0.753*** (0.113)
Days to Expiration	0.0139*** (0.00376)	-0.000450 (0.0116)	0.0383*** (0.00521)	0.0731*** (0.0183)	0.0507*** (0.0132)
Number of Prior Redemptions			-0.449*** (0.0894)	-0.480*** (0.150)	0.0973 (0.154)
Number of Coupons*Treatment			-0.494*** (0.0756)	-0.438*** (0.133)	-0.568*** (0.127)
Days to Expiration*Treatment			-0.0637*** (0.0126)	-0.0984*** (0.0236)	-0.0757*** (0.0177)
Constant	-1.327*** (0.209)	-0.674 (0.427)	-3.009*** (0.268)	-3.175*** (0.681)	-2.567*** (0.504)
Age, Gender	Y	Y	Y	Y	Y
App Usage Behavior	Y	Y	Y	Y	Y

Parts of Day, Day of Week	Y	Y	Y	Y	Y
Product	Y	Y	Y	Y	Y
Observations	7,632	664	14,741	2,782	3,564
Number of Users	7,632	664	9,928	1,274	2,244
LL	-3672	-369.2	-7711	-1577	-2046

Significance levels: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. Robust standard errors are enclosed in parentheses.

5.2. Inclusion of User Location Control Variables

Stress levels may differ not only across users on different routes (e.g., commuting and non-commuting routes) but also across those in different location (e.g., metropolitan area and rural area). To validate whether the results remain robust even after controlling for the fixed-effects of user location, we obtained information on where users redeem their mobile coupons from the two participating retailers (i.e., Dunkin Donuts and CU). Note that because the information was collected when users redeemed their coupons, we could not identify the locations of users who did not exchange any of their mobile coupons. Additionally, the locations where users redeem their mobile coupons do not always correspond to where their homes or workplaces are located. Nevertheless, we can infer where users live based on the information that was readily available to us. Using such data, we classified users into four groups; *Metropolitan users* [Users who redeemed all their mobile coupons only in metropolitan areas (i.e. the capital and satellite cities near the capital that share a public transit system)], *Rural users* [Users who redeemed all their mobile coupons only in rural areas (i.e. all locations, except the capital and the satellite cities near the capital)], *Travelling users* (Users who redeemed their mobile coupons in both metropolitan and rural areas), and *Not-redeemed users* (Users who have not redeemed any of their mobile coupons). We then employed *not-redeeming users* as a base group and included three dummy variables in the model for *one or more coupon users*. We focused only on *one or more coupon users* because the fixed effects can accurately predict the redemption behaviors of *one coupon users*. As shown in Table 6, the results are largely consistent with those obtained in the main analysis, thereby reinforcing the robustness of our results against location fixed effects.

Table 6. Results for Users Who Receive One or More Coupons after Addressing Location Effect

Variables	Static Matching	Dynamic Matching
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Treatment	1.788*** (0.672)	1.847*** (0.585)
Number of Coupons	-0.156 (0.108)	-0.0248 (0.108)
Days to Expiration	0.0123 (0.0158)	-0.000973 (0.0131)
Number of Prior Redemptions	-0.277** (0.136)	-0.121 (0.126)
Number of Coupons*Treatment	-0.193* (0.112)	-0.218* (0.116)
Days to Expiration*Treatment	-0.0483** (0.0206)	-0.0357** (0.0173)
Constant	-2.221*** (0.567)	-2.035*** (0.497)
Location	Y	Y
App Usage Behavior	Y	Y
Parts of Day, Day of Week	Y	Y
Product	Y	Y
Observations	2,782	3,564
Number of Users	1,274	2,250
LL	-1073	-1369

Significance levels: *p < 0.1, **p < 0.05, ***p < 0.01. Robust standard errors are enclosed in parentheses.

5.3. Endogeneity of App Usage Behaviors

Previous redemption experiences can exert the positive effects on app usage. This possibility raises concerns regarding the possible endogeneity of app usage behaviors driven by previous redemption experiences (Pearl 2009; Morgan and Winship 2015). For example, if users realize that they can receive mobile coupons when using the app, they may be motivated to increase app usage. To validate such possibility, we conducted additional analyses as a robustness check. For linear models, common approaches to addressing such endogeneity problems is to identify instrument variables, which are highly correlated with endogenous variables but uncorrelated with error terms and to include predicted values of endogenous covariates into the models. However, these methods may be inappropriate for nonlinear models, such as logit and probit models, which come with a binary dependent variable (Wooldridge 2010). As an alternative, a two-step residual approach is widely used in the marketing literature (e.g., Che et al. 2012; Danaher et al. 2015) and has been proven effective in reducing endogeneity bias in parameter estimation (Terza et al. 2008).

Using an ordinary least squares estimator, we first regressed *Usage Amount*, which is considered to be endogenous, on *Number of Prior Redemptions* and on all the other model covariates, such as *Number of Coupons*, *Days to Expiration*, *part of day*, *day of week*, and *product*. We also included the lagged value of *Usage Amount* as an additional regressor because previous app usage behaviors may account for a large part of the current app usage. We replicated the procedure for *Usage Frequency* and *Avg Usage Amount*. The residuals from the three regressions were incorporated into the model as additional covariates, and the model was re-estimated using two samples: (1) *one or more coupon users* matched after static matching and (2) *one or more coupon users* after dynamic matching. Note that the endogeneity of app usage behaviors due to previous redemption experiences matters only to *one or more coupon users* because *one coupon users* have no previous redemption experience.

Table 7. Results for Users Who Receive One or More Coupons after Addressing Endogeneity

Variables	Static Matching	Dynamic Matching
Treatment	4.318*** (0.803)	5.606*** (0.659)
Number of Coupons	0.427*** (0.122)	1.013*** (0.124)
Days to Expiration	0.0742*** (0.0184)	0.0446*** (0.0138)
Number of Prior Redemptions	-0.467*** (0.149)	0.139 (0.155)
Number of Coupons*Treatment	-0.449*** (0.132)	-0.902*** (0.133)
Days to Expiration*Treatment	-0.0998*** (0.0236)	-0.0769*** (0.0183)
Constant	-3.181*** (0.685)	-3.443*** (0.541)
Residuals	Y	Y
App Usage Behavior	Y	Y
Parts of Day, Day of Week	Y	Y
Product	Y	Y
Observations	2,782	3,564
Number of Users	1,274	2,250
LL	-1582	-1958

Significance levels: *p < 0.1, **p < 0.05, ***p < 0.01. Robust standard errors are enclosed in parentheses.

As can be seen in Table 7, the results are largely consistent with those obtained in the main analysis,

suggesting that the endogeneity of app usage driven by previous redemptions is not a serious concern in our analyses.

5.4. Assessment of Alternative Scenario

The treatment and control group users may experience systematically different events while they hold a coupon (i.e., from the day they receive a coupon until the day they redeem it), and this could drive different redemption rates. If this alternative explanation holds true, the treatment effect is greater for users who redeem a coupon later (i.e., users who hold a coupon for longer), but is relatively limited for users who redeem a coupon at an earlier time. To assess the alternative scenario, we conducted a subsample analysis using *Redemption Period (RdP)*, which refers to the number of days between the receipt and redemption of a coupon. We classified the *one coupon users* into seven subgroups, namely, *Redeem on the same day* ($RdP = 0$), *Redeem within a week* ($0 < RdP \leq 7$), *Redeem within two weeks* ($7 < RdP \leq 14$), *Redeem within three weeks* ($14 < RdP \leq 21$), *Redeem within four weeks* ($21 < RdP \leq 28$), *Redeem within five weeks* ($28 < RdP \leq 35$), and *Don't redeem*¹³. We then constructed six subsamples by combining the *Don't Redeem* subgroup with the other six subgroups and generated matched pairs of the treatment and control groups within each subsample by adopting the PSM described in Section 4.1.

Table 8 presents the results for each of the six subsamples. The treatment effect for users who redeem a coupon on the same day is significantly positive and is greater than that for average *one coupon users* after matching (0.923, see Table 3). However, such an effect gradually decreases and becomes insignificant as *Redemption Period* increases. Figure 7 shows the 95% confidence intervals for the treatment effect estimates with different redemption periods. The black horizontal line represents the treatment effect estimates for average *one coupon users* after matching (0.923, see Table 3). The treatment effect is prevalent for users who redeem a coupon at an earlier time (e.g., on the same day when they receive the coupon) but diminishes and becomes insignificant as *Redemption Period* increases. These results are in contrast with

¹³ We exclude 17 users who redeem after five weeks ($35 < RdP$), due to a lack of observation.

the expected outcomes under the alternative scenario. Therefore, these results reduce the possibility of the alternative explanation and support our arguments.

Table 8. Results for Each Redemption Period

Variables	RdP=0	0<RdP≤7	7<RdP≤14	14<RdP≤21	21<RdP≤28	28<RdP≤35
Treatment	1.258** (0.567)	0.889*** (0.289)	0.791** (0.324)	0.439 (0.488)	0.820 (0.513)	0.121 (0.598)
Constant	-2.623** (1.268)	-1.245** (0.605)	-1.608** (0.814)	-1.462 (1.054)	-3.164*** (1.113)	-13.97*** (3.519)
App Usage Behavior	Y	Y	Y	Y	Y	Y
Days to Expiration	Y	Y	Y	Y	Y	Y
Parts of Day, Day of Week	Y	Y	Y	Y	Y	Y
Product	Y	Y	Y	Y	Y	Y
Observations	383	503	474	434	439	425
LL	-60.52	-178.9	-146.9	-75.66	-76.70	-44.03

Significance levels: *p < 0.1, **p < 0.05, ***p < 0.01. Robust standard errors are enclosed in parentheses.

Figure 7. Treatment Effect Estimates with Different Redemption Periods

5.5. Effects on Redemption Period

Redemption period *RdP* can be an endogenous outcome variable rather than an exogenous treatment. Hence, we considered redemption period as an endogenous dependent variable and additionally examined the effect of commuting-based contextual targeting on redemption speed and redemption rate. We conducted a standard cox proportional hazards regression, which is usually adopted to model time variables

with continuous time-varying covariates and is expressed as follows:

$$h(t, X) = h_0(t) \exp \left\{ \sum_i \beta_i x_i + t \left(\sum_j \gamma_j z_j \right) \right\}, \quad (4)$$

where hazard function $h(t, X)$ represents the rate of mobile coupon redemption (i.e., failure) on each day t , $h_0(t)$ refers to the baseline hazard function, and x_i and z_j indicate time-invariant and time-varying covariates, respectively. The treatment group dummy was regarded as time-invariant covariate x_i , and time-varying covariate z_j includes *Number of Coupons*, *Days to Expiration*, *Number of Prior Redemptions*, and the three mobile app usage variables.

We applied the hazard model to three different samples: (1) *one-coupon users* after matching, (2) *one-or-more coupon users* after static matching, and (3) *one or more coupon users* after dynamic matching. The cox proportional hazard regression analyses confirm that commuting-based contextual targeting has a significantly positive effect on redemption speed and redemption rate (Table 9). In other words, users on commuting routes are likely to redeem a coupon faster than those on non-commuting routes.

Table 9. Results of Cox Proportional Hazard Regression

Variables		One Coupon Users	One or More Coupon Users	
			Static Matching	Dynamic Matching
x_i	Treatment	0.635*** (0.154)	0.313*** (0.0606)	0.849*** (0.0553)
z_j	Number of Coupons	Y	Y	Y
	Days to Expiration	Y	Y	Y
	Number of Prior Redemptions	Y	Y	Y
	App Usage Behavior	Y	Y	Y
LL		-1071	-8070	-10876

Significance levels: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. Standard errors are enclosed in parentheses.

The results further reinforce our theoretical argument on stress (i.e., Users who are under stress may redeem more frequently and at a faster rate), and the managerial implications of commuting-based contextual targeting for greater marketing effectiveness, thereby enhancing the contributions of our study.

5.6. Additional Evidence of Commuting Stress

Commuter targeting shows a greater likelihood of coupon redemption than non-commuter targeting. We conducted additional analyses in support of the argument that this difference was not attributed to factors other than the *stress* of commuting. If the argument holds true, the treatment effects become greater during periods with higher commuting stress, such as rush hours. Similar to the previous analysis, we classified *one coupon users* into five subgroups, namely: *Redeem in the Morning*, *Redeem in the Afternoon*, *Redeem in the Evening*, *Redeem at Night*, and *Don't redeem*. Traffic is especially heavy in the *Morning* and *Evening* because of the large number of commuters. We constructed four subsamples by combining the *Don't Redeem* subgroup with the other four subgroups and then generated a matched control group within each subsample by adopting the PSM procedure described in Section 4.1.

Table 10 indicates that the treatment effects are insignificant for users who redeem a coupon in the *Afternoon* and at *Night*, but are significantly positive for those who redeem a coupon in the *Morning* and *Evening* when traffic is usually heavy. Given that traffic can be the main cause of commuting stress (Eden 2002), the results support the argument that our findings are attributed to commuting stress. In other words, the results imply that targeting commuters leads to greater redemption rates compared to targeting non-commuters (i.e. control group) only in the *Morning* and *Evening* during which the behaviors of commuters and non-commuters are differentiated by the level of commuting stress that they experience. To validate these results further, we identified rush hours (three-hour periods) that are more specific than *Morning* (seven-hour period) and *Evening* (five-hour period), and conduct similar analyses. The last two columns of Table 10 represent 7:00–10:00 (*Rush Hour1*) and 18:00–21:00 (*Rush Hour2*), which are the peak hours of traffic during *Morning* and *Evening*. The treatment estimates for *Rush Hour1* and *Rush Hour2* are also significantly positive. These results provide further support for our theoretical argument on stress.

Table 10. Results for Each Part of Day

Variables	Morning	Afternoon	Evening	Night	Rush Hour1	Rush Hour2
Treatment	0.999*** (0.375)	0.352 (0.282)	1.119*** (0.284)	0.121 (0.673)	2.354*** (0.738)	1.228*** (0.378)

Constant	-2.337*** (0.793)	-1.608** (0.704)	-1.971*** (0.663)	1.410 (1.348)	-5.476*** (1.624)	-1.783** (0.836)
App Usage Behavior	Y	Y	Y	Y	Y	Y
Days to Expiration	Y	Y	Y	Y	Y	Y
Parts of Day, Day of Week	Y	Y	Y	Y	Y	Y
Product	Y	Y	Y	Y	Y	Y
Observations	466	487	516	421	444	478
LL	-129.2	-183.2	-188.4	-39.92	-58.93	-134.4

Significance levels: *p < 0.1, **p < 0.05, ***p < 0.01. Robust standard errors are enclosed in parentheses.

5.7. Within-Effects of Commuter Targeting

To alleviate the concerns related to endogeneity and unobserved individual-level confounding effects, we scrutinized users who received multiple coupons on both commuting and non-commuting routes and conducted an additional fixed-effect analysis. Specifically, 5,456 users with 20,532 mobile coupons remained in our sample. It should be noted that users who redeemed all coupons or any of the coupons are excluded given that fixed-effects can accurately explain their redemption behaviors. We then replicated the main analysis by using a fixed-effect estimator. The results are presented in Table 11. As can be seen in the table, the results are robust against individual level heterogeneity. The table also indicates that commuting-based contextual targeting exerts a positive within effect on the rate of mobile coupon redemption. Put differently, a user is more likely to redeem a mobile coupon when he/she is targeted in commuting routes than when he/she receives the same coupon on non-commuting routes. The results further reinforce the validity of the causal interpretations and suggest that the endogeneity and unobserved individual-level effects are not serious concerns in our analyses.

Table 11. Results for Users Who Receive Multiple Coupons on both Commuting and Non-Commuting Routes

Variables	Model 1	Model 2	Model 3	Model 4
Treatment	0.749*** (0.0763)	0.424*** (0.156)	1.405*** (0.193)	1.335*** (0.358)
Number of Coupons	0.0315 (0.0360)	0.0149 (0.0366)	0.0255 (0.0360)	0.0238 (0.0368)
Days to Expiration	0.0613*** (0.00650)	0.0603*** (0.00652)	0.0630*** (0.00653)	0.0628*** (0.00659)
Number of Prior Redemptions	-1.042*** (0.0425)	-1.046*** (0.0426)	-1.047*** (0.0427)	-1.047*** (0.0427)

Number of Coupons*Treatment		0.110** (0.0463)		0.0133 (0.0577)
Days to Expiration*Treatment			-0.0343*** (0.00921)	-0.0327*** (0.0115)
App Usage Behavior	Y	Y	Y	Y
Parts of Day, Day of Week	Y	Y	Y	Y
Product	Y	Y	Y	Y
Observations	20,532	20,532	20,532	20,532
Number of Users	5,456	5,456	5,456	5,456
LL	-6074	-6071	-6067	-6067

Significance levels: *p < 0.1, **p < 0.05, ***p < 0.01. Robust standard errors are enclosed in parentheses.

5.8. Other Robustness Checks¹⁴

We replicate the main analyses without adopting any of the dynamic and the static matching procedures and find that the results are qualitatively similar to those of the main analyses. This implies that selection bias is not a serious concern in the analyses. We further confirm the robustness of our results by adopting a probit estimator. Specifically, we replace the logistic distributions of Equations 1 and 2 with the cumulative density function of the standard normal distribution as follows:

$$RedemptionLikelihood = \Phi(U) = \frac{1}{\sqrt{2\pi}} \int_{-\infty}^U e^{-\frac{1}{2}Z^2} dZ. \quad (4)$$

We find that results are qualitatively the same as those obtained in the main analyses. This indicates that our findings are robust against the alternative estimation method.

6. Conclusion

Despite the growing importance of contextual marketing in business (Salz 2015), relatively few studies have inquired into such phenomenon given the difficulty of identifying and targeting consumer contexts. Research has centered on individual effects originating from the geographical and temporal features of targeting with efforts extending only as far as the investigation of these features' simple interaction effects. Because time and space are interrelated (Luo et al. 2014), however, each of geographical and temporal feature cannot sufficiently demonstrate the contexts of customers and is insufficient as a basis for targeting

¹⁴ The specific results are available upon request.

the right people in the right (i.e., intended) context. Along with Andrews et al. (2016), who looked into how context (i.e., crowdedness) affects consumer responses to mobile coupons, our study is among the first to assess the effects of contextual targeting with commuting on mobile coupon redemption behaviors. The current research contributes to the growing body of the literature on contextual targeting in at least three key ways. First, we delved into a wider scope of contextual dimension in an effort to deepen our understanding of contextual targeting. We extended the intriguing spatial context (i.e., crowdedness) that Andrews et al. (2016) explored to commuting, in which individuals dynamically interact with a given space. Although people in the same spatial environment are confronted with a similar level of crowdedness, their commuting statuses (i.e., commuters or non-commuters) can vary. Our findings suggest that people traveling over the same route and experiencing the same level of perceived crowdedness can differ in terms of redemption rates—a difference that is contingent upon commuting status. Second, commuting is a more easily identifiable context than crowdedness and thereby presents more wide-ranging opportunities for the implementation of mobile marketing. Mobile businesses can effortlessly distinguish between commuting and non-commuting consumers by using an API provided by map apps or adopting an SDK that is intended to detect users' home and workplace addresses. Commuting therefore facilitates targeting via various mobile apps—a strategy that is not as achievable on the basis of perceived crowdedness given that such context may be difficult to capture and leverage. Finally, we included various elements of mobile coupons and corresponding treatment effects into our analysis, providing a holistic insight into designs and distribution-related strategies for mobile couponing (e.g., targeting contexts, number of coupons, expiry length, and prior redemption experiences).

Several implications for research and practice can be gleaned from our results. This study expanded our understanding of the consequences of commuting and investigated such phenomenon beyond its negative aspects. Extensive research on commuting has been devoted mostly to unfavorable effects, such as increased anxiety and hostility and decreased tolerance for frustration (Koslowsky et al. 1995). Carrying out a field study on the behaviors of 9,928 consumers who use mobile public transit apps, we instead

identified how marketers can benefit from exploiting the commuting context, which is an easily identifiable routine that occurs throughout the world. The commuting context is considerably associated with a high likelihood of response to mobile coupons and at a fast redemption speed. Mobile marketers may capitalize on commuting to enhance the effectiveness of their mobile marketing strategies in different ways. For instance, mobile apps designed for food delivery (e.g., Domino's Pizza) can expand the mobile marketing strategies of the business by limiting the coverage of mobile coupon distribution to commuters. Map applications (e.g., Google Maps) and local restaurant apps (e.g., Yelp), which have been evolving as marketing platforms, can also enjoy improved marketing effectiveness and profitability through exploitation of the commuting context. Google Maps, which now allows local businesses to provide mobile coupons to its users, can supply commuter targeting functions at high bid prices. Online advertising services (e.g., Google AdWords) feature already differentiated bid prices according to various targeting methods.

Whereas most studies on mobile promotions restricted the number of coupons per individual to one, we allowed users to receive multiple coupons and then identified how the treatment effects change with multiple coupons. Furthermore, by adopting both dynamic and static matching procedures to generate matched control and treatment group users, we obtained less biased estimates of the changes in treatment effects across multiple coupons (Table 4). Accordingly, our results offer a number of constructive implications for mobile coupon distribution. The effect of *Number of Coupons* on redemption rate is significantly positive for the control group ($p < 0.01$), but insignificant or significantly less positive for the treatment group (Table 4). These results imply that although marketers can increase the mobile coupon redemption rate of non-commuters by providing them with multiple coupons, such effectiveness does not extend to commuters. Therefore, for managers interested in directing their marketing strategies toward non-commuters, offering multiple coupons to each non-commuter can elevate their marketing performance. Conversely, marketing activities geared toward commuters must be restricted to offering only one coupon per commuter while increasing the number of targeted commuters to enhance the efficiency of the campaigns.

We also identified the different relationships between expiry lengths and redemption rates for commuters and non-commuters, providing fruitful implications for mobile coupon design. Mobile coupons with short redemption periods (e.g., expiry with a few hours or within a day) are more effective for commuters, whereas those with longer redemption periods (e.g., long exchange periods or regular redemption reminders) work more effectively for non-commuters (Table 4). Marketers can also increase the mobile coupon redemption rates of commuters by utilizing coupons with short exchange periods.

Researchers and practitioners can likewise benefit from our explanation of why commuter targeting generates higher redemption rates than does non-commuter targeting. On the basis of psychological and physiological theories, we developed the argument that *stress*, which is exacerbated by commuting, increases commuters' coupon redemption rate. We provide empirical support for this argument through additional analyses and show that marketers can further increase response rates by focusing on specific periods of the day when commuting stress is relatively high (e.g., rush hours) (Section 5.6). The results can be applicable to people facing similar stresses. People doing housework, for instance, are potential targets as housework is another important source of chronic stress (Kahneman et al. 2004). Despite the value provided by the study, however, the results should be interpreted with caution. Without further research, we cannot guarantee that the findings are indeed applicable to different types of stress (e.g., acute stress) and coupons of different products (e.g., clothes or movie tickets).

Similar to other studies, the current work has a number of limitations. The study involved food and beverage coupons given that products in such categories help diminish commuters' stress. High response rates can be associated with the choice of product offerings available through coupon incentives. To increase the generalizability of the findings and control for potential product effects, products in alternative categories or brands should be offered in promotional coupon campaigns. Furthermore, the promotion literature suggests that consumers' redemption behaviors may vary depending on specified or displayed savings (e.g. Chen et al. 1998, Della Bitta et al. 1981). Accordingly, future studies along this line of inquiry should vary the format of coupons in terms of discount rates and presentation of savings (i.e., 50% vs. \$10

off). Another limitation revolves around insufficient information about users' demographic characteristics, such as income level and occupation. The availability of such demographic details would enable a more comprehensive exploration of coupon redemption behaviors that may vary across diverse groups. Because of potential concerns about privacy, the public transit app studied in this research collects demographic data only from users who volunteer to supply such information. Finally, this study centered on the context of commuting-driven stress and its effects on coupon redemption propensities. Other stress-provoking situations must be tested to reinforce the reliability of the findings.

Given the prevalence of mobile devices and their arms' reach availability all the time, mobile-based targeting is increasingly becoming an integral aspect of firms' marketing campaigns. As we move closer toward the app-based mobile economy, the importance of mobile apps as a bridge between online and offline channels is rapidly growing. Understanding consumers' state of mind and satisfying their in-the-moment needs through the analysis of temporal and spatial contexts will strongly encourage them to make offline purchases and enable firms to pave the way for successful marketing innovation.

Appendix

Table A1. Covariate Balance before and after Matching

	Treatment Group	Control group					
		Before Matching			After Matching		
		Mean	Mean	Mean diff.	t stat.	Mean	Mean diff.
Usage Frequency	1.521	1.367	0.154	1.872	1.584	0.0623	0.477
Usage Amount	3.346	3.060	0.286	0.996	3.646	0.300	0.755
Days to Expiration	25.79	23.70	2.093	4.53	26.38	0.589	0.892
Morning	0.827	0.987	0.160	21.108	0.827	0.000	0.000
Night	0.173	0.013	0.160	21.108	0.173	0.000	0.000
Monday	0.314	0.222	0.092	4.05	0.289	0.025	0.737
Tuesday	0.246	0.207	0.039	1.780	0.263	0.017	0.518
Wednesday	0.144	0.197	0.053	2.438	0.153	0.008	0.317
Thursday	0.164	0.206	0.042	1.899	0.173	0.008	0.301
Candy Bar	0.286	0.303	0.017	0.687	0.306	0.020	0.576
Two Donuts	0.212	0.203	0.009	0.433	0.235	0.023	0.722
Muffin and Coffee	0.017	0.031	0.014	1.512	0.020	0.003	0.280
Korean Rice Roll	0.422	0.360	0.062	2.366	0.382	0.040	1.074
Strawberry Juice	0.062	0.102	0.040	2.448	0.057	0.005	0.318

Table A2. Standardized Bias before and after Matching

	Static Matching			Dynamic Matching		
	Std. Bias (Before)	Std. Bias (After)	Percentage Improvement	Std. Bias (Before)	Std. Bias (After)	Percentage Improvement
Usage Frequency	0.440	0.084	80.8	0.335	0.093	72.2
Usage Amount	0.146	0.111	23.7	0.097	0.052	46.3
Days to Expiration	0.128	0.054	58.2	0.086	0.080	7.9
Number of Prior Redemptions	0.245	0.022	91.1	0.254	0.022	91.4
Candy Bar	0.100	0.010	89.6	0.043	0.019	55.4
Two Donuts	0.006	0.018	-183.3	0.062	0.011	82.9
Muffin and Coffee	0.176	0.035	80.3	0.148	0.008	94.7
Korean Rice Roll	0.075	0.009	88.2	0.044	0.009	80.5
Strawberry Juice	0.078	0.007	90.9	0.077	0.007	90.6
Morning	0.347	0.046	86.6	0.540	0.244	54.7
Night	0.347	0.046	86.6	0.540	0.244	54.7
Monday	0.232	0.028	87.9	0.215	0.006	97.3
Tuesday	0.089	0.048	46.1	0.106	0.034	67.6
Wednesday	0.230	0.014	94.0	0.261	0.012	95.4
Thursday	0.102	0.024	76.1	0.115	0.051	56.2
Friday	0.107	0.059	45.0	0.055	0.030	44.2
Average	0.178	0.038	58.9	0.186	0.058	68.3

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