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In-App Couponing or Group-Couponing: The Impact of Mobile Marketing Strategies on Branded App Adoption

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ABSTRACT

While mobile marketers have devoted increased marketing efforts to promote their apps, little is known about the effectiveness of mobile marketing strategies on consumers' adoption of branded apps. This study investigates whether two mobile in-app marketing strategies— in-app couponing and in-app group-couponing—impact consumer adoption and how social influences from both existing adopters and people in a physical environment strengthen or weaken the effectiveness of these two strategies.

Based on a proprietary data collected from a large Chinese shopping mall, this study analyzed both daily aggregate adoption data across eight months and daily individual adoption data of 1,908,082 consumers. Surprisingly, our results showed that while both in-app couponing and group-couponing are two various couponing strategies, their impacts on consumers' adoption of branded apps are opposite. Specifically, we found that while the likelihood of consumer adoption was positively associated with the frequent use of in-app group-coupons, it was negatively associated with the frequent use of in-app coupons. Interestingly, this study also revealed opposite moderating effects of social interactions from existing adopters and from people in a physical environment. These findings imply that the impacts of two in-app marketing strategies are not constant but dynamic with the increase in the number of adopters and the crowdedness of a physical environment.

Keywords: Mobile App Adoption, Branded Apps, Mobile In-App Marketing Strategy, Mobile Group Coupon, Mobile Coupon, Social Influence

In recent years, the mobile app market has experienced immense growth with the rapid penetration of mobile devices. As of the fourth quarter of 2019, a total of more than 4.4 million apps were available in the Google Play Store and Apple App Store (Statista 2020). Cumulative downloads from the Apple App Store and Google Play App Store reached 205.4 billion in 2018 and are expected to grow to 258.2 billion in 2022 (Statista 2019). Among the fastest-growing categories of mobile apps, branded applications, which feature the brand logos or icons of companies (Bellman et al. 2011), have become an important channel for market communication and distribution (Boyd, Kannan and Slotegraaf 2019; Kim, Wang and Malthouse 2015; van Noort and van Reijmersdal 2019).

To enhance consumer adoption of their branded apps, companies have devoted increased marketing efforts to promote their apps. In practice, many companies communicate with consumers about the launch of their branded apps at the point of purchase or through social media, along with a so-called welcome offer or app-exclusive offer to incentivize consumers. For example, McDonald's launched its mobile app before Easter in Germany with 32 straight days of different offers only available through the app, which led to more than 5 million downloads, making it the most downloaded app in Germany in February 2018 (Williams 2018). In the hospitality industry, many agents or hotels provide mobile app-exclusive offers to motivate consumers to download their mobile apps. Orbitz, for instance, offered consumers an extra 18% off that is only available in the app before black Friday 2019 (PCWorld 2019). Among all app-exclusive offers, mobile in-app couponing, including regular couponing and group-buying couponing, has become one of the most commonly utilized mobile marketing strategies when companies launch their branded apps. A mobile in-app coupon is an electronic ticket delivered or solicited by mobile phones that can be exchanged for a financial discount or rebate when consumers make purchases (Mobile Marketing Association 2007). Whole Foods Markets, for example, issued in-app coupons for consumers to get discounts when they downloaded the Whole Foods mobile app (McNew 2016). McDonald's also gave away a “buy one Big Mac get one free” deal for consumers after they downloaded McDonald’s app and registered an account when McDonald's introduced their mobile application (Pope 2015). As a special form of in-app coupons, group-buying coupons are also frequently issued to provide discounted products or services that are activated only when a certain number of people pay for the deal or are “tipped” into the deal (Hu and Winner 2017; Jing and Xie 2011; Song et al. 2016). This kind of group coupon is usually set with a maximum number of coupons pre-specified (Edelman, Jaffe and Komlners 2016; Hu et al. 2019), and often indicates savings, remaining purchase time, and deal popularity by showing the number of people who have already downloaded/redeemed the vouchers (Luo et al. 2014). The Chinese e-commerce platform Pinduoduo, which offers low price group-buying products (or “team purchases”), had attracted over 20 million registered users by February 2016, six months since it had been launched in September 2015 (CIW Team 2019).

Despite these active practices of mobile in-app couponing strategies, we lack an understanding of whether and how mobile in-app marketing strategies affect consumers’ adoption of companies’ branded apps. Intuitively, one may question how likely mobile in-app marketing could affect consumers’ adoption of a mobile app when consumers have not yet downloaded it. While consumers could not be informed directly within a mobile app about the company’s in-app marketing offerings, we suggest that consumers can still learn about these in-app offerings through many other channels outside their apps (e.g., TV ads, emails, or social media). Thus, it is possible that the more frequent companies release mobile in-app incentives, the more likely consumers become aware of these incentives and are then motivated to download the apps. Furthermore, as consumers could also learn about mobile in-app offers through their social networks or at the point of purchase in brick-mortar stores, it is also likely that existing adopters and/or people surrounding a brick-mortar store may strengthen or weaken the potential influences of mobile in-app marketing activities. For example, we may observe that the more consumers have adopted a mobile app, the more likely others will become known about the mobile in-app offers and hence will follow the suit. However, since a large crowd in a physical location (e.g., stores) may affect consumers to observe and learn about mobile in-app offers, the potential influences of mobile in-app activities may be hindered.

To address these issues, in this research, we investigate the impact of companies' mobile in-app marketing on consumers' adoption of companies' branded apps by focusing on two mobile in-app marketing strategies (i.e., mobile in-app couponing and mobile in-app group-buying couponing). For ease of discussion, we hereafter refer to regular in-app couponing and group-buying couponing as in-app couponing and in-app group-couponing, respectively. Specifically, we are interested in understanding three research questions: (1) Whether and how do these two types of mobile in-app strategies affect consumers' adoption of branded apps? (2) Are there any differences in the adoption effects of these two mobile marketing strategies? And (3) How (if at all) do social influences from an installed-user base (i.e., the existing adopters of a branded app) and from a physical environment (i.e., crowdedness of a physical location) moderate the impact of these two mobile marketing strategies?

A few recent studies in information systems and marketing have investigated the driving forces involving consumers' adoption of mobile apps, but mainly focused on issues such as (1) the impact of mobile app features on consumer adoption (Ha et al. 2012; Yang 2013; Peng, Chen and Wen 2014; Pentina et al. 2016; Shen 2015; Xu et al. 2016), (2) the impact of marketing in other channels outside of a brand's app (e.g., Ghose and Han 2014; Sun, Shi, Viswanathan and Zheleva 2019), and (3) free versioning (Arora, Hofstede and Mahajan 2017). To the best of our knowledge, however, none of the extant studies in the mobile marketing literature has examined how a company's mobile in-app couponing and group-couponing affects consumers' adoption of its branded app.

We empirically investigate our research questions by using the adoption data of a branded app of a Chinese supermall from January 1 to August 15, 2015, after the app was launched on April 1, 2014. Our analyses using both daily aggregate adoption data across eight months and the daily individual adoption data of 1,908,082 consumers in eight months revealed several consistent results. Surprisingly, our results showed that although both in-app coupons and in-app group-coupons are two different couponing practices, they created opposite impacts on consumers' adoption of branded apps. Specifically, we found that while a large number of in-app group coupons are associated with a higher consumers' adoption of the branded app, a large number of mobile in-app coupons are associated with a lower adoption rate. These two opposite results imply that although the frequent use of mobile in-app coupons provide consumers incentives such as informational or monetary values to download a mobile app, consumers are probably also concerned about potential costs from downloading an app, which could include, for example, information overload and annoyance. As a result, more frequent use of mobile in-app couponing induces higher concerns about potential information annoyance, leading to a negative influence on app adoption. In contrast, when marketers issue in-app group coupons, the unique design of group coupons stimulates people to make use of their social relationships to reach the required group size (Jing and Xie 2011). Such social interaction facilitates the information dissemination regarding the benefits of group coupons and the app, which helps ease concerns of information overload and annoyance, thereby leading to a positive adoption effect from the use of in-app group coupons.

More interestingly, we found that social influences from existing adopters created opposite moderating effects on the impact of in-app couponing and in-app group-couponing: a positive moderating effect on the impact of mobile in-app couponing, but a negative moderating effect on the impact of in-app group-couponing. As expected earlier, a large number of existing app users make it possible for people to learn from others about the benefits of in-app coupons and help release consumers' concerns of information annoyance, leading to a positive moderating effect from the installed users. This effect, in turn, attenuates the negative impact of in-app coupons and even changes it from a negative to a positive impact. The negative moderating effect on the impact of in-app group-couponing, however, is counter-intuitive. Perhaps because the social interaction created by all existing adopters plays the same role in showing/educating potential adopters as the social interaction stimulated by the design of group-couponing, the two sources of social interaction are substitutive to each other. Accordingly, as more consumers adopt the app, such an installed-user base can weaken the positive impact of in-app group-couponing, leading to a negative moderating effect of the installed-user base.

Contrary to the moderating effects of installed-user-based social interaction, we found that the crowdedness of a physical environment intensified both the negative impact of in-app couponing and the positive impact of in-app group-couponing. Specifically, as a physical environment became more crowded, its crowdedness created a negative moderating effect on the impact of mobile in-app couponing, but a positive moderating effect on the impact of in-app group-couponing. The negative moderating effect of location-based social interaction is consistent as expected, suggesting that when a physical location becomes crowded, it becomes difficult for consumers to observe and learn about the availability of mobile in-app coupons, which is often displayed in stores. Besides, a large crowd in a physical environment could also make people feel anxious or annoyed who thus lose interest in shopping further. Counterintuitively, if mobile in-app group coupons are issued, while observational learning becomes not easy and the negative anxiety effect may also take place in a crowded environment, social influences stimulated by the unique design of group-coupon may motivate people to download the app even more quickly in afraid of missing out good deals before the maximum limit is reached. Consequently, a positive impact of in-app group couponing becomes even stronger when a physical location is crowded.

These findings contribute to the mobile marketing literature and provide important implications for marketers when introducing mobile apps. First, although many industry practitioners advocate the use of mobile exclusive in-app offers to promote branded apps (Levi 2016; Mindbody n.d.), little attention has been devoted to empirically examine if and how mobile in-app incentives affect consumers' adoption of mobile apps. Our study fills this gap and contributes new and surprising empirical findings involving the opposite adoption effects of mobile in-app couponing and mobile in-app group-couponing. Specifically, our findings showed that at the early stage of a mobile app introduction, while the frequent use of in-app group-couponing can increase the adoption rate of a mobile app, the frequent use of in-app couponing could even reduce the adoption rate. Accordingly, mobile marketers should implement more in-app group coupons rather than regular coupons, as the former enhances while the latter impedes consumers' adoption of mobile apps.

Second, with consumers being increasingly influenced by social media through intense use of mobile devices, marketers are faced with the pressing need of understanding whether and how social influences among consumers strengthen or weaken the adoption effect of mobile in-app marketing strategies when issuing a new mobile app. Our findings of the opposite moderating effects of social influences from existing adopters and from the physical environment add to the mobile marketing literature by showing that the adoption effects of these two in-app couponing strategies are not constant but dynamic. Marketers should consider two contingencies together and develop dynamic and targeted mobile marketing strategies accordingly to enhance consumers' adoption of newly launched mobile apps. Specifically, marketers should take into account (1) the stage of their mobile app introduction (e.g., at the early stage when a small number of consumers have adopted a mobile app vs. the late stage when there are a large number of existing adopters) and (2) the location of consumers (i.e., whether they are located online vs. offline, in a less vs. more crowded environment) when determining their dynamic and targeted mobile in-app marketing strategies in different market scenarios.

Third, our findings regarding the adoption effects of group coupons also enhance our understanding of the new values created by this marketing practice. Previous research has contributed an important understanding and empirical findings regarding how group-couponing practice affects consumer behavior (Hu, Dang and Chintagunta 2019; Hu and Winner 2017; Song et al. 2016; Luo et al. 2014; Wu et al. 2015), retailer behavior (Cao et al. 2018; Edelman et al. 2016; Hu, Shi and Wu 2013; Marinesi et al. 2018), and sales effectiveness, as compared to other marketing practices, such as referral (Jing and Xie 2011). In addition to these influences, our study provides new findings about the adoption effects of group coupons. Although the practice of group coupons has recently been declining in the US (Jochem Vroom 2016; Johnson 2014), our study offers evidence concerning the new value of group-couponing on enhancing consumers' adoption of mobile apps. Particularly, if marketers allow consumers to voluntarily form a group by taking advantage of consumers' social networks and by setting a clear expiration time and a limit to the maximum number of group coupons, as implemented by the new eCommerce platform, Pinduoduo, they can significantly increase consumers' adoption of mobile apps.

Lastly, our findings contribute to the literature on location-based marketing. Extant studies in this literature have primarily concentrated on investigating how the sales impact of mobile marketing strategies varies with consumers' location and with their physical environment (Fang et al. 2015; Fong, Fang and Luo 2015). Little research, however, has investigated how the adoption effect of mobile marketing strategies varies with consumers' physical environment in a location (i.e., in a less- vs. more-crowded environment). Our findings regarding the negative moderating effect of crowdedness in a physical environment suggest that marketers should take into consideration the impact of mobile in-app couponing on both consumers' adoption of these apps and product sales. For example, although mobile in-app couponing may be effective in increasing sales, marketers should understand that it may be harmful to consumers' app adoption in the early stage when a mobile app is introduced. Therefore, when the number of adopters is still small, the primary consideration for marketers should be given to the impact of mobile marketing strategies on the adoption of their apps rather than sales.

We organize the remainder of the research as follows. In the next section, we first review the relevant literature and develop our hypotheses regarding the impact of two mobile in-app couponing strategies and the moderating effects of social influences. We then describe our empirical data and estimation methods and present our empirical findings. Finally, we conclude with a summary discussion of our research contributions, managerial implications, and suggestions for future research.

Theoretical Background and Hypothesis Development

The rapid proliferation of mobile apps has stimulated a growing number of studies examining the driving forces of consumers' mobile app adoption. A majority of these studies, however, have focused on the features of mobile apps (e.g., icon appearance and app type) and consumer characteristics (e.g., cultural background and demographics) (Ha et al. 2012; Peng, Chen and Wen 2014; Pentina et al. 2016; Yang 2013). Two recent studies in information research have also examined the impact of message framing (i.e., promotion- vs. prevention-focused) and consumer personality characteristics (e.g., extraversion, agreeableness, and conscientiousness) on mobile app adoption (Shen 2015; Xu et al. 2016). In mobile marketing literature, extant studies have been predominantly interested in investigating the impact of mobile marketing strategies on consumers' purchase behavior and firm performance (Bart, Stephen and Sarvary 2019; Boyd, Kannan and Slotegraaf 2019; Kim, Wang and Malthouse 2015; Hao, Guo and Easley 2017; Ji, Wang and Gou 2019; Liu et al. 2019; Wu, Tan, Chen and Liang 2018; Narang and Shankar 2019, van Noort and van Renjmersdal 2019). However, little attention has been paid to mobile app adoption. While two recent studies have taken the first step to investigate the impact of marketing strategies on consumers' adoption of mobile apps (e.g., email marketing in Sun et al. 2019; mobile in-app advertisements from third parties in Ghose and Han 2014), the impact of mobile in-app marketing strategies initiated by focal firms remains underexplored.

In the current study, we suggest that mobile marketing activities in branded apps (i.e., mobile in-app couponing and group-couponing) not only create values to potential adopters, but also impose problems to them. The former can enhance the perceived values of a branded app and in turn, can increase the likelihood for consumers to adopt the mobile app, but the latter may decrease their willingness to adopt it. Hence, the overall impact of mobile in-app marketing activities on consumers' adoption of branded apps depends on the relative strength of the benefits and costs created by mobile in-app marketing activities, which may differ for in-app couponing and group-couponing. Furthermore, as two important sources for consumers to learn about the potential values/costs created by companies' mobile in-app marketing strategies (e.g., through social networks or at the point of purchase), social influences may strengthen or weaken the impact of mobile in-app marketing activities on consumers' adoption of branded apps.

Impact of In-App Couponing and Group-Couponing

In general, mobile in-app marketing activities could create two aspects of values: (1) information values and (2) financial values to potential adopters, each of which can enhance the perceived values of a mobile app and in turn, the likelihood for consumers to adopt the mobile app. First, the regular use of mobile in-app marketing activities in a mobile app provides essential information about the brand's products, stores, and promotions, thus creating information values to potential adopters. For example, most manufacturers and retailers constantly release information within their branded apps concerning new products/new arrivals and promotions/discounts through mobile in-app couponing/group-couponing to mobile app users. Different from marketing activities that are implemented in traditional media (e.g., in print media, in stores, or on TV), which are costly for consumers to search, store and retrieve, the design of most mobile apps makes it much easier for consumers to do the above for marketing activities that are implemented within branded apps. Thus, a large number of mobile in-app activities can provide great information values to consumers, and hence, can stimulate them to download the mobile app.

Second, many firms provide an exchange of financial value to consumers with the use of these two mobile in-app marketing strategies. It can be a price discount, a free sample, a certain type of promotion, or a gift after making a purchase (Andrews et al. 2016). To stimulate consumers' interest in a mobile app, such financial benefits are often provided to them when they download and use the mobile app for the first time. Mobile in-app couponing and group-couponing, in particular, are often used by merchants as cost-saving or financial benefit certificates. Compared to traditional print coupons in newspapers/magazines, mobile in-app coupons are much more convenient for consumers to use for searching, storing, and retrieving. Hence, due to these potential financial values provided to consumers, a large number of mobile in-app marketing activities can also increase consumers' interest in adopting mobile apps.

However, we also recognize the potential problems with the use of mobile in-app marketing strategies. These potential problems could be caused by information overload and/or annoyance. Compared to PCs, the display spaces in mobile apps are generally much smaller. Because of the constraints of the display space on mobile devices, consumers can easily develop negative feelings of information overload when a mobile app uses more mobile in-app marketing activities (Shankar et al. 2016). When a mobile app overloads consumers with an overwhelming amount of marketing strategies (e.g., mobile promotions), consumers may become less likely to recognize the relevant deals they need. To make matters worse, these consumers may consider such mobile strategies as cumbersome and useless (Dickinger and Kleijnen 2008). Furthermore, mobile in-app strategies can create annoyance or irritation for consumers, thereby reducing the perceived values created from the use of mobile in-app marketing strategies. Sometimes these mobile marketing in-app couponing strategies are delivered through a mass-target methodology rather than a more selective one (Andrews et al. 2016). When receiving these mobile in-app strategies at the wrong time or place, consumers may find them annoying rather than convenient and valuable. Such irrelevant information released through mobile in-app marketing activities can also be regarded as an invasion of consumer privacy (Liu et al. 2012). Ghose and Han (2014) also point out the annoyance effect on consumers' adoption of a mobile app and demonstrate empirical evidence regarding the negative impact of in-app advertisements from third-party companies.

With an understanding of the potential values and problems created by mobile in-app marketing activities, we suggest that the impact of these two mobile in-app marketing strategies might differ due to the various designs of in-app couponing and group-couponing. Different from in-app couponing, the design of group-couponing exhibits two unique characteristics: (1) social interaction initiated due to the size of the group required for group-couponing, and (2) the maximum number of coupons pre-specified at the time when the group coupons are released. These two unique characteristics may lead to a positive impact of in-app group-couponing on consumers' adoption of a mobile app. For example, when a consumer becomes aware of the release of group coupons in a branded app, she may have an incentive to refer her social networks to the branded app and the benefits created by group coupons so that she can attract her friends to join the group and in turn, redeem the coupon after reaching the required group size. Such social interaction initiated by the design of group coupons stimulates social learning about the app and the benefits from group coupons and may lead to possible social herding behaviors among consumers' social networks. This, in turn, can strongly increase the likelihood that consumers will adopt the mobile app.

Furthermore, the design of a maximum number of coupons pre-specified can also create a threshold effect so that more consumers are stimulated to join the group in fear of missing out on the deal before the maximum number of coupons is reached (Luo et al. 2014; Marinesi, Girotra and Netessine 2018; Wu, Shi and Hu 2015). On many apps and platforms, such information as how many consumers have joined the group and/or how many coupons have been redeemed is often made accessible and salient. As a result, consumers can feel strong pressures to make adoption decisions as quickly as they can to avoid the regret of missing out on a good deal. Thus, although consumers may still be worried about information overload and annoyance with the use of in-app group-couponing, the social learning effect and threshold effect generated through the unique design of group coupons may lead consumers to be more focused on the benefits provided by group coupons. Accordingly, we may expect a positive impact of in-app group-couponing on the adoption of a mobile app.

In comparison, while the use of coupons also allows consumers to voluntarily disseminate the information about the coupons and the app to their social networks, their incentives for doing so may be lower without the group requirement. In the practice of coupons, as there is no maximum number of coupons clearly defined, we expect that the threshold effect would also be much weaker, as compared to that of group coupons. Thus, if consumers are more concerned about the potential problems of information overload and annoyance with a large number of coupons issued in a mobile app, they may be less likely to adopt it. Nevertheless, consumers may still find such an app useful and may be attracted by the information and financial values created through the use of coupons. It is also possible that the couponing strategy may create a positive impact on the adoption of an app.

Moderating Effects of Social Interaction

As consumers may not be aware of the values/problems created by mobile in-app marketing strategies without adopting a mobile app, social influences can play an important role in strengthening/weakening the impact of mobile in-app marketing strategies. Specifically, we investigate the moderating effects of two types of social influence: installed-user-based social influence and location-based social influence. The former social influence refers to the moderating effect generated through social interaction between existing and potential adopters, whereas the latter refers to the moderating effect generated through social interaction among people in a physical environment. We suggest that while both types of social interaction can create a social learning effect, which can moderate the impact of mobile in-app marketing strategies, they can also differ in other unique effects generated.

Moderating Effect of Installed-User-Based Social Interaction. The social interaction between existing and potential adopters allows existing app users to share information with potential mobile users regarding a mobile app and the benefits/problems created from mobile in-app marketing strategies through social media, such as Facebook, Twitter, and so on. Hence, the larger the installed user-base of a mobile app, the higher the chances that potential mobile users can learn from existing adopters, thus creating a social learning effect that moderates the impact of mobile in-app marketing strategies. Accordingly, we may expect that the installed-user base of existing adopters can generate a positive moderating effect on the impact of in-app couponing strategies. Consequently, as more consumers adopt a mobile app, the impact of in-app couponing may become less negative (more positive) if the main effect of in-app couponing is negative (positive) at the time when an app is introduced. However, since social learning can take place from all existing adopters, even without the design of group-couponing, the social learning initiated by the design of group-couponing becomes less important and influential as the number of existing adopters grows larger. This suggests that the two sources of social interaction (initiated due to the design of group-couponing and generated from all existing adopters) are substitutive to each other. As a result, the impact of in-app group-couponing becomes less influential as the size of the installed-user base increases.

Moderating Effect of Location-Based Social Interaction. In a similar vein, social interaction among people in a physical environment can also create a social learning effect through observational learning and/or direct communication. For example, to promote their mobile apps, manufacturers and retailers often display the QR codes of their mobile apps in offline stores to draw consumers' attention to their branded apps. Mobile users can also observe how people present an electronic coupon on their phones to get a discount at the time of purchase, and hence, learn that they can download a mobile app and obtain the e-coupon as well. Nowadays many offline stores even allow mobile users to directly order items using the store's app. Moreover, to help mobile users learn about the benefits of a mobile app, store employees are often encouraged to introduce the app to mobile users and teach them how to use it. All of these various ways of social interaction facilitate social learning among mobile users in a physical environment about the potential values/problems associated with mobile in-app marketing strategies, which in turn, may moderate the impact of mobile in-app marketing strategies.

Different from the installed-user-based social interaction, however, location-based social interaction may also create a unique effect: a negative anxiety effect. As stated earlier, a crowded environment can create barriers for shopping and can make consumers feel anxious (Hui, Fader and Bradlow 2009; Zhang et al. 2014). For example, the presence of crowded shoppers makes it difficult for consumers to observe others' behaviors, interact with others/employees, and hence, make any transactions. Most importantly, when a physical environment is so crowded, consumers may lose shopping (touring) interest and may simply choose to leave the environment. As a result, they may have a lower chance of learning and understanding a company's mobile in-app marketing strategies, as well as the associated values, leading to a negative anxiety effect.

With both the positive social learning effect and the negative anxiety effect in place, the overall moderating effect of social interaction in a physical environment may differ for in-app couponing and group-couponing. Specifically, when a limited number of coupons are pre-specified in the design of group coupons, a large crowd can impose much stronger pressures that may push consumers to download the branded app quickly to not miss out on good deals after they learn about the app from people surrounding them, which magnifies the threshold effect and in turn, leads to a stronger positive impact of in-app group-couponing. Without such a maximum constraint, however, the crowdedness of the environment can also create a stronger negative-anxiety effect, even though a crowded environment may create chances for consumers to observe and learn about the values of mobile in-app coupons during the period when the mobile in-app coupons are issued. This negative anxiety effect may make consumers so anxious in a crowded environment that they may lose interest in learning about the benefits from mobile in-app marketing, and may simply choose to leave the shopping location. Hence, we expect that social interaction in a crowded environment can strengthen the positive impact of in-app group-couponing, such that consumers may become much more likely to adopt a mobile app when marketers issue a large number of group coupons in the app. When a large number of coupons are issued, on the other hand, social interaction in a crowded environment can weaken the positive impact (or strengthen the negative impact) of in-app couponing, such that consumers become much less likely to adopt the app.

Empirical Analysis

Data and Variables

We collected a proprietary dataset from a large shopping mall in China to investigate both the proposed main effect of mobile marketing strategies and their interaction effects with social influence from the installed-user base and from the physical environment. This four-level mall has 2.9 million square feet and features more than 500 famous brands of stores and restaurants. From the time when the shopping mall launched its branded app in late April of 2014 to the end of December 2014, 26,687 people had adopted it. We were able to obtain a dataset containing the daily number of consumers who had registered for the mobile app and the daily in-app marketing activity information from January 1 to August 15, 2015.

Dependent Variable. We used the daily number of consumers who had registered for the mobile app as the dependent variable in our analysis. Because it is difficult for marketers to access information regarding the number of consumers who had downloaded the app daily (as well as the consumers' information), we used the number of registered consumers as a proxy for the number of adopters in our analysis. While the number of registered consumers may not be the same as the number of downloaded consumers, our definition of mobile app adopters captures those serious adopters who want to obtain information regularly about the mall, products/services offered, and mobile coupons issued by stores in the mall through using the app.

Mobile In-App Couponing and In-App Group-Couponing. We counted the number of mobile in-app coupons and in-app group coupons issued each day to measure the intensity of mobile in-app marketing strategies. On average, the shopping mall and its stores issued 3.26 mobile in-app coupons and 11.72 mobile in-app group coupons per day in our data period. Figure 1 shows the weekly number of adopters and mobile in-app marketing activities during our data period.

[Insert Figure 1 about here]

Installed-User Base and Crowdedness. Following the literature on network effects (e.g., Brynjolfsson and Kemerer 1996; Wang and Xie 2011), we measured the installed-user base as the cumulative number of existing adopters from the beginning of our data period, which is 26,687 as introduced earlier, to the previous day of our focal data point. We followed Andrew et al. (2005) and measured the crowdedness as the number of consumers entering the mall each day divided by the size of the mall in square meters.

Other Variables. We also incorporated consumer- and time-specific variables into our analysis. Specifically, to capture the impact of consumers' loyalty to the mall on their adoption of the mall's mobile app, we incorporated the average shopping frequency and the average duration (in seconds) of consumers who entered the mall each day. The average shopping frequency of consumers was calculated based on the cumulative number of days that consumers visited the mall from the beginning of our data period to the focal data point. We calculated the average duration that consumers stayed in the mall at a time point based on the entering and exiting times of each consumer on that day. The shopping mall adopted a probing technology that allows the mall to detect a consumer's mobile MAC address whenever each consumer enters and exits the mall. To capture the potential time variations in consumers' adoption behavior, we incorporated two quarter dummies, a weekend dummy, and a holiday dummy, into our analysis. The two quarter dummies, *Q1* and *Q2*, correspond to the first quarter (i.e., from January to March) and the second quarter (i.e., from April to June) of a year. We denoted the weekend dummy as 1 when the respective day was either Saturday or Sunday and as 0 otherwise. Lastly, the holiday dummy was denoted as 1 when the respectively day was a Chinese holiday, and as 0 otherwise.[1] The descriptive statistics of all variables are summarized in Table 1.

[Insert Table 1 about here]

[1] Chinese holidays in our data period include "New Year's Day" (01/01/2015-01/03/2015), "Chinese New Year" (02/18/2015-02/24/2015), "Qingming Festival" (04/04/2015-04/06/2015), "May Day" (05/01/2015-05/03/2015), and "Dragon Boat Festival" (06/20/2015-06/22/2015).

Model

We developed a Poisson model to estimate the impact of mobile in-app marketing strategies and the moderating effects of social influence on consumers' adoption of a mobile app. Specifically, we assumed that the number of adopters each day would follow a Poisson distribution, with the probability function given by

$$\Pr\left(Y = y_t \middle| X_t\right) = \frac{\mu_t^{y_t} \exp(-\mu_t)}{y_t!}, \tag{1}$$

where Y denotes the number of daily adopters, a random variable assumed to follow the Poisson distribution. y_t denotes the observed number of adopters at time t. μ_t denotes the distribution mean. Following the literature (Cameron and Trivedi 1986; Greene 2003), we define the distribution mean to be an exponential function of the influential variables X_t. That is,

$$\begin{aligned}\mu_t = \exp(&\beta_0 + \beta_1 Groups_t + \beta_2 Coupons_t + \beta_3 Groups_t \times UB_t + \beta_4 Coupons_t \times UB_t \\ &+ \beta_5 Groups_t \times Crowd_t + \beta_6 Coupons_t \times Crowd_t + \beta_7 UB_t + \beta_8 Crowd_t \\ &+ \beta_9 Frequent_t + \beta_{10} Duration_t + \beta_{11} Q1_t + \beta_{12} Q2_t + \beta_{13} Weekend_t + \beta_{14} Holiday_t),\end{aligned} \tag{2}$$

where *Groups* and *Coupons* denote the number of mobile in-app group coupons and in-app coupons issued at time *t*, respectively. The two moderators, *UB* and *Crowd*, indicate the size of the installed-user base and crowdedness of the mall at time *t*, which as stated early, are measured as the cumulative number of mobile app adopters up to time *t* and the number of visitors per square meter in the mall at time *t*. The two interaction terms $Groups \times UB$ and $Coupons \times UB$ capture the moderating effects of installed-user-based social interaction, while the other two interaction terms $Groups \times Crowd$ and $Coupons \times Crowd$ capture the moderating effects of location-based social interaction. The two consumer-specific variables, *Frequent* and *Duration*, denote the average shopping frequency and average shopping duration of consumers who enter the mall at time *t*. As explained earlier, the time-specific dummy variables *Q1*, *Q2*, *Weekend* and

Holiday refer to whether the data point at time *t* corresponds to the first or second quarter, and weekend days (Saturday or Sunday) and holidays, respectively.

Given the probability function in Equation (1), the log-likelihood function of our model can be derived as $L = \prod_{t=1}^{T} \Pr\left(Y = y_t \middle| X_t\right)$. Accordingly, the parameters (*βs*) in Equation (2) can be estimated by maximizing this log-likelihood function.

Results

We estimated our model in Equations (1) and (2) by using three different model specifications to compare the goodness of model fit. The first model included only the control variables, while the second and third models included the two mobile in-app marketing variables (i.e., *Groups* and *Coupons*) and both the two mobile in-app marketing variables and their interaction with the variables of the installed-user base and crowdedness, respectively. The estimation results using these three different model specifications are presented in Table 2. As shown in Table 2, Model 3 provides a significantly higher log-likelihood value than those in Models 1 and 2, implying that incorporating the impact of mobile in-app marketing strategies and the moderating effects of installed-user-based and location-based social influences significantly improves the goodness of model fit. Furthermore, we noticed that by incorporating in-app marketing strategies and the moderating effects of social influences, the main effect of in-app couponing changed from positive to negative, indicating that there might exist dynamic impacts of in-app marketing strategies due to changes in the installed-user base and crowdedness, which we will demonstrate in our discussion of managerial implications. Thus, we discuss our estimation results based on Model 3 of Table 2.

[Insert Table 2 about here]

Concerning the main effects of two in-app couponing strategies, as shown in Model 3 of

Table 2, we found that the coefficient of *Groups* is significantly positive (β_1= .122, p<.01), but the coefficient of *Coupons* is significantly negative (β_2= -.264, p<.01). These results indicate two opposite impacts of two in-app couponing strategies: a positive impact of mobile in-app group-couponing, but a negative impact of mobile in-app couponing on consumers' adoption of a mobile app. The latter result of the negative impact of in-app couponing is surprising to us, suggesting that consumers are more concerned about the potential costs of information overload and annoyance when they observe a frequent use of in-app couponing. When group-couponing is frequently used instead, the social interactions induced due to the unique design of group-couponing can help highlight the potential benefits from group-coupons and in turn, lead to a positive impact of in-app group-couponing on app adoption.

With regard to the moderating effect of installed-user-based social interaction, our results in Model 3 of Table 2 showed that the coefficient of the interaction term $Groups \times UB$ is significantly negative (β_3 =-1.35E-06, p<.01), while the coefficient of $Coupons \times UB$ is significantly positive (β_4 = 5.53E-06, p<.01). The positive moderating effect of the installed-user base on the impact of in-app couponing demonstrates the important role of social learning/signaling effects that are generated with an increased number of adopters, which helps lessen consumers' concerns about potential information annoyance and amplifies the potential benefits derived from coupons in a mobile app. However, when marketers issued in-app coupons, the negative moderating effect of the installed-user base revealed empirical evidence regarding the substitutive relationship between the social interaction initiated by the design of group coupons and the social interaction from existing adopters.

To further examine the interaction effects of $Groups \times UB$ and $Coupons \times UB$, we also derived the marginal interaction effects of these two interaction terms (see Ai and Norton 2003 for the test of marginal interaction effects in discrete models). Our test of the marginal interaction effects also revealed significantly negative marginal interaction effects of *Groups*×*UB* (-.001, p<.01), but significantly positive marginal interaction effects of *Coupons*×*UB* (.003, p<.01), when holding all other variables at their mean values.

Contrary to the moderating effect of the installed-user base, we found significantly positive coefficients of *Groups* ×*Crowd* (β_5= .322, p<.01), but significantly negative coefficients of *Coupons* ×*Crowd* (β_6= -.163, p<.01), as shown in Model 3 of Table 2. Similarly, we also derived marginal interaction effects of *Groups* ×*Crowd* and *Coupons* ×*Crowd*, and found the marginal interaction effects of *Groups* ×*Crowd* to be significantly positive (153.305, p<.01) and the marginal interaction effects of *Coupons* ×*Crowd* to be significantly negative (-77.802, p<.01). These results indicate opposite moderating effects of social interaction in a physical environment on the impact of in-app group-couponing and in-app couponing.

Earlier, we suggested that location-based social interaction may create an observational learning effect and a negative anxiety effect, generating either a positive or negative moderating effect on mobile in-app marketing activities. Our empirical finding of the negative moderating effect of location-based social interaction with mobile in-app couponing implies a stronger anxiety effect generated from a crowded environment, which dominates the positive observational learning effect. In contrast, due to the design of group coupons with a maximum number of group coupons allowed, our empirical finding of the positive moderating effects of location-based social interaction with mobile in-app group-couponing suggests that the threshold effect is magnified when the physical environment becomes crowded. This effect imposes much stronger pressures for consumers to make adoption decisions to enjoy the great deals provided by group coupons.

Robustness and Validity of Results

We conducted several additional analyses to examine the robustness and validity of our results. First, we estimated three alternative models to validate our results. The first alternative model we estimated was the negative binomial model, which is also a commonly used model for count variables. Compared to the Poisson model, which assumes the same sample mean and variance, a negative binomial distribution is especially useful for over-dispersed data, in which the sample variance can exceed the sample mean. In the second and third models, we considered the issue of truncation. Since the count variable in our data (the number of daily adopters) includes only positive values, but no zero, we estimated a zero-truncated Poisson model and a zero-truncated negative binomial model to examine the robustness of our results when the truncation issue was handled. Table 3 presents the estimation results using these alternative models. As we can see from Table 3, these results showed consistent patterns regarding the impact of in-app marketing strategies when these alternative models were used, although the significance level was lower when using negative binomial models.

[Insert Table 3 about here]

Second, we investigated whether our estimation is subject to endogeneity issues. As mobile in-app coupons and in-app group coupons are strategic variables that firms may determine, based on the existing number of mobile app adopters and other unobservable variables, a potential endogeneity issue might exist. To control for this potential endogeneity issue, we re-estimated our Poisson model by assuming continuous endogenous variables of mobile in-app coupons and in-app group coupons. Specifically, we adopted the estimation of the Poisson model with continuous endogenous covariates in Stata and incorporated exogenous variables such as the installed-user base, crowdedness, number of coupons, and group coupons in the previous day, Q1 and Q2, and weekly holiday variables as the instruments. As reported in Table 4, our key findings still hold when the endogeneity variables are controlled, which indicates that endogeneity was not a serious issue in our estimations.

[Insert Table 4 about here]

Third, we also validated our results by analyzing individual adoption data. Such individual adoption data allow us to examine the adoption effects of mobile in-app strategies while controlling for consumer heterogeneity in their adoption decisions. Specifically, in the individual adoption data, each individual consumer is recorded in terms of whether and when she adopted the mobile app during our data period from Jan. 1 to Aug. 15, 2015. Given that the consumers in our data may have entered the mall on multiple days, our individual adoption data constitute an unbalanced panel observation of an individual consumer's adoption behaviors. Overall, we were able to obtain a panel dataset with the individual adoptions of 1,908,082 consumers. Among the 1,908,082 consumers in our individual adoption data, 5.1% adopted the mobile app at the end of our data period. We estimated a panel logistic regression model with random effects controlled, and we presented the estimation results in Table 5 (see the Appendix for the details of our analysis model and variable measurements). As shown in Table 5, our key results still hold when we analyzed the individual adoption data. These additional analyses by adopting alternative models, testing the endogeneity and using individual adoption data while controlling for heterogeneity, further enhance our confidence in the key findings.

[Insert Table 5 about here]

Conclusion

Despite the rapid proliferation of mobile apps, limited attention has been given to investigating influential factors on consumers' adoption of mobile apps. This study investigates how two mobile in-app marketing strategies, mobile in-app couponing and in-app group-couponing, affect consumers' adoption of branded apps. We develop a theoretical framework to examine the adoption effects of these two mobile in-app marketing strategies, and how such effects vary with the growth of the installed-user base and with the increase of crowdedness in a physical environment. Our empirical findings contribute to mobile marketing literature and provide implications to marketers.

Managerial Implications

Our findings provide managerial implications in three folds. First, marketers should understand the potential values, as well as the costs, associated with the use of mobile in-app marketing strategies. Although both mobile in-app couponing and group-couponing provide information and financial values to marketers, which stimulate consumers' interest in adopting a mobile app, a large number of these mobile in-app marketing activities could also create information overload and annoyance to consumers. Our findings regarding the two opposite impacts of mobile in-app couponing and in-app group-couponing imply that consumers would be more concerned about the costs of information overload and annoyance if marketers issue many in-app coupons at the early stage when introducing their branded apps. In contrast, if marketers could motivate consumers to voluntarily serve as the company's representatives, advocating the mobile app through the use of in-app group coupons, they could largely enhance consumers' adoption of their mobile apps.

Second, marketers should take into account the dynamic impacts of mobile in-app marketing strategies when making mobile marketing decisions. Our findings of the opposite moderating effects of the installed-user base on the impact of in-app couponing and in-app group-couponing suggest that the adoption effects of these two mobile in-app marketing strategies are not constant but dynamic with an increase in the number of adopters. To demonstrate the dynamic patterns regarding the impact of these two mobile in-app marketing strategies, we calculated the marginal effects of in-app couponing and group-couponing, based on our estimation results of Model 3 in Table 2, by varying the value of the installed-user base from zero to its maximum value in the data, while holding all other variables at their mean level and holding crowdedness at the levels of small (i.e., mean-2sd.), medium, and large (i.e., mean+2sd), respectively. We presented the dynamic impacts of in-app couponing and group-couponing when holding crowdedness at three levels in Figures 2a-2c, respectively. As shown in Figures 2a-2c, while the impact of in-app couponing changes from negative to positive as the number of adopters grows, the positive impact of in-app group-couponing diminishes. In particular, at the early stage when a mobile app is introduced (i.e., when the installed base of adopters is small), while it is beneficial for marketers to issue in-app group coupons, it is harmful to consumers' app adoption if marketers issue many in-app coupons. Only when a certain number of adopters are accumulated, the impact of in-app couponing becomes positive. Hence, in order to enhance the adoption of a mobile app, marketers should make their mobile in-app marketing decisions dynamically in the two stages of a mobile app introduction: allocating a larger budget on mobile in-app group-couponing at the early stage of a mobile app's introduction when the installed-user base is small, and then switch to in-app couponing in the later stages when a certain number of adopters have been established.

[Insert Figure 2 about here]

Third, marketers should also implement location-based mobile in-app marketing strategies, if feasible, when promoting a mobile app. Our result involving the moderating effects of crowdedness in a physical environment also suggests that the impacts of mobile in-app couponing and group-couponing vary with crowdedness in a physical environment (i.e., less crowded vs. much more crowded). To illustrate how the impacts of these two mobile in-app marketing strategies varied with crowdedness, we also calculated the marginal effects of in-app couponing and group-couponing in a similar way as we did for Figures 2a-2c. We presented the dynamic impacts of in-app couponing and group-couponing with the change in crowdedness while holding the installed-user base at small, medium and large levels, as shown in Figures 2d-2f, respectively. Interestingly, we can see that Figures 2d-2f demonstrate different impacts of in-app couponing and group-couponing when the installed-user base is held at small, medium and large levels (i.e., at the early, middle, and late stages of a mobile app introduction).

These figures further underline the importance for marketers to consider two contingencies together (i.e., early vs. late stage, a less- vs. more-crowded environment) when developing dynamic and location-based in-app marketing strategies. In particular, Figure 2d suggests that at the early stage of a mobile app introduction, it would be more effective for marketers to offer mobile in-app group coupons to consumers, regardless of whether they are in a more or less crowded physical environment. When marketers have accumulated a certain number of adopters (i.e., at the middle stage of a mobile app introduction), as shown in Figure 2e, marketers can offer either in-app coupons or group coupons to consumers who are in a crowded environment, depending on which in-app marketing strategy is most cost-effective. At the later stage of a mobile app introduction, however, mobile in-app couponing becomes more effective than in-app group-couponing if marketers still intend to enlarge their mobile app adoption.

Limitations and Directions for Future Research

This study is subject to some limitations, which provide opportunities for future research. First, as a first step in investigating the impact of mobile in-app marketing strategies on consumers' adoption of branded apps, we analyzed only the adoption data from one of the largest shopping malls in China. Future research could examine the generalizability of our key findings if the data from other companies are available with respect to consumers' adoption and mobile in-app marketing activities. Second, it would also be more insightful to marketers if researchers had access to information regarding not only the quantities, but also the details of mobile in-app marketing activities (e.g., the face value and discount rate of coupons, deal contents and types, etc.). Lastly, researchers could also consider using other research methodologies, such as field experiments, to disentangle the underlying mechanisms that lead to the differential impacts of mobile in-app couponing and group-couponing.

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TABLE 1
Variable Definition and Descriptive Statistics (N=227)

Variable	Definition	M	SD
Number of Adopters	The number of consumers who registered for the mobile app each day	476.63	349.61
Coupons	The number of mobile in-app coupons released each day	3.26	4.43
Groups	The number of mobile in-app group coupons released each day	11.72	4.91
Installed-Use-Base (*UB*)	The cumulative number of adopters of the mobile app up to the focal day	83535.42	30320.39
Crowdedness (*Crowd*)	The number of consumers who entered the mall per square meter each day	.081	.028
Q1	A dummy variable indicating the first quarter	.40	.49
Q2	A dummy variable indicating the second quarter	.40	.49
Weekend	A dummy variable indicating weekends in a week.	.29	.45
Holiday	A dummy variable indicating whether the respective day is a holiday or not, based on the Chinese calendar	.08	.28
Duration	The average duration (in seconds) that consumers spent in the mall each day	6323.90	859.99
Frequency	The average shopping frequency of consumers who entered the mall each day	2.66	1.31

TABLE 2
Estimation Results Using the Poisson Model

Variables	Model 1	Model 2	Model 3
Constant	6.693*** (.038)	7.446*** (.053)	7.921*** (.075)
Coupons		.005*** (.001)	-.264*** (.007)
Groups		.031*** (.001)	.122*** (.004)
Coupons×UB			5.53E-06*** (1.04E-07)
Groups×UB			-1.35E-06*** (2.74E-08)
Coupons×Crowd			-.163*** (.026)
Groups×Crowd			.322*** (.021)
UB		-2.65E-05*** (6.92E-07)	-1.67E-05*** (8.19E-07)
Crowd		4.641*** (.237)	.444 (.364)
Frequency	-.175*** (.006)	.299*** (.013)	.065*** (.016)
Duration	-2.15E-06 (4.13E-06)	-3.19E-05*** (6.33E-06)	6.61E-06 (5.74E-06)
Q1	-.360*** (.018)	-.950*** (.027)	-2.051*** (.034)
Q2	-.117*** (.010)	-.521*** (.015)	-1.061*** (.018)
Weekend	.424*** (.007)	.422*** (.010)	.303*** (.010)
Holiday	-.124*** (.011)	.003 (.013)	.004 (.013)
Log Likelihood	-17716.874	-15712.598	-12552.66

Note: Numbers in parentheses are the estimated standard error. Sample size=227.
*: *p<.1*; **: *p<.05*; ***: *p<.01* (two tail); †: *p<.1* (one tail).

TABLE 3
Robustness of Our Results Using Different Models

Variables	Negative Binomial Model	Zero-Truncated Poisson Model	Zero-Truncated Negative Binomial Model
Constant	8.188*** (.732)	7.921*** (.075)	8.189*** (.732)
Coupons	-.269*** (.063)	-.264*** (.007)	-.269*** (.063)
Groups	.105*** (.035)	.122*** (.004)	.105*** (.035)
Coupons×UB	5.53E-06*** (1.03E-06)	5.53E-06*** (1.04E-07)	5.53E-06*** (1.03E-06)
Groups×UB	-1.17E-06*** (2.74E-07)	-1.35E-06*** (2.74E-08)	-1.17E-06*** (2.74E-07)
Coupons×Crowd	-.082 (.247)	-.163*** (.026)	-.082 (.247)
Groups×Crowd	.338* (.209)	.322*** (.021)	.338* (.209)
UB	-1.88E-05** (8.17E-06)	-1.67E-05*** (8.19E-07)	-1.88E-05** (8.17E-06)
Crowd	-.038 (3.649)	.444 (.364)	-.037 (3.650)
Frequency	.081 (.149)	.065*** (.016)	.081 (.149)
Duration	2.36E-07 (5.84E-05)	6.61E-06 (5.74E-06)	2.35E-07 (5.84E-05)
Q1	-2.085*** (.336)	-2.051*** (.034)	-2.086*** (.336)
Q2	-1.134*** (.177)	-1.061*** (.018)	-1.134*** (.177)
Weekend	.267*** (.100)	.303*** (.010)	.267*** (.100)
Holiday	.042 (.123)	.004 (.013)	.042 (.123)
Log-Likelihood Value	-1520.9	-12552.66	-1520.9

Note: Numbers in parentheses are the estimated standard error. Sample size=227.
*: *p<.1*; **: *p<.05*; ***: *p<.01*(two tail); †: *p<.1*(one tail).

TABLE 4
Estimation Results with Endogeneity Controlled

Variables	**Estimate**
Constant	8.056^{***} (.076)
Coupons	$-.302^{***}$ (.007)
Groups	$.100^{***}$ (.004)
Coupons×UB	$5.80E\text{-}06^{***}$ (1.04E-07)
Groups×UB	$-1.18E\text{-}06^{***}$ (2.78E-08)
Coupons×Crowd	$-.131^{***}$ (.026)
Groups×Crowd	$.144^{***}$ (.023)
UB	$-1.3E\text{-}05^{***}$ (8.23E-07)
Crowd	1.341^{***} (.374)
Frequency	$-.028^{*}$ (.016)
Duration	-1.13E-06 (5.74E-06)
Q1	-1.817^{***} (.035)
Q2	-1.008^{***} (.019)
Weekend	$.310^{***}$ (.011)
Holiday	$-.049^{***}$ (.014)

Note: Numbers in parentheses are the estimated standard error. Sample size=226. *: p<.1; **: p<.05; ***: p<.01 (two tail).

TABLE 5
Estimation Results Using Individual Adoption Data

Variables	Estimate
Constant	-21.112*** (.260)
Coupons	-.068*** (.020)
Groups	.015 (.013)
Coupons×UB	1.47E-06*** (3.36E-07)
Groups×UB	-4.38E-07*** (9.87E-08)
Coupons×Crowd	-.137* (.078)
Groups×Crowd	.245*** (.084)
UB	-2.42E-05*** (1.97E-06)
Crowd	-5.952*** (1.386)
Frequency	.040*** (.005)
Duration	5.53E-05*** (1.72E-06)
Q1	-.666*** (.124)
Q2	-.301*** (.068)
Weekend	.326*** (.036)
Holiday	.104*** (.041)
Log-Likelihood Value	-157983.6
Wald Test	Chi square = 3432.86 Prob > chi2 = .0000
LR test VS logit Model	Chi square = 5.9E+05 Prob >chi2 = .0000

Notes: Numbers in parentheses are the estimated standard error. Sample size=4,548,299.
***: p<.01; **: p<.05; *: p<.1.

Figure 1. The Weekly Number of Adoption and Mobile In-App Marketing Activities

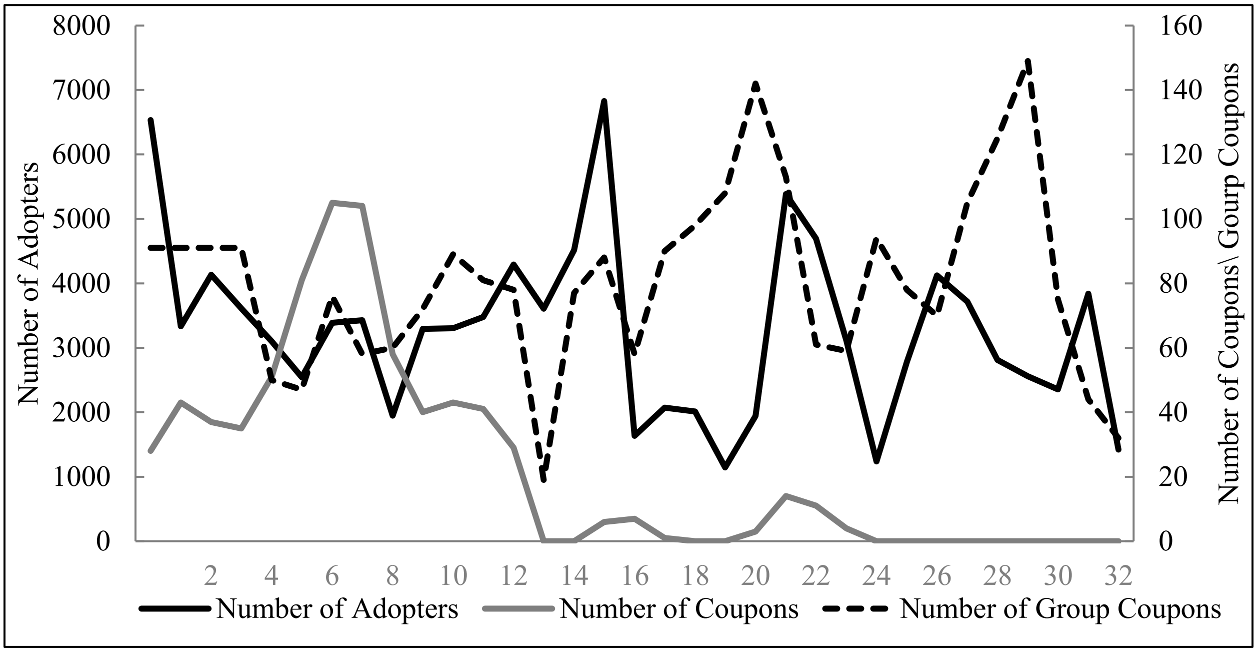

Figure 2. Marginal Effects of Mobile In-App Couponing and Group-Couponing

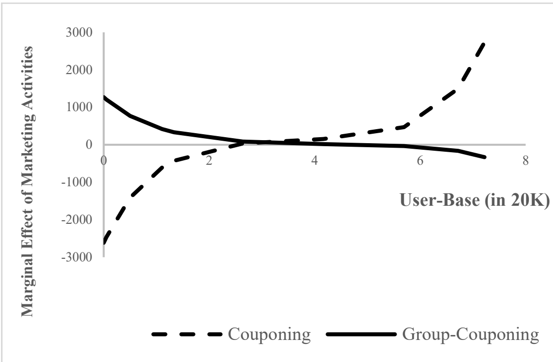

Figure 2a. Marginal Effects of Mobile In-App Marketing Varying with Installed-User Base (Crowdedness=mean-2sd)

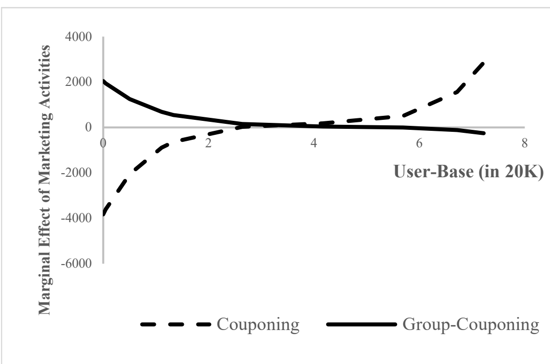

Figure 2b. Marginal Effects of Mobile In-App Marketing Varying with Installed-User Base (Crowdedness=mean)

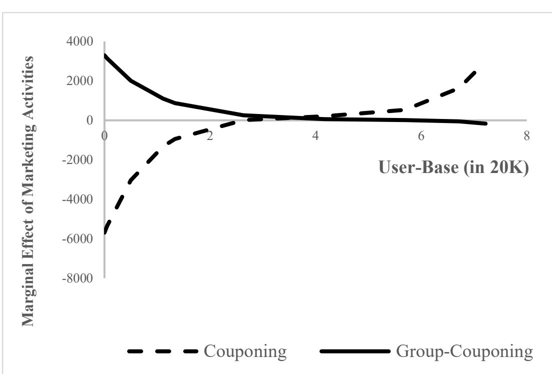

Figure 2c. Marginal Effects of Mobile In-App Marketing Varying with Installed-User Base (Crowdedness=mean+2sd)

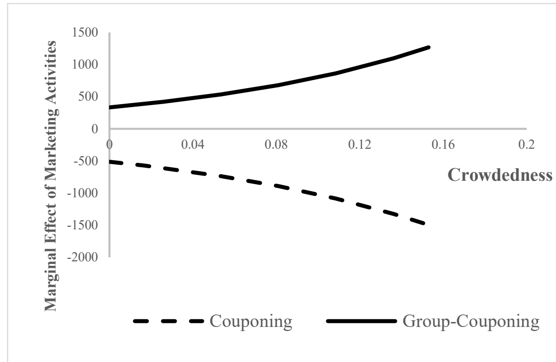

Figure 2d. Marginal Effects of Mobile In-App Marketing Varying with Crowdedness (Installed-user base = mean-2sd)

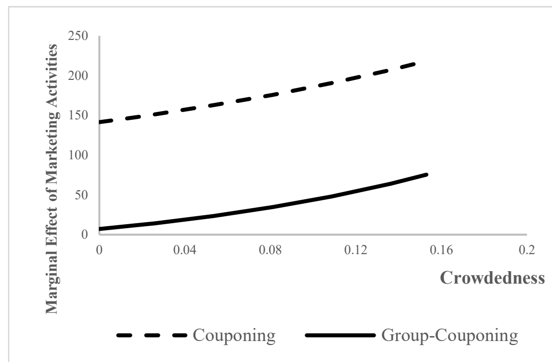

Figure 2e. Marginal Effects of Mobile In-App Marketing Varying with Crowdedness (Installed-user base=mean)

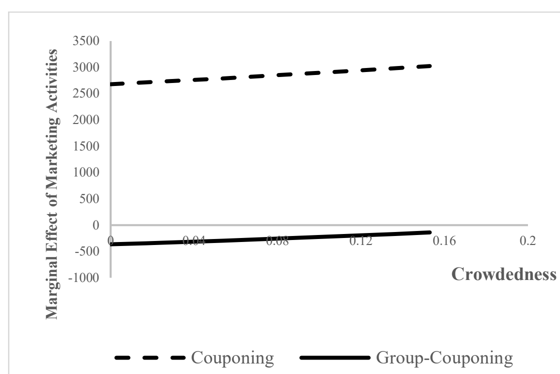

Figure 2f. Marginal Effects of Mobile In-App Marketing Varying with Crowdedness (Installed-user base = mean+2sd)

Appendix: The Random-Effect Logistic Model Using Individual Adoption Data

We analyzed our individual adoption data by using a logistic regression model with random effects incorporated. Specifically, we assumed a consumer *i*'s utility function at time *t,* as given by:

$$U_{it} = X_{it}\beta + v_i + \varepsilon_{it} \tag{A1}$$

where the random variable v_i captures consumers' heterogeneity in our data and is assumed to identically and independently follow a normal distribution (i.e., $v_i \sim i.i.d.N(0,\sigma^2)$). The error term ε_{it}, which is independent of v_i, follows a logistic distribution. X_{it} denotes the vector of the explanatory variables, and $X_{it}\beta$ is specified similarly as below:

$$\begin{aligned} X_{it}\beta = \beta_0 &+ \beta_1 Groups_t + \beta_2 Coupons_t + \beta_3 Groups_t \times UB_t + \beta_4 Coupons_t \times UB_t \\ &+ \beta_5 Groups_t \times Crowd_t + \beta_6 Coupons_t \times Crowd_t + \beta_7 UB_t + \beta_8 Crowd_t \\ &+ \beta_9 Frequency_t + \beta_{10} Duration_t + \beta_{11} Q1_t + \beta_{12} Q2_t + \beta_{13} Weekend_t + \beta_{14} Holiday_t. \end{aligned} \tag{A2}$$

Note that, different from the measurement of exploratory variables in Equation (2) for analyzing aggregate adoption data, the variables in the specification (A2) are measured at each individual consumer level. When we match the individual adoption data with the mobile in-app marketing data, consumers' mall visitation data, and other control variables, three scenarios arise: (1) consumers who had registered their accounts in the app while they were at the mall; (2) consumers who had registered their accounts in the app after they visited the mall; and (3) consumers who had never registered their accounts in the app after they visited the mall. For the first type of consumers, we recorded their adoption decisions as 1 and used the measures of in-app marketing, crowdedness, and other control variables corresponding to the date when they had visited the mall and registered in the app. For the second type of consumers, we recorded their adoption decisions as 1 on the date of their registration, but used the crowdedness measure on the previous one day before they had visited the mall. However, if the second type of consumers had registered in the app two days or longer after they visited the mall, we used the measure of crowdedness as 0. For the third type of consumers, we recorded their adoption decisions as 0 on the date when they visited the mall, and we used the measures of in-app marketing, crowdedness, and other control variables corresponding to their mall visitation dates. Note that, different from the measurements of frequency and duration in the aggregate adoption data, where we used the average of frequency and duration across all consumers who visited the mall each day, these two variables were measured at each consumer's level in our individual adoption data, which consist of the number of visits to mall that each consumer had made prior to the focal date, and the hours that the consumer spent in the mall on the focal date, respectively.

Given that a consumer adopts a mobile app when her utility is greater than 0 (i.e., $U_{it} > 0$), we can derive the probability of each consumer *i*'s adoption of a mobile app as $\Pr_{it}(y_{it} | X_{it}, v_i) = \Pr_{it}(U_{it} > 0 | X_{it}, v_i) = \frac{1}{1+\exp(-X_{it}\beta + v_i)}$, conditional on v_i. Then, the joint probability function of consumer *i* over a time period from $t = 1, \cdots, T_i$, conditional on v_i, can written as:

$$\Pr(y_{i1}, \cdots, y_{iT_i} | X_{i1}, \ldots, X_{iT_i}, v_i) = \prod_{t=1}^{T_i} F_{it}\left(y_{it}, X_{it}\beta + v_i\right) \tag{A3}$$

where we denote the adoption probability of consumer *i* at time *t* as $F_{it}(y_{it} | X_{it}, v_i)$ to simplify the equation. Thus, we have

$$F_{it}(y_{it} | X_{it}, v_i) = \begin{cases} \frac{\exp(X_{it}\beta + v_i)}{1+\exp(X_{it}\beta + v_i)} & if\ y_{it} = 1 \\ \frac{1}{1+\exp(X_{it}\beta + v_i)} & if\ y_{it} = 0 \end{cases}$$

Taking the integral of v_i over the normal distribution, $N(0, \sigma^2)$, we can derive the joint probability function of consumer *i* over a time period from $t = 1, \cdots, T_i$ while controlling for consumers' random effects, as given by:

$$\Pr(y_{i1},\cdots,y_{iT_i}\left|X_{i1},\ldots,X_{iT_i}\right.) = \int_{-\infty}^{\infty} \frac{\exp\left(\frac{-v_i^2}{2\sigma_v^2}\right)}{\sqrt{2\pi}\sigma_v}\left\{\prod_{t=1}^{T_i} F\left(y_{it}, X_{it}\beta + v_i\right)\right\}dv_i = \int_{-\infty}^{\infty}\left\{g_{it}\left(y_{it}, X_{it}\beta + v_i\right)\right\}dv_i \qquad \text{(A4)}$$

Finally, the log-likelihood LL can be derived as the sum of the logarithm of the panel-level likelihoods in (A4) over all consumers *N*, which is $LL \equiv \sum_{i=1}^{N} \log\left\{\int_{-\infty}^{\infty} g_{it}(y_{it}, X_{it}, v_i)dv_i\right\}$. Accordingly, maximizing such a log-likelihood LL yields the estimates of the parameters in Equation (A2).