ABSTRACT

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	Dongwon Lee Ph.D. Candidate in Information Systems, 2017
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This dissertation focuses on understanding the value of customer analytics in the mobile channel through three essays. Specifically, I study customer behaviors and technology use in mobile ecosystems. The first essay of this dissertation examines the difference in the effects of recommendation systems across the PC and mobile channels on customer-level decision outcomes and market. I conduct two randomized field experiments and find that the impact of the recommendation systems is higher for the mobile channel than the PC channel on customer-level decision outcomes. With respect to the market, I observe no direct effect of recommendation systems on sales diversity but I find that diversity of both product sales and views are higher on the mobile channels compared to the PC channel. In the second essay, I study the composite effect of mobile push notifications and recommendation systems on views and sales in the context of mobile retailing. While the direct effect of such notifications on the pushed product is to be expected, I find interestingly that the effect of the notification is significantly higher

for recommended products, suggesting a complementarity between push notifications and recommendation systems that has not yet been addressed in the literature. Finally, I broaden the scope of my studies in my third essay by studying a context that which has received little attention within the mobile context – charitable giving and cause marketing. I study how mobile devices may be used to encourage charitable giving through cause marketing campaign by conducting a large-scale randomized field experiment, focusing on the influence of push notifications, monetary subsidies, and intertemporal choices of subsidy in mobile cause marketing context. Results of the experiment demonstrate that push notifications have a remarkably high effect on donation outcomes. Contrary to previous findings from offline contexts, I find that donation decision and donation amount are significantly higher with rebate subsidies, compared to matching subsidies. Taken as a whole, this dissertation contributes to a better understanding of customer behavior and the role of the technology use in the mobile ecosystem.

ESSAYS ON CUSTOMER ANALYTICS IN MOBLIE ECOSYSTEMS

By

Dongwon Lee

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Advisory Committee:
Professor Anandasivam Gopal, Chair
Professor Sunil Mithas
Professor Gordon Gao
Professor Dokyun Lee
Professor Joydeep Srivastava
Professor Kent Norman, Dean's Representative

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Dedication

For my parents, Youngja Lee and Jai Hyun Lee, and beloved wife You-Jin Song for their love, endless support, encouragement, and belief in me.

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CHAPTER 1: OVERVIEW

Mobile channels are increasingly central to the customer experience given the growing number of smartphone users. Despite the importance of the mobile channel, there are significant gaps in our understanding of how the use of mobile channel affects consumer behavior (Ghose et al., 2013; Grewal et al., 2016; Shankar et al., 2016). This dissertation focuses on customer analytics with an emphasis on the impact of technology use in mobile ecosystems. Specifically, I study how organizations can use mobile channels and technology to interact with customers and to improve business outcomes. Through collaborations with leading data analytics companies and retailing companies in the US and East Asia, the three essays in this dissertation address specific research questions in the context of retailing and charitable giving. This dissertation will enhance our understanding of how the mobile channel may be utilized in different settings to create or enhance value for different stakeholders.

The first essay examines the difference in the effects of recommendation systems across PC-based and mobile channels on sales. The benefits of recommendation systems in online retail contexts have received much attention in previous research. The majority of previous studies have been conducted in PC-based settings (Brynjolfsson et al., 2011; De et al., 2010; Fleder and Hosanagar, 2009; Hosanagar et al., 2014; Lee and Hosanagar, 2014; Oestreicher-Singer and

Sundararajan, 2012a, 2012b; Pathak et al., 2010), instead of mobile devices which are becoming a substantial channel in the online shopping experience. In this essay, I first examine differences in the effects of recommendation systems across the PC-based and mobile channel on customer-level decision outcomes. Second, I focus on the role of recommendation systems and mobile channel on the market, in terms of sales diversity. I conduct two randomized field experiments by collaborating with online retailing firms in East Asia. In each experiment, the treatment is access to a recommendation system. The results from the experiments show that the use of recommendation systems increases customer-level decision outcomes such as overall sales, views and sales of recommended products, click-through rate, and conversion. More importantly, the marginal impacts of the recommendation systems are significantly higher for mobile users, indicating that the higher search costs imposed through mobile devices are more effectively reduced through recommendation systems. With respect to sales diversity, I observe that while the mobile channel leads to more diverse sales, there are no interactive effects of the recommendation system and mobile use on sales diversity. These results provide boundary conditions for the efficacy of recommendation systems in retail contexts where online sales occur across both PC-based and mobile channels.

The second essay builds on the first essay but by considering the composite effect of mobile push notifications and recommendation systems on views and sales in the mobile retailing context. Despite the widespread use of push notifications in mobile commerce (Minkara, 2014), there is no systematic evidence of the efficacy of these notifications on desired behavior in the form of additional views or sales of the targeted product. I first investigate the direct effects of push notifications on the views and sales of targeted products, a baseline effect that would be directly expected from the form of the push notification itself, since it draws specific attention to the pushed product. On the targeted product's landing page, however, customers also view a recommendation panel that introduces a set of recommended products. It is possible that these recommended products resulting from the push notification, actually provide an additional payoff beyond the observed effects on the pushed product. Therefore, I investigate the spillover effect of the push notification on the views and sales of the recommended products, given that the consumer is viewing the pushed product's page. Using a difference-in-difference approach to exploit a natural experiment, I find that push notifications lead to a significant effect not only on the views and sales of the targeted products, but also on the sales and views of the recommended product, indicating a serendipitous effect that may not have been originally conceived of by the retailer. In effect, I observe that recommendation systems help amplify the effect of the push notification by leading customers deeper into the conversion funnel.

Finally, I broaden the scope of the dissertation in the third essay by studying a context that has received little attention in the mobile context – charitable giving and cause marketing. The ongoing revolution in monetary transactions spurred by the mobile devices is slowly extending to contexts where non-profit organizations may be able to leverage mobile apps to solicit micro-donations through a mobile cause marketing campaign. In the third essay, I study how to incentivize the mobile application users to encourage charitable giving through the mobile cause marketing campaign by conducting a large-scale randomized field experiment on a mobile rewards application service in the US. Users are able to divert part of their in-app credits to charitable organizations. They are nudged to contribute the equivalent monetary amount to charity rather than spend the rewards on other options. Specifically, this study focuses on the influence of push notifications, monetary subsidies (rebate vs. matching), and intertemporal choices of subsidy (now vs. later) on donation behavior. Results of the experiment demonstrate that push notifications have a remarkably high effect on donation outcomes. Contrary to previous findings from offline contexts (Davis et al., 2005; Eckel and Grossman, 2017; Eckel and Grossman, 2003, 2008), I find that donation decisions are significantly higher when the mobile cause marketing campaign offers rebate subsidies, compared to matching subsidies. Given the increasing prominence of the mobile channel and its associated conveniences, this study firstly reveals the role of push notifications through a mobile application and monetary subsidies and generates insights associated with a decision-making process of donation.

In conclusion, this dissertation contributes to understanding how the mobile channel and technology interact with customers. In turn, this allows organizations to achieve better business outcomes in the context of retailing and cause marketing based charitable giving. In each essay, I analyze real-world customer data by conducting field experiments or by exploiting natural experiments. The results have both theoretical and practical implications for understanding mobile customer behavior and the role of the technology use in the mobile ecosystem.

CHAPTER 2: “MOBILE & ME”: FIELD EXPERIMENTS ON THE IMPACT OF RECOMMENDATION SYSTEMS IN THE MOBILE CHANNEL

2.1 Introduction

Recommendation systems that use input about a customer’s interests to generate a list of recommended items are pervasive in online retailing and web services (Linden et al., 2003). By creating a personalized shopping experience for each customer, recommendation systems offer retailers with an effective strategy for targeted marketing. The presence of recommendation systems can significantly enhance customers’ shopping experience by reducing the steps required to locate products, thereby allowing customers to discover relevant products that they may not have sought out otherwise (De et al., 2010). Recommendation systems not only influence how customers utilize their prior product knowledge in terms of their prior purchase behavior, but also alter how customers search for product information based on information provided from other customers’ behavior. Not surprisingly, 62% of US online consumers have found the presence of product recommendations on retail websites very useful during the purchasing process (Mulpuru et al., 2010). Correspondingly, 76% of retail websites listed personalized product recommendations as a priority for their online sales strategy (IBM, 2014) while also attesting to their positive effects on revenues (Accenture, 2014). Indeed, interviews with online retailers (Mulpuru et al., 2010) indicate that recommendation systems drive between 2% and 20% of their revenue. Therefore, it is established that recommendation systems help improve conversion rates, increase average order value by helping online customers find the products they are looking for, and help customers discover new products (IBM, 2014).

The academic literature studying the impacts of recommendation systems on sales and sales diversity has also documented the positive effects of such systems on a variety of outcome measures in online retail contexts (Brynjolfsson et al., 2011; De et al., 2010; Fleder and Hosanagar, 2009; Hosanagar et al., 2014; Lee and Hosanagar, 2014; Oestreicher-Singer and Sundararajan, 2012a, 2012b; Pathak et al., 2010). However, much of this existing work on recommendation systems, as well as the practitioner-based reports, is still based on contexts where customers are on desktops, in stark contrast to the retail world which is going increasingly “mobile”. Given the growing number of smartphone shoppers, mobile devices have become increasingly central to the online shopping experience (Einav et al., 2014). According to comScore (Lella and Lipsman, 2016), mobile commerce showed an annual growth of 56% in 2015, far outpacing the ecommerce growth rate of 8%. Though mobile represents 60% of time spent shopping online, the mobile channel only accounts for 16% of all retail dollars spent (Lella and Lipsman, 2016). Hence, it is not directly obvious that prior results from PC-based contexts on the relationship between recommendation systems and sales translate to the mobile channel for multiple reasons.

Physically, mobile devices have smaller screens and low resolutions than do PCs (Ghose et al., 2013). Customer preferences and purchase behavior on mobile devices show different patterns, compared to online contexts (Daurer et al., 2015). Mobile devices build on the properties of ubiquity, convenience, and ease of use, to influence consumer behavior in their particular context (Fong et al., 2015). Additionally, customers' search costs on mobile devices, especially in the retail context, tend to be structurally different from those in PC contexts (Ghose et al., 2013), leading to the observation that the mobile Internet is "less Internet-like". Given these characteristics of the mobile channel, and the implied differences from the PC channel, we believe that examining channel-specific differences in the relationship between recommendation systems and consumer behavior deserves further attention. It is this very gap in the literature that we address in this paper – we extend extant work studying the efficacy of recommendation systems to the mobile context.

Specifically, we ask two specific research questions. The first question seeks to investigate the effect of recommendation systems on customer-level decision outcomes (product sales and views) *across* the mobile and PC channels, focused on the retail sector. Building on existing work (De et al., 2010; Fleder and Hosanagar, 2009; Häubl and Trifts, 2000; Lee and Hosanagar, 2014; Pathak et al., 2010), we examine whether the use of a recommendation system leads to differences in customer purchase behavior between mobile and PC channels. The second research question pertains to the inconsistent findings in the literature regarding the effects of recommendation systems on product diversity, a market-level outcome of particular interest (Brynjolfsson et al., 2011; Hosanagar et al., 2014). On the one hand, prior work shows that these systems help to homogenize the market, while there is also some evidence for how they increase sales diversity (Fleder and Hosanagar 2009; Hosanagar et al. 2014; Li and Karahanna 2015). We empirically examine this question but also explore these effects across the mobile and PC channels.

We use empirical data from a South Korean online fashion retailing website to conduct our analysis. Despite the increasing relevance of mobile in online retailing (Einav et al., 2014; Ghose et al., 2013), empirical research in this sector is sparse due to the unavailability of data. We overcome this hurdle by partnering with the research site in conducting two randomized field experiments to examine the use of a recommendation system across the mobile and PC channel. In these experiments, we randomly assign the availability of a recommendation system to the retailer's customers as the treatment. Subsequently, we examine their purchase behavior on both the PC and mobile channels. Through the design of the experiments (described later), we are able to account for channel selection as well as other sources of consumer heterogeneity.

As a baseline, we find that the use of recommendation systems increase sales and sales quantities at the customer-level, consistent with prior work (De et al., 2010; Pathak et al., 2010). However, we find evidence for our expectations that the effect of recommendation systems is significant mostly for mobile users. This suggests that higher search costs imposed through the mobile channel are more effectively reduced through such systems, while the ubiquity of the mobile channel further helps enhance their effectiveness. Finally, with respect to sales diversity, we find no direct effect of recommendation systems on sales diversity. However, we do observe that the diversity of both product sales and views are higher in the mobile channels compared to the PC channel. Thus, our results suggest a contingent and nuanced effect of these systems on the market, compared to prior work showing a direct homogenizing or heterogenizing effect (Li and Karahanna, 2015).

These results highlight the two primary contributions of our work to the literature. First, we extend the study of recommendation systems to the mobile context. We theorize about the specific features of mobile platforms and how they may moderate the traditional wisdom regarding the value of such systems. Using a field experiment methodology potentially allows for the cleanest identification of the effects of a recommendation system; we thus build on recent work using such an approach (Lee and Hosanagar, 2014). Second, we provide evidence of the impact of recommendation systems on sales diversity, resolving some equivocal findings in the literature. Our results provide clear boundary conditions for the efficacy of recommendation systems in retail contexts where online sales occur in both PC-based and mobile channels.

2.2 Literature Review

Our work in this paper sits at the intersection of three streams of research that are equally relevant – recent work on differences between the mobile and PC channels, the role of recommendation systems in retail, and the implications of these systems for sales diversity at the market level. Therefore, we start by briefly reviewing the literature on differences between mobile and PC-based contexts first, and then discuss the literature pertaining to recommendation systems' effects on consumer behavior, and on sales diversity subsequently. Through this review, we then provide arguments for the results we expect to observe from the empirical analysis.

PC Versus Mobile Channels – How are they different in retail?

As mobile devices have proliferated, their use in economic activity has become increasingly mainstream. This raises questions pertaining to whether the mobile channel is indeed different from the PC channel in terms of how users and firms interact with mobile devices. Table 2.1 describes the current literature addressing these differences, or lack thereof, that we base our literature review on. Recent work addressing this question has suggested that there are structural differences between the PC channel and mobile channel that emerge from inherent differences between the fixed Internet and the mobile Internet (Bang et al., 2013; Ghose et al., 2013; Xu et al., 2016). In terms of accessing content on the Internet, the mobile and online (PC) channels share similar capabilities (such as access to the same product assortment, for instance). However, previous research shows that the mobile and PC channels are differentiated by *access* and *search* capabilities due to differences in the extent to which each channel is usable and provides ubiquitous access (Bang et al., 2013; Burtch and Hong, 2014; Chae and Kim, 2003; Huang et al., 2016; Jung et al., 2014; Xu et al., 2016). These differences in terms of usability and ubiquity play a key role in driving user behavior in these channels, and correspondingly, how firms may interact with users.

More specifically, the mobile channel provides higher and significantly easier access capability to online content than PC channel (Bang et al., 2013; Chae and Kim, 2003; Huang et al., 2016; Jung et al., 2014; Wang et al., 2015; Xu et al., 2016). Mobile devices are attached to the consumer in an increasingly personal manner, transcending their role as a purely technological device to access the Internet or telephony. This resulting ubiquity enables the user to access content on the Internet anywhere and anytime. Viewed differently, the mobile channel applies fewer constraints on the user in regard to time and space. This increased convenience leads to greater visits to websites on the Internet (Jung et al., 2014; Xu et al., 2014). When viewed through the lens of retail, the mobile channel therefore tends to increase demand for online sales (Wang et al., 2015) largely attributable to the increased availability and ubiquity of the channel compared to the PC.

Although the mobile channel significantly enhances access to content relative to the PC, with respect to search capabilities, the effects are more nuanced. The literature argues that for search involving low-information intensity or habitual needs that do not require much incremental search or cognition, the mobile channel works well compared to the PC (Chae and Kim, 2003; Maity and Dass, 2014; Wang et al., 2015). However, as tasks become more information-intensive and as search costs increase, the mobile channel is limited largely due to physical constraints such as the small screen sizes on mobile devices and low usability levels for complex tasks (Bang et al., 2013). Specifically, small screen size and information structure of a mobile device influence a user's navigation activities and a user's perception about mobile internet use (Chae and Kim, 2003). These constraints lead to increased costs in search activities associated with interaction, navigation, reading and viewing options, and evaluation tasks. The small screens also impose an obstacle to usability on the m-commerce website (Venkatesh et al., 2003), increasing the relative costs of product and feature search while reducing the extent to which accurate recall is possible in such environments.

Empirical work addressing the role of search costs in mobile environments attest to these hypothesized effects. The use of mobile has led to an increase in the impact of ranking (ranking effects) (Ghose et al., 2013) while the deployment of mobile channels has enhanced value in the case of simple decision-making tasks (Maity and Dass, 2014), low-risk products (Chae and Kim, 2003), low information-intensive product sales (Bang et al., 2013; Chae and Kim, 2003), and the purchase of habitual products (Wang et al., 2015). Einav et al. (2014) also find that while mobile commerce adoption is associated with an immediate and sustained increase in total retailing sales, mobile purchases are skewed towards commodity products rather than idiosyncratic products that require careful inspection ex ante. These differences in effectiveness for search capabilities on the mobile channel has also been reported in practice, where a significant gap has been identified between time spent on mobile devices versus mobile spending, attributable to difficulties in navigation and product comparisons (Fulgoni and Lipsman, 2016). It is interesting that these search costs within the retail context are typically addressed by the development of recommendation systems, which help to reduce the cognitive effort associated with product search. We address this stream of literature next.

The Effects of Recommendation Systems in Retail

Recommendation systems are defined as "software agents that elicit the interests or preferences of individual customers for products and make recommendations accordingly" (Xiao and Benbasat, 2007). Online retailers offer a large number of product choices, incorporating significant amounts of product-related information to their customers. However, customers often find it difficult to efficiently and effectively identify products that meet their needs, due to the cognitive constraints of human information processing (Xiao and Benbasat, 2007). To the extent that further information can be offered to ease the cognitive load, the purchasing process is likely to be positively influenced, thereby leading to a more effective purchasing outcome for both the seller as well as the customer. Thus, most online retailers across all channels offer recommendation systems that are designed to assist customers in product search and selection while simultaneously aiding product customization (Li and Karahanna, 2015).. The literature on the effect of recommendation systems on customer decision making suggests three specific mechanisms – lowering search costs, triggering the recall and retrieval process, and a signaling effect (see Table 2.2 for a summary of prior research in this area). We briefly describe these mechanisms below.

Information processing theory contends that individuals satisfice in processing information and making decisions because of limited cognitive capacity (Simon, 1955). Individuals minimize cognitive load in making purchase decisions by reducing the set of alternative products and evaluating products in the consideration set (Payne et al., 1992). By accessing the customer's shopping history or choices made by other customers with similar profiles, recommendations systems can improve the quality of the decisions customers make when searching and selecting among myriad product choices (Resnick and Varian, 1997). Specifically, recommendation systems assist customers in the initial screening of available alternatives and facilitate in-depth comparisons among selected alternatives (Häubl and Trifts, 2000; Resnick and Varian, 1997; Xiao and Benbasat, 2007), thereby reducing information overload as well as information search costs (Dellaert and Häubl, 2012; Häubl and Murray, 2006; Häubl and Trifts, 2000; Kumar and Benbasat, 2006; Lee and Benbasat, 2010; Senecal and Nantel, 2004; Zhang et al., 2011).

Beyond reducing search costs, recommendation systems also trigger the recall and retrieval process (Bettman, 1979; Lynch and Srull, 1982) by presenting customers with a focal product (i.e., what you viewed last time) and related recommended products (i.e., people who viewed this product also viewed these other products) (Linden et al., 2003). Customers can use the focal product as a retrieval cue. Thus, the visual saliency provided by recommendation systems increases a customer's ability to retrieve focal product information from memory because the focal product is based on the customer's last viewing or purchasing behavior. Hence, recall of the customer's previous search behavior and the memory retrieval process facilitated by the recommendation system also influence purchase decisions positively (Bettman, 1979; Lynch and Srull, 1982).

Finally, most recommendation systems generate a list of recommended products for the focal customer based on prior views or purchases by other similar customers by using a collaborative filtering algorithm, thereby also providing an indirect signal of quality (Linden et al., 2003). Since recommendation systems provide prominent landing page spaces to recommended products, these act as decentralized signals of quality and potential demand, thereby enhancing the appeal of such products (Pathak et al., 2010). Such exposure reduces uncertainty in the specific product and helps customers "discover" a larger number of desirable products.

The specific mechanism notwithstanding, empirical work has shown that recommendation systems have a significant effect on retail sales. De et al. (2010)

show that compared to search engines, the use of a recommendation system has a positive effect on the sales of not only the promoted product, but also on non-promoted products. . Similarly, Pathak et al. (2010) find that these systems lead to higher sales in the context of online books. Oestreicher-Singer and Sundararajan (2012b) show that the visibility accorded by recommendation system increases the shared purchasing of complimentary books. In more recent work, Lee and Hosanagar (2014) compare alternative algorithms that generate the list of recommended products for a particular customer in an effort to understand which approach may deliver the best results. They report that purchase-based collaborative filtering algorithm significantly increases both views and sales of movie titles on an online retailing website. Adamopoulos and Tuzhilin (2015) show that recommendation systems in a mobile urban guide app has a positive impact on restaurant demand. In general, there is consensus in the literature that recommendation systems increase the demand of online retailers.

We juxtapose the literature on the differences between mobile and PC channels, with that from the recommendation systems, to consider how the efficacy of a recommendation system may differ across the two channels. The literature on recommendation systems mostly focused on the PC channel (with the notable exception of Adamopoulos and Tuzhilin (2015)) has argued for how search costs are reduced and for how recall is enhanced by these systems. The literature on the differences between mobile and PC channels has also addressed how search capabilities on the mobile devices are limited and pose structural constraints. Combining these arguments suggests that the efficacy of recommendation systems on retail sales observed on the mobile channel are likely to be significantly different from that observed in PC channels. We argue that such differences relating to purchase behavior on mobile can be conceptualized in terms of low search capabilities.

Clearly, mobile devices impose higher search costs and cognitive loads on customers as they move through the purchase process. Due to the physical limitations, mobile-based customers view less content on their main page than PC customers do, thereby consuming less product and competitor information than do their PC counterparts given the same amount of time. Since recommendation systems lower search costs, help trigger the recall and retrieval process, and provide indirect signal of quality thereby supporting the discovery of a larger number of products as well as reducing the cognitive burden of product evaluation, their marginal effect is likely to be higher in the case of mobile customers than PC customers. In addition, the ubiquity and ease of access associated with mobile devices is likely to enhance the efficacy of recommendation systems in the retail context, since it allows for quick decision making, quick recall and immediate purchase. Therefore, we expect that the recommendation system will be more effective in the mobile channel, relative to the PC channel. In lieu of formal hypotheses, we allow the empirical analysis to provide us guidance.

The Effects of Recommendation Systems on Sales Diversity

Beyond studying the impact of recommendation systems in customer decision making, prior work has also examined the impact of recommendation systems on sales diversity, a market-level outcome of some interest. Though sales diversity represents a second-order effect of a recommendation system, it is critical in that it significantly influences long-term consumer behavior as well as important long-term outcomes such as customer retention (Park and Han, 2013). The relationship between recommendation systems and sales diversity, summarized in Table 2.3, has been the object of considerable debate in the literature. Specifically there have been conflicting ideas on whether these systems homogenize or heterogenize the sales distribution (Li and Karahanna, 2015), as described below.

One line of research argues for a positive outcome where recommendation systems tend to increase sales diversity. Increased sales diversity allows consumers to obtain a more ideal product mix while also ensuring that most products in the product mix retain some probability of purchase, rather than concentrating sales around a few select popular items. By increasing awareness of niche products and encouraging the exploration of products that may not be directly in the consumer's consideration set, recommendation systems can shift demand towards the "long tail" (Pathak et al., 2010). Indeed, Brynjolfsson et al. (2011) show that the use of recommendation systems in e-commerce contexts are associated with significant increases in the sales of niche products, thereby enhancing sales diversity. In a different context, Oestreicher-Singer and

Sundararajan (2012a) also present evidence showing that the use of recommendation systems shift demand from popular items to niche items. Hence, increasing demand for niche products indicates that recommendation systems are expected to increase aggregate sales diversity.

However, an alternative viewpoint argues for exactly the opposite effect in the context of online contexts. Fleder and Hosanagar (2009) argue that recommendation systems can lead to increased individual-level diversity but *decreased* aggregate diversity. While recommendation systems tend to push each individual customer towards new products, they recommend the same products to similar users at the aggregate level (Fleder and Hosanagar, 2009). Consistent with the simulations in Fleder and Hosanagar (2009), Hinz et al. (2011) empirically show that recommendation systems shift demand from niches to blockbuster products. Hosanagar et al. (2014) also find that recommendation systems are indeed associated with an increase in commonality, and that users do indeed purchase more similar products upon the introduction of a recommendation system. In more recent work, Lee and Hosanagar (2014) provide evidence showing that collaborative filtering-based recommendation systems decrease aggregate sales diversity while increasing individual consumption diversity.

Given this divergence in the literature, we conclude that the net effect of recommendation systems on sales diversity is still equivocal and requires further testing. A significant roadblock in this research has been the difficulty in obtaining field data that provides a contrast between users exposed to recommendation systems and those that are not (Li and Karahanna, 2015). Furthermore, beyond sales diversity per se, a resolution to this question may be found in considering interim outcomes, such as product views on online retail websites. It is possible that recommendation systems may enhance view diversity differently than sales diversity, while also displaying different effects across the mobile and PC channels. In the absence of clear theoretical predictions, we allow the empirical analysis to provide some insights.

2.3 Experimental Design and Data

To study the causal impact of recommendation system usage on sales and sales diversity across mobile and PC based channel, we conducted two randomized field experiments in collaboration with two retailer firms located in South Korea. The first firm is an online fashion retailing website (Experiment 1) while the second firm operates an online retailer selling duty-free merchandise (Experiment 2). As we will explain later in this section, each experiment allows us to examine the research questions under different, and complementary conditions. Since these are field experiments, each of the research sites imposed additional constraints on the experimental design. Therefore, while each experiment provides some insight, we believe both experiments together provide a more complete picture of the effects of recommendation systems across the mobile and PC channels, as well as on sales diversity. In terms of chronology, the first experiment was conducted before the second, and several adjustments to the experimental design for the second experiment were made based on feedback received from the first experiment.

The online fashion retailing website which hosted Experiment 1 sells imported men's and women's multi-brand clothing and accessories. The fashion retailer which operates purely online launched the online fashion retailing website for both PC and mobile in 2001. The products and service features are identical, regardless of whether a customer accesses the website through a PC or a mobile phone. The research site hosting Experiment 2 is an online duty-free website that sells cosmetics, accessories, and clothes, similar to those available in most duty-free retail outlets in airports. The retailer also utilizes a PC and mobile version of their site, which are identical. Since each experiment was conducted over a non-overlapping time period between two different firms, combining the datasets for analysis purposes in inappropriate. Therefore, we analyze each experiment independently below.

In both cases, we worked with the research sites in implementing a personalized recommendation feature on the landing page of websites across both the mobile and PC-based pages. Across both experiments, the treatment of interest is the availability of the *recommendation panel*, which is randomly assigned to customers based on the PCID. The PCID is a device identifier and is widely used in Internet marketing practices. The PCID is a persistent cookie containing an encrypted unique 23-digit string stored on the customer's device. Whenever a new customer visits the website, the customer is randomly assigned to the control group (*without* recommendation panel) or the treatment group (*with* recommendation panel) depending on whether the PCID is odd or even. In the treatment group (even PCID), customers are shown the most recent view-based collaborative filtering recommendation panel in a landing page. The recommendation panel shows the recently viewed item as well as a set of recommended items generated through an item-to-item collaborative filtering algorithm, which is the mostly commonly used algorithm in e-commerce (Hosanagar et al., 2014; Lee and Hosanagar, 2014; Linden et al., 2003). In the control group (odd PCID), customers do not see the recommendation panel on their landing page. Since randomization is applied to the recommendation system access for individual customers, our analysis is effectively between-subjects (customers) for sales/sales quantity and aggregated at the market level for sales diversity.

Experiment 1

Experiment 1 was conducted over 120 days between February to May, 2014 and yielded a large sample of 145,098 transactions from 77,305 distinct customers. As mentioned above, the treatment was the availability of the item-to-item collaborative filtering-based recommendation panel. The data for the experiment comes from the actual purchase information (all orders) placed during the experimental period, therefore we focus only on those consumers who have made at least one purchase during the study period. This strategy is consistent with the sample selection approach in the existing literature (De et al., 2010). Since the treatment (presence of a recommendation system) is randomized across the full sample of consumers, not only across those with purchases during the experimental period, we check to see whether the treatment retains parity across the treated and control groups in the final purchase-based sample, in order to rule out any obvious selection-based biases.

Of the 77,305 unique customers who made at least one purchase, 37,811 appeared in the control group (48.9%) while 39,494 customers are in the treatment group (51.1%), suggesting that the treatment appears well-distributed in the sample. Further, Table 2.4 provides variable descriptions of our data and descriptive statistics between the control group and the treatment group. The average sales per customer during the experiment period was \$172.64[1], and is higher in the treatment group (\$180.72) compared to control group (\$164.19). Beyond total sales per customer, we also consider sales quantity, i.e. the number of products purchased during the experimental period. The average sales quantity by a customer during the experiment period is 1.94. Since our interest is in differentiating between PC and mobile users, we use a dichotomous measure to distinguish those customers who only use the PC versus those who also use mobile

[1] We use the average foreign exchange rate between February 01, 2014, and May 31, 2014, retrieved from http://www.federalreserve.gov/releases/h10/hist/.

device. Accordingly, we code the variable Mobile=0 for all customers who exclusively use the PC channel to make purchases across the experiment period. The remaining customers therefore have at least one purchase in the experiment period on the mobile channel – we code these as 1. In certain cases, we observe users with inconsistent treatment exposure, i.e., in some cases, customers may change devices or use browser settings that resets their PCID. In other cases, we observe users across both channels that are assigned to the treatment group on one channel but to the control group on the other. We exclude these customers from the analysis. These exclusions account for less than 5% of the final sample. We also ensure that the sample is well balanced across customer-level variables, i.e., Female, Age, and Tenure, indicating that the randomization is successful and has not led to a skewed distribution. Table 2.5 provides the correlation table for Experiment 1.

One of the concerns with the design of Experiment 1 was the inability to randomize over the channel per se. Recall that our objective is to examine the efficacy of recommendation systems across the mobile and PC channels. While we are able to randomize across the recommendation treatment, we are unable to do so for the channel. Ideally, channel treatment should be randomized, i.e., some consumers should be randomly assigned to the PC while other consumers are randomly assigned to the mobile device, with no channel switching. Randomizing across channel use is infeasible since most retailers resist limiting access to its channels, even for the purposes of a field experiment. Moreover, exogenously restricting access to the mobile channel for customers is not possible for any third-party entity (like us). Thus, we are constrained by not being able to randomize channel use. This raises the concern of channel-switching, i.e. we cannot identify consumers who may choose the switch from the PC to the mobile channel (or vice versa) as a response to the treatment. Ideally, this situation can be handled through studying pre-treatment trends (Bertrand et al. 2004). Unfortunately, in Experiment 1, the firm did not have access to pre-treatment trends for sales. However, we had access to data on pre-treatment *views* of products. We use this information in the construction of the *Mobility Index* variable (described in the Analysis section) but recognize this limitation in experimental design. In order to address some of these limitations described above, we conducted a second experiment. Thus, before delving into the empirical analysis for Experiment 1, we briefly describe the experimental design for Experiment 2 below.

Experiment 2

Experiment 2 was conducted over 3 days in February 2016 to build on and complement Experiment 1 in four specific ways. First, in Experiment 2, we were able to collect data on a series of other outcomes associated with recommendation systems, such as views and sales of *recommended products* specifically (as opposed to average total sales per customer), click-through, as well as conversion (i.e. whether a purchase occurred or not), so as to provide greater visibility into how mobile and PC users differ. Second, as discussed above, we collect pre-treatment data on customers in order to control for channel selection as well as other sources of unobservable heterogeneity in our analysis. Third, the treatment group was provided access to a recommendation panel of products associated with the focal product, using the same algorithm as Experiment 1, while the control group was exposed to a landing page that included a panel showing the same number of best-selling items (regardless of the focal product or product category). The interface was identical between the treatment group and the control group, except for the recommendation panel in one case and best-selling items panel in the other. This is in contrast to Experiment 1 where the recommendation panel was added to the landing page; the control group had no such panel. This design decision in Experiment 2 was made to alleviate concerns about visual salience that may occur from the presence of the panel in Experiment 1. Finally, we were able to cleanly identify pure PC-based and pure-mobile customers in Experiment 2, based on clickstream data across the pre-treatment and treatment periods. Multi-channel customers (i.e. those who used both channels in accessing content) were excluded from the analysis to ensure clean identification across channel use. Thus, Experiment 2 provides more granularity and in-depth analyses for assessing the efficacy of recommendation systems across mobile and PC channels.

Similar to Experiment 1, we randomize the recommendation system treatment but not channel use. Since we have access to pre-treatment trends in this experiment, a theoretically valid approach to estimating the effects of recommendation systems across channels is to use a difference-in-differences model that would account for pre-treatment trends on channel while randomizing on the recommendation treatment. This is fully consistent with prior work where exogenous shocks have been used to study the responses of individuals or firms that vary along non-randomized covariates (Angrist and Pischke, 2008). Therefore, the fact that channel use was not randomly assigned does not rule out estimating the moderating effects of the channel on relationship between recommendation system use and customer-level sales. Since we have access to pre-treatment data on all customers, restricted to 3 days to match the post-treatment period of 3 days, we can also account for channel switching behavior by customers. The final dataset shows that roughly 81% of the customers remained within the same channel before and after the treatment, was applied.

Returning to the data gathered for Experiment 2, of the 18,196 unique customers based on product views data, 9,068 customers are in the treatment group (49.8%) while 9,128 appeared in the control group (50.2%), suggesting that the treatment appears well-distributed. Table 2.6 provides variable descriptions and descriptive statistics between the control group and the treatment group[2]. On the basis of pre-treatment data, we can identify pure PC users, pure mobile users, multi-channel users, and users who shift channels (potentially due to the

[2] In this experiment, we chose to not include the customer demographics data since this data was incomplete and not fully available for the full period of the experiment.

treatment). We observed 11,623 pure mobile users and 2,567 pure PC users, 546 multi-channel users, and 3,460 channel-transition users. We observe that the sample is well balanced across the pure mobile and pure PC consumers. In addition, we see similar values for channel switching across the treatment and control groups as well (*Channel Transition*). We note a higher proportion of pure mobile users relative to Experiment 1, reflective of mobile usage trends in East Asia (Criteo, 2016). The majority of users in Experiment 2 are mobile-based, while the majority of users in Experiment 1 conducted in 2014 were PC users. Table 2.7 provides the correlation table for Experiment 2. In the next section, we describe the empirical analyses for both experiments.

2.4 Empirical Analyses

The Effects of Recommendation Systems and Channel on Sales

Experiment 1

We use regression models to examine the contingent effects of recommendation systems usage on product sales for Experiment 1. The unit of analysis is the individual customer, since the treatment is applied at the level of the individual customer through the PCID. The baseline model for Experiment 1 includes recommendation system treatment, access channel (mobile / PC), and customer-specific variables:

$$\ln(Sales_i) = \beta_0 + \beta_1 Recommendation_i + \beta_2 Mobile_i + \beta_3 Female_i + \beta_4 Age_i + \beta_5 Tenure_i + \varepsilon_i \quad (1)$$

$Sales_i$ indicates customer i's total purchases during the experiment period. The dummy variable $Recommendation_i$ indicates whether customer i is assigned to the treatment group. The dummy variable $Mobile_i$ indicates whether customer i is categorized as a mobile user or a PC user. As discussed above, channel use is potentially endogenous; in robustness tests reported later, we further classify mobile users into levels of mobile device use through the use of customer-level browsing behavior from pre-treatment periods. In baseline analyses for Experiment 1, we retain the dummy variable defined here, acknowledging the relative coarseness of the variable. The variables $Female_i$, Age_i, and $Tenure_i$ captures customer i's gender, age, and tenure on the website for Experiment 1.

Since the recommendation system is randomized across customers, the coefficient β_1 is estimated without bias. In addition, we observe that the sales quantity per consumer is low (mean=1.94), suggesting that while consumers may browse many products, their purchases are not as frequent. Therefore, we cross-sectionalize the sample across the four months of observation for Experiment 1. Furthermore, while clustering on the consumer is possible, the low order quantity per consumer makes this unnecessary[3] (Bertrand et al., 2004). Therefore, we use an OLS model to estimate equation (1) for sales (in dollars), shown in Table 2.8.

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[3] Robustness tests with standard errors clustered on consumers provided fully consistent results.

Columns (1) and (3) of Table 2.8 show that the treatment, i.e. presence of a recommendation system, has a significantly positive effect on customer-level sales (β_1=0.051, $p<0.01$; β_1=0.046, $p<0.01$ respectively). On average, recommendation system usage increases sales by 4.6% of sales. In column (2), we replace the recommendation system dummy with the mobile dummy. The results show that mobile users spend more on the site, all else being equal, providing baseline evidence for the positive effects of mobile ubiquity and convenience, of course without controlling for channel selection. In column (3), we add both variables, showing that their effects on sales retain magnitude and significance (β_2=0.147, $p<0.01$; β_2=0.145, $p<0.01$).

In addition to total sales per customer, we also consider the effects of the treatment on sales quantity per customer. Since sales quantity is a nonnegative count variable, with a lower bound of 1, we cannot use OLS (Greene, 2011). The variance of the sales quantity exceeds its mean (mean = 1.94, variance = 2.43, see Table 2.4). Therefore, the Poisson model is also inappropriate because it assumes that mean and variance of the counts are equal (Cameron and Trivedi, 1990). We use the negative binomial regression, which corrects for over-dispersion and accounts for omitted variable bias, with robust standard errors to estimate the following model (Greene, 2011)[4]:

[4] We also estimate a zero-inflated negative binomial model for sales quantity, which yields fully consistent results. These results are available upon request from the authors.

$$SalesQuantity_i = \exp[\beta_0 + \beta_1 Recommendation_i + \beta_2 Mobile_i + \beta_3 Female_i + \beta_4 Age_i + \beta_5 Tenure_i + \varepsilon_i] \quad (2)$$

$SalesQuantity_i$ indicates customer i's total sales quantity during the experiment period while other covariates remain the same as equation (1). Columns (4) to (6) of Table 2.4 show the estimates of the equation (2). The direct effects of recommendation system usage (β_1=0.066, p<0.01; β_1=0.056, p<0.01) and mobile use (β_2=0.198, p<0.01; β_2=0.194, p<0.01) have a significantly positive effect on sales quantity, consistent with results from total sales from above.

As a baseline, it is useful to note that the results from the estimates of equations (1) and (2) are consistent with prior research showing the direct influence of customized recommendation systems on sales and sales quantity (De et al., 2010; Lee and Hosanagar, 2014; Pathak et al., 2010). In addition, these results also reinforce the finding that mobile-based customers tend to be active buyers, driven by the convenience and ubiquity of mobile retail channels, in contrast to online users in general (Einav et al., 2014; Wang et al., 2015).

Having established the baseline results, we now shift to testing for our primary research questions specifically. Our first research question pertains to the differences in the effectiveness of the recommendation system between channels. We estimate this moderation effect in two ways. First, we conduct subsample analyses by splitting the sample into mobile and PC-based subsamples and estimating equations (1) and (2) for each subsample, an acceptable method in prior marketing research (Sharma et al., 1981). We use the Chow's test (Chow, 1960) to test for the equality of the treatment effect across the two subsamples. Second, we use the interaction approach, where we interact the treatment dummy with the mobile dummy to evaluate moderation (Carte and Russell, 2003). Table 2.9 shows the results of both forms of analyses on overall sales and sales quantity across mobile and PC channel.

The first three columns in Table 2.9 pertain to total sales while the next three columns are for sales quantity. From columns (1) and (2) of Table 2.9, we see that the treatment (i.e. recommendation system usage) has a significantly positive effect on sales for mobile-based customers (β=0.195, p<0.01), whereas this effect is not significant for PC-based customers (β=-0.002, ns). The Chow's test provides further evidence for this strong moderation effect; the coefficients are significantly different between mobile and PC customers (F=90.07, p<0.01). The interaction approach also shows a positive moderation effect, as seen in column (3) (β=0.197, p<0.01), indicating that the recommendation system effect is significantly stronger in the case of mobile channel, compared to pure PC consumers. All else equal, providing access to a recommendation system leads to 19.7% higher sales for mobile-based customers.

The results for sales quantity in columns (3) and (4) of Table 2.5 shows fully consistent results. Recommendation system usage has a positive effect on sales quantity for mobile customers (β=0.203, p<0.01) but no effect for PC-based customers (β=0.003, ns). The coefficients are also significantly different between mobile and PC-based customers (F=405.84, p<0.01). Moreover, the interaction coefficient in column (6) is positive and significant (β=0.201, $p<0.01$). In summary, we see strong evidence of the interaction effect between the use of the mobile channel and recommendation system for sales and sales quantity. In line with previous studies (Einav et al., 2014; Wang et al., 2015), we argue that these effects are driven by the higher search and navigation costs that consumers experience on the mobile device; these users are likely to directly benefit from the recommendation systems that help ease the cognitive and ergonomic costs of the mobile interface (Chae and Kim, 2003; Ghose et al., 2013; Venkatesh et al., 2003).

As discussed above, the coefficient for mobile here is potentially biased since the use of the channel is endogenous to the actual purchase decision. In other words, it is possible that some omitted variable influences the decision to purchase the product as well as use the mobile channel, thereby rendering a biased correlation between mobile and sales. One way to rule this out is to consider pre-treatment trends, which unfortunately we cannot do for lack of data. This bias may even influence the interaction term between the recommendation treatment and the mobile variable, since it is possible for consumers to use the mobile channel more as a response to the recommendation treatment, thus rendering the interaction term of mobile and recommendation system biased. We are able to address these issues in Experiment 2 in some detail.

In the specific case of Experiment 1, we recognize that mobile users were characterized relatively coarsely; consumers with even one mobile purchase were categorized as mobile users. Using this definition, our results show that mobile users have higher sales, all else being equal. However, the coarse measurement may mask further differences between customers in terms of their actual mobile use, and hence their search costs. Users who use the mobile device only occasionally to complete their purchase may not experience significant search costs, and are unlikely to be influenced by the recommendation system. Alternatively, heavy mobile users are likely to incur systematically higher search costs and thereby, benefit significantly more from a recommendation system. We require a measure of the user's level of mobile use that satisfies the following conditions in order to differentiate frequent mobile users from occasional users. First, the measure should ideally be collected before the period of the experiment. Second, the measure should provide granularity on how mobile-intensive the consumer's online behavior is.

We develop such an alternative measure of mobile use through the customers' pre-treatment browsing history, made available by the research site. We capture all browsing data on the platform (mobile and PC-based) for the period November 1, 2013 and December 31, 2013, a month before the start of the experiment. The browsing data for customers was matched with data from the experimental period on customers with at least one purchase. The intersection of these two sets provided 21,204 customers with pre-treatment browsing history and at least one purchase during the first experiment period, allowing us to characterize their mobile usage before the experiment. These customers made an average of 2.61 purchases during the study period while they viewed 69.18

individual pages in the pre-treatment period. We use this information to create a *mobility index* (MI) to represent the customer's use of the mobile channel, calculated as the ratio of the customer's browsing behavior conducted on the mobile channel as a percentage of total browsing behavior. To differentiate between heavy and light users, we weight the mobile browsing percentage appropriately. Thus, the mobility index for customer i is calculated as follows[5]:

$$Mobility\ Index_i = \frac{Mobile\ Browsing_i}{Total\ Browsing_i} \times Population\ Quintile\ of\ Total\ Browsing_i \qquad (3)$$

We consider the total browsing behavior of all users and divide the distribution of browsing into quintiles. We use the quintile score (from one to five over five) to weight the ratio of mobile to total browsing. Effectively, the MI ranges in value from zero to one. For customers using the PC channel exclusively for browsing, the MI score is zero. Alternatively, a customer that also uses mobile to browse will obtain MI values ranging from 0.2 to 1.0. We use the MI in lieu of the mobile dummy to evaluate the robustness of our results[6].

Table 2.10 shows the results using MI scores on both sales and sales quantity. As reported in columns (1) and (2), the direct effects of recommendation

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[5] It is arguable that heavy users of mobile devices can overcome the structural limitations of mobile interfaces through learning. While this is possible, it is more likely that users who spend considerable time on mobile devices, and more time online, will experience higher search costs in general, even after accounting for any learning effects (Ghose et al., 2013). Therefore, we add the second term representing total browsing behavior to the measure.

[6] To complement the earlier use of a mobile dummy, we also dichotomize the MI variable (PC only = 0, at least one observed use of mobile device for browsing = 1). The results using this variable alongside a control variable for browsing volume are fully consistent and are available upon request.

system usage and MI score on sales are positive and significant (β=0.098, $p<0.01$; β=0.320, $p<0.01$ respectively), consistent with the results in Table 2.8. Columns (5) and (6) show that the direct effects of recommendation system usage and MI score on sales quantity are also significant (β=0.103, $p<0.01$; β=0.352, $p<0.01$ respectively). In column (4), we note the moderating effect of MI score on the relationship between recommendation system and sales is positive and significant (β=0.134, $p<0.05$), consistent with the results in Table 2.9. This result suggests that heavy mobile users (regardless of whether they purchase on mobile or PC channels) are more likely to be influenced by the recommendation system in terms of their purchases on the platform. Similarly, the interaction effect between MI and recommendation system on sales quantity, as presented in column (8), is also positive and significant (β=0.213, $p<0.05$). In summary, we find that using a more fine-grained measure of mobile use, albeit with a smaller sample, show that the efficacy of a recommendation system is higher in the context of mobile-based customers compared to PC users. The higher search costs imposed by mobile channels are mitigated partly by such systems. We now describe the empirical analysis for Experiment 2 below.

Experiment 2

The regression analysis for Experiment 2 differs from that presented above since we have access to pre-treatment information for the customers who do purchase products in the post-treatment period. Recall that the treatment here is the availability of the recommendation panel, based on the PCID.[7] Our dataset for analysis here includes 3 days of pre-treatment data matched to 3 days of post-treatment data. On the basis of pre-treatment data, we can identify pure PC users, pure mobile users, multi-channel users, and users who shift channels. We observed 11,623 pure mobile users and 2,567 pure PC users, 546 multi-channel users, and 3,460 channel-transition users. For our analysis, we focus only on the pure PC and pure mobile users.

Since the time period of the analysis is small, we aggregate the data for the pre- and post-treatment periods respectively for each customer, and estimate the effect of the recommendation system across the two channels using a difference-in-differences model. Experiment 2 also complements Experiment 1 by considering alternative customer-level outcomes, such as views, dollar sales, and sales quantity of recommended products specifically, click-though, and conversion to provide greater visibility into how mobile and PC users differ. The general form of the difference-in-differences model is shown in equation (4) below:

$$y_{it} = \beta_0 + \beta_1 Treatment_t + \beta_2 Recommendation_i + \beta_3 Treatment_t \times Recommendation_i + \beta_4 TotalViews_{it} + \varepsilon_{it} \quad (4)$$

The coefficient of interest is β_3 representing the effect of the

[7] We are limited to 3 days post-treatment because the research site wanted to terminate the experiment and roll out the recommendation system to all their customers. The economic impacts of the recommendation system, discussed in the Discussion section, were too significant to justify continuing with the experiment. The short post-treatment duration remains a limitation of our analysis and can be attributed to the costs of running experiments in the field.

recommendation system availability across the pre- / post-treatment periods. By comparing the estimates of this coefficient across the mobile and PC channels, we can assess the differential impact of recommendation systems across the two channels. We estimate versions of this model for five dependent variables: recommended product views (*Rec Views*), sales of recommended products (*Rec Sales*), sales quantity of recommended products (*Rec SalesQ*), click-through rate, and conversion. Consistent with prior research, we use negative binomial regression for count variables (*Rec Views, Rec SalesQ*), tobit regression for *Rec Sales* to account for the left censoring at zero sales, generalized linear models with binomial distribution and logit link for proportion variables (*Click-Through*), and logistic regression for *Conversion* (Greene, 2011). The results are shown in Tables 2.11 and 2.12.

The first two columns of Table 2.11 show the recommendation system's effect on views of recommended products across the PC and mobile channel. Focusing on the highlighted interaction term, the effects of the recommendation system treatment are positive and significant for both channels ($\beta=1.280$, $p<0.01$; $\beta=1.613$, $p<0.01$ respectively). However, the effect size is much larger for the mobile channel, indicating that the presence of the recommendation system renders more views on the mobile channel. Switching to product sales, the results in columns (3) and (4) of Table 2.12 show that the effect of the recommendation system on sales of recommended products is significant for mobile channel users ($\beta=5.473$, $p<0.01$) but has not discernible effect on PC-based customers ($\beta=3.105$, ns). Finally, from columns (5) and (6) of Table 2.12, we observe consistent results for sales quantities of recommended products as well; a positive effect on sales quantity for mobile-based customers (β=1.202, $p<0.01$) but not for PC-based customers (β=0.501, ns). We consistently find that the effect of the recommendation system is significantly higher for the mobile-based customers than PC-based customers when we account for pre-treatment trends.

Table 2.12 shows the results for click-through and conversion across the two channels. The results here mirror those seen above in that the effects are positive and significant for mobile customers compared to PC-based customers. In the case of click-through, while both sets of customers show positive effects, the mobile customers obtain higher effect sizes (β=1.318, $p<0.01$; β=1.511, $p<0.01$ respectively). In the case of conversion, mobile consumers are clearly more responsive to the availability of the recommendation system compared to their PC-based counterparts (β=1.390, $p<0.01$; β=0.648, ns).

A potential concern here is that the availability of the recommendation system (as a treatment) may induce customers to switch channels, i.e. they may move from pure PC users to also using the mobile device for viewing and purchasing products. Recall that this was a concern in Experiment 1 as well, but we were limited in our ability to address it there. However, in this particular context, we can test for these effects, if any. Of the 18,196 unique customers, 3,460 customers were observed to switch channels, i.e. use the PC channel and then use the mobile channel (or vice versa), during the 6 days of observation. We would like to test if this transition is linked to being in the treatment group, i.e. having the recommendation system available. We do so using equation (5) below, where channel transition is the dependent variable, the treatment status of the customer is an independent variable, and we also control for log-transformed total views (to account for heavy versus light users):

$$\ln\left(\frac{P(ChannelTransition)}{1-P(ChannelTransition)}\right) = \beta_0 + \beta_1 Recommendation_i + \beta_2 TotalViews_i \qquad (5)$$

Table 2.13 shows the results of the analysis for the effect of recommendation system usage on channel transition. If there is systematic channel switching in response to the recommendation system treatment (e.g., users exposed to the recommendation system treatment decide to switch from being PC users to being multi-channel or mobile users), the recommendation system treatment would be significant. As shown in columns (1) and (2) of Table 2.13, there is no significant relationship between the treatment and channel transition (β=-0.022, ns; β=-0.026, ns respectively).

To summarize, our results from Experiment 2 add some validity to the thesis that recommendation systems are more efficacious on the mobile channel compared to the PC channel. When considering alternative outcome variables such as click-through and conversion, mobile users appear to respond with greater effect to the presence of recommendation systems, speaking to the argument that search costs imposed through the mobile channel are more effectively reduced through recommendation systems. We next address the impact of these systems on sales diversity.

Recommendation Systems, Mobile Channel, and Sales Diversity

The second research question of this study is empirically examining the role of recommendation systems and channel difference on sales and view diversity, representing market-level outcomes of interest. In testing for these effects, we follow recent work by (Lee and Hosanagar, 2014).

As the first step, we calculate the aggregate views (Experiment 2) and sales (Experiments 1 and 2) for each product on the marketplace. We then use the Lorenz curve and Gini coefficients to study the concentration of product sales across the treatment and control subsamples, as well as channel-specific subsamples. Lorenz curves and Gini coefficients have long been used to measure income inequality and wealth distribution (Gini, 1921; Lorenz, 1905), and more recently, sales diversity (Brynjolfsson et al., 2011; Lee and Hosanagar, 2014; Oestreicher-Singer and Sundararajan, 2012a). The Lorenz curve is drawn with cumulative percentage of products on the x-axis and cumulative percentage of views or sales on the y-axis. The Gini coefficient is the ratio of the area between the Lorenz curve and the 45-degree line to the total area under the 45-degree line. When sales (views) are perfectly evenly distributed among products, the Lorenz curve coincides with the 45-degree line, and the Gini coefficient equals zero. As sales (views) become concentrated, the Lorenz curve curves away from the 45-

degree line, while the Gini coefficient increases.

Figure 2.1 shows the Lorenz curves and Gini coefficients for subsamples pertaining to the recommendation system treated and control groups, as well as based on channel use for both experiments. The Lorenz curves shown in Figure 2.1 qualitatively show no differences in sales diversity between the treated and control groups with respect to the recommendation system treatment for both experiments. Indeed, both subsamples have very similar Gini coefficients: 0.597 and 0.596 for Experiment 1, 0.637 and 0.619 for Experiment 2. In contrast, the Lorenz curve for mobile customers has a steeper curve compared to PC-based customers across both experiments (Gini=0.538 and 0.619 for mobile, Gini=0.633 and 0.656 for PC). Since we have product view data for Experiment 2, we consider the diversity of views as well. Interestingly, we find differences in the Lorenz curve and Gini coefficient for the recommendation treatment (Gini=0.498 for treatment group, Gini=0.674 for control group) but no differences in view diversity between mobile and PC channels (Gini=0.490 for mobile, Gini=0.471 for PC).

Comparing the Lorenz curves and the Gini coefficient are useful but do not provide the means to compute statistical differences. We utilize the permutation test (Good, 2006; Hosanagar et al., 2014; Lee and Hosanagar, 2014) to test for statistically significant differences in Gini coefficients between groups. In order to produce a p-value, we repeatedly and randomly shuffle the dataset to produce null distributions for any test statistics. By comparing statistics from null distributions to the actual test statistics from the real distribution and assessing how many times null distribution statistics exceed the actual distribution statistics, we can determine p-values, and infer statistical significance. We use two-sided tests to provide conservative inferences of differences, if any. In our study, we use 1,000 iterations to get an accurate p-value and the results are shown in Figure 2.2.

As expected from the raw Gini coefficients, recommendation system usage has no significant effect on aggregate sales diversity ($p=0.926$ for Experiment 1, $p=0.279$ for Experiment 2), which runs counter to prior studies shown in Table 2.3. However, customers who use mobile devices show statistically different sales diversities compared to PC-only customers ($p<0.01$ for experiment 1, $p<0.05$ for experiment 2), indicating that mobile-based customers tend to purchase a higher diversity of products than PC-based customers do. In contrast to sales diversity, intriguingly we find that recommendation system usage increases view diversity ($p<0.01$) but the use of mobile leads to very similar view diversities as the PC channel. We also test the moderating role of channel difference on the effect of recommendation system on sales and view diversity, by creating and comparing specific subsamples. We find no significant interaction effect between recommendation system and use of mobile channel on sales diversity.

In contrast to prior work that shows a significant effect of the recommendation system on sales diversity (Brynjolfsson et al., 2011; Fleder and Hosanagar, 2009; Hinz et al., 2011; Hosanagar et al., 2014; Lee and Hosanagar, 2014; Oestreicher-Singer and Sundararajan, 2012a; Pathak et al., 2010), the use of recommendation system appears to have no discernible effect on sales diversity. The recommendation system does lead to greater view diversity, i.e. consumers do browse a greater range of products compared to those who do not have this option. However, this browsing does not lead to serendipitous purchase behavior. In summary, we see an increase in dollar sales and sales quantity from recommendation systems but no significant increase in sales diversity, implying that recommendation systems may increase both niche product consumption and commonality.

The mobile channel, when viewed independently, appears to be associated with greater sales diversity. This effect is not influenced by the presence of the recommendation system (as evidenced by comparisons from Experiment 2). Thus, mobile users in general tend to be more diverse in their purchase behavior – a contingent result that is new to the literature. While sales diversities have been associated with recommendation system availability, the form of the recommendation system, and the specific nature of the products being sold, our exploratory work here shows how the channel itself could influence sales diversity.

2.5 Discussion and Conclusion

The benefits of customized recommendation systems in the context of online commerce have been established in the literature as well as in practice over the last decade. Considerable work has argued that such systems reduce cognitive effort on the part of the customer, while also allowing retailers and marketers to direct demand to niche or “long tail” products, thereby creating a “win-win” situation for all concerned. Our work in this paper started from this juncture; we argued that while extant research provided many insights into the value of recommendation systems, there were two significant gaps in the literature. First, there was a paucity of research addressing the use of recommendation systems in the *mobile* context, an increasingly relevant channel for online commerce (Einav et al., 2014). Indeed, recent research addressing the differences between mobile and PC channels provided strong priors to believe that the efficacy of recommendation systems may be higher in mobile channels, given the higher search and navigation costs. Second, the effect of recommendation systems on sales diversity in e-commerce settings was still unresolved, with evidence showing their tendency to homogenize as well as heterogenize the market (Brynjolfsson et al., 2011; Fleder and Hosanagar, 2009; Hosanagar et al., 2014; Li and Karahanna, 2015). Furthermore, the impact of mobile, as a channel to access content, on sales diversity also remained unexplored. In this study, we address both of these gaps in the literature.

Our work provides an assessment of the impact of recommendation systems on customer-level decision outcomes in the context of online fashion retailing across mobile based and PC based customers. Through two randomized experiments conducted in the field, we first show that consistent with prior work, the presence of a recommendation system is indeed associated with higher sales quantities, all else equal. Building on this baseline result, we show that these effects are particularly strong in the case of mobile users, thereby indicating a significant moderating effect of the channel. The definition of who actually constitutes a mobile customer is potentially complex; in the first experiment, we use the Mobility Index based on the customer's browsing behavior prior to the experiment, thereby providing a cleaner view of the customer's mobile usage. Building on the first experiment, we conduct a second experiment that exploits a quasi-experimental design by considering pre-treatment trends. We also confirm that changes in channel use (channel-switching) is not likely to be driven by the recommendation treatment. Viewed together, the results from both experiments provide us with a clear and reasonably accurate effect of the mobile channel on the relationship between recommendation system use and customer-level decisions.

Prior work has attested to the cognitive effort and search costs imposed on users by mobile devices, especially smartphones (Bang et al., 2013; Ghose et al., 2013; Maity and Dass, 2014). In such conditions, the benefits provided by recommendation systems are particularly appealing. We thus see that mobile users provide the most immediate and obvious uptick, not only on sales but also on views, click-through, and conversion from the system. Our results also provide insights to online retailers with significant investments in mobile in terms of how they may design and implement recommendation systems; mobile webpages are limited by screen size, bandwidth issues, and processing power. In such conditions, retailers would benefit from eliminating unnecessary features on their landing pages, while highlighting the value of even simple recommendation systems. In economic terms, the use of recommendation systems contributes an incremental \$2.3 million in annual sales to the research site for our first experiment, and an incremental \$7.6 million for the retailer that hosted our second experiment. In both cases, the approximate costs of deploying the systems through the existing mobile infrastructure was roughly \$50,000 (for the Experiment 1 client in 2014) and \$150,000 (for the Experiment 2 client in 2016) respectively. Clearly, our experiments showed both firms the business value of the provision of even a reasonable recommendation system on mobile devices. It was for this reason that our second experiment was limited to only three days post-treatment.

In terms of our second exploratory research objective, pertaining to the ongoing debate of recommendation systems on sales diversity (Brynjolfsson et al., 2011; Hosanagar et al., 2014), our results show that these systems appear to have no significant effect either way. The results from the Gini coefficients are statistically indistinguishable between the treatment and control groups, indicating that though recommendation systems have positive and significant impact on view diversity, they appear to ultimately increase the sales of both niche and popular product consumptions. This could be a feature of the specific retailers we work with: neither retailer has the size of product mix observed in firms like Amazon.com or large American retailers like the Gap Inc. In both cases, the target demographics are very specific ("young, urban, fashion-conscious") and this might have influenced these results. Additionally, the experiments were conducted in South Korea, while most of the earlier work has been conducted in the United States. Further work is needed to examine if these factors influence the effects of recommendation systems on sales diversity.

With respect to mobile consumers, we do observe differences in the Gini coefficients relative to PC users. Even within the target demographic across both experiments, users on the mobile devices show greater diversity in their sales, suggesting that there might be value in designing specific recommendation algorithms for these consumers that are first, personalized to their tastes, and second, designed around the limitations of mobile devices. Indeed, in future work, we are working on field experiments where we incorporate a customized recommendation system for mobile users (rather than the collaborative filtering based algorithm used in this study) to gauge the effects on sales and sales diversity. More broadly, as mobile retail becomes more ubiquitous and context becomes increasingly important, the ability to show consumers highly customized recommendations will become important as retailers look to increase their sales diversity.

We also discuss the limitations in the work presented here. While randomization is based on the unique ID of the cookie downloaded onto the consumer's machine, it is possible to reset this if the customer were to change machines or user IDs during the course of the experiment. This does occur in a small percentage of cases; we remove all such customers from our analysis.

Second, as pointed out, we were occasionally constrained by the retailers we worked with in terms of experimental design, in terms of data availability or duration of experimental period across both experiments. Through a series of robustness tests and by replicating the main findings across both experiments, we believe we have addressed most of these limitations. Finally, both experiments were conducted in a specific retail sector (fashion retail and merchandise) in East Asia. While the results across the experiments are robust, their generalizability to other retail contexts or countries will need to be established through more empirical work in the future.

Our work points out to several avenues for future research. Clearly, there is potential for significant work in omni-channel use, in terms of understanding the implications of not only mobile device use but also other channels including both online and offline channels on consumer behavior. Further work on examining the inter-relationships between channels is needed to understand how retailers can operate optimally across them. Specific to recommendation systems, as discussed above, more work is needed to examine the changing relationship between recommendation systems and more contextual factors such as location, industry sector, and multi-channel use. There is tremendous potential on mobile ecosystems for advertising, promotions, and targeted sales, all of which are exciting areas for future research in IS. In this paper, we provide examples of randomized experiments that can be deployed to examine the effects of recommendation system use across mobile and PC channels on both customer decision outcomes and market outcomes in the retail sector. There are several other questions of interest at the intersection of mobile platforms, retail commerce, and personalization technologies that are in the sweet-spot for IS research; we hope that our current work helps to further this type of research in the future.

CHAPTER 3: WHEN PUSH COMES TO SHOP: ON IDENTIFYING THE EFFECTS OF PUSH NOTIFICATIONS ON MOBILE RETAIL SALES

3.1 Introduction

“The medium is the message.” –Marshall McLuhan (1964)

In an era of enormous content creation and availability, it is not surprising that the role of the medium has become increasingly important. Beyond the content itself, the medium influences the manner in which the message is perceived, processed and responded to (McLuhan, 1964). As new technologies emerge, the resulting new forms of media and channels have allowed firms and customers to interact and to exchange content. The Internet represented one such quantum leap in terms of providing new channels for communication and coordination between firms and customers (IBM, 2013), while also allowing for the development of new content uniquely tailored to the online experience. More recently, we are witnessing the assimilation of another channel that is providing enhanced access and interactivity, and is becoming increasingly central to the customer experience – the mobile channel. Allowing for simpler content, the mobile channel allows greater convenience to the customer, while enabling firms to achieve greater engagement with their customer base (Einav et al., 2014). Therefore, it is not surprising that mobile-based sales in the U.S. grew 87% between 2013 and 2014 (Mulpuru, 2015), while spending on mobile advertising totaled $20.7 billion in

2015, accounting for 35% of digital advertising and 100% year over year growth from 2010 (IAB, 2016).

A central component of the transition into the mobile channel on the part of firms is the mobile app, deployed to enrich customer engagement, improve conversion, monetization, usage and loyalty (IBM, 2013). Mobile apps serve as a direct and proximal communication channel with customers, thus incentivizing many firms specifically in the retail sector to invest in the development of firm-specific apps, in addition to their ongoing investments in other channels such as e-commerce websites, mobile websites, and search engine optimization. Indeed, Minkara (2014) reports that over 44% of surveyed companies had deployed mobile apps as part of their customer interaction channel strategy (Minkara, 2014). Within the mobile app environment, a new and interesting phenomena that enables customer interaction is emerging in the form of push notifications. Push notifcations are short messages invoked by mobile apps downloaded on the mobile device that show up on the device's home or lock screen (eMarkter, 2015). Push notifications help alert customers who have already installed the app by leading the customer from the notification directly to the landing page of the app for action. While simplistic in terms of content, push notifications represent a new channel that is used by online retailers. For instance, a retailer can quickly and easily notify all its app users of a sales promotion – the shortened message shows up on the notification page on the mobile device which can be viewed even if the customer is not currently using the mobile app. Push notifications thus inform customers in an economical manner through alerts, driving desired behaviors such as app revisits, app use, and click-throughs to the landing page of targeted products. Thus, push notifications represent a new channel option that potentially allows greater engagement with high-value customers who have already downloaded the firm's app.

Are push notifications effective? Practitioners argue that they help increase customer engagement through message delivery, while improving retention rates with respect to app usage, a standard problem in the app economy (Minkara, 2014). However, there is no systematic evidence from an academic perspective for the effectiveness of push notifications on desired customer actions (i.e., views and sales of targeted product). Within the mobile context, recent work has addressed other forms or channels in which firms interact with customers, including the use of email, short message service (SMS), and online display advertising (Andrews et al., 2015; Bart et al., 2014; Fang et al., 2015; Fong et al., 2015; Ghose et al., 2013; Luo et al., 2014; Molitor et al., 2016; Xu et al., 2014). Each of these channels help facilitate one-way or two-way communication with customers (Li and Kannan, 2014), varying along dimensions of communication velocity and viscosity. Push notifications represent yet another mobile channel available to the marketer, albeit representing a different set of attributes compared to these existing channels. In the absence of any insight regarding their efficacy, a primary objective of this study is to investigate the direct effect of push notifications on primary outcomes of interest to online retailers - views and sales of targeted products.

Beyond targeted products within a specific push notification, the presence of a recommendation system within the mobile app can provide an additional spillover benefit that may be attributed to the push notification. When customers receive a push notification and navigate to the landing page of the targeted product, they see not only the product but also a panel of other recommended products. Prior work suggests that recommendation systems can help reduce search costs, thereby increasing product sales (De et al., 2010). Thus, arguably, the presence of a push notification that leads the user directly to the landing page of the product may also enhance the efficacy of the recommendation system, all else being equal. This forms the second research objective of this paper – to explore the indirect effect of a push notification through the views and sales that result on recommended products on the targeted product page. Although it is possible for customers to invoke the app, search for and purchase recommended products organically, we are able to trace all the cases where the sale and view of a recommended product originated from a push notification. Thus, we provide a more complete analysis of the ex-post effects of push notifications on product views and sales on the mobile channel.

Studying push notifications necessitates collaborations with firms that have a vibrant mobile sales channel and utilize push notifications on a systematic basis. Therefore, we collaborated with a mobile analytics firm that managed push notifications and recommendation systems for an online fashion retailer. We procured a longitudinal dataset from the analytics firm comprised of over 20 million views and 387,913 individual transactions over the period June to November 2015. This data included customer responses to 135 mobile push notifications that were chosen and deployed through an internal experiment by the analytics firm for the retailer client, and included views and sales data across the client's mobile website, as well as the mobile app. Empirically, we exploit two sources of variation in our analysis. First, we utilize the random process by which specific push notifications (associated with particular products) were selected; this process allows us to consider the ex-post effects of a push notification without the risk of selection bias. Second, we construct a natural experiment to investigate the direct and indirect effects of the push notification. By constructing hourly views and sales of targeted, recommended, and total products (10 hours pre and post the specific push) of the push notification, and using sales and views on the mobile app as the treatment group, and the mobile website as the control group, we execute a difference-in-difference strategy to estimate the effect of the push notification. This strategy hinges on the fact that push notifications are not available to customers accessing the site on mobile browsers, thus providing a reasonable control group.

Our results indicate that push notifications increase the views of targeted products by up to 3600%, while increasing the views of recommended products by roughly 30%. Clearly, the majority of the views accrue to the targeted product. With respect to sales, we observe a boost of 96.8% for targeted products, relative to the control group, but this effect wanes two hours after the push notification is sent. Interestingly, we find steadily positive effects on sales for recommended (up to 169%) and total products (up to 76%) in the 2-hour, 5-hour, and 10-hour time periods after the push is sent. Taken together, our results show that push notifications lead to a significant effect on views of targeted products, alongside a smaller marginal effect on the sales of targeted products. However, it is noteworthy that the effects on recommended and total products, attributable to the push notification, appear more compelling in magnitude, speaking to the joint effect of the push as well as the recommendation system. We explore these results using a series of robustness tests wherein we change the control group by using temporally shifted counterfactuals and observe consistent results. We also estimate a relative time model and find largely consistent results. Finally, in post hoc analysis, we explore how specific features of the push notification itself (push heterogeneity) may be affecting customer behavior and observe that notifications that include celebrity information and price discounts are highly influential.

These results highlight the two primary contributions of our study. First, we contribute to the growing literature on the mobile channel, and show the demand-side efficacy of push notifications. As push notifications become commonplace alongside SMS messages, mobile coupons, and trajectory-based promotions, a rigorous evaluation of their effects on sales and views is necessary; to our knowledge, our study is the first to address this question in the context of retail sales. Second, we augment our study of push notifications by studying the interaction of the notification with the presence of a recommendation system within the app. While a push notification helps grab the potential customers' attention and draw him/her to the landing page, recommendation systems help amplify that effect by leading customers deeper into the conversion funnel. We thus contribute to the literature on mobile-based recommendation systems as well, by indicating the presence of clear complementarities between the functionalities of push notifications and recommendations, with clear implications for managers looking to optimize their customer experiences through push notifications and recommendation systems.

3.2 Literature Review

Push notifications, at their core, represent a new channel by which firms may reach their customers with information about promotions and product information. Industry reports indicate that push notifications typically do not include new content, but incorporate existing content tailored to suit the limited space available through the notifications functionality on mobile devices (Minkara, 2014). Thus, there are distinct commonalities between push notifications and prior research in advertising, specifically mobile advertising, where the objective is to capture the customer's attention. Therefore, we briefly review the literature on mobile advertising before addressing the particular case of push notifications.

Mobile Advertising

The small but growing stream of research on mobile advertising that has, emerged in the last few years has significantly enriched our understanding of the mobile ecosystem. Building on the adoption of smartphones, mobile devices, and enterprise apps, the goals of mobile advertising are primarily to generate awareness and draw attention to aspects of the product in a personalized manner through the mobile device (Grewal et al., 2016). In addition, mobile advertisements enable customers to engage with the brand, help enhance purchase intention, and “convert” the sale. Thus, the literature thus far has focused mostly on the extent to which different forms of mobile advertisements may lead to conversion, and in some cases, enhanced brand attitudes and engagement (Grewal et al., 2016).

The most common forms of mobile advertisement technologies that have been studied thus far pertain to mobile display advertising (Bart et al., 2014; Ghose et al., 2013) and SMS (short message service)-based mobile coupons (Andrews et al., 2015; Baker et al., 2014; Fang et al., 2015; Fong et al., 2015; Ghose et al., 2015; Hui et al., 2013; Li et al., 2015; Luo et al., 2014). Bart et al. (2014) show that mobile display advertising is particularly effective for high involvement and utilitarian products in terms of customers’ attitude and purchase intention. In a different vein, Ghose et al. (2013) find that while search costs are higher using mobile devices, the location dimension is more important for mobile users, since they can be targeted based on their current locations. With respect to mobile SMS-based coupons, much of the current literature shows that location-based mobile coupon targeting is highly influential on coupon redemption rates, sales of promotional vouchers and the concordant sales of offline retailers (Danaher et al., 2015; Fang et al., 2015; Fong et al., 2015; Ghose et al., 2015; Hui et al., 2013; Luo et al., 2014; Molitor et al., 2016). In this research, the causal mechanism at play is the ability of the mobile coupon to draw customer attention to the underlying promotions, thereby leading to conversion (Grewal et al., 2016). In as much as certain contextual factors can help enhance the salience of the coupon to the customer, the greater is the resulting conversion. Thus, contextual factors such as weather (Li et al., 2015), timeliness (Baker et al., 2014; Danaher et al., 2015), expiry length of coupon (Danaher et al., 2015), and crowdedness of physical environment (Andrews et al., 2015) have been shown to significantly influence the customers' response to SMS-based mobile advertising.

Our work here adds to this stream of research, but is also differentiated from this body of work in three distinct ways. First, prior work has focused on the contingent effect of user context in mobile advertising rather than the effect of mobile advertising per se. Our work here, by contrast, primarily focuses on the mere exposure effect of mobile advertising on business outcomes in mobile commerce. Recall that push notifications represent in-app communication that is very concise and spare, thus representing the simplest form of a mobile advertising message. We thus start by addressing the demand-side effect of these notifications, by focusing on views, sales, and conversion. Second, beyond the push notification, we also investigate how the presence of a recommendation system may help complement the heightened attention that results from the push itself, again going beyond simply evaluating the user context. Third, we conduct our study in the field organically, thereby studying customers' responses to everyday mobile advertisements (in the form of push notifications), rather than opt for a small number of temporary SMS-based mobile advertisements or service vouchers. Thus, we observe the actual working of the notification in the field and derive our identification strategy from variations observed across mobile channels. Studying the phenomena in its natural context allows us to link the treatment (i.e. the push) to actual customers' views and purchases. In the next section, we outline specific arguments for the effect of mobile push notifications on sales and views.

Direct Effect of Push Notifications on Mobile Shopping

Push notifications represent a form of mobile advertising, enabling firms to reach customers regardless of location and time while allowing customers to browse and purchase at their convenience (Grewal et al., 2016). Mobile apps released by retailers help to improve brand awareness and to increase average spending (Kim et al., 2015). However, retailer apps tend to fight an uphill battle for the average user's attention. Though smartphone users have an average of 40 apps on their devices, less than 15 apps are used frequently (Gupta, 2013). Thus, the odds of a retail app being frequently used are small. As a first step, therefore, retailers relying on the mobile app as a viable sales channel face the challenge of ensuring that the user actually does use the downloaded app (Gupta, 2013); mere downloads do not address the problem adequately.

Push notifications help by addressing this specific need; they represent an innovative channel for drawing the attention of the mobile app customer, and alerting her to the advertised message on the device home or lock screen (Shankar et al., 2016). The customer may choose to opt out of the notification on the lock screen, but this is relatively rare among those customers who have downloaded the app (Grewal et al., 2016). When compared to other mobile advertisement channels (e.g. interstitial display advertising), push notifications are less obtrusive while being concise and succinct, since they are easy to check with a glance and equally easy to ignore. Having garnered the customer's attention, how do push notifications help the retailer?

Prior theory in marketing argues that advertising works because customers tend to pay attention to advertisements before they move closer to a desired action (Teixeira, 2014). Attention represents a certain amount of mental effort or cognitive capacity allocated to the advertisement stimulus (Kahneman, 1973). As a limited cognitive resource, attention can be allocated in varying degrees to the advertisement or to an alternative task on the mobile device, such as checking a Facebook feed, browsing the Internet through the mobile browser, or even on other offline stimuli (Grewal et al., 2016; Maclnnis and Jaworski, 1989). Since the push acts as an advertisement, it garners greater attention from the customer, whereby higher cognitive resources are expended in evaluating and understanding the content of the notification. Greater attention leads to a deeper processing of the advertisement, and the associated promotion of a product/service (Maclnnis and Jaworski, 1989), a more developed cognitive process of evaluation, (e.g., high elaboration) (Petty and Cacioppo, 1986). Prior work in mere exposure theory (Zajonc and Markus, 1982) argues that repeated presentation of stimuli, such as push notifications from the retailer on the app, increases positive affect on customers on the basis of elements such as liking and emotions induced by mere exposure to the advertisement. Customers are easily able to process messages they have already encountered because a representation of those objects already exists in their mind and fluent processing leads to positive affective responses (Monin, 2003; Winkielman and Cacioppo, 2001).

Moreover, the fact that customers explicitly download the retailer app, in the first case, and therefore primed to be positively inclined to the personalized nature of the push messages (Jarvenpaa and Lang, 2005) suggests that rate at which positive affect results from notifications here are likely greater than from intrusive advertisements from other channels prevalent online, such as in pop-up ads (Edwards et al., 2002). In addition, though the format of the push notification is consistent, each specific notification varies in terms of the product being promoted and the message theme, enhancing the unexpected nature of the advertisement, and thus the extent to which the notification is able to lead to positive affect.

There is, however, also reason to expect push notifications to have no significant effect or, in the worst case, create a negative brand association with the retailer. Prior work in intrusive pop-ads or push advertisements have argued for how these forms of unsolicited promotions can lead to a significant negative response from consumers (Truong and Simmons, 2010). Consumers view these promotional effects as leading to loss of control and resort to avoidance behavior (McCoy et al., 2007). Alternatively, consumers can respond to the perceived loss of privacy and respond negatively (Truong and Simmons, 2010). Viewed through this lens, it is therefore possible for push notifications to not have any discernible effects on sales or views, or even lead to a negative effect. We argue that this is unlikely in this context because notifications are only received by consumers who have downloaded the mobile app, indicating a baseline level of engagement with the retailer (Grewal et al., 2016). To the extent that customers experience engagement and identification with the advertiser, the negative responses tend to be muted (Grewal et al., 2016). On balance, therefore, we expect that the push notification will lead to an increased likelihood of the customer (a) viewing the landing page of the targeted product, and (b) purchasing the targeted product.

Indirect Effects of Push Notifications on Mobile Shopping

As noted above, the push notification leads the customer directly to the landing page of the targeted product. In the specific case of our research site, the landing page was also populated with a set of recommended products by using a non-personalized item-based collaborative filtering algorithm (e.g., people who bought this item also bought items X through Z) (Linden et al., 2003). The use of this algorithm was invariant throughout the period of data collection, and was the standard algorithm the retailer applied across all channels. The presence of recommended products is a valuable marketing tool here. Research has shown that recommendation systems can help reduce search costs for the customer while also leading to greater variety in search behavior, often leading to serendipitous purchasing behavior (De et al., 2010). Applying that viewpoint here indicates that while the push notification helps direct the customers' attention towards an unmet need or purchase opportunity via the targeted product, customers are often motivated to seek more variety (Ratner et al., 1999). In mobile contexts, where smaller screen sizes and lower resolutions make organic search more cumbersome and costly (Chae and Kim, 2003; Ghose et al., 2013), recommendation systems help reduce these costs, as argued in the literature. Specifically, recommendation systems assist customers in the initial screening of available alternatives and facilitate in-depth comparisons among selected alternatives (Häubl and Trifts, 2000; Resnick and Varian, 1997; Xiao and Benbasat, 2007), thereby reducing information overload as well as search costs (Häubl and Murray, 2006).

These arguments indicate the possibility of a clear complementarity between the presence of the recommendation system and push notifications on the mobile platform – the push notification helps draw the customer into the targeted product's landing page, while the recommendation system allows the customer to avail of variety in viewing and purchasing behavior. Therefore, an indirect effect of the push notification is to positively affect the views and sales of recommended products from the targeted product's landing page, all else being equal. We believe this effect is consistent with prior work that shows how advertising for one product can spill over and enhance sales for all other products within the same company (Balachander and Ghose, 2003). Indeed, it is also possible that the push notification induces the customer to deploy the app, visit the targeted landing page, and search organically from there on. Thus, we conjecture that the notification may lead to higher views and sales of even unrelated products on the retailer's platform, thereby enhancing total sales and overall views of all products. While we do not explicitly hypothesize about these effects, we allow the empirical analysis to provide guidance on these questions.

3.3 Methodology

Context and Data

Our empirical analysis was conducted on a dataset collated through collaboration with a marketing analytics firm that managed push notifications and recommendation systems for a retailer client in East Asia. The retailer specialized in fashion merchandise focused on the youth segment, with particular emphasis on young women. In general, this target population is more comfortable with online sales, use of mobile devices for shopping, and also download retail apps more willingly (Mulpuru, 2015). They are also likely to respond more positively to promotional information sent through mobile channels, including SMS, email, and push notifications. While the context, thus, seems appropriate for the study of the demand-side effects of push notifications, it also limits the extent to which results observed here can be generalized to other contexts or customer populations.

We briefly describe the process by which push notifications were issued in our dataset. Decisions pertaining to the actual notifications were fully delegated by the retailer client to the marketing analytics firm, with the intention of understanding the effects of push notifications on short-term sales and views outcomes. The analytics firm thus had control over the form of the push notification as well as the process by which they were issued, under broad contractual directions from the client. In order to estimate the effects of push notifications without selection bias, a set of push notifications for a randomly selected set of 135 products were created ex ante. Subsequently, one of these push notifications were chosen at random and issued per day. In all, over the period from June 1, 2015 to November 20, 2015, the 135 individual push notifications were issued by the analytics firm on behalf of the retailer. To further create variation, the notifications were issued at randomly varying times of the day, with large densities at 8:00 AM, 12:00 noon, and 8:00 PM. No push notifications were sent between the hours of midnight and early morning as a matter of firm policy.

As specified earlier, these notifications are only available through the downloaded mobile app, even though mobile app and mobile web users are able to see identical HTML5-based mobile webpages. As part of the study design, the fashion retailer did not engage in any other mobile advertising initiatives (such as coupons or SMS-based promotions) during the period of data collection. Additionally, no significant changes were made to the layout or organization of the retailer's mobile application or mobile website. This allowed for a relatively static environment in which to conduct the analysis, without any biases driven by selection of specific products.

The dataset collected thus contains information on all product-level views and sales of the fashion retailer across the mobile application and mobile web channel during the push notification marketing period. For users using the mobile app, an observation in our dataset refers to a push notification induced views and sales, recommendation system usage based views and sales, and organic views and sales. We are able to attribute all such views and sales to a specific push notification through a push notification tracker that is recorded by the mobile platform. Beyond the push tracker, the views and sales data include user identifier, IP address, product identifier, product information, time, channel information, and recommendation system identifier. Furthermore, information regarding the specific push message is recorded, including the actual push message, push notification day and time, target product, and landing page URL. For those users who access the retailer's mobile website through the browser, the dataset includes the number of views and purchases of the products in the retailer's catalog over the same time period, but no push notification information since these are not available. In all, our dataset consists of a total of 20,773,399 views from 1,735,592 unique customers, as well as 387,913 individual product sales by 127,097 unique customers. Of these unique viewers, 24% (262,102) used the mobile app while 76% (1,482,212) used the mobile web. In the final sample, the visit-to-purchase conversion rate is 1.86% while 7.32% of the customers made purchases.

Using this composite dataset, we first construct data for each of the 135 push notifications, hourly views and sales of each targeted product, recommended products, and total products from June 1, 2015 to November 20, 2015. Figure 3.1 shows the distribution of push notifications and mean total product views, by mobile web and mobile app, throughout the day. We observe that the number of product views increase from 5:00 AM to midnight and decline from midnight to 5:00 AM. Furthermore, product views through the mobile app peak several times during the day, typically around 8:00 AM, 12:00 noon, 3:00 PM, and 8:00 PM. At first glance, these peaks are associated with the push notifications, providing model-free evidence of the positive relationship between the notifications and the associated views.

Prior research suggests that the effects of mobile advertising are likely to be time-sensitive, with their efficacy decaying over time (Grewal et al., 2016). Therefore, as a first step, we examine our data to see how long the effects of push notifications are likely to manifest. Using sales data that can be attributed to each push notification through the notification tracker, we draw Kaplan-Meier survival curves for notifications, shown in Figure 3.2. Kaplan-Meier survival curves are used to show effects of treatment or survival over time, and are often used to examine how long it takes for a treatment's effect to subside (Kaplan and Meier, 1958). The Kaplan-Meier survival estimation of push-induced sales on the app shows that about 90% of targeted products are sold within 5 hours of the notification, while 85% of recommended and total products sales occur within 10 hours.

Since the vast majority of sales attributable to the push notifications occur within 10 hours, we constructed a panel dataset that captured sales and views of targeted product, recommended products, and total products based on pre- and post- 10 hour windows of the 135 push notifications by the mobile app and the mobile web. All subsequent analyses estimating the effects of push notifications were conducted on this panel dataset, which comprises of 4,968 observations spanning pre- and post- 10-hour of 135 push notifications across two channels, the mobile app representing the treatment group and the mobile web the control group. Summary statistics and correlations for this dataset can be found in Table 3.1.

Variable Definitions

Dependent Variables

Since our focus in this paper is on the demand-side effects, the dependent variables consist of the sales and views of specific products offered by the retailer. We use the log-transformed sales of the push-targeted product, *ln(Push Sales,* as our first dependent variable. In addition, we also consider the sales of recommended products, *ln(Rec Sales),* and sales of all products that result from the push, *ln(Total*

Sales). Recall that the push tracker allows us to track those sales that occur through the mobile app, attributable to the push notification. More formally, each variable is the natural log(+1) of the dollar sales of product(s) (targeted, recommended, total) attributable to push notification *i* during window hour *t* on mobile channel *j*. Logging the variable permits us to interpret the effect as a percentage change and resolves a normality concern.

In robustness tests, we also analyze unit sales for all three cases, captured by *Push SalesQ*, *Rec SalesQ*, and *Total SalesQ*. These variables are not confounded by product price variations. *Push SalesQ* (*Rec SalesQ, Total SalesQ*) is the sales quantities of targeted product (recommended products, total products) relating to push notification *i* during window hour *t* on mobile channel *j*.

In addition to sales, we also analyzing the views of product pages that result from push notifications. Analogous to sales, we consider three dependent variables, *Push Views*, *Rec Views and Total Views*. *Push Views* (*Rec Views, Total Views*) is the total number of targeted product (recommended products, total products) pages viewed that can be attributed to push notification *i* during window hour *t* on mobile channel *j*.

Independent Variables

Our primary empirical strategy is a difference-in-differences estimator. Therefore, we are interested in how sales/views are affected by the treatment (push notification), when compared to the control group, sales/views on the mobile web. The estimate of this effect is provided by the interaction of two dichotomous variables. The first, *App* (mobile app=1, mobile web=0), captures the first structural difference in sales and views between the two channels, while the second, *AfterPush* (t=1 for all time periods post-push, t=0 for all time periods pre-push) captures the treatment effect. The interaction of *App* and *AfterPush* provides the required estimate of how the push notification affects sales/views of the product, relative to the control group. In addition to these variables, we also include the time (hour of the day) and push notification fixed effects in our analyses to account for any further unobservable heterogeneity.

Empirical Estimation

The empirical strategy described above allows us to conduct a quasi-experiment using observational data, since the treatment is only applied to mobile app users. The use of the panel dataset around the specific treatment also allows us to examine, and account, for pre-treatment trends that may exist relative to specific push notifications. In addition, including push and hour of day fixed effects allows us to account for heterogeneity specific to the time of the day (exogenous events that affect demand at that time of the day) as well as idiosyncratic factors related to the specific push message. Given the panel structure of the data, we estimate the treatment effects using the following equation:

$$y_{ijt} = \alpha + \beta_1 AfterPush_t + \beta_2 App_j + \beta_3 AfterPush_t \times App_j + \gamma_i + + \tau_{it} + \varepsilon_{ijt} \quad (1)$$

where y_{ijt} are views and sales dependent variables regarding to push notification i during window hour t on mobile channel j. $AfterPush_t$ captures the pre/post push time, App_j denotes mobile app or mobile web. The coefficient β_3 is of interest since it captures the difference-in-difference estimate. γ_i represents fixed effects for push notifications. Time fixed effects for push notification i and window hour t are captured by τ_{it} while ε_{ijt} is the residual error term. For all regressions involving logged sales as the dependent variable, we report OLS estimates of equation (1), with robust standard errors, clustered by mobile channel and push notification. OLS allows easily interpretable coefficients and clean estimation of the differences-in-differences treatment effect (Bertrand et al., 2004).

For those regression specifications where the dependent variable is a count measure (i.e., views and sales quantity), we employ a Poisson Pseudo-Maximum Likelihood (or Poisson Quasi-Maximum Likelihood, hereafter referred to as PPML) estimator to provide more reliable estimates (Cameron and Trivedi, 2013; Wooldridge, 1997). A PPML estimator can be used for non-negative count dependent variables even if the data has a large proportion of zeros (Silva and Tenreyro, 2011), like targeted product sales data. This PPML estimator also allows both for under- and over-dispersion (Silva and Tenreyro, 2011; Wooldridge, 1997). In robustness tests, we also estimate negative binomial and Poisson models, which provide consistent results, available from the authors upon request.

3.4 Results

We first start with the results of the analysis on the views and sales of the targeted product, shown in Table 3.2. The first three columns provide results for views of the targeted product across the 2-hour, 5-hour, and 10-hour time periods, while the remaining columns provide similar results but for sales of targeted products. As mentioned above, the coefficient of interest is the interaction coefficient (*App*After_push*). Columns (1) to (3) of Table 3.2 show that views of the targeted product are consistently positive and significantly associated with the push notification across the 2-hour, 5-hour, and 10-hour windows. As expected, the marginal impact of the push notification is the highest in the shortest time-period; views of the targeted product in the 2-hour period experience an increase of approximately 3604% (β_3=3.612, $p<0.01$). We observe marginal effects of 2133% (β_3=3.106, $p<0.01$) and 1643% (β_3=2.858, $p<0.01$) for targeted product views within 5-hour and 10-hour periods.

Views represent the first stage of the conversion funnel, ideally leading to eventual sale. We see mixed results here. Unlike the effects on views, the push notification appears to have a significant positive effect on sales only for the shortest 2-hour window (Columns (4) to (6) of Table 3.2). Economically, these results suggest an average increase in targeted product sales of 96.8% (β_3=0.968, $p<0.05$) by push notifications in 2-hour. Incremental sales farther from the time of the push are not significant, even though views of the product page increase. It is noteworthy that the direct effect of the push treatment (coefficient of *After_push*) is significant across the 2-hour and 5-hour window but it is important to consider pre-treatment trends, if any, to gain an accurate picture of the true effect of the push. As seen in Figure 3.3, where the effects of the push notification on the treatment and control group are graphed, there is a clear and short-term peak in sales associated with the push, while the effect on views lasts longer. The control group appears to have a slight positive pre-treatment trend, but is clearly not affected by the treatment, adding veracity to our results. In real terms, the push notification more than quadruples the sale of the targeted product on average, from roughly 0.5 units to 2 units. Since our sample of 135 notifications only address 135 specific products, the incremental sales may not appear very high; indeed, for a full accounting, we consider sales of recommended products next.

The results for recommended and total product sales/views are shown in Tables 3.3 and 3.4 respectively, following the same structure as Table 3.2. The results for recommended product sales and views are remarkably strong. As shown in Table 3.3, the effect of the push notifications on views and sales are strongly positive across the 2-hour, 5-hour, and 10-hour windows. Columns (1) to (3) of Table 3.3 show effect sizes of 29.4% (β_3=0.258, $p<0.01$), 13.3% (β_3=0.125, $p<0.01$), and 6.9% (β_3=0.0665, $p<0.05$) lifts of recommended products' views within 2, 5, and 10 hours, respectively. Although the relative effect on views of recommended products are smaller than views of targeted products, we find that the effective sales lift for recommended products is higher - 169% in 2 hours (β_3=1.693, $p<0.01$). We also find consistent sales growth in 5 hours (β_3=1.684,

$p<0.01$) and 10 hours ($\beta_3=1.149$, $p<0.01$). Unlike targeted products, the set of recommended products is larger for the 135 push notifications. In addition, since the recommendation algorithm tends to select those products that are similar to the targeted product but also have the highest sales, the odds of customers buying these products are higher than those associated with the targeted product. In other words, the cumulative effect of the push notification appears to be more compelling for recommended products, providing some evidence for the complementary benefits that push notifications and recommendation systems provide through the mobile app channel.

Finally, with respect to total product sales and views attributable to the push, Table 3.4 documents these results. Columns (1) to (3) of Table 3.4 show that push notifications increase the view of total products by 64.9% ($\beta_3=0.500$, $p<0.01$), 34.3% ($\beta_3=0.295$, $p<0.01$), and 22.8% ($\beta_3=0.205$, $p<0.01$), in 2, 5, and 10-hour windows respectively. Furthermore, push notifications provide a significant lift in sales across all three windows: 59.1% ($\beta_3=0.591$, $p<0.01$), 76% ($\beta_3=0.760$, $p<0.01$), and 47.2% ($\beta_3=0.472$, $p<0.01$) respectively. The results for total product mirror those from recommended products, in that push notifications help direct the consumer to deploy the app, visit the landing page of the targeted product, and from that point onwards, allow the user to engage in search of recommended products as well as organic search. The value of the push notification arises from the observation that this search behavior leads to incremental sales on the mobile app, relative to the control group. Thus, the results indicate a clear demand-side benefit of push notifications through the mobile app channel.

We present these results graphically in Figure 3.4, where sales and views for recommended and total products on the mobile app are shown relative to the push notification. In the case of views, there is no discernible pre-treatment trend across all three product types, but the associated spike in views from the push is evident. Similarly, for sales, there is no statistical evidence of a pre-treatment trend, though there appears to be a slight upward trend in the figure. Here too, the effect of the push notification is clear and statistically significant. Note that the figure does not include trends from the control group, in the interest of clarity. The trends for the control groups show no effects from the push notifications, corroborating the results in the tables.

The estimation results as well as graphical representations provide strong evidence that push notifications increase sales and views of targeted, recommended, and total products. The sales and views skyrocket within the first 2 hours, and gradually decrease over the 5-hour and 10-hour window. Though the effect on views appears to be highest for targeted products, the effect on sales is more striking in the case of recommended products. Beyond these baseline estimations, we conducted a series of robustness tests to examine the strength of the results. We describe these robustness tests in some detail in the next section.

3.5 Robustness Tests and Additional Analyses

Unit Sales

In the analyses reported earlier, we used dollar sales as our dependent variable. In a robustness test, we use unit sales as our dependent variable, to check for the effects of push notifications without the intervening influence of price. Because unit sales are count data, we use the PPML specification, with the results shown in Table 3.5. As is evident, we find strong evidence for the positive effect of push notifications on the unit sales of targeted, recommended, and total products on the mobile app. The effects of the push are significant and positive across all three period windows. In the case of total sales over 10 hours, the effect is significant at $p<0.10$.

Unlike dollar sales, the effects of push notifications on unit sales are highest for targeted product throughout all time windows. Specifically, the effect size for targeted products in the 2-hour range is 250.1% (Column (1) of Table 3.5, β_3=1.253, p<0.01) while the effect size for recommended and total unit sales are 61.8% and 15% respectively (Column (4) of Table 3.5, β_3=0.481, p<0.01; Column (7) of Table 3.5, β_3=0.140, p<0.01). Consistent with the earlier set of results, we see the effect of push notifications diminish each hour after the notification was sent. While unit sales for the targeted product do increase significantly, the resulting revenue gains are higher from the indirect effect of the push notification, thanks in part to the recommendation system and the effective drawing of the customer's attention to the mobile app.

Relative Time Model

Our baseline empirical strategy has been to use the aggregate difference-in-differences approach between treated (i.e., mobile app) and control (i.e., mobile web) mobile channels by comparing pre- and post- 2, 5, and 10-hour of time window. A significant concern that emerges in these models is the possibility of a parallel pre-treatment trend between the treated and control channels (Angrist and Pischke, 2008). One way to test for these effects, using the panel dataset, is to estimate a relative time model, i.e. estimate a model that includes time dummies relative to the treatment that indicate the chronological distance between an observation time and the time the push notification *i* was sent. These dummies are referred to as RT_n where *n* refers to the time of the observation relative to the treatment. Formally, the relative time model specification is represented below in Equation (2):

$$y_{ijt} = \alpha + \beta_1 AfterPush_t + \beta_2 App_j + \sum\nolimits_n \beta_{3n} \left(AfterPush_t \times App_j \times RT_n \right) + \gamma_i + +\tau_{it} + \varepsilon_{ijt} \quad (2)$$

As before, y_{ijt} are views and sales regarding to push notification *i* during window hour *t* on mobile channel *j*, $AfterPush_t$ is an indicator whether window hour *t* is a post-push window hour, and App_j is an indicator for channel *j*. γ_i, δ_j, and τ_{it} are fixed effects for push notifications, mobile channels, and hour of day, respectively while ε_{ijt} indicates the error term. $\beta_{3(1\ldots n)}$ are coefficients of variables for the interest in the time relative model. Standard errors are robust and clustered at the mobile channel use and the push notification level.

This model allows us to determine whether there is a pre-treatment trend of push notifications that may disproportionately affect the mobile app channel, as opposed to the mobile web channel. The model results also help determine how long it takes for significant effects to manifest following the push notification treatment. The results of the analysis are available in Appendix 3B and are consistent with the findings from before. In addition, they help alleviate any concerns regarding pre-treatment trends within the difference-in-difference specification. In most cases, we see relatively few significant pre-treatment trends – five of the 54 pre-treatment coefficients are significant at $p<0.05$, suggesting that the difference-in-difference model is able to capture the treatment effect of push notifications reasonably well. In addition, most of the significant coefficients are negative, which is contrary to the expectation of a confounding pre-treatment trend, confirming that the post-treatment positive effect of push notifications on sales and views through the mobile app are indeed cleanly identified. The results also provide evidence for the notion that while the effect of push notifications are higher and last longer for targeted products, their economic impacts are higher for recommended and total products, underscoring the sense that the indirect effects of push notifications are higher than direct effects.

Temporal Shifting Counterfactuals

In previously reported analyses, we use data from the mobile web use as counterfactuals. However, this approach is prone to one criticism – it does not fully account for self-selection in the use of the mobile app, i.e. users who download and install the app are frequent buyers of the retailer's products and therefore potentially more likely to respond to push notifications. The counterfactuals from an alternative channel may not fully account for these differences. An alternative strategy would be to identify counterfactuals from *within* the mobile app user base itself. Therefore, we adopt the strategy of temporally shifted counterfactuals, wherein the control group is composed of views and sales for the *same* targeted products on the mobile app, but based on a time period one week before and after the observed push notification. Since the effects of notifications seldom last beyond 24 hours, from our earlier analysis (Kaplan-Meier plots in Figure 3.2), comparing the treatment group to a control group on the mobile app but at a different time-period can help serve as suitable counterfactuals. In addition, this strategy reduces the effects of any unobservable differences between customers who use the mobile web and those that have downloaded the mobile app. Thus, two control groups are created for targeted, recommended, and total products for each notification, one based on views/sales one week prior to the notification and the second one based on one week after the notification. We create the counterfactual groups at exactly the time of the push notification, i.e. if the notification was issued at 9:00 AM, the counterfactual groups are constructed from 9:00 AM a week before/after. We then re-estimate the difference-in-difference model using Equation (3):

$$y_{ijt} = \alpha + \beta_1 AfterPush_t + \beta_2 Period_j + \beta_3 AfterPush_t \times Period_j + \gamma_i + \tau_{it} + \varepsilon_{ijt} \quad (3)$$

where $Period_j$ is an indicator whether the period j is the pre-/post- period, and all other parameters remain consistent with prior analyses. The coefficient β_3 captures the treatment effect. Given the use of the last and first week of data for creating the counterfactuals, the sample sizes for this analyses are marginally smaller than those reported earlier, since we lose data for the first and last weeks of the panel. In the interest of space, we only report results for the 5-hour models in Tables 3.6 and 3.7; the full set of results are available upon request from the authors.

For product views, results in Table 3.6 strongly support the findings discussed above, even with a different set of counterfactuals. Interestingly, we observe that the coefficients for the sample with counterfactuals one week before and after the push are similar, indicating that the notification's effect does not last long and dissipates quickly, allowing views of products to return to their organic levels (consistent with the Kaplan-Meier plots). Additionally, the effect sizes noted here are consistent with those reported in Column (2) of Tables 3.2 through 3.4. Both sets of analyses render coefficients of roughly 3.10 for views of targeted products, suggesting stable and robust results with respect to the push notification.

Switching to the effect on sales, Table 3.7 again shows results that are similar to those discussed earlier, with the difference being increased statistical significance. For instance, the effect on targeted product sales is positive and significant within the 5-hour window of temporally shifted counterfactuals, while the results were insignificant in earlier analyses. Additionally, the effect sizes are larger using the temporally shifted counterfactuals. We also estimate the relative time model of sales and unit sales using the temporally shifted counterfactuals and find the same pattern – the results are fully consistent, and in specific cases provide significant coefficients where they were insignificant before.[8] An interesting exception to this arises from the results with respect to total product sales; using the temporally shifted counterfactuals, we see no significant effect of push notifications on total product sales.

Figure 3.5 shows plots of the treatment effects based on both sets of temporally shifted counterfactuals, to further illustrate the results. There is no statistically significant evidence for a pre-treatment trend among the push, pre-1 week, and post-1 week periods. The plot on the left shows that the effect of push notifications on targeted product *views* is higher than the effect on recommended product views. In contrast, the plot on the right shows that the indirect sales effects on recommended products is significantly higher than the sales of targeted products. Thus, these results confirm that push notifications do lead to more views of targeted, recommended, and total products while the dollar sales are higher in particular for recommended products, even within the realm of mobile app users.

[8] The results from these analyses are available upon request.

These results suggest that push notifications provide a more nuanced set of benefits to the retailer than simply garnering the customer's attention.

Exploratory Analysis of Push Notification Heterogeneity

We explore the effects of how features of the push message itself may affect customer responses. While the push notifications were issued randomly by the marketing analytics firm, on behalf of the retailer, and the products to be "pushed" were selected randomly among the more current set of products within the retailer's product line, we prefer to remain conservative in terms of potential bias, and provide these analyses for exploratory purposes here. In order to examine the effect of these heterogeneities, we only use data from the mobile app (i.e. only the treated group) and regress views and sales on push message attributes. Push messages in our sample vary on certain dimensions such as the use of a celebrity, explicit information on promotions or prices within the message, and the use of the product name explicitly. We characterize each message along these dimensions using a set of dummy variables. We also include the log of message length, a dummy variable for the use of special characters, log of product price, and a control for the number of hours since the previous push notification. We include fixed effects for product categories (8 categories) and time (23 week, 6 day and 10 hour of the day dummies).

Table 3.8 shows the results from this exploratory analysis of push heterogeneities on views and sales. The results show that celebrity and popularity information in push messages are positively associated with targeted product views. We also find that longer messages and special character use are negatively related to views of targeted product. Interestingly, celebrity information has no link to the sales of targeted products. With respect to targeted product sales, popularity information and shorter messages are positively associated. In summary, these exploratory analyses show that shorter messages that include information on celebrities, popularity of the product and promotions are more likely to lead to click-through and sales, all else equal. However, further research is needed to establish these relationships; our sample of 135 push messages is too small to generate enough power and identification.

Exploratory Analysis of Heterogeneity of Push Effects on Recommended Products

We finally explore the effects of the push notifications on the recommended products individually, to examine the possibility that the push notification may have varying impacts on the views and sales of recommended products. Recall that in our earlier analysis, we had only considered the effect of the push notification on *aggregate* views and sales of products in the recommendation panel; it is conceivable that the notification has heterogeneous effects on recommended products, based on their attributes relative to the targeted product. Accordingly, we consider the effects of the push notification for each recommended product individually in the analysis. Customers can see 15 recommended products per landing page of the targeted product. Analogous to the previous analysis, we construct a panel of views and sales for these recommended products, using the mobile web as the control group, and re-estimate the analysis for views, sales and sales quantities for the recommended products. We report the analyses for the 5-hour window; the results are consistent for the other time windows and are available from the authors upon request. For the sales and sales quantity, we use Tobit and Zero Inflated Negative Binomial estimation, respectively, due to the disproportional number of observations with zero sales, as expected in online retail[9].

As covariates, we include the log of the recommended product price, the category of the product, as well as the log of the absolute price difference between the targeted product and the recommended product. Since the targeted product sets the reference anchor for the consumer, the attractiveness of recommended products may be influenced by the extent of the price difference between the two products. As before, we include fixed effects for the push notification, recommended item, hour of day, app and cluster standard errors on the push notification, recommended item and group. The results, shown in Appendix 3C, clearly show the effect of the push notification on 5-hour views, sales, and sales quantities respectively of the recommended products. In addition, we see that

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[9] The final sample size is lesser than expected (44550) for two reasons. First, some of the push notifications were not separated enough in time to warrant the full 20-hour difference needed to create a fully balanced panel. Second, some of the recommended products were repeated across consecutive push notifications, creating potential for bias in estimating the effect of the push notification on sales or views. These instances were deleted from the dataset.

higher priced items tend to garner more views, but not necessarily higher sales. However, this effect reduces the farther the price of the recommended product is from the targeted product's price. The higher this difference, the lower is the probability of product views as well as sales. In this study, the recommendation panel for the targeted product did not vary during the duration of our observation window (i.e. 10 hours) and all users saw the same set of products based on item-to-item collaborative filtering algorithm. The results, absent user heterogeneity, do however show that all else equal, the average user tends to view recommended products that are higher priced but does not purchase products that are too far away in price from the targeted product, thus providing some actionable insight to managers selecting products to display within the recommendation panel.

3.6 Discussion and Conclusion

The mobile channel is increasingly becoming central to the process by which firms interact and engage with their customers, yet there is a need to gain a fuller understanding of how these interactions benefit firms and individuals. Indeed, as stated by the Vice-President of mobile at TripAdvisor: "Mobile is an absolutely critical piece of our strategy. Long term, it's the center of everything we're doing".[10] Even within the academic literature, scholars have argued first, that the

[10] http://www.businessinsider.com/the-travel-industry-invests-in-mobile-2014-3

mobile channel is of vital interest to understanding the new forms of interactions that may emerge between agents in the economy (Grewal et al., 2016), and second, that it is too simplistic to simply assume that the mobile channel is merely an extension of the Internet (Ghose et al., 2013). Thus, a full-fledged examination of the benefits, and the associated costs, that the mobile channel offers to firms, individuals, and collectives is necessary. One of the first steps in this direction is to understand how the use of specific mobile channels may affect the demand-side outcomes that are important to firms. The work we present in this paper addresses this question directly, by focusing on an emerging mobile channel – the push notification.

We study the effect of mobile push notifications and recommendation systems on views and sales in the context of mobile retailing, operating on the notion that the medium here is instrumental in drawing the consumer's attention. While the use of push notifications, especially in the online retail sector, is growing rapidly, there is no systematic evidence of the efficacy of push notifications on desired customer actions, in the form of additional views or sales of targeted products. Using a detailed dataset of push notifications and the associated views and sales through the mobile app, we find that push notifications lead to a remarkably high effect on views of targeted products and a reasonably large sales effect. Intriguingly, the indirect effects on recommended and total products that may be attributed to the push notifications appear more compelling in magnitude. Using a series of regression specifications, and variations of a differences-in-differences empirical strategy, we are able to show these effects with a high level of robustness and confidence.

Our work makes two primary contributions to the small yet growing literature studying the mobile channel. First, we provide evidence for the effects that even a simple mobile channel, such as the push notification, can have on attracting consumers to the mobile app, and in moving them further along the conversion funnel. Though the literature has studied other channels on mobile, such as SMS messages, coupons, and trajectory-based promotions, all of these channels involve significantly higher set-up costs, compared to push notifications (Minkara, 2014). Thus, from a value-add perspective, the ability to prod consumers into deploying the downloaded app, view targeted and recommended products, and potentially even double unit sales (based on our results), at very low marginal cost, makes this particular channel attractive. We acknowledge that there is always a risk of over-exposure (Shankar et al., 2016) – excessive use of push notifications are likely to lead to customers either turning the functionality off on their devices or ignoring the notifications, both of which are undesirable behaviors arising from irritation or fatigue. There is clearly an optimal frequency at which push notifications provide the most value. While we do not vary the rate at which notifications are sent in our study, the responses of the consumers in our analysis suggest that we are not at the threshold of what would be excessive, since we see no systematic drop-off in views or sales through the study period. The optimal rate of issuing push notifications depends on the context, the target customer base, and product feature (Grewal et al., 2016), in addition to technological constraints; a fuller examination of this optimal rate remains an important topic for future research.

The second contribution of our work is building on the considerable body of work studying the efficacy of recommendation systems in online commerce (De et al., 2010). Recent work studying the role of recommendation systems in the mobile channel shows that recommendation systems are more useful in mobile than in PC-based environments in terms of sales and views (Lee et al., 2015). However, in the context of mobile apps, firms still face the uphill battle of getting the customer to actually use the app. Our study shows how push notifications can help by bringing consumers to the product landing page, at which point the benefits of recommendation systems can kick in, thereby leading consumers deeper into the conversion funnel. When viewed from the perspective of the retailer, there are clear complementarities between the deployment of push notifications, that draw consumers in, and recommendation systems, that help reduce search cost and promote serendipitous purchase behavior (De et al., 2010; Xiao and Benbasat, 2007). Specifically, push notifications increase the views and sales of recommended products by up to 29.4% and 169% respectively, while leading to a more durable effect over time. Interestingly, the effect of the push notification on sales of recommended products are higher than for targeted products.

There are several unanswered questions that our work raises, all of which represent interesting avenues for future research. First, we informally examine the specific features within the push notification that may lead to higher views, but we are limited by the small sample (135). A deeper examination of the heterogeneity of push messages would be highly informative to retailers as they seek to match targeted products with the appropriate push notifications. Second, while the push notifications we study were sent out as broadcasted messages through the mobile app, it is possible to customize these notifications further by taking the specific customer preferences and purchase history into account – effectively, each app user receives a specific push notification, rather than a generic notification. While the retailer we were working with has not taken this next step, it raises an empirical question as to whether such a customized model would work better than generic push notifications. Finally, we note that push notifications represent one mobile channel, in addition to SMS-based messages, coupons, and trajectory-based promotions – are they all equally effective across product categories and market segments? While current research tends to study these channels in isolation (like the analyses we report here), firms are likely to invest in multiple forms of mobile functionality, raising the issue of how portfolios of mobile channel use may be devised, contingent on product type and market segment. We believe this would be an extremely ambitious but highly useful project for managers looking to add value to their retail practice through the appropriate use of the mobile channel. Given the growing ubiquity and relevance of the mobile channel, there are many such research opportunities in this area, and our work here adds to this growing literature.

CHAPTER 4: MICRO-GIVING: ON THE USE OF MOBILE DEVICES AND MONETARY SUBSIDIES IN CHARITABLE GIVING

4.1 Introduction

The use of the mobile device and the associated adoption of mobile services have opened up several avenues for economic activity within the traditional for-profit sector. Whether in the retail sector as a way to reach and interact with customers (Ghose and Han, 2014) or in specific domains like healthcare, to interact with and care for patients (Boudreaux et al., 2014), the mobile channel is increasingly becoming an important component of the technology mix. Over time, the mobile channel has also started to become relevant in hitherto heavily institutionalized fields like finance, in particular in online financial transaction systems. Mobile use in banking, for instance, is reaching critical mass in terms of network size (Gupta, 2013) and includes retail payment systems such as Apple Pay (Liu et al., 2015) as well in money transfer systems such as M-Pesa and Venmo (Dodgson et al., 2015; Jack and Suri, 2014). At their core, these mobile systems provide a multitude of benefits to consumers, including lower transaction costs, portability, ease of use, and ubiquity (Jack and Suri, 2014). Interestingly, a new trend has emerged within this juxtaposition of the mobile channel and financial payment systems – the ability to use mobile apps as a medium for charitable giving to specific causes in relatively small denominations, an activity that we term *micro-giving*. In this paper, for the first time in the literature, we study how micro-giving through the mobile channel can be influenced by a combination of incentives and notifications, using a series of field experiments.

Charitable giving in small quantities in the pursuit of specific causes is often referred to as cause marketing, in contrast to the systematic fund-raising campaigns carried out by larger organizations such as the Red Cross (Ryzhov et al., 2015). Cause marketing is “characterized by an offer from the firm to contribute a specified amount to a designated cause when customers engage in revenue-providing exchanges that satisfy organizational and individual objectives” (Varadarajan and Menon, 1988). A common example of cause marketing is the point-of-sales campaign, wherein retailers like Walmart and Sam’s Club ask their customers to donate $1, $2 or $5 at the cash register for charities like the Children’s Miracle Network Hospital. In this specific example, the point-of-sales campaign through Walmart and Sam’s Club raised more than $40 million for the Hospital in 2014 (Cause Marketing Forum, 2016). Extending context from offline retailing to the mobile context, firms like Lyft, for instance, allow passengers to round up their fares to the nearest dollar and donate the difference to charity (McFarland, 2017). If the wide adoption and use of mobile apps through the mobile channel can be leveraged for cause marketing through the appropriate messaging and incentive mechanisms, there is a tremendous potential for influencing social outcomes while concurrently enhancing the value of the mobile channel. Mobile-based charitable giving can be viewed as an extension of online charitable giving, which grew by 9.2% in 2015, in comparison to overall charitable giving which increased by 1.6% in the same time period (MacLaughlin et al., 2016). More importantly, about 14% of online charitable giving was conducted using a mobile device (MacLaughlin et al., 2016), clearly implicating the important role that the mobile channel plays in this context.

Through the work reported in this paper, we believe the contribution of such charitable giving through the pathways of cause marketing and the mobile channel can be further enhanced, thereby creating social value as well as economic value for the mobile customer, non-profits, as well as mobile platforms. Within this mobile-based micro-giving model, each individual contributes a relatively small amount of money per donation decision. Thus, even though a single user may contribute a small amount ($1 or $2 per month, for instance), when aggregated over all users of the app over time, this can represent a non-trivial sum of money available for charitable purposes. While this cause marketing is not meant to substitute for the institutional fund-raising campaigns that are directly conducted by charitable organizations such as the Red Cross or for non-profit such as NPR, it can easily be viewed as a supplementary source of revenues for ancillary activities that can be supported on an ongoing basis, since these contributions may appear on a regular basis from app users, thus enhancing sustainability of the model. As these cumulative amounts increase and become stable components of fund-raising activities, thereby creating strategic alliances between charitable organizations and application service providers, they can also represent important components of corporate social responsibility (CSR) initiatives for service providers at relatively low cost and effort.

The main challenge within the mobile cause marketing context remains: how best to incentivize users to engage with the campaign and thereby choose to donate. To answer this question, we collaborated with an application service firm that had introduced a mobile rewards app on the Android platform within the United States. The mobile rewards app, once downloaded and deployed on the mobile device, displays a series of news and advertisements on the device's lock screen. In return, users accumulate in-app reward points that can be used as gift cards or as cash at specific retailers associated with the service provider. Alternatively, the user could also choose to donate the accumulated rewards points, or some proportion of it, to a specific charity. From a cause marketing perspective, therefore, our objective is to highlight the option of charitable giving to these users, and through this increased salience, use incentives to promote higher contributions to the charitable organization, all else being equal. This devolves into two "nudges" that are necessary (Sunstein, 2014): first, the user needs to be nudged into *choosing* to contribute the equivalent monetary amount of app rewards to charity rather than spend the rewards, and second, given the decision to contribute, to *increase* the marginal contribution. There is considerable research within economics on charitable giving that provide insights into how incentives may be structured to enhance the odds of giving as well as increase the amount. We use this literature to construct a set of field experiments, where the specific forms of incentives are randomized across the user base. We then consider the impact of these treatments on the probability of receiving a donation as well as the amount donated by each user.

The treatments we examine in the field experiments pertain to three specific mechanisms drawn from two streams of literature. First, we use the growing literature on the use of mobile devices in the retail sector that addresses how the mobile channel may be used to effectively manage customer relationships (Andrews et al., 2015; Fang et al., 2015; Fong et al., 2015; Ghose et al., 2013; Lee and Gopal, 2016; Luo et al., 2014). Second, we tap into the literature on charitable giving within economics, which is mostly focused in offline settings, to understand how incentives may be devised to influence donor behavior (Anik et al., 2014; Ariely et al., 2009; Davis et al., 2005; Dubé et al., 2017; Eckel and Grossman, 2003, 2008; Karlan and List, 2007; List, 2008). Drawing upon this research, we consider the use of specific treatments that should enhance the salience of the mobile cause marketing campaign as well as increase the donated amounts. The three treatments we consider here are, respectively, mobile push notifications, the use of monetary subsidies (rebate versus matching), and the use of inter-temporal choice (receive subsidies now or later). We use a full factorial experimental design and test for the efficacy of the treatments on the *decision* to donate, the donation *amount*, and the number of *views* of the donation page on the app.

Our experimental results generate three main findings. First, we see that push notifications have a remarkably high effect on donation decision, donation amount, and donation view. Push notifications are emerging as a key technology enabler to communicate with application users, given the relatively low cost in generating them as well as the non-intrusive nature of their functionality (Lee and Gopal, 2016). The results also demonstrate that the marginal impact of push notifications are higher on donation behavior when users are offered monetary subsidies, an intriguing result that suggests that low donation rates may simply be due to inadequate attention and transaction costs rather than a reluctance to donate per se. Second, in contrast to previous findings from the offline charitable giving literature (Davis et al., 2005; Eckel and Grossman, 2003, 2008), we find that the decision to donate, donation amount, and donation views are positively influenced by offering rebates rather than matching subsidies. Offering either form of subsidies is, of course, more effective than the control group where no such subsidy was offered. Finally, contrary to prior work from the retail sector (Dasgupta and Maskin, 2005; Green and Myerson, 2004), we find no significant effect of intertemporal choice associated with monetary subsidies on giving behavior. Consumers appear to be indifferent to whether their subsidies are made available immediately or in the future. However, those users who are offered rebates prefer them to be available immediately, based on significant interaction effects between the form of rebate and inter-temporal choice. Beyond these effects, we also conduct a series of post-hoc tests to explore heterogeneity in the treatment effects, based on factors such as how active the user is, user gender, and tenure on the platform.

Our work contributes to extant research in multiple ways. First, we are the first to study the use of mobile apps in the context of cause marketing, specifically in the domain of micro-giving. While recent papers have considered the role of SMS messaging in the context of pro-social behavior (Dubé et al., 2017), we believe that the true value of the mobile channel is likely to emerge from in-app purchases and earnings that may then be transferred to charitable causes with ease, through the ubiquity and ease of use of the channel. Second, we extend work in charitable giving by explicitly considering incentives within the mobile sector. While many charitable organizations use the mobile channel to reach and inform potential donors (MacLaughlin et al., 2016), little work has considered raising funds through appropriate incentives deployed on the mobile channel. Finally, we add to the growing literature on the value of the mobile channel within the IS literature; current estimates suggest that the mobile ecosystem will likely supplant traditional PC-based channels within the retail sector. A deeper understanding of how the mobile channel may be utilized across the retail sector is thus critical; we study one such unique setting where mobile devices lead to increased pro-social behavior.

4.2 Literature Review

The domain of our work draws from two streams of research, with implications for empirical testing. First, we draw on the literature on cause marketing, with a specific focus on mobile cause marketing. Cause marketing has been studied mostly in the offline setting, and we extend the context to include the mobile context here. Second, we review the literature on charitable giving, specifically the use of incentives to influence donors. Here again, existing work is based on offline giving in relatively larger amounts, while our work is based on micro-giving.

Mobile Cause Marketing

Cause marketing involves the cooperative efforts of a for-profit business and a non-profit organization for mutual benefit (Varadarajan and Menon, 1988). Cause marketing is characterized by a firm involvement in prosocial behaviors through distinct campaigns designed to enhance the sustainability and responsibility of the firm's products or services (Robinson et al., 2012). The point-of-sale campaign is a representative example of cause marketing. A customer asked to round up their purchase or donate a dollar when they check out so a donation solicited by a company at the point-of-sale but made by a customer. In practice, the point-of-sale campaign has become a popular marketing tactic in recent years, $388 million was raised through 77 over million dollar point-of-sales campaigns in 2014 (Cause Marketing Forum, 2016). Not only with traditional offline retailers, charitable organizations may be able to collaborate with mobile application service providers to launch point-of-sales like mobile cause marketing with low transaction cost and high scalability. Although mobile channel has strong potential for a charitable organization, which accounts for 14% of online giving (MacLaughlin et al., 2016), there is scant of research in mobile cause marketing context.

In mobile cause marketing context, Andrews et al. (2014) show SMS (Short Message Service) based cause marketing campaign increases consumer purchase of movie ticket. They also find that the impact of cause marketing on sales of movie ticket through mobile channel is moderated by price discounts in an inverted U shape (Andrews et al., 2014). To extend findings from Andrews et al. (2014), Dubé et al.

(2017) also conduct mobile cause marketing experiment by sending a movie ticket promotion SMS with variations of the price discount level of the movie ticket and the donation level. They find that larger donation amounts reduce ticket demand at the large discount levels, which indicates non-complementarity between donation amounts and price discounts (Dubé et al., 2017). Indeed, even in critical contexts, Sun et al. (2016) show that sending a SMS message to generate voluntary contributions in the event of a shortage of blood leads to more donations, as well as more volunteers willing to donate. Even compared to the standard email channel. Damgaard and Gravert (2017) find that soliciting via SMS has higher response rate.

Our work here differs from previous studies in cause marketing in two ways. First, the objective of this study is how to enhance the saliency of the mobile cause marketing campaign as well as increase the donated amounts, rather than measuring the direct or indirect effect of cause marketing on sales outcomes. Second, rather than using money that is largely fungible in terms of determining the outcome of the cause marketing campaign, we consider the use of rewards that are generated within the app environment itself. Users are given the option of contributing these "earned" rewards to a charity in lieu of cashing out in the form of gift cards. To the extent that the generated surplus is entirely on the app environment and not fully fungible outside this environment, the sustainability of the charitable giving model is potentially enhanced. Given the unique setting, we explore how users may respond to manipulations that help nudge them towards the goal of making a contribution. The first manipulation we consider is a functionality that has been used in prior work in the mobile ecosystem – the use of a *push notification*.

Push notifications represent a form of mobile advertising, enabling firms to reach customers regardless of location and time while allowing customers to browse and purchase at their convenience (Grewal et al., 2016). Push notifications include short messages invoked by mobile applications downloaded on the mobile device that show up on the device's home or lock screen (eMarkter, 2015). The notification helps alert customers who have already installed the app and leads the customer directly to the landing page of the app for desired action (Lee and Gopal, 2016). They thus inform customers in an economical manner through alerts to drive desired behavior such as app revisits, app use, and click-through to the landing page of the targeted product. Since the push acts as an advertisement, it garners greater attention from the customer. Greater attention leads to a deeper processing of the advertisement, and the associated promotion of a product/service (Maclnnis and Jaworski, 1989), a more developed cognitive process of evaluation (Petty and Cacioppo, 1986). Lee and Gopal (2016) show the demand-side efficacy of push notifications in mobile retailing context and find that push notifications increase the views and sales of targeted products because push notification helps grab the potential customers' attention and draw them to the targeted product landing pages. In the charitable giving context, push notification is a relatively low-pressure communication tactic compared to door-to-door fundraising, phone calls, and charity banquets (DellaVigna et al., 2012; Sun et al., 2016). By highlighting the potential to contribute to a recognized charity, the push notification will act as a nudge factor, directing the consumer to the app as a precursor to the actual decision to donate. Hence, we expect that the issuing of a push notification, all else being equal, will lead to an increased likelihood of the participating donation campaign as well as the donation amount.

Incentives in Charitable Giving

Beyond the use of a push notification, we also consider the use of incentives to induce pro-social behavior on the part of the consumer. Specifically, two forms of incentives used in offline settings are considered here – the use of monetary subsidies and the ability to temporally postpone the actual donation decision (inter-temporal choice), described next.

Monetary Subsidies: Matching vs. Rebate

Monetary subsidies have been widely used in the context of charitable giving primarily since they lower the price of giving (Andreoni and Payne, 2013). Previous studies have shown that charitable giving can be increased by monetary subsidies to donors, in one of two forms (Anik et al., 2014; Dubé et al., 2017; Eckel and Grossman, 2003; Karlan and List, 2007; List, 2008). First, donors are informed of the presence of a *matching* grant. Corporations also often match employees' contribution to encourage charitable giving, as do charities in offline giving. In general, providing a matching subsidy (M) reduces the cost of contributing \$1 to charity to $P=1/(1+M)$. By reducing the cost of giving, the matching grant serves the purpose of encouraging the more price sensitive donor to give. Empirically, Karlan and List (2007) show that the presence of a matching grant increases donation participation and donation amount based on mail solicitations of a nonprofit organization in the United States. While matching increases the donation participation, Karlan and List (2007) find that larger match ratios have no additional impact. Indeed, in a subsequent study, Karlan et al. (2011) find that larger example amounts for the match (i.e., $20 match for $100 rather than $2 match for $10) tend to have a negative effect on donation behavior, suggesting that beyond the proportion of matching grants used, the actual amount of funding sought can also influence the efficacy of the subsidy.

A second subsidizing strategy used is to offer consumers a *rebate*, such as those offered by the federal tax policy to itemizing taxpayers who contribute to charitable organizations – these contributions are exempted from taxes. Rebates can even come in the form of gifts, such as t-shirts and mugs for contributing to specific causes. Effectively, rebates offer the donor some form of compensation in order to incentivize the actual giving, thereby reducing the perceived cost of the decision to donate. In the context of mobile-based cause marketing, a rebate can be provided to the consumer in the form of a discount on prices for other services on the application, in return for donating to the charitable organization. Viewed this way, a rebate subsidy (R) offered to the consumer reduces the "price" of a $1 contribution to $P=1-R$.

While rebates and matching grants both represent forms of subsidies, they can be designed to provide the same expected value to the consumer. Thus, economic theory would suggest that a rational donor should be indifferent between rebates and matching if the expected value of the matching is equal (i.e., when $M=R/(1-R)$). However, previous research shows that two subsidy types do not produce equivalent results (Davis et al., 2005; Eckel and Grossman, 2017; Eckel and Grossman, 2003, 2008). Specifically, the total amount of donation obtained is greater with matching subsidies than with equivalent rebate subsidies. These findings are consistent with previous studies on saving contexts that saving matching has a stronger effect on take-up and saving levels than cash-back rebate or credit subsidies (Duflo et al., 2006; Saez, 2009). There are several potential explanations for why donors may respond more expansively to matching compared to rebates. First, Eckel and Grossman (2003) suggest that the framing effect offers an explanation for why rebate subsidies may be less effective than matching subsidies. Framing the price reduction as a rebate induces a perceptual focus on the material cost of donation, and helps create a *rewards* frame. Under the rewards frame, donation behavior is rewarded by the third party and donation is solely based on the individual endeavor. In contrast, donors with a matching subsidy recognize that their giving will result in some level of giving to the same charity by a third party. Thus, framing the price reduction as a matching grant yields a perceptual focus on the benefits that accrue to the eventual beneficiaries of donations, thereby creating a *cooperation* frame. Under the cooperation frame, the act of contributing to the public good is a cooperative endeavor between the donor and the third party. Thus, donors may be more willing to donate if others are also viewed as doing their share (Eckel and Grossman, 2003).

According to Davis (2006), isolation effects (McCaffery and Baron, 2003, 2006) also provide a possible explanation for the higher charity receipts generated with matching relative to rebates. Isolation effects suggest that when given a multi-dimensional problem, people tend to disaggregate dimensions of the problem and focus on only those components that they control most directly or that affect them most directly (McCaffery and Baron, 2003, 2006). Donors may focus on the direct consequences of giving away portions of their givings, rather than on the indirect consequences for themselves or the charity. Viewed through this lens, donors fixate on the actual amount presented to the charity (in isolation of other factors) in making their decisions – the net charity receipts under a matching grant strictly exceed those under an equivalent rebate scheme. Thus, a matching grant elicits higher levels of charitable giving, compared to the equivalent rebate scheme.

Finally, scholars have identified the effects of a feel-good factor when making charitable contributions. It is hypothesized that donors may experience feelings of "greed" when they accept a rebate in the context of giving, thereby reducing the extent to which they feel a "warm glow" (Bénabou and Tirole, 2006). This effect induced by rebates is absent in the presence of a matching grant. To the extent that the mobile device is viewed as a personal and private channel, the response to feelings of greed or shame may be less influential than in offline settings. Moreover, users in the mobile rewards application generate their rewards based on their individual endeavor, which induces a more indvidualistic orientation rather than a collective orientation which appears in offline fund-raising. Regardless of the individual mechanisms discussed here, it is an open empirical question as to whether rebates or matching lead to higher micro-giving in the specific mobile context. Therefore, in lieu of formal hypotheses, we allow the empirical analysis to provide us with guidance on the relative merits of rebates and matching.

Inter-temporal Choice

Inter-temporal choice is an important issue in the context of charitable giving since it drives the extent to which individuals are willing to postpone the benefits from charitable giving. While many individuals are willing to donate to charity, these donations are often made in the form of future grants, or in some cases, in contexts where subsidies kick in at a later time (Breman, 2011). Even in the case of tax rebates, for instance, the benefits are typically temporally delayed, to be availed at during the time of tax processing. Altruistic behavior, by definition, has a temporal aspect to it, in terms of returns that are necessarily in the future (Saez-Marti and Weibull, 2005). The normative model for inter-temporal choice, based on discounted utility theory, suggests that a rational decision maker will discount the costs or benefits from all delayed events (Samuelson, 1937; Strotz, 1955). Thus, individuals are likely to ascribe greater value to rewards as they move away from their temporal horizons and towards the "now" (Dasgupta and Maskin, 2005; Green and Myerson, 2004). However, in contrast, Rogers and Bazerman (2008) find that people are more likely to choose distant future than the near future when they serve the "should-self" (e.g., charitable giving and saving). They examine retaining or donating money based on temporal distance, i.e. action today versus one week later, and find that people are more generous when donating future money versus present money (Rogers and Bazerman, 2008). Breman (2011) also find that increases in donation amount are higher when donors are asked to commit to future donation than to commit immediately, based on field evidence, consistent with the findings from Thaler and Benartzi (2004)'s study in the context of savings. However, more recent work suggests that the temporal distance has no effect; Damgaard and Gravert (2017) examine the effects of the matching deadline on charitable giving and find that donations are equally distributed regardless of the deadlines. Thus, we see significant differences in terms of temporal factors affect behavior in terms of whether the context is altruistic versus self-oriented behavior.

In our specific context, discounted utility theory (Samuelson, 1937; Strotz, 1955) indicates that monetary subsidies offered to consumers as an incentive to donate and that manifest immediately should be preferable to those that manifest in the future. Therefore, when offered the subsidies in the "now", consumers should respond with greater alacrity compared to deferred subsidies. However, charitable giving through cause marketing may be associated with "should-self" behavior, where research suggests that individuals may prefer monetary subsidies that manifest in the future (Breman, 2011; Rogers and Bazerman, 2008). This raises one empirical question – does the direct effect of temporal choice affect the actual decision to give on the mobile platform? Furthermore, note that the rebate subsidy yields a rewards frame, where the donor tends to focus on his or her economic benefit. In contrast, the matching subsidy induces a cooperative frame, which draws the donor to focus on the net proceeds to the charity. It thus follows that the efficacy of temporal discounting may also vary by the specific subsidy used in eliciting charitable giving – the effect of immediate subsidy relative to delayed subsidy is likely to be higher under the rebate subsidy setting compared to matching. Again, rather than propose formal hypotheses, we allow the analysis to provide us with insight into the interactive effects of the type of subsidy and temporal discounting. In the next section, we describe the experimental design and the methodology in greater detail.

4.3 Experimental Design and Data

To study the effect of our treatments on the micro-giving campaign, we conducted a randomized field experiment in April 2016 in the United States in collaboration with a mobile application service provider. The mobile application company operates a mobile rewards application which, when deployed on a mobile device, displays a series of news and advertisements on the lock screen. Users who consume these advertisements are awarded in-app reward points that can be encashed at select retailers and charities that are part of the service provider's ecosystem. We investigate the effects of push notifications, monetary subsidies, and inter-temporal choices, on the extent to which users are induced to donate their mobile rewards to a charitable organization which we selected a nation-wide charitable organization for hunger relief and food rescue. Given the three treatments, we used a full factorial 2x2x2 between-subjects research design, thereby assigning individual users to one of the eight possible cells. At the time of the experiment, the research site had identified 52,324 registered consumers who had downloaded the app as well as had started to accumulate rewards that could be redeemed. These users were randomly assigned to one of nine groups. The first group is a control group. The remaining eight groups were randomly assigned based on a 2x2x2 design (push notification, monetary subsidies, and intertemporal choices) as shown in Table 4.1.

In particular, T5 to T8 groups received push notifications regarding their monetary subsidy and temporal distance manipulation. As discussed above, for monetary subsidies, a rebate subsidy of rate R is functionally equivalent to a matching subsidy of rate $M=R/(1-R)$ (Eckel and Grossman, 2003). Thus, a matching subsidy of 25% is equivalent to a 20% rebate subsidy. For the temporal discounting treatment, we compare instant monetary subsidy with monetary subsidy that kicked in after 10 business days (delayed subsidy). For example, consumers in T6 group received a push notification reading: "*Time to be a hero. An anonymous superhero has offered a grant to encourage your donation so you can receive a 25% match of your donation within 10 business days*". Similarly, groups T2 and T6 received the following message incorporating matching and delayed payout: "*You can get a 25% match of your donation within 10 business days*" while groups T3 and T7 received: "*You can instantly get a 20% cashback of your donation*" (See Appendix 4A for mobile page screen shots by group).

The experiment was conducted for a period of 29 days in April 2016, thereby incorporating one full cycle of rewards as well as redemption. In the cases where a push notification was sent, one push notification was sent in the first day of April 2016.

Before presenting the results from the experiment, we first tested for the integrity of the randomization as well as to test if the treatments were successful. Tables 4.2 and 4.3 shows there is no detectable variation across the various experimental groups in terms of available balance, months of use, and gender. We also check the randomization by using pairwise comparisons of means using Tukey's HSD. We find no significant difference among groups and the well-balanced sample indicates that our randomization is at work. Table 4.3 describes 29,327 active users who made at least one transaction in April among 52,324 total users in Table 4.2. According to Tables 4.2 and 4.3, we find significant differences between inactive users and active users in terms of their individual covariates. Specifically, active users have an average of $6.26 available balance while inactive users have an average of $140.98 because inactive users have not redeemed and cumulate their balance. In order to estimate the effect of the treatments, we focus on the active users in the analysis reported in the next section. All of our results are consistent with the full sample as well, except for the magnitude of the effect sizes, which are smaller given the low responses from the inactive user base.

Table 4.4 summarizes key outcomes across treatment groups in aggregate, without a full set of control variables. We focus on three key outcomes in our experiment, consistent with prior work in charitable giving (Sudhir et al., 2016) – the decision to donate (Yes/No), the donation amount (averaged over the full month) and the number of views of the donation page on the mobile app. On average, the donation rate in our sample during the experiment period is 1.69%. Comparing control group to treatment groups (T1 to T8) shows that there are sizable treatment effects. While the donation rate is 0.69% in the control group, we find that donation rates increased to between 1.24% (T1) and 2.83% (T7) in treatment groups. The most striking increase is treatment group T7 with push notification and instant rebate subsidy, with a relative increase of more than 300% over than control group. Table 4.4 also shows differences between control group and treatment groups in terms of average donation amount and average donation page view. We discuss more details in following section with estimations of treatment effects on various donation outcomes. We also find no significant variation across the groups in terms of average cash out and average view by using pairwise comparisons, which describes that our randomization is at work and treatments have no association with other cash-out behaviors.

4.4 Results

This study analyzes the experimental data using a logistic regression on donation choice (i.e. 0/1 – observed donation outcome), a Tobit regression on donation amounts (in dollars) because donations are left censored at zero, and a negative binomial regression on donation page view since donation page is a nonnegative count variable. While the summary statistics in Table 4.4 provide evidence on the impact of treatments, we formally test such impact using regressions. For comparing treatment groups to the control group to establish a base effect, Table 4.5 shows estimation results with the indicators for treatment groups and control variables for balance, months of use, and gender.

In Table 4.5, Columns (1) and (2) shows that all treatment groups have a significantly higher effect on donation decision than the control group. Treatment group with push notification and instant match (T7) shows the largest impact (β=1.440, $p<0.01$) on donation decision; thus, push notification and instant match increase odds of donation decision by 322% as compared to control group.

Similar to findings on donation decision, Columns (3) to (6) of Table 4.5 provide that all treatment groups have a substantially higher impact on donation amount and donation page view. For example, Column (4) of Table 4.5 show that donation amount is increased to between $2.25 (T1) to $5.88 (T7) in treatment groups as compared to control group. We also find between 253% (T2) to 401% (T8) increase in odds of donation page view as compared to control group in Column (6) of Table 4.5. As a baseline, we find that treatment groups T1 to T8 have a significantly higher probability of donation, donation amount, and donation views than the control group, which indicate that monetary subsidy has positive and significant impacts on donation outcomes.

Conditional on given monetary subsidy, the objective of this study are 1) testing the effectiveness of push notification on donation outcomes, 2) comparing specific types of monetary subsidy (i.e., matching vs. rebate), and 3) examining moderating role of intertemporal choice of subsidy on the impact of monetary subsidy on donation outcomes. Thus, we exclude control group from the analyses as shown in Table 4.6 and the analyses are limited to 23,524 subjects who receive a monetary subsidy from treatment groups T1 to T8. Table 4.6 shows the impact of treatments – push notification, monetary subsidy type, and intertemporal choice of subsidy – on donation decision, donation amount, and donation page view.

Columns (1) and (2) of Table 4.6 describe treatments effect on donation decision and we can find consistent results with or without controls. Specifically, sending a push notification increases odds of donation decision by 66% (β=0.506, $p<0.01$). Interestingly, we find that subjects prefer rebate subsidy to matching subsidy as opposed to previous charitable giving research (Davis et al., 2005; Eckel and Grossman, 2017; Eckel and Grossman, 2003, 2008). Subjects with rebate subsidy have 49.5% higher odds of donation decision as compared to subjects with matching subsidy (β=0.402, $p<0.01$). We find no significant impact of delayed monetary subsidy; however, there is a certain negative trend between rebate subsidy and delayed monetary subsidy (β=-0.342, $p<0.1$), which indicates that subjects tend to prefer immediate subsidy to delayed subsidy under rebate subsidy context. According to Columns (3) and (4) of Table 4.6, we find consistent results on donation amount. Push notification increases donation by \$2.03 and subjects with rebate subsidy donate \$1.69 more than subjects with matching subsidy do.

Columns (5) and (6) of Table 4.6 also show push notification and rebate subsidy has a significant effect on donation page view. While push notification effect is higher than the difference between matching and rebate subsidy on donation decision and donation amount, rebate subsidy has significantly higher impact on donation page view

(β=0.252, $p<0.01$) and size of its impact is larger than push notification impact on donation view (β=0.157, $p<0.01$). We will discuss boundary conditions and potential explanations of treatment effects in the following section.

4.5 Heterogeneous Treatment Effects

While we find evidence for positive effects of push notification and rebate subsidy and negative interaction effect between rebate and delayed subsidy, this study also explores heterogeneous treatment effects regarding to level of user activity (Table 4.7), gender (Table 4.8), tenure (Table 4.9), and available balance (Table 4.10). Heterogeneous treatment effects provide clear boundaries of the treatment effects in this study and yield important insights for both research and practice.

We find that treatment effects vary by level of user activity. We classified sample into active users and idle users. Idle users defined as those that do not open the application in a month prior to the start of the experiment. Columns (1) and (2) of Table 4.7 suggest that push notification has a significant effect on donation decision for idle users (β=0.722, $p<0.01$) but is not significant for active users (β=0.198, ns). The major roles of push notification are alerting users and leading users directly to the desired action so results indicate that saliency of push notification may be higher for idle users than active users. We find a consistent result that push notification increases donation amount for idle users but not for active users (Columns (3) and (4) of Table 4.7).

Besides, rebate subsidy is significant for active users ($\beta=0.677$, $p<0.01$) while rebate subsidy has no difference from matching subsidy for idle users on donation decision and donation view. This result indicates that monetary subsidy tends to be more salient for active users than for idle users for donation page view and donation decision ($\chi^2=4.95$, $p<0.05$; $\chi^2=2.83$, $p<0.1$ respectively). Although we find negative and significant interaction effect between rebate subsidy and delayed subsidy for active users in Columns (2) and (4) of Table 4.7 ($\beta=-0.651$, $p<0.05$; $\beta=-1.984$, $p<0.05$ respectively), differences between coefficients for the interaction effects are not significant regarding to level of user activity. These results suggest clear boundary conditions for the effects of push notification and monetary subsidy type on donation outcomes regarding the level of user activity on the mobile platform.

We examine whether gender moderates the treatment effects on donation outcomes because previous research has found mixed evidence of the gender differences in charitable giving (Andreoni and Vesterlund, 2001; Wiepking and Bekkers, 2012). The result in Table 4.8 suggest that push notification effect is significant for both female and male users and the impact is higher for females than males on donation decision and donation amount ($\chi2=2.95$, $p<0.1$; $\chi2=4.51$, $p<0.05$ respectively). We also find strong evidence that males prefer rebate subsidy to matching subsidy on donation decision and donation amount as compared to females ($\chi2=6.67$, $p<0.01$; $\chi2=5.51$, $p<0.05$ respectively) while rebate subsidy increases donation page view for both male and females users ($\beta=0.209$, $p<0.05$; $\beta=0.349$, $p<0.01$ respectively). Besides, Table 4.8 shows negative interaction effects between the rebate and delayed subsidy on donation decision and donation amount for only male users (β=-0.694, $p<0.01$; β=2.583, $p<0.01$ respectively). We find male users are more susceptible to reward frame than the cooperative frame in line with previous findings that cost mechanism has a stronger effect on male than on female (Andreoni et al., 2003; Andreoni and Vesterlund, 2001). These provide more nuanced evidence of gender differences in donation behavior in the presence of push notification and monetary subsidy.

This study further examines the moderating effects of tenure on mobile reward application on the relationship between treatments and donation behavior. Table 4.9 shows that both push notification and rebate subsidy have significantly higher effect for users with a longer tenure than for users with shorter tenure on donation outcomes. Specifically, push notification has a positive effect on donation decision and donation amount for both longer tenured users and shorter tenured users but the effect sizes are larger for longer-tenured users ($\chi2$=5.19, $p<0.05$; $\chi2$=7.60, $p<0.01$ respectively). Moreover, push notification increases donation view only for longer-tenured users (β=0.327, $p<0.01$; $\chi2$=8.92, $p<0.01$). Users with longer tenure have a longer relationship with the mobile application and they have greater trust (Gefen et al., 2003) so those users tend to more compliant with cause marketing campaign through push notification.

Results have shown in Table 4.9 suggest that users with long tenure prefer rebate subsidy to matching subsidy as compared to users with short tenure on donation decision and donation amount ($\chi2$=3.94, $p<0.05$; $\chi2$=6.20, $p<0.05$ respectively). It is possible that longer-tenured users of the mobile application are more familiar to receive a reward from the application than shorter tenured users. Hence, these results provide the insight that longer tenure users prefer monetary subsidy with reward frame to the same amount of subsidy with corporative subsidy in cause marketing campaign through the mobile rewards application.

Table 4.10 presents heterogeneous treatment effects by available balance in the mobile application. We find a strong evidence push notification effect on donation outcomes for users with a higher balance. Specifically, users with higher balance are more compliant with push notifications in terms of donation decision, donation amount, and donation page view than users with low balance do ($\chi 2=7.53$, $p<0.01$; $\chi 2=14.71$, $p<0.01$; $\chi 2=4.42$, $p<0.01$ respectively). These results are consistent with the relationship between tenure status and push notification as shown in Table 4.9 because users with higher balance tend to have longer tenure. Although we see significant and positive effects of rebate subsidy for users with lower balance, we see no significant difference of rebate subsidy effect on donation outcomes between a user with lower balance and higher balance.

We find that main findings of this study – effects of push notification, subsidy type (rebate vs. matching), and interaction between subsidy type and intertemporal choice (immediate vs. 10 days later) on donation outcomes – are varying by level of user activity, gender, tenure status, and available balance on the mobile application. These heterogeneous treatment effects provide clear boundary conditions and further insights into the efficacy of push notification, monetary subsidy types, and intertemporal choice of subsidy in mobile cause marketing context.

4.6 Discussion and Conclusion

This study conducts a field experiment to examine the effects of push notification, monetary subsidies, and intertemporal choice of monetary subsidy on donation outcomes in mobile cause marketing context. Our experimental results generate three main findings. First, we see that push notifications have a remarkably high effect on donation decision, donation amount, and donation view. Push notifications are emerging as a key technology enabler to communicate with application users, given their relatively low cost in generating them as well as the non-intrusive nature of their functionality (Lee and Gopal, 2016). The results also demonstrate that the marginal impact of push notifications are higher than monetary subsidies on donation decision and donation amount, an intriguing result suggests that low donation rates may simply be due to inadequate attention and transaction costs rather than a reluctance to donate per se. If push notifications succeed in drawing individual attention to the possibility of donating, absent any specific subsidies, technology may indeed have a significant role to play here. Moreover, this study also explores that push notification impacts are more salient for females, idle users, longer tenured, and users with higher available balance.

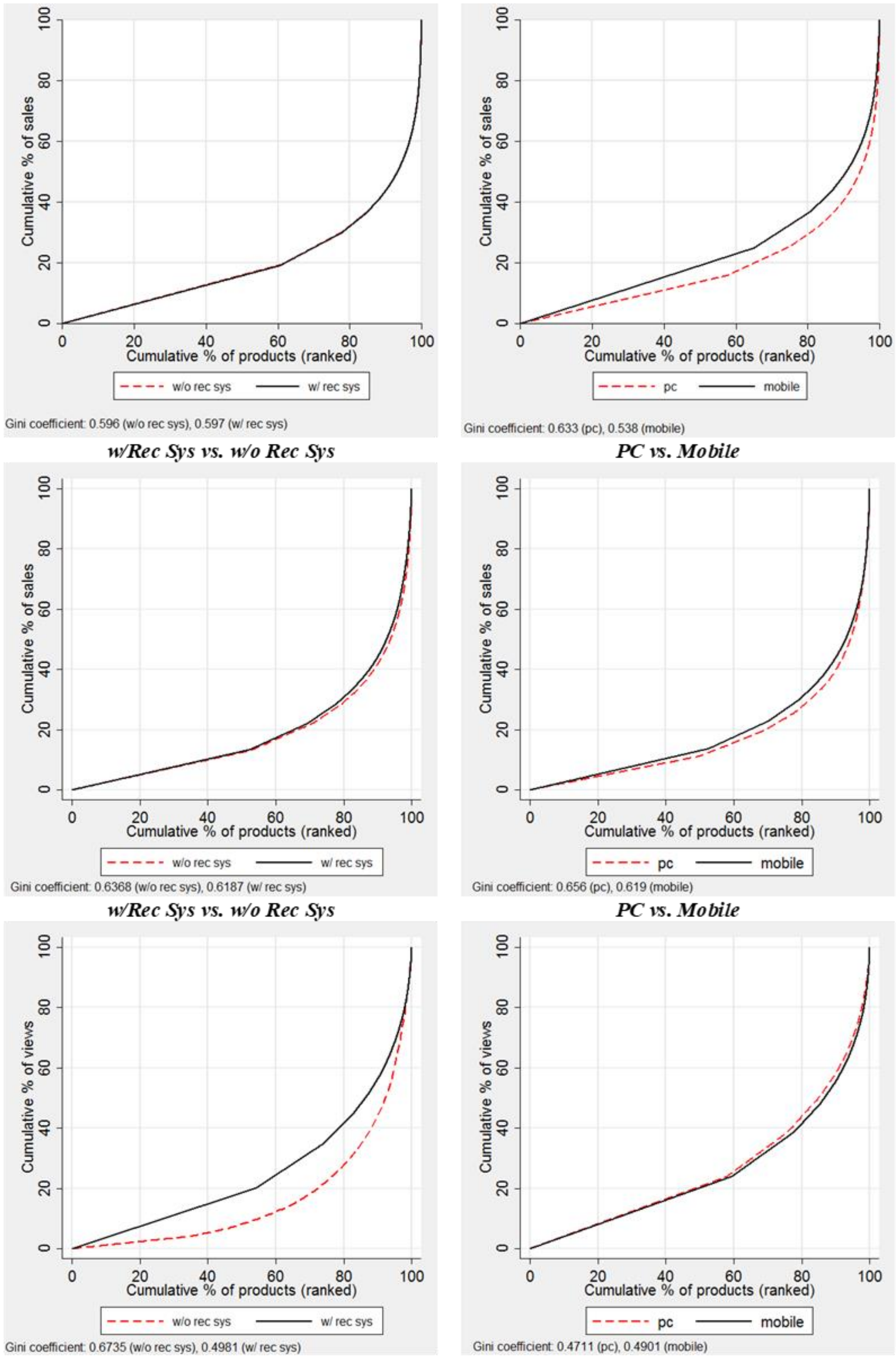
Second, in contrast to previous findings from offline-based charitable giving (Davis et al., 2005; Eckel and Grossman, 2017; Eckel and Grossman, 2003, 2008), we find that the decision to donate, donation amount, and donation views are significantly higher with rebate subsidies than with matching subsidies. Indeed, consumers prefer to be rewarded directly for their charitable giving, while matching grants are less effective on average in mobile cause marketing context. Previous studies show that cooperation frame created by matching subsidy engender more generosity than the rewards frame created by a rebate subsidy in traditional charitable giving context (Eckel and Grossman, 2017; Eckel and Grossman, 2003, 2008). However, the mobile rewards application users get the mobile rewards based on their individual endeavor and users are more individualistic oriented. Moreover, mobile channel has personal and private use environment. Thus, congruence between the contextual orientation of user and subsidy framing may play a role in this study. Both forms of subsidies are, of course, better than the control group where no such subsidy was offered. Furthermore, we also explore that rebate subsidy is much preferable for males, active, and longer tenured users.

Finally, contrary to prior work from the retail sector (Dasgupta and Maskin, 2005; Green and Myerson, 2004), we find no significant effect of intertemporal choice effect on donation outcomes. In general, users appear to be indifferent to whether their subsidies are made available immediately or in the future. However, we find that users prefer immediate subsidy to delayed subsidy under rebate subsidy condition. According to isolation effect (McCaffery and Baron, 2003, 2006), users focus on the individual endeavor and benefit under rewards framing created by rebate subsidy so they isolate individual rewards from charity receipts. Users, therefore, prefer to receive monetary subsidy immediately under rebate condition. This study further explores that male users have a strong preference to receive immediate rebate subsidy.

In conclusion, we study the role of the mobile channel on cause marketing, by drawing on the abilities of the mobile channel to reduce transaction and coordination costs for the individual as well as both profit and non-profit organizations (Jack and Suri, 2014). Given the increasing prominence of the mobile channel and the associated conveniences, our field experiment reveals the role of push notification through a mobile application and monetary subsidies and generates insights associated with an average donor's decision-making process. The findings of this study have important implications for corporate social responsibility (CSR) program design and charitable organizations as well as charitable solicitations through the mobile cause marketing.

FIGURES

Figure 2.1 Lorenz Curve Comparisons – Sales and View Diversities



Sales Diversity – Exp 1: *w/Rec Sys vs. w/o Rec Sys* | *PC vs. Mobile*

Sales Diversity – Exp 2: *w/Rec Sys vs. w/o Rec Sys* | *PC vs. Mobile*

View Diversity – Exp 2: *w/Rec Sys vs. w/o Rec Sys* | *PC vs. Mobile*

Figure 2.2 Gini Coefficient Comparisons – Sales and View Diversities

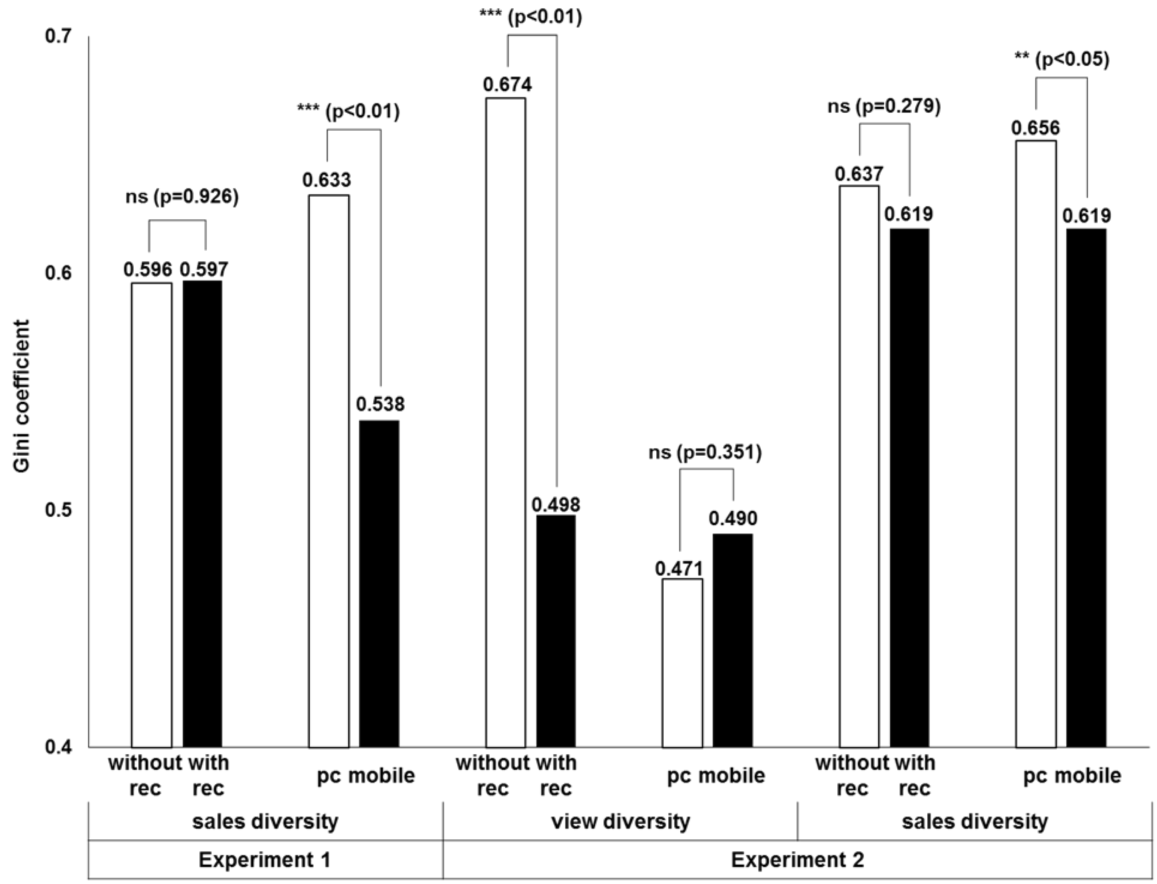


Figure 3.1 Distribution of Push Notification Send Times and Views Through the Day

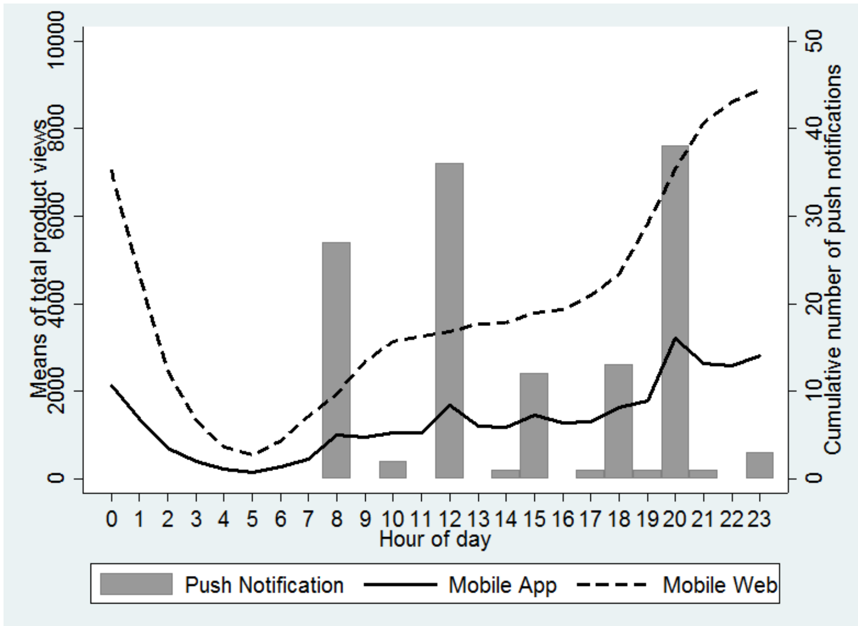


Figure 3.2 Kaplan-Meier Survival Estimates of Push Notification Induced Sales

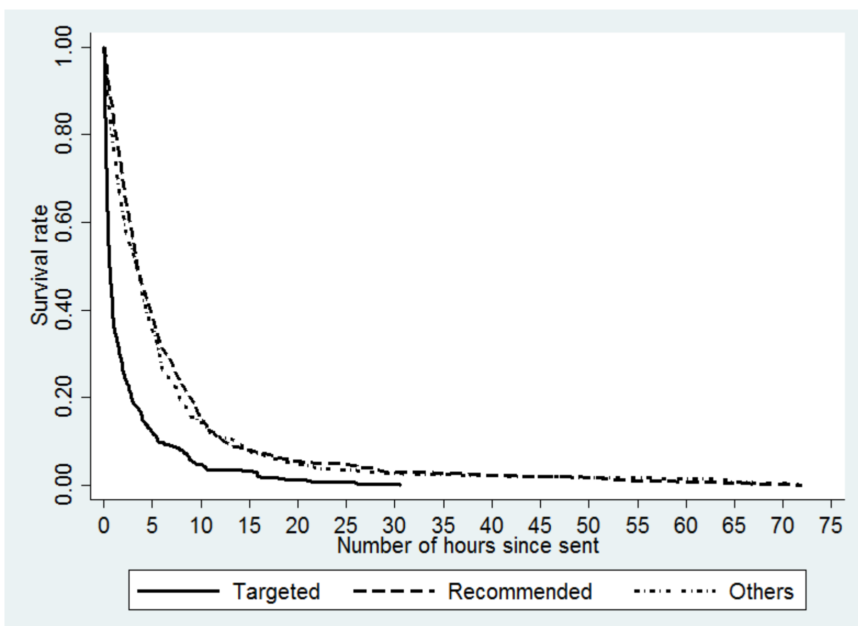


Figure 3.3 Targeted Product Views and Sales

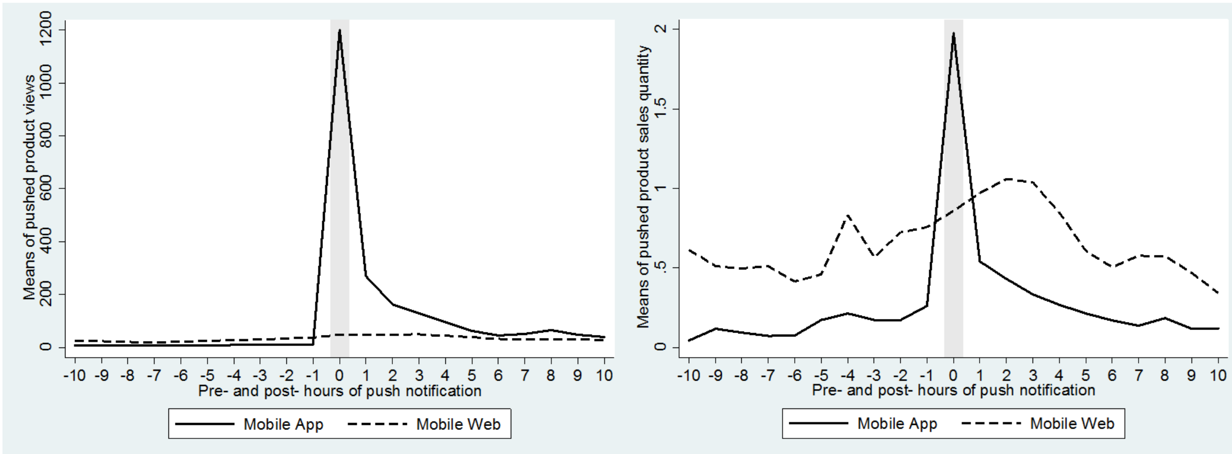


Figure 3.4 Targeted Product, Recommended Products, and Total Products Views and Sales

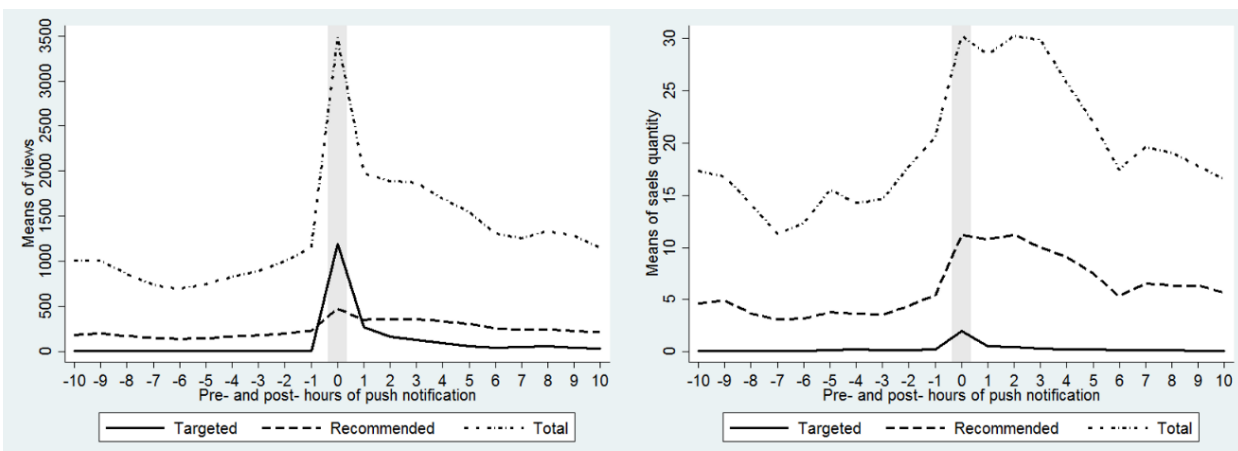
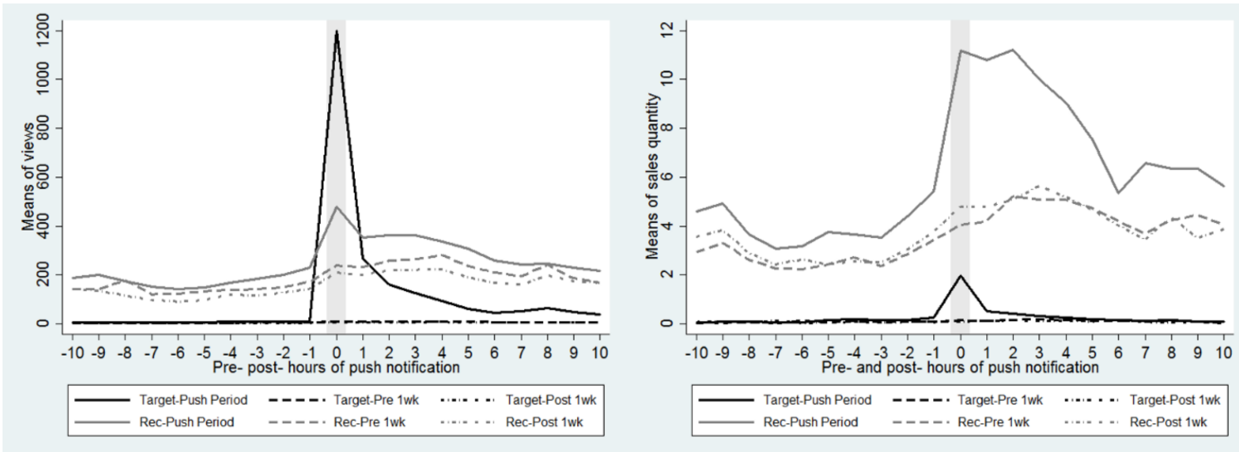


Figure 3.5 Temporally Shifting Counterfactual —

Targeted and Recommended Products



TABLES

Table 2.1 Differences between Mobile and PC Channel

Study	Empirical Context	Theoretical Basis / Mechanism	Key Findings
Chae and Kim (2003)	Analysis of three consecutive online surveys in Korea	Resource availability, ubiquity, user identity, risk, information search cost,	Mobile customers prefer to purchase low-risk products than high-risk products. Mobile users prefer low-intensity contents and customized contents.
Ghose et al. (2013)	Analysis of user posting behavior of the microblogging service website in Korea	Ranking effect, information search cost, cognitive load, geographical proximity	Due to the higher search cost, ranking effects are higher on mobile channel than on PC channel. Mobile users have stroger local interest than PC users..
Bang et al. (2013)	Analysis of online and mobile transaction data of Korean e-commerce company	Ubiquity, usability, access capabilities, search capabilities	Mobile channel complemnts the PC channel. Performance impact of mobile channel depends on time criticality and information intensity of product.
Burtch and Hong (2014)	Analysis of random sample of TripAdvisor	Convenience, fading affect bias, typing and navigating difficulties, temporal distance,	Mobile based online reviews have lower and more varied star ratings, have more concrete and emotional text, and are perceived as more helpful.
Einav et al. (2014)	Analysis of eBay transaction data	Information search cost	Mobile commerce adoption lead to both immediate and sustained increase in total retailing website sales. Mobile purchases are skewed towards commodity products rather than idiosyncratic products that require careful inspection.
Jung et al. (2014)	Analaysis of about 50,000 users of online dating websites	Impulsivity, ubiquity, information search costs	Mobile application adoption lead users login more often across more hours in the day (i.e., ubiquity) and increase social engagement activities on online dating platform.
Maity and Dass (2014)	Analysis of three lab experiments about airline ticket reservation and food menu selection	Media richness theory, cognitive cost model, information search	Consumers prefer mobile channel for a simple decision-making task to for a complex one. Perceived media richness-task fit, satisfaction, and channel choice are the lowest in mobile channel.

Xu et al. (2014)	Analysis of Fox News websites visit regarding to their mobile app release by using comScore MobiLens data	Sampling effect, selective exposure	Mobile news app adoption increases the visiting of mobile website. Complementarity is stronger for consumers who favor concentrated news content.
Wang et al. (2015)	Analysis of customers' transactions of Internet based grocery retailer	Convenience, temporal and spatial flexibility, information search cost, habitual interaction	Mobile channel adoption lead to increase order rate. Mobile channel customers tend to purchase habitual products that they have purchased.
Huang et al. (2016)	Analysis of purchase data of Chinese e-commerce company that expanded its web service onto a mobile platfom	Ubiquity, ease of information, personalization, information search	While mobile channel cannibalizes the web channel, synergy effect between mobile and PC channel override the cannibalization effect.
Xu et al. (2016)	Analysis of purchase data regarding to tablet applications release of Taobao	Usability, ubiquity, channel interdependence	Tablet channel substitutes PC channel while tablet complements mobile channel. Use of tablet leads purchase of more impulse products and a wider diversity of products.

Table 2.2 Effects of Recommendation System on Consumer Decision Making

Study	Empirical Context	Theoretical Basis / Mechanism	Key Findings
Häubl and Trifts (2000)	Analysis of 249 students for shopping back-packing tents and compact stereo system in an online store by conducting lab experiment	Information search cost, quality of decision outcome, consumer information processing	Recommendation system reduces consumer search effort for product information. Recommendation system improves the quality of consideration set and quality of purchase decision.
Senecal and Nantel (2004)	Analysis of 487 subjects for shopping mouse, calculator, and red wine in an online store by conducting online experiment	Information search cost, information source, attribution theory,	Recommendation system is the most influential recommendation source than human experts and other consumers.
Häubl and Murray (2006)	Analysis of 265 consumers for shopping a notebook computer at an online store by conducting lab experiment	Information search cost, quality of decision outcome, consumer information processing	Recommendation system reduces consumer search effort for product information. Recommendation system improves decision quality.
Tam and Ho (2006)	Analysis of 207 subjects for personalized banner lab experiment and 182 subjects for personalized music recommendation field experiment	social cognition, consumer information processing	Recommendation relevance and personalized offering significantly affect consumers' cognition and perceptions in decision making stages.
Kumar and Benbasat (2006)	Analysis of 60 subjects for shopping CD using Amazon.com's recommendation system and customer reviews by conducting lab experiment	Technology acceptance model, social presence, information search cost	Recommendations and consumer reviews increases the usefulness and social presence of the website.
Fleder and Hosanagar (2009)	N/A, Analytical modeling and simulation	Consumer utility maximization, information search cost	Recommendation systems increase sales.
De et al. (2010)	Analysis of medium-sized women's clothing company's Internet channel sales in April 2006	Information search cost	Recommendation systems increase sales of both promoted and non-promoted products by lowering search costs.

Lee and Benbasat (2010)	Analysis of 75 subjects printer shopping in an artificial store using mobile recommendation systems by conducting a lab experiment	Cognitive effort, quality of decision outcome, consumer information processing,	Mobile recommendation system use in a retail store reduces perceived effort and increases accuracy of the decisions.
Pathak et al. (2010)	Analysis of 156 books for 52 days from Amazon.com and B&N.com	Information quality, signaling and advertising, customer loyalty and switching cost	Recommendation systems increase sales. The recency of the product positively moderates the impact of recommendation systems on sales.
Zhang et al. (2011)	Analysis of a two-phase lab experiment with 253 subjects for online DVD shopping	Retailer learning, information search cost, consumer information processing, customer retention	Higher quality recommendation systems amplify customer retention by reducing product screening cost and improving consumer decision-making quality. Higher quality recommendation systems are associated with higher product evaluation cost.
Dellaert and Häubl (2012)	Analyses 438 panels stereo product preference survey, 60 subjects product search lab experiment, and 169 subjects product search online experiment	Consumer utility maximization, consumer product search process model, choice deferral	Recommendation systems lead customers to make broader comparisons among alternative products. Recommendation system causes customers to terminate product search sooner.
Oestreicher-Singer and Sundararajan (2012b)	Analysis of Amazon's recommendation networks for 250,000 books over a period of a year and B&N's co-purchase network.	Network of products, attention, observational learning	The visibility of the recommendation system increases the shared purchasing of complimentary products.
Lee and Hosanagar (2014)	Analysis of Blu-ray discs and DVDs sales from North America retailer website over two weeks by conducting field experiment	Design of recommendation systems	Purchase-based collaborative filtering recommendation system increases sales.
Adamopoulos and Tuzhilin (2015)	Analyses of the restaurants in the mobile urban guide app for the 15 most popular cities from December 2014 to March 2015 by using discrete-choice models	Consumer utility maximization, design of recommendation systems	Recommendation system has a positive impact on demand of restaurants. The effect of in-the-moment recommendations is stable across various levels of popularity.

Table 2.3 Effects of Recommendation Systems on Sales Diversity

Study	Empirical Context	Theoretical Basis / Mechanism	Key Findings
Fleder and Hosanagar (2009)	N/A, analytical modeling and simulation	Consumer utility maximization, information cascade, Internet balkanization	Recommendation systems decrease aggregate sales diversity.
Brynjolfsson et al. (2011)	Analysis of medium-sized women's clothing company's 734 products in Internet and catalog channels between Aug 16 to Sep 12 in 2006.	Information search cost	Recommendation systems increase sales diversity.
Hinz et al. (2011)	Analysis of 843,922 purchases from 143,939 customers from video-on-demand operator over 111 weeks	The long-tail of demand, information search cost	Recommendation systems shift demand from niches to blockbusters while search functionalities lead to a shift in demand from blockbusters to niches.
Oestreicher-Singer and Sundararajan (2012a)	Analysis of Amazon's recommendation networks for comprising over 250,000 books over 28 days in 2007.	The long-tail of demand	Recommendation system is associated with a more even or flatter distribution of both revenue and demand.
Hosanagar et al. (2014)	Analysis of online music services data between January and July 2007.	Fragmentation vs. homogenization, product-mix effect, volume effect	Recommendations systems are associated with an increase in commonality.
Lee and Hosanagar (2014)	Analysis of Blu-ray discs and DVDs sales from North America retailer website over two weeks by conducting field experiment	Design of recommendation systems	Collaborative filtering based recommendation algorithm increases individual consumption diversity while decreases overall aggregate sales diversity.

Table 2.4 Variable Definition and Descriptive Statistics for Experiment 1

Variable	Definition	Treatment Group	Control Group	Total
		n=39,494	n=37,811	n=77,305
Sales	Total dollar amount spent by a customer during Experiment 1 period	180.72 (329.96)	164.19 (234.34)	172.64 (287.31)
SalesQty	Total sales quantify by a customer during Experiment 1 Period	2.00 (2.64)	1.87 (2.20)	1.94 (2.43)
Recommendation	0: without recommendation (control group) 1: with recommendation (treatment group)	1.00 (0.00)	0.00 (0.00)	0.51 (0.50)
Mobile	0: purchase through PC channel only 1: purchase through mobile channel at least once	0.26 (0.44)	0.22 (0.42)	0.24 (0.43)
Female	0: Male, 1: Female	0.71 (0.45)	0.71 (0.46)	0.71 (0.45)
Age	Customer age in 2014	31.55 (7.98)	31.42 (7.86)	31.48 (7.92)
Tenure	Number of months from a customer's first signed up date to May 31, 2014	59.93 (54.34)	58.66 (54.35)	59.31 (54.35)

Table 2.5 Correlations for Experiment 1

	Variable	**(1)**	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**	**(7)**
(1)	ln(Sales)	1.000						
(2)	SalesQty	0.390	1.000					
(3)	Recommendation	0.027	0.028	1.000				
(4)	Mobile	0.066	0.069	0.043	1.000			
(5)	Female	0.047	0.024	0.007	0.116	1.000		
(6)	Age	0.099	0.103	0.008	-0.053	0.046	1.000	
(7)	Tenure	0.121	0.093	0.012	0.044	0.174	0.292	1.000

Table 2.6 Variable Definition and Descriptive Statistics for Experiment 2

Variable	Definition	Treatment Group	Control Group	Total
		n= 9,068	n= 9,128	n= 18,196
RecViews	Total views of recommended/best-selling products by a customer during Experiment 2 period	0.36 (1.25)	0.06 (0.34)	0.20 (0.93)
RecSales	Total dollar amount spent for recommended/best-selling products by a customer during Experiment 2 period	2.30 (22.45)	0.59 (10.14)	1.44 (17.42)
RecSalesQ	Total sales quantities for recommended/best-selling products by a customer during Experiment 2 Period	0.06 (0.65)	0.02 (0.27)	0.04 (0.50)
ClickThrough	RecView / TotalView	0.03 (0.09)	0.01 (0.04)	0.02 (0.07)
Conversion	0: not purchase recommended product 1: purchase recommended product(s)	0.02 (0.14)	0.01 (0.07)	0.01 (0.11)
Recommendation	0: without recommendation (control group) 1: with recommendation (treatment group)	1.00 (0.00)	0.00 (0.00)	0.50 (0.50)
Mobile	0: PC channel 0 < Mobile < 1: Multi-channel 1: Mobile channel	0.77 (0.40)	0.77 (0.40)	0.77 (0.40)
Channel Transition	0: no channel transition from pre-treatment to post-treatment period 1: channel transition from pre-treatment to post-treatment period	0.19 (0.39)	0.19 (0.39)	0.19 (0.39)
TotalViews	Total views of product page by a customer during Experiment 2 period	9.22 (13.41)	8.87 (12.61)	9.05 (13.01)

Table 2.7 Descriptive Statistics and Correlations for Experiment 2

	Variable	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
(1)	RecViews	1.000								
(2)	ln(RecSales)	0.247	1.000							
(3)	RecSalesQ	0.171	0.745	1.000						
(4)	ClickThrough	0.549	0.151	0.092	1.000					
(5)	Conversion	0.250	0.978	0.690	0.158	1.000				
(6)	Recommendation	0.062	0.033	0.031	0.067	0.034	1.000			
(7)	Mobile	-0.029	-0.007	-0.002	-0.048	-0.005	0.003	1.000		
(8)	Channel Transition	0.032	0.011	0.006	0.009	0.010	-0.009	-0.190	1.000	
(9)	TotalViews	0.459	0.168	0.145	0.078	0.165	0.009	0.010	0.074	1.000

Table 2.8 Effects of Recommendation System and Mobile Channel –

Experiment 1

DV	**Sales**			**Sales Quantity**		
	(1)	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**
Recommendation	0.051*** (0.007)		0.046*** (0.007)	0.066*** (0.009)		0.056*** (0.009)
Mobile		0.147*** (0.009)	0.145*** (0.009)		0.198*** (0.011)	0.194*** (0.011)
Female	0.060*** (0.008)	0.045*** (0.008)	0.045*** (0.008)	0.022** (0.010)	0.001 (0.010)	0.001 (0.010)
Age	0.009*** (0.000)	0.009*** (0.000)	0.009*** (0.000)	0.013*** (0.001)	0.014*** (0.001)	0.014*** (0.001)
Tenure	0.002*** (0.000)	0.002*** (0.000)	0.002*** (0.000)	0.002*** (0.000)	0.001*** (0.000)	0.001*** (0.000)
Constant	4.197*** (0.015)	4.183*** (0.015)	4.161*** (0.016)	0.099*** (0.018)	0.075*** (0.018)	0.048*** (0.019)
Observations	77305	77305	77305	77305	77305	77305
R-squared	0.020	0.024	0.024			

Note: Robust standard errors in parentheses. *** $p < 0.01$, ** $p < 0.05$, *$p < 0.1$

Table 2.9 Effects of Recommendation System Across Mobile and PC – Experiment 1

DV	**Sales**			**Sales Quantity**		
	(1) Mobile	**(2) PC**	**(3) Total**	**(4) Mobile**	**(5) PC**	**(6) Total**
Recommendation	0.195*** (0.015)	-0.002 (0.008)	-0.002 (0.008)	0.203*** (0.019)	0.003 (0.010)	0.003 (0.010)
Mobile			0.039*** (0.012)			0.082*** (0.015)
Recommendation x Mobile			0.197*** (0.017)			0.201*** (0.021)
Female	0.041** (0.018)	0.045*** (0.008)	0.045*** (0.008)	0.007 (0.023)	-0.001 (0.011)	0.001 (0.010)
Age	0.011*** (0.001)	0.009*** (0.001)	0.009*** (0.000)	0.015*** (0.001)	0.013*** (0.001)	0.014*** (0.001)
Tenure	0.002*** (0.000)	0.002*** (0.000)	0.002*** (0.000)	0.002*** (0.000)	0.001*** (0.000)	0.001*** (0.000)
Constant	4.174*** (0.036)	4.198*** (0.017)	4.185*** (0.016)	0.093** (0.043)	0.095*** (0.020)	0.075*** (0.019)
Observations	18799	58506	77305	18799	58506	77305
R-squared	0.026	0.020	0.026			

Note: Robust standard errors in parentheses. *** p < 0.01, ** p < 0.05, *p <0.1

Table 2.10 Mobility Index as a Moderator – Experiment 1

DV	Sales				Sales Quantity			
	(1)	(2)	(3)	(4)	(5	(6)	(7)	(8)
Recommendation	0.098*** (0.014)		0.095*** (0.014)	0.078*** (0.016)	0.103*** (0.017)		0.097*** (0.017)	0.068*** (0.018)
Mobility Index (MI)		0.320*** (0.031)	0.315*** (0.031)	0.242*** (0.044)		0.352*** (0.043)	0.345*** (0.043)	0.225*** (0.057)
Recommendation x Mobility Index				0.134** (0.061)				0.213** (0.083)
Female	0.126*** (0.017)	0.114*** (0.017)	0.113*** (0.017)	0.113*** (0.017)	0.017 (0.021)	0.003 (0.021)	0.002 (0.021)	0.003 (0.021)
Age	0.012*** (0.001)	0.012*** (0.001)	0.013*** (0.001)	0.013*** (0.001)	0.018*** (0.001)	0.018*** (0.001)	0.018*** (0.001)	0.018*** (0.001)
Tenure	0.001*** (0.000)	0.001*** (0.000)	0.001*** (0.000)	0.001*** (0.000)	0.000*** (0.000)	0.000*** (0.000)	0.000*** (0.000)	0.000*** (0.000)
Constant	4.393*** (0.036)	4.399*** (0.035)	4.349*** (0.036)	4.358*** (0.036)	0.257*** (0.042)	0.256*** (0.041)	0.204*** (0.042)	0.219*** (0.042)
Observations	21204	21204	21204	21204	21204	21204	21204	21204
R-squared	0.014	0.017	0.019	0.020				

Note: Robust standard errors in parentheses. *** $p < 0.01$, ** $p < 0.05$, *$p < 0.1$

Table 2.11 Recommendation System and Channel Differences on Recommended Products – Experiment 2

DV	Rec Views		Rec Sales		Rec SalesQ	
	(1) PC	**(2) Mobile**	**(3) PC**	**(4) Mobile**	**(5) PC**	**(6) Mobile**
Treatment	-1.289***	-1.671***	0.006	-3.274***	0.746	-0.391
	(0.148)	(0.0835)	(1.904)	(0.807)	(0.651)	(0.385)
Recommendation	0.230**	0.0171	3.202**	-0.532	1.094**	-0.299
	(0.0981)	(0.0528)	(1.561)	(0.657)	(0.534)	(0.239)
Treatment x Recommendation	1.280***	1.613***	3.105	5.473***	0.501	1.202***
	(0.175)	(0.0974)	(2.274)	(1.010)	(0.725)	(0.438)
View	0.079***	0.076***	5.395***	5.611***	0.121***	0.103***
	(0.00438)	(0.00198)	(0.467)	(0.210)	(0.0133)	(0.00700)
Constant	-2.155***	-2.320***	-37.77***	-34.67***	-6.269***	-5.095***
	(0.0863)	(0.0442)	(1.768)	(0.835)	(0.507)	(0.203)
Observations	5,134	23,246	5134	23,246	5,134	23,246
Log-Likelihood	-2920.296	-11295.92	-492.122	-2013.705	-457.916	-1959.563

Note: Robust standard errors in parentheses. *** $p < 0.01$, ** $p < 0.05$, *$p < 0.1$

Table 2.12 Recommendation System and Channel Difference on Click-Through and Conversion – Experiment 2

DV	Click-Through		Conversion	
	(1) PC	**(2) Mobile**	**(3) PC**	**(4) Mobile**
Treatment	-1.289***	-1.592***	-0.104	-0.865***
	(0.169)	(0.107)	(0.480)	(0.214)
Recommendation	0.183	-0.031	0.801**	-0.125
	(0.120)	(0.0629)	(0.387)	(0.166)
Treatment x Recommendation	1.318***	1.511***	0.648	1.390***
	(0.203)	(0.123)	(0.562)	(0.265)
ln(View)			1.163***	1.374***
			(0.112)	(0.0576)
Constant	-3.369***	-3.596***	-7.534***	-7.668***
	(0.0867)	(0.0448)	(0.396)	(0.206)
Observations	5,134	23,246	5,134	23,246
Log-Likelihood	-585.128	-1948.943	-321.431	-1959.563

Note: Robust standard errors in parentheses. *** $p < 0.01$, ** $p < 0.05$, *$p < 0.1$

Table 2.13 Recommendation System and Channel Transition

DV	**Channel Transition**	
	(1)	**(2)**
Recommendation	-0.022	-0.026
	(0.0378)	(0.0379)
ln(View)		0.171***
		(0.0206)
Constant	-1.438***	-1.760***
	(0.0266)	(0.0474)
Observations	18,196	18,196
Log-Likelihood	-8851.147	-8816.965

Note: Robust standard errors in parentheses. *** $p < 0.01$, ** $p < 0.05$, *$p < 0.1$

Table 3.1 Summary Statistics and Correlations—10 Hour Windows (N=4968)

	Variables	**Mean**	**S.D.**	**(1)**	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**	**(7)**	**(8)**	**(9)**	**(10)**	**(11)**
(1)	ln(Target Sales)	2.25	4.19											
(2)	ln(Rec Sales)	9.65	4.53	0.26										
(3)	ln(Total Sales)	12.32	3.08	0.25	0.69									
(4)	Target SalesQ	0.49	1.96	0.50	0.15	0.14								
(5)	Rec SalesQ	14.44	22.47	0.34	0.48	0.40	0.28							
(6)	Total SalesQ	53.17	62.20	0.37	0.52	0.50	0.29	0.89						
(7)	Target Views	2654.82	2483.27	0.33	0.47	0.49	0.24	0.71	0.85					
(8)	Rec Views	487.68	666.70	0.33	0.47	0.40	0.24	0.91	0.83	0.82				
(9)	Total Views	75.70	226.71	0.17	0.10	0.07	0.30	0.06	0.01	0.15	0.08			
(10)	App	0.50	0.50	-0.20	-0.30	-0.37	-0.10	-0.36	-0.53	-0.53	-0.35	0.19		
(11)	After Push	0.52	0.50	0.10	0.15	0.09	0.06	0.15	0.17	0.27	0.19	0.25	0.00	
(12)	Hour of Day	11.75	6.71	0.16	0.27	0.28	0.12	0.26	0.32	0.43	0.31	0.19	0.00	0.23

Table 3.2 Estimations of Push Notification on Targeted Product Views and Sales

DV	**(1) PPML Target views**	**(2) PPML Target views**	**(3) PPML Target views**	**(4) OLS ln(Target sales)**	**(5) OLS ln(Target sales)**	**(6) OLS ln(Target sales)**
Time Window	**2 hours**	**5 hours**	**10 hours**	**2 hours**	**5 hours**	**10 hours**
App*After push	3.612*** (0.136)	3.106*** (0.131)	2.858*** (0.140)	0.968** (0.445)	0.314 (0.299)	0.344 (0.235)
After push	2.155*** (0.160)	2.102*** (0.143)	1.132*** (0.197)	2.410*** (0.767)	0.900*** (0.321)	-0.0220 (0.180)
App	-1.179*** (0.154)	-1.153*** (0.140)	-1.158*** (0.133)	-0.581** (0.267)	-2.971*** (0.274)	-2.200*** (0.170)
Constant	-13.47*** (1.079)	-5.067*** (0.537)	-0.202 (0.490)	-2.765 (3.186)	1.987*** (0.751)	3.411*** (0.326)
Observations	1,348	2,896	4,968	1,348	2,896	4,968
R-squared	0.940	0.820	0.661	0.565	0.475	0.406
Push FE	YES	YES	YES	YES	YES	YES
Hour of Day FE	YES	YES	YES	YES	YES	YES

Robust standard errors in parentheses (clustered on push notification and channel), *** p<0.01, ** p<0.05, * p<0.1

Table 3.3 Estimations of Push Notification on Recommended Product Views and Sales

DV	(1) PPML Rec views	(2) PPML Rec views	(3) PPML Rec views	(4) OLS ln(Rec sales)	(5) OLS ln(Rec sales)	(6) OLS ln(Rec sales)
Time Window	**2 hours**	**5 hours**	**10 hours**	**2 hours**	**5 hours**	**10 hours**
App*After push	0.258*** (0.0302)	0.125*** (0.0300)	0.0665** (0.0304)	1.693*** (0.333)	1.684*** (0.243)	1.149*** (0.206)
After push	0.260*** (0.0477)	0.177*** (0.0236)	0.0362 (0.0232)	-0.118 (0.263)	-0.173 (0.220)	-0.319** (0.137)
App	-1.144*** (0.0249)	-1.112*** (0.0257)	-1.093*** (0.0246)	4.235*** (1.561)	-4.078*** (0.270)	2.638*** (0.156)
Constant	4.811*** (0.269)	5.534*** (0.0966)	6.084*** (0.0772)	10.81*** (1.109)	10.62*** (0.389)	11.12*** (0.179)
Observations	1,338	2,876	4,938	1,338	2,876	4,938
R-squared	0.964	0.963	0.952	0.663	0.617	0.578
Push FE	YES	YES	YES	YES	YES	YES
Hour of Day FE	YES	YES	YES	YES	YES	YES

Robust standard errors in parentheses (clustered on push notification and channel), *** p<0.01, ** p<0.05, * p<0.1

Table 3.4 Estimations of Push Notification on Total Views and Sales

DV	(1) PPML Total views	(2) PPML Total views	(3) PPML Total views	(4) OLS ln(Total sales)	(5) OLS ln(Total sales)	(6) OLS ln(Total sales)
Time Window	**2 hours**	**5 hours**	**10 hours**	**2 hours**	**5 hours**	**10 hours**
App*After push	0.500*** (0.0220)	0.295*** (0.0233)	0.205*** (0.0255)	0.591*** (0.195)	0.760*** (0.158)	0.472*** (0.160)
After push	0.328*** (0.0392)	0.212*** (0.0182)	0.0266 (0.0224)	-0.0784 (0.131)	-0.0802 (0.148)	-0.448*** (0.118)
App	-1.239*** (0.0180)	-1.213*** (0.0197)	-1.209*** (0.0208)	-1.809*** (0.117)	-4.717*** (0.201)	-1.762*** (0.0976)
Constant	6.715*** (0.268)	7.884*** (0.0743)	8.617*** (0.0618)	13.47*** (0.398)	12.77*** (0.299)	13.60*** (0.118)
Observations	1,348	2,896	4,968	1,348	2,896	4,968
R-squared	0.927	0.924	0.905	0.672	0.521	0.464
Push FE	YES	YES	YES	YES	YES	YES
Hour of Day FE	YES	YES	YES	YES	YES	YES

Robust standard errors in parentheses (clustered on push notification and channel), *** p<0.01, ** p<0.05, * p<0.1

Table 3.5 Estimations of Push Notification on Unit Sales

DV	(1) PPML Target SalesQ	(2) PPML Target SalesQ	(3) PPML Target SalesQ	(4) PPML Rec SalesQ	(5) PPML Rec SalesQ	(6) PPML Rec SalesQ	(7) PPML Total SalesQ	(8) PPML Total SalesQ	(9) PPML Total SalesQ
Time Window	**2 hours**	**5 hours**	**10 hours**	**2 hours**	**5 hours**	**10 hours**	**2 hours**	**5 hours**	**10 hours**
App*After push	1.253***	0.873***	0.898***	0.481***	0.379***	0.330***	0.140***	0.0661**	0.0525
	(0.178)	(0.235)	(0.230)	(0.0525)	(0.0427)	(0.0407)	(0.0403)	(0.0332)	(0.0332)
After push	0.480*	0.550***	0.0242	0.175***	0.125***	0.0132	0.140***	0.102***	0.0199
	(0.248)	(0.169)	(0.0909)	(0.0660)	(0.0288)	(0.0272)	(0.0477)	(0.0240)	(0.0208)
App	-1.233***	-1.222***	-1.414***	-1.422***	-1.466***	-1.487***	-1.446***	-1.464***	-1.495***
	(0.187)	(0.162)	(0.146)	(0.0414)	(0.0351)	(0.0318)	(0.0337)	(0.0281)	(0.0256)
Constant	-7.329***	-5.365***	-3.436***	1.219*	1.364***	1.834***	4.019***	4.125***	4.302***
	(1.402)	(0.846)	(0.821)	(0.647)	(0.310)	(0.186)	(0.287)	(0.0810)	(0.0562)
Observations	1,348	2,896	4,968	1,338	2,876	4,938	1,348	2,896	4,968
R-squared	0.649	0.468	0.401	0.923	0.915	0.908	0.924	0.906	0.897
Push FE	YES	YES	YES	YES	YES	YES	YES	YES	YES
Hour of Day FE	YES	YES	YES	YES	YES	YES	YES	YES	YES

Robust standard errors in parentheses (clustered on push notification and channel), *** $p<0.01$, ** $p<0.05$, * $p<0.1$

Table 3.6 Temporally Shifting Counterfactual—Views

	Pre 1week			Post 1week		
DV	**(1) PPML Target views**	**(2) PPML Rec views**	**(3) PPML Total views**	**(4) PPML Target views**	**(5) PPML Rec views**	**(6) PPML Total views**
Time Window	**5 hours**	**5 hours**	**5 hours**	**5 hours**	**5 hours**	**5 hours**
Period*After push	3.105*** (0.152)	0.165*** (0.0563)	0.293*** (0.0341)	3.016*** (0.155)	0.118*** (0.0446)	0.288*** (0.0327)
After push	2.679*** (0.157)	0.260*** (0.0569)	0.373*** (0.0411)	2.861*** (0.155)	0.293*** (0.0477)	0.347*** (0.0432)
Period	0.301 (0.228)	0.239*** (0.0500)	-0.0222 (0.0270)	0.709*** (0.197)	0.335*** (0.0394)	-0.125*** (0.0269)
Constant	-8.431*** (0.540)	3.349*** (0.225)	5.746*** (0.195)	-9.352*** (0.482)	3.402*** (0.111)	6.211*** (0.119)
Observations	2,752	2,734	2,752	2,656	2,638	2,656
R-squared	0.921	0.844	0.781	0.947	0.873	0.748
Push FE	YES	YES	YES	YES	YES	YES
Hour of Day FE	YES	YES	YES	YES	YES	YES

Robust standard errors in parentheses (clustered on push notification and period), *** p<0.01, ** p<0.05, * p<0.1

Table 3.7 Temporally Shifting Counterfactual—Sales

	Pre 1week			Post 1week		
DV	**(1) OLS ln(Target sales)**	**(2) OLS ln(Rec sales)**	**(3) OLS ln(Total sales)**	**(4) OLS ln(Target sales)**	**(5) OLS ln(Rec sales)**	**(6) OLS ln(Total sales)**
Time Window	**5 hours**	**5 hours**	**5 hours**	**5 hours**	**5 hours**	**5 hours**
Period *After push	1.116*** (0.258)	1.404*** (0.269)	0.140 (0.192)	0.903*** (0.277)	1.282*** (0.288)	0.163 (0.187)
After push	0.399 (0.254)	-0.256 (0.285)	0.278 (0.214)	0.336 (0.296)	0.324 (0.298)	0.437** (0.218)
Period	0.903*** (0.188)	0.918*** (0.312)	0.595*** (0.181)	-0.934*** (0.258)	-1.044*** (0.318)	-0.471** (0.217)
Constant	0.0222 (0.606)	9.769*** (0.496)	12.03*** (0.353)	0.882 (0.699)	8.235*** (0.527)	11.17*** (0.395)
Observations	2,752	2,734	2,752	2,656	2,638	2,656
R-squared	0.354	0.589	0.540	0.323	0.619	0.711
Push FE	YES	YES	YES	YES	YES	YES
Hour of Day FE	YES	YES	YES	YES	YES	YES

Robust standard errors in parentheses (clustered on push notification and period), *** p<0.01, ** p<0.05, * p<0.1

Table 3.8 Estimations of Push Message Heterogeneities on Views and Sales

DV	(1) PPML Target views	(2) PPML Target views	(3) PPML Target views	(4) OLS ln(Target sales)	(5) OLS ln(Target sales)	(6) OLS ln(Target sales)
Cumulative Hours	**2 hours**	**5 hours**	**10 hours**	**2 hours**	**5 hours**	**10 hours**
Celebrity Info	0.627*** (0.123)	0.592*** (0.114)	0.618*** (0.102)	0.773 (1.752)	1.272 (2.022)	0.885 (2.082)
Popularity Info	0.174** (0.0842)	0.164** (0.0765)	0.196*** (0.0698)	5.991*** (1.328)	3.796** (1.502)	2.408* (1.440)
Promotion Info	-0.0117 (0.0855)	-0.0180 (0.0805)	-0.0356 (0.0773)	4.901*** (1.262)	3.772*** (1.218)	3.647*** (1.271)
Price in Msg.	0.0609 (0.0825)	0.0883 (0.0786)	0.0877 (0.0746)	0.657 (1.290)	-0.364 (1.437)	-0.223 (1.451)
Product Name in Msg.	-0.0440 (0.0793)	-0.0368 (0.0757)	-0.0411 (0.0720)	0.429 (1.065)	0.349 (1.212)	1.150 (1.157)
ln(Message Length)	-0.504*** (0.145)	-0.485*** (0.133)	-0.480*** (0.130)	-3.471 (2.103)	-5.654** (2.418)	-6.497*** (2.378)
Special Character Use	-0.183** (0.0822)	-0.144* (0.0780)	-0.121 (0.0737)	1.481 (1.223)	2.526* (1.297)	2.065* (1.223)
ln(Targeted Price)	-0.0217 (0.0986)	-0.00680 (0.0921)	-0.0545 (0.0926)	-0.701 (1.365)	-0.790 (1.428)	-1.240 (1.504)
ln(Hours Since Last Push)	0.0786 (0.0488)	0.0736 (0.0463)	0.0377 (0.0449)	-0.215 (0.929)	0.471 (0.931)	0.791 (0.865)
Constant	8.363*** (1.191)	8.411*** (1.069)	9.267*** (1.046)	20.22 (16.91)	30.38* (17.42)	37.20** (17.59)
Observations	135	135	135	135	135	135
R-squared	0.779	0.735	0.680	0.620	0.539	0.491
Category Control	YES	YES	YES	YES	YES	YES
Week Control	YES	YES	YES	YES	YES	YES
Day Control	YES	YES	YES	YES	YES	YES
Hour Control	YES	YES	YES	YES	YES	YES

Robust standard errors in parentheses, *** p<0.01, ** p<0.05, * p<0.1

Table 4.1 Experimental Design

Group	Push	Monetary Subsidy		Temporal Distance	
		Match	Rebate	Instant	Delay
Control					
T1		✓		✓	
T2		✓			✓
T3			✓	✓	
T4			✓		✓
T5	✓	✓		✓	
T6	✓	✓			✓
T7	✓		✓	✓	
T8	✓		✓		✓

Table 4.2 Manipulation Check for Total Users

Group	Obs.	%	Balance ($) as of Mar 31	Life Time Balance ($)	Months of Use	Female (%)
Control	10,338	19.76%	66.02	112.94	8.29	36.41%
T1	5,299	10.13%	64.76	113.92	8.33	37.06%
T2	5,310	10.15%	67.24	116.98	8.39	37.23%
T3	5,109	9.76%	63.91	112.59	8.13	37.01%
T4	5,195	9.93%	63.39	106.57	8.07	37.42%
T5	5,220	9.98%	64.63	114.09	8.39	36.92%
T6	5,264	10.06%	68.53	118.58	8.45	37.10%
T7	5,293	10.12%	65.53	112.27	8.41	38.67%
T8	5,296	10.12%	64.61	110.20	8.34	37.27%
Total	52,324	100.00%	65.47	113.12	8.31	37.16%

Table 4.3 Manipulation Check for Active Users

Group	Obs.	%	Balance ($) as of Mar 31	Life Time Balance ($)	Months of Use	Female (%)
Control	5,803	19.79%	6.28	20.22	7.87	33.14%
T1	2,972	10.13%	6.23	20.25	7.78	33.85%
T2	2,928	9.98%	6.20	20.24	7.92	33.85%
T3	2,834	9.66%	6.20	19.46	7.58	34.26%
T4	2,935	10.01%	6.18	19.43	7.68	33.87%
T5	2,930	9.99%	6.12	20.02	7.87	34.98%
T6	2,903	9.90%	6.35	20.10	7.88	33.69%
T7	3,006	10.25%	6.19	20.04	7.86	34.56%
T8	3,016	10.28%	6.52	20.46	7.96	33.36%
Total	29,327	100.00%	6.26	20.05	7.83	33.87%

Table 4.4 Summary Statistics

Group	Obs.	Donation (Donation Rate)	Avg. Donation ($)	Avg. Donation View	Avg. Cash Out ($)	Avg. View
Control	5,803	40 (0.69%)	0.034	0.04	5.17	2.56
T1	2,972	37 (1.24%)	0.044	0.144	5.19	2.56
T2	2,928	40 (1.37%)	0.069	0.14	5.15	2.85
T3	2,835	53 (1.87%)	0.072	0.181	5.12	2.82
T4	2,936	40 (1.36%)	0.057	0.146	5.12	2.64
T5	2,930	56 (1.91%)	0.078	0.148	5.01	2.61
T6	2,903	67 (2.31%)	0.09	0.175	5.2	2.61
T7	3,007	85 (2.83%)	0.099	0.197	5.08	2.64
T8	3,016	77 (2.55%)	0.089	0.201	5.28	2.73
Total	29,330	495 (1.69%)	0.067	0.142	5.15	2.66

Table 4.5 Cell by Cell Treatment Effects (Baseline: Control)

DV	(1) Donation Decision	(2) Donation Decision	(3) Donation Amount ($)	(4) Donation Amount ($)	(5) Donation View	(6) Donation View
T1	0.597*** (0.229)	0.602*** (0.230)	2.245** (0.947)	2.250** (0.930)	1.277*** (0.124)	1.277*** (0.123)
T2	0.691*** (0.225)	0.696*** (0.225)	2.867*** (1.019)	2.783*** (0.982)	1.249*** (0.120)	1.261*** (0.119)
T3	1.010*** (0.211)	1.007*** (0.212)	4.066*** (0.928)	3.983*** (0.903)	1.506*** (0.118)	1.504*** (0.116)
T4	0.688*** (0.225)	0.696*** (0.225)	2.725*** (0.953)	2.746*** (0.935)	1.290*** (0.123)	1.288*** (0.122)
T5	1.032*** (0.208)	1.039*** (0.209)	4.206*** (0.915)	4.115*** (0.890)	1.305*** (0.123)	1.320*** (0.122)
T6	1.225*** (0.201)	1.232*** (0.202)	5.031*** (0.904)	4.979*** (0.878)	1.470*** (0.128)	1.427*** (0.122)
T7	1.433*** (0.193)	1.440*** (0.194)	5.911*** (0.893)	5.878*** (0.866)	1.592*** (0.115)	1.600*** (0.114)
T8	1.328*** (0.196)	1.324*** (0.197)	5.429*** (0.893)	5.228*** (0.855)	1.610*** (0.115)	1.611*** (0.114)
Balance		0.041*** (0.004)		0.242*** (0.036)		0.032*** (0.004)
Months of Use		-0.026*** (0.008)		-0.126*** (0.036)		-0.014*** (0.005)
Female		0.382*** (0.092)		1.589*** (0.418)		-0.127** (0.056)
Constant	-4.970*** (0.159)	-5.216*** (0.177)	-27.373*** (2.187)	-27.896*** (2.161)	-3.215*** (0.089)	-3.287*** (0.095)
Observations	29,327	29,327	29,327	29,327	29,327	29,327

Robust standard errors in parentheses, *** p<0.01, ** p<0.05, * p<0.1

Table 4.6 Treatment Effects

DV	(1) Donation Decision	(2) Donation Decision	(3) Donation Amount ($)	(4) Donation Amount ($)	(5) Donation View	(6) Donation View
Push	0.507*** (0.098)	0.506*** (0.098)	2.099*** (0.424)	2.034*** (0.411)	0.165*** (0.057)	0.157*** (0.057)
Rebate	0.405*** (0.136)	0.402*** (0.136)	1.699*** (0.600)	1.693*** (0.582)	0.255*** (0.080)	0.252*** (0.080)
Delay	0.154 (0.143)	0.154 (0.144)	0.720 (0.627)	0.702 (0.608)	0.068 (0.086)	0.045 (0.084)
Rebate x Delay	-0.339* (0.191)	-0.342* (0.192)	-1.522* (0.852)	-1.563* (0.828)	-0.160 (0.115)	-0.140 (0.113)
Balance		0.041*** (0.004)		0.238*** (0.039)		0.033*** (0.004)
Months of Use		-0.022*** (0.008)		-0.104*** (0.036)		-0.013*** (0.005)
Female		0.395*** (0.096)		1.627*** (0.432)		-0.122** (0.059)
Constant	-4.417*** (0.122)	-4.690*** (0.144)	-24.463*** (2.137)	-25.146*** (2.125)	-2.005*** (0.067)	-2.073*** (0.080)
Observations	23,524	23,524	23,524	23,524	23,524	23,524

Robust standard errors in parentheses, *** p<0.01, ** p<0.05, * p<0.1

Table 4.7 Heterogeneous Treatment Effect by Level of User Activity

DV	(1) Donation Decision	(2) Donation Decision	χ^2	(3) Donation Amount	(4) Donation Amount	χ^2	(5) Donation View	(6) Donation View	χ^2
	Idle	**Active**		**Idle**	**Active**		**Idle**	**Active**	
Push	0.722*** (0.131)	0.198 (0.150)	6.93***	3.398*** (0.652)	0.569 (0.442)	12.90***	0.193** (0.081)	0.147* (0.079)	0.17
Rebate	0.206 (0.175)	0.677*** (0.218)	2.83*	0.958 (0.880)	2.080*** (0.635)	1.07	0.058 (0.118)	0.417*** (0.110)	4.95**
Delay	-0.013 (0.184)	0.364 (0.233)	1.62	0.065 (0.923)	1.096 (0.670)	0.82	0.027 (0.117)	0.069 (0.119)	0.06
Rebate x Delay	-0.114 (0.249)	-0.651** (0.304)	1.86	-0.757 (1.263)	-1.984** (0.891)	0.63	-0.049 (0.164)	-0.218 (0.157)	0.55
Balance	0.029*** (0.005)	0.059*** (0.013)	4.26**	0.211*** (0.051)	0.240*** (0.049)	0.17	0.027*** (0.006)	0.068*** (0.012)	9.16***
Months of Use	-0.015 (0.011)	-0.010 (0.012)	0.08	-0.099* (0.058)	-0.030 (0.036)	1.00	-0.025*** (0.009)	-0.003 (0.006)	3.90**
Gender	0.213* (0.127)	0.661*** (0.150)	5.18	1.062 (0.659)	1.947*** (0.443)	1.24	-0.111 (0.086)	-0.137* (0.080)	0.05
Constant	-4.385*** (0.184)	-5.206*** (0.233)		-27.419*** (3.071)	-19.997*** (1.136)		-1.882*** (0.108)	-2.411*** (0.125)	
Observations	10,464	13,060		10,464	13,060		10,464	13,060	

Robust standard errors in parentheses, *** p<0.01, ** p<0.05, * p<0.1

Table 4.8 Heterogeneous Treatment Effect by Gender

DV	(1) Donation Decision	(2) Donation Decision	χ^2	(3) Donation Amount	(4) Donation Amount	χ^2	(5) Donation View	(6) Donation View	χ^2
	Male	**Female**		**Male**	**Female**		**Male**	**Female**	
Push	0.360*** (0.129)	0.704*** (0.153)	2.95*	1.293*** (0.498)	3.138*** (0.712)	4.51**	0.112 (0.071)	0.257*** (0.093)	1.54
Rebate	0.701*** (0.183)	-0.021 (0.211)	6.67***	2.710*** (0.737)	-0.090 (0.938)	5.51**	0.209** (0.099)	0.349*** (0.135)	0.70
Delay	0.249 (0.199)	0.051 (0.209)	0.47	0.852 (0.760)	0.528 (0.961)	0.07	-0.040 (0.103)	0.225 (0.145)	2.23
Rebate x Delay	-0.694*** (0.260)	0.140 (0.291)	4.57**	-2.583** (1.017)	0.177 (1.304)	2.79*	-0.089 (0.142)	-0.258 (0.187)	0.52
Balance	0.037*** (0.005)	0.047*** (0.007)	1.44	0.197*** (0.035)	0.302*** (0.079)	1.49	0.038*** (0.005)	0.024*** (0.007)	2.65
Months of Use	-0.023** (0.011)	-0.020 (0.013)	0.03	-0.101** (0.045)	-0.104* (0.056)	0.00	-0.012* (0.006)	-0.018** (0.007)	0.46
Constant	-4.691*** (0.192)	-4.347*** (0.208)		-23.868*** (1.810)	-24.993*** (3.744)		-2.044*** (0.096)	-2.259*** (0.143)	
Observations	15,514	8,010		15,514	8,010		15,514	8,010	

Robust standard errors in parentheses, *** $p<0.01$, ** $p<0.05$, * $p<0.1$

Table 4.9 Heterogeneous Treatment Effect by Tenure

DV	(1) Donation Decision	(2) Donation Decision	χ^2	(3) Donation Amount	(4) Donation Amount	χ^2	(5) Donation View	(6) Donation View	χ^2
	Short-tenure	Long-tenure		Short-tenure	Long-tenure		Short-tenure	Long-tenure	
Push	0.280** (0.137)	0.732*** (0.144)	5.19**	0.983** (0.479)	3.301*** (0.691)	7.60***	-0.012 (0.080)	0.327*** (0.081)	8.92***
Rebate	0.131 (0.192)	0.678*** (0.198)	3.94**	0.377 (0.670)	3.392*** (1.009)	6.20**	0.187 (0.115)	0.325*** (0.112)	0.74
Delay	0.082 (0.195)	0.256 (0.213)	0.36	0.238 (0.684)	1.390 (1.040)	0.86	-0.014 (0.114)	0.096 (0.123)	0.43
Rebate x Delay	-0.171 (0.272)	-0.525* (0.276)	0.84	-0.624 (0.951)	-2.772** (1.395)	1.62	-0.067 (0.160)	-0.211 (0.160)	0.40
Balance	0.049*** (0.010)	0.034*** (0.005)	2.01	0.244*** (0.047)	0.231*** (0.052)	0.04	0.086*** (0.012)	0.020*** (0.005)	26.59***
Gender	0.239* (0.143)	0.485*** (0.135)	1.56	0.795 (0.509)	2.321*** (0.717)	3.01*	-0.166* (0.088)	-0.142* (0.080)	0.04
Constant	-4.553*** (0.178)	-5.184*** (0.198)		-20.774*** (1.123)	-31.040*** (3.891)		-2.314*** (0.115)	-2.204*** (0.110)	
Observations	12,486	11,038		12,486	11,038		12,486	11,038	

Robust standard errors in parentheses, *** $p<0.01$, ** $p<0.05$, * $p<0.1$

Table 4.10 Heterogeneous Treatment Effect by Available Balance

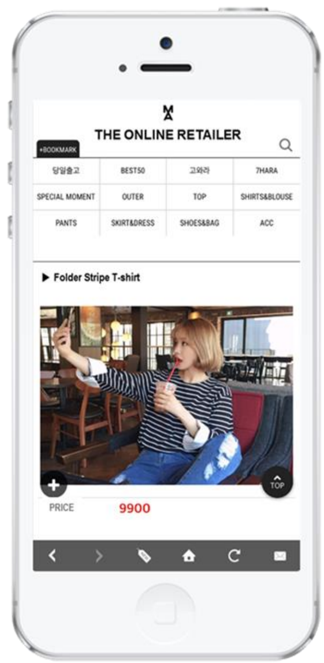
DV	**(1) Donation Decision**	**(2) Donation Decision**	χ^2	**(3) Donation Amount**	**(4) Donation Amount**	χ^2	**(5) Donation View**	**(6) Donation View**	χ^2
	Low Balance	**High Balance**		**Low Balance**	**High Balance**		**Low Balance**	**High Balance**	
Push	0.256* (0.133)	0.801*** (0.148)	7.53***	0.717* (0.378)	4.152*** (0.812)	14.71***	0.081 (0.070)	0.334*** (0.095)	4.42**
Rebate	0.510*** (0.185)	0.247 (0.201)	0.93	1.438*** (0.523)	1.496 (1.139)	0.00	0.246** (0.098)	0.285** (0.135)	0.10
Delay	0.149 (0.200)	0.134 (0.206)	0.00	0.409 (0.563)	0.974 (1.188)	0.18	-0.010 (0.102)	0.198 (0.145)	1.03
Rebate x Delay	-0.515* (0.267)	-0.116 (0.277)	1.07	-1.476* (0.759)	-1.025 (1.588)	0.07	-0.124 (0.140)	-0.228 (0.189)	0.14
Months of Use	-0.022* (0.011)	-0.018 (0.011)	0.06	-0.067** (0.033)	-0.096 (0.062)	0.18	-0.005 (0.006)	-0.016 (0.010)	3.27*
Gender	0.267* (0.137)	0.407*** (0.138)	0.52	0.750* (0.393)	2.304*** (0.846)	2.78*	-0.067 (0.074)	-0.285*** (0.098)	2.47
Constant	-4.553*** (0.192)	-4.046*** (0.223)		-17.167*** (0.725)	-27.812*** (3.576)		-1.998*** (0.094)	-1.639*** (0.145)	
Observations	16,856	6,668		16,856	6,668		16,856	6,668	

Robust standard errors in parentheses, *** p<0.01, ** p<0.05, * p<0.1

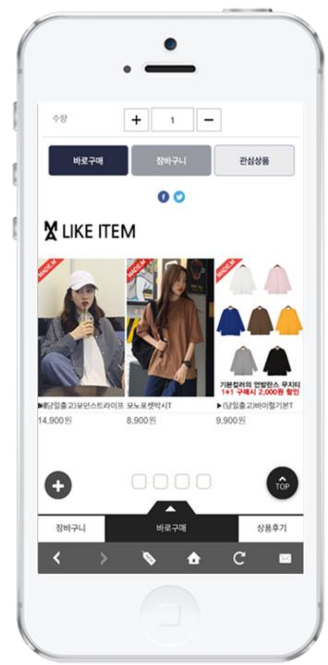
APPENDICES

Appendix 3A Screenshots of the Push Notification Context

Push Notification on Lock Screen



Target Product Landing Page



Recommendation Panel on the Target Product Landing Page

Appendix 3B Relative Time Model

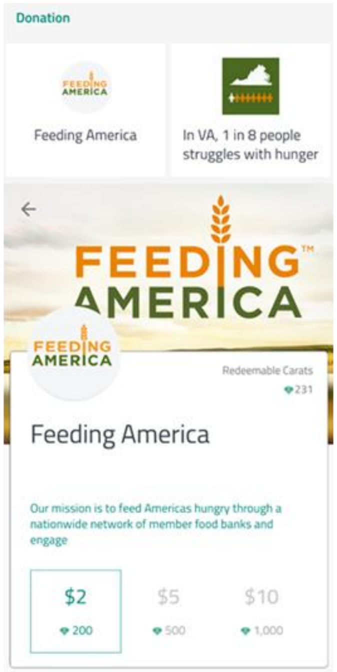
DV	(1) PPML Target views	(2) PPML Rec views	(3) PPML Total views	(4) OLS ln(Target sales)	(5) OLS ln(Rec sales)	(6) OLS ln(Total sales)
After push	0.0924 (0.0645)	0.0285 (0.0222)	0.0149 (0.0206)	-0.0269 (0.179)	-0.316** (0.131)	-0.449*** (0.110)
App	-1.038*** (0.144)	-1.105*** (0.0274)	-1.200*** (0.0233)	-3.644*** (0.280)	1.138*** (0.313)	-0.892*** (0.219)
Rel Time$_{(t-10)}$	-0.323** (0.159)	-0.0601 (0.0404)	-0.0622* (0.0371)	-0.902** (0.384)	-0.791 (0.503)	-0.0431 (0.411)
Rel Time$_{(t-9)}$	-0.120 (0.155)	0.00394 (0.0389)	-0.0414 (0.0322)	-0.268 (0.452)	-0.714 (0.515)	-0.738* (0.414)
Rel Time$_{(t-8)}$	-0.222 (0.155)	0.0207 (0.0424)	-0.0236 (0.0366)	-0.258 (0.372)	-0.861* (0.480)	-1.045** (0.429)
Rel Time$_{(t-7)}$	-0.125 (0.165)	0.0377 (0.0360)	-0.0182 (0.0282)	-0.0324 (0.375)	-0.847* (0.472)	-0.955** (0.399)
Rel Time$_{(t-6)}$	-0.164 (0.150)	0.0170 (0.0392)	-0.0210 (0.0297)	-0.294 (0.338)	0.0168 (0.459)	-0.0910 (0.373)
Rel Time$_{(t-5)}$	-0.0850 (0.0959)	0.0354 (0.0287)	0.0215 (0.0247)	0.259 (0.334)	-0.268 (0.444)	-0.120 (0.359)
Rel Time$_{(t-4)}$	-0.0608 (0.0957)	0.0382 (0.0253)	0.0421* (0.0215)	0.119 (0.356)	-0.536 (0.493)	-0.473 (0.367)
Rel Time$_{(t-3)}$	-0.183** (0.0723)	0.0289 (0.0210)	0.00217 (0.0191)	-0.239 (0.320)	-0.518 (0.429)	-0.399 (0.315)
Rel Time$_{(t-2)}$	-0.0714 (0.0676)	0.000697 (0.0171)	-0.00763 (0.0132)	-0.688* (0.359)	-0.525 (0.423)	-0.238 (0.263)
Rel Time$_{(t-1)}$				*omitted*		
Rel Time$_{(t0)}$	4.341*** (0.158)	0.567*** (0.0386)	0.961*** (0.0314)	2.095*** (0.531)	1.948*** (0.398)	0.748*** (0.248)
Rel Time$_{(t+1)}$	2.824*** (0.155)	0.129*** (0.0387)	0.275*** (0.0271)	0.979** (0.467)	1.089*** (0.401)	0.732*** (0.235)
Rel Time$_{(t+2)}$	2.300*** (0.149)	0.0637** (0.0315)	0.155*** (0.0273)	0.0972 (0.432)	1.413*** (0.442)	1.013*** (0.254)
Rel Time$_{(t+3)}$	2.103*** (0.142)	0.0172 (0.0324)	0.0878*** (0.0281)	-0.0303 (0.469)	1.256*** (0.393)	0.573** (0.239)
Rel Time$_{(t+4)}$	1.807*** (0.150)	-0.0132 (0.0371)	0.0407 (0.0363)	-0.549 (0.422)	0.755* (0.457)	-0.00517 (0.355)
Rel Time$_{(t+5)}$	1.541*** (0.138)	-0.0233 (0.0393)	0.0230 (0.0330)	-0.452 (0.468)	0.760 (0.477)	0.179 (0.290)
Rel Time$_{(t+6)}$	1.406*** (0.136)	-0.0282 (0.0415)	-0.00143 (0.0356)	-0.00947 (0.421)	-0.720 (0.486)	-0.560 (0.390)
Rel Time$_{(t+7)}$	1.505*** (0.149)	-0.0323 (0.0413)	0.000438 (0.0343)	-0.214 (0.431)	0.0594 (0.464)	-0.346 (0.396)
Rel Time$_{(t+8)}$	1.618*** (0.163)	-0.00552 (0.0476)	0.0268 (0.0388)	-0.415 (0.450)	0.00825 (0.557)	-0.856* (0.488)
Rel Time$_{(t+9)}$	1.364*** (0.151)	-0.0492 (0.0461)	-0.0289 (0.0369)	-0.106 (0.433)	0.203 (0.506)	-0.633 (0.447)
Rel Time$_{(t+10)}$	1.178*** (0.164)	-0.0964 (0.0673)	-0.156** (0.0695)	-0.761* (0.386)	-0.503 (0.657)	-1.113** (0.555)
Constant	3.331*** (0.170)	6.119*** (0.0682)	8.676*** (0.0461)	3.708*** (0.357)	11.52*** (0.246)	13.98*** (0.164)
Observations	4,968	4,938	4,968	4,968	4,938	4,968
R-squared	0.849	0.954	0.923	0.415	0.587	0.478
Push FE	YES	YES	YES	YES	YES	YES
Hour of Day FE	YES	YES	YES	YES	YES	YES

Appendix 3C Heterogeneity of Push Effects on Recommended Products

DV	(1) PPML Views	(2) PPML Views	(3) Tobit ln(Sales)	(4) Tobit ln(Sales)	(5) ZINB SalesQ	(6) ZINB SalesQ
Time Window	**5 hours**	**5 hours**	**5 hours**	**5 hours**	**5 hours**	**5 hours**
App*After push	0.288*** (0.0331)	0.288*** (0.0338)	0.777*** (0.204)	0.811*** (0.208)	0.142*** (0.0326)	0.140*** (0.0316)
After push	0.229*** (0.0160)	0.229*** (0.0158)	0.526*** (0.184)	0.529*** (0.186)	0.125*** (0.0243)	0.125*** (0.0238)
App	-1.200*** (0.0151)	-1.200*** (0.0245)	-8.528*** (0.169)	-8.615*** (0.188)	-1.577*** (0.0270)	-1.580*** (0.0312)
ln(Item price)		0.124** (0.0609)				-0.413*** (0.0500)
Same category		0.0566* (0.0322)		0.141 (0.190)		0.00561 (0.0312)
ln(Price difference)		-0.0532*** (0.00899)		-0.112*** (0.0404)		-0.0163** (0.00745)
Constant	3.251*** (0.213)	2.029*** (0.621)	-12.68*** (1.432)	4.969*** (1.080)	-3.273*** (0.262)	4.206*** (0.492)
Observations	43,440	43,440	43,440	43,440	43,440	43,440
R-squared	0.583	0.411				
Log-Likelihood	-347391.6	-525767.6	-72080.5	-73851.4	-41832.1	-44593.8
Product Category	NO	YES	NO	YES	NO	YES
Product FE	YES	NO	YES	NO	YES	NO
Push FE	YES	YES	YES	YES	YES	YES
Hour of Day FE	YES	YES	YES	YES	YES	YES

Robust standard errors in parentheses (clustered on push notification, recommended item, and channel), *** p<0.01, ** p<0.05, * p<0.1

Appendix 4A Donation Page Screen Shots by Group



Control

T1 & T5

T2 & T6

T3 & T7

T4 & T8

Push example for T6 (Push, Match, Delay)

Push

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