Motivating Mobile App Adoption:

Evidence from a Large-scale Randomized Field Experiment

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Abstract

Prior literature has established a positive association between mobile app adoption and customers' purchase behavior. However, it is not clear whether firms can *actively* influence customers' mobile app adoption and increase their purchases. Using a randomized field experiment involving 250,000 customers, we investigate i) whether and how a firm can motivate customers to adopt mobile apps and ii) the causal effect of *induced* mobile app adoptions on customers' purchase behaviors. We find that i) both providing information and monetary incentive can lead to significant increase in customers' mobile app adoption, with the relative increase 447% and 146%, respectively; ii) the effect of mobile app adoption varies greatly depending on how customers are motivated. Although providing monetary incentives may lead to larger increase in mobile app adoption, such induced adoption does not result in more purchases in the long run. In contrast, providing information leads to effective mobile adoption that sustainably increases customers' purchases, and overall profits of the firm. We further examine customers' multichannel browsing and purchase behavior and find additional evidence for how induced app adoptions affect customers' purchase behaviors. In summary, by leveraging a randomized field experiment, our study provides actionable insights for firms designing interventions to motivate effective mobile adoptions.

Introduction

The adoption and usage of mobile channels has not only grown significantly, but has also altered users' experience and behaviors in a multi-screen world (Ghose et al. 2012, Einav et al. 2014, Fang et al. 2015, Luo et al. 2013, Verhoef et al. 2009, De Haan et al. 2015). According to comScore (2015), mobile commerce in the Nov-Dec 2015 holiday season is predicted to account for $11.7 billion of retail spending, representing 17 % of total digital commerce. Recognizing this disruptive effect, firms have been increasingly investing in mobile channels, with a strong emphasis on the development and promotion of mobile apps.

Prior literature has established a positive association between mobile app adoption and business outcomes using observational data. Customers who adopt mobile apps are likely to make more purchases (Xu et al. 2016), be more socially engaged (Jung et al. 2014) and consume more news (Xu et al. 2014). Given the value of mobile app adoption, a natural question for the firms is: can such findings be put into action? In other words, can firms actively influence customers to adopt mobile apps, and whether such induced adoptions can lead to an increase in firms' profits?

In this study, we focus on the above questions and seek to provide actionable insights on designing interventions to motivate app adoptions and improve firm outcomes. Specifically, our study aims to address the following questions:

Q1. Can firms motivate customers to adopt mobile apps, and if so how?

Q2. What is the causal effect of induced mobile app adoptions on customers' purchase behavior?

Q3. How do the different inducements impact customers' purchases and firm profitability?

Q4. What are the underlying drivers of the differences between the different inducements?

Answers to these questions are valuable as they provide direct managerial implications to firms interested in designing strategies to motivate mobile app adoptions.

It is pertinent to note that the prior studies have not addressed these questions. First, previous studies mostly focus on organic mobile app adoptions rather than induced adoptions. As demonstrated in various contexts including technology adoption (Dupas et al. 2014), customer acquisition, and multichannel purchases (Montaguti et al. 2015), induced adopters may fundamentally differ from organic adopters in observed characteristics such as demographics and historical behaviors. In addition, customers who organically adopt the technology may use it in ways different from induced adopters. Specifically, customers who organically adopt mobile apps may do so because of unobserved needs or preferences. Such unobserved needs (e.g. convenience) may drive them to use the app in specific ways that could lead to more purchases. The same insights may not hold for customers who are nudged or incentivized to adopt the app. Consequently, it is not clear whether induced mobile adoptions would always lead to desirable outcomes and be beneficial to the firms. Since the firms can only actively influence the level of induced adoptions (rather than organic adoptions), it is crucial to separately understand the causal effect of induced adoptions on customers' purchase behaviors.

More interestingly and importantly, the effect of induced app adoptions may depend on *how* customers are motivated. In the context of technology adoption, two mechanisms are commonly used by firms to encourage adoption. One is providing information about the benefits of the technology, and the other is providing incentives for adoption. Previous literature on technology adoption has demonstrated that the provision of incentives may act as a double-edge sword: on the one hand, providing incentives may boost learning and facilitate habit formation (Charness and Gneezy 2009, Dupas 2014), thus increasing the effect of technology adoption; on the other

hand, the use of short-run incentives may encourage adverse selection and discourage continuous usage (Ashraf et al. 2010), thus countering the effects of adoption. Such trade-off is especially salient in the case of mobile app adoption. On the one hand, a mobile app is fundamentally an experience good; providing incentives may help customers overcome the fixed cost (of downloading app and setting up payments) and boost learning. On the other hand, continuous use of the app is required to drive purchases and contribute to firm profitability; providing incentives may attract customers who only enjoy short-run benefits and not use the app in the long run. While there is a strong tension in theory and a very consequential debate in practice about whether firms should provide incentives to motivate mobile app adoption (Business Insider 2011, Techcrunch 2015, Miller 2015), no empirical study has investigated this tradeoff. The comparison between the effects of incentive-induced adoptions with that of information-induced adoptions is especially valuable for firms in designing optimal interventions.

To address the above questions, we collaborate with a leading daily deal platform in the US and conduct a large scale randomized field experiment to examine whether and how the firms can actively influence customers' adoption of mobile apps, and whether such induced adoptions can lead to an increase in customers' purchases. We randomly choose 250,000 customers who have already accessed the platform using an iPhone but have never downloaded the platform's mobile app, and randomly assign them into one of three experimental groups: Control group with no information or incentives, Treatment 1 with an email highlight incentives for adoption (5 deal bucks), and Treatment 2 with an email highlighting information about the ease of discovering deals using mobile app. With the experiment, we can answer Q1 and Q3 through direct comparison between experiment groups, and address Q2 (identification of the causal effect of

induced app adoption) using the framework of Local Average Treatment Effect (LATE) (Angrist 1996, 2001) (i.e. use random assignment of test group as an instrument for app adoptions).

Our experiment generates three main findings. First, both providing monetary incentives and information can lead to a significant increase in customers' mobile app adoption, with a relative increase of 447% and 146%, respectively. Second, the causal effect of mobile app adoptions on customers' purchase behaviors varies greatly depending on how customers are induced. Although providing monetary incentives may lead to a larger increase in mobile app adoptions, such induced adoptions do not result in more purchases in the long run. In contrast, providing information leads to more effective mobile adoptions that sustainably increases customers' purchases. Finally, we find providing information can significantly increase overall profits of the firm, while providing incentives does not lead to significant increase in customers' purchase in the long run thus may not justify the initial cost (i.e. 5 deal bucks for each adopter).

We then examine customers' multichannel browsing and purchase behaviors to explore the underlying mechanisms on how induced app adoptions affect customers' purchase behaviors (Q4). The analysis shows that providing information and incentive induces customers to use mobile app differently. Specifically, adopters induced by information mainly use the mobile app as a browsing tool, and increase their purchases through the desktop channel. Such a complementary effect between the (mobile) app and the (desktop) web leads to a significant increase in the total number of purchases, even in the long run. In contrast, adopters induced by incentives complete more purchases using mobile apps after adoption, but at the cost of reducing purchases through alternative channels (for instance, the mobile web channel). The substitution effect is large enough to nullify the increase in purchases through the mobile app and any corresponding increase in profitability.

Further analyses of multichannel browsing behaviors reveals that the difference in the usage of mobile app (in conjunction with other channels) also leads to different shopping behaviors. Compared to the control group, the additional purchases made by those adopters induced by information are more likely to be in the category with stronger information needs and lower transaction uncertainty. As shown by our analyses of clickstream data, customers are more likely to purchase those products using multiple channels (i.e. browsing through mobile app + transaction through desktop website). Such analyses on the moderating effects of product characteristics provide further evidence of the mechanisms at work.

In summary, our study is among the first to investigate how firms can actively influence customers' adoption of mobile app and increase profitability. Our experiment shows that the effect of induced app adoptions may critically depend on *how* customers are motivated. Although providing monetary incentives may lead to a larger increase in mobile app adoption, such induced adoption does not result in more purchases in the long run. In contrast, providing information leads to effective mobile adoption that sustainably increases customers' purchases and overall profits of the firm. Further examination of customers' multichannel browsing and purchase behaviors suggests different inducements affect customers' mobile browsing and purchase behaviors in different ways. The findings of the study not only provide guidelines for designing interventions to motivate effective mobile app adoptions, but also add to our understanding of the role of mobile apps in improving customers' online shopping experience.

Related Literature

There is a growing literature on the role of mobile devices in influencing customers' browsing and purchase behaviors (Xu et al. 2016, Jung et al. 2014, Xu et al. 2014). Our study is closely related to three streams of research that spans information systems and marketing, among others.

The first and probably most relevant stream of literature is on the causal effect of mobile app adoption on customers' engagement and purchase behaviors. Using propensity score matching and other methods on observational data, previous studies have found that customers' adoption of mobile apps can lead to more purchases (Xu et al. 2016), more social engagement (Jung et al. 2014) and higher consumption of news (Xu et al. 2014). However, from the perspective of firms, a natural question is whether firms can *actively* influence customers to adopt mobile apps, and whether such *induced* adoptions can increase firms' profits. Our study contributes to this research stream in two ways. First, we focus on the causal effects of *induced* mobile app adoptions on customers' purchase behavior. Most of the previous studies focus on organic adoptions rather than on induced adoptions. Our study complements these by focusing on induced adoptions. Also, as noted earlier, induced adopters may not only differ from organic adopters in fundamental ways but also use the app differently. Since marketers can only actively influence induced adoptions, it is crucial to understand the causal effects of induced adoptions on outcomes. Thus, our results can provide practical guidelines for firms designing interventions to motivate *effective* mobile adoptions. Second, the usage of a randomized field experiment allows us to cleanly identify the effect of different interventions in driving mobile app adoption (Q1) and customer profitability (Q3). The combination of a randomized experiment with an instrumental variable approach (LATE) allows us to identify the causal effect of induced adoption on customers' purchase behavior (Q2).

The second important stream of research (for instance see, Charness and Gneezy 2009, Dupas 2014, Ashraf et al. 2010) relates to the role of incentives in driving technology adoption and customer acquisition. As highlighted earlier, of central importance is the tradeoff between adoption and usage. Very interestingly, our study shows that the effect of induced app adoptions

on outcomes may crucially depend on how customers are induced/motivated. While there is a strong tension in theory between adoption and usage and a lively debate in practice about whether firms should provide incentives to motivate mobile app adoptions, no empirical study has thus far investigated these tradeoffs. Our study is among the first to identify the causal effect of these interventions and compare their relative effectiveness.

Another closely related stream of literature is the role of mobile apps in influencing customers' online shopping journey across multiple channels. Recent studies have demonstrated strong interdependence between different channels, especially the substitution or complementarity between channels (Brynjolfsson et al. 2009, Forman 2009). The interdependence has been also been confirmed in the context of mobile commerce (Xu et al. 2016). A recent study using clickstream data (De Haan et al. 2015) hypothesized that mobile and alternative channels may be used separately to fulfill different flows (e.g. information vs. transaction) in a customer's online journey. Our study complements this stream of literature with new evidence on substitution/complementarity effects between mobile apps and alternate channels. We also use clickstream data to shed light on the role of mobile app in customers' path to purchase.

Experiment Design

In collaboration with a leading daily deal sharing platform in US, we conduct a large scale randomized field experiment. The platform offers a wide range of daily deals for local services and standard products at a high discount and has a large customer base. Users can use three channels (desktop, mobile web and mobile app) to browse and purchase deals on the platform. The platform offers mobile app on iOS and Android systems. However, at the time of our experiment, only a small portion of the customers had downloaded the mobile app. The platform

observes the customers' browsing behavior and mobile app adoption status, and can target them with information or incentives through email.

Our experiment focuses on customers who have already accessed the platform using iPhone (e.g. email or web browsing) but have never downloaded its mobile app (i.e. the target customer of the mobile app). We randomly select 250,000 eligible customers from the platform's database (who have at least used iPhone once in browsing), and randomly assign them into one of three experimental treatments: (i) Control group with no information or incentives (150K subjects); (ii) Treatment 1 with email including incentive ($5 deal-bucks) for adoption (50K), and (iii) Treatment 2 with email including just information about the ease of discovering deals using the app (50K). The sample size of both treatment groups is smaller than the control group because of relative large cost involved in sending out emails and promotions.

The emails are sent out in a single day at almost the same time. Customers in the treatment groups receive the email only once during the test period, and can click a link to download the app. Customers in T1 will automatically get 5$ deal-bucks after they download and login the mobile app. The deal bucks can be used towards any deal purchase and would expire in two weeks. The experiment is designed to prevent spillovers across different test groups. First, all the promotion/information is provided only through the email channel; thus customers cannot participate through alternative channels. Second, the 5$ incentive is automatically tied to account ID of the customer in T1; thus other customers are not eligible for the promotion.

Empirical Strategy

We seek to understand the causal effect of the two treatments (T1: incentive and T2: information) on three outcomes: a) the adoption decision of recipients; b) the purchase behaviors of recipients who have been induced to adopt the app ('induced adopters'); c) the purchase

behaviors of all recipients. The relationship between the adoption and purchase outcomes is illustrated in Figure 1. The outcome a) - c) ('Adoption', 'LATE', 'ATT'), corresponds to Q1-Q3, respectively. Specifically, we answer Q1 and Q3 through direct comparison between test groups, and address Q2 using the framework of Local Average Treatment Effect (LATE) (Angrist 1996, 2001) (i.e. use random assignment of test group as an instrument for mobile adoptions).

Data

The randomized field experiment was run on the platform for a short period of time and we are able to collect information for the entire sample of 250,000 unique customers over a long period after the experiment. For every customer, we record information including the unique hashed identifier of the customers, the assigned test group, the mobile app adoption status (and adoption time), and all purchases before and after the experiment. For each purchase, we record detailed information including the purchased deal, the revenue/discount from the purchase, as well as the purchase channel. We further augment the above dataset with clickstream data on customers' multichannel browsing behaviors (however, clickstream data only becomes available 14 months after the experiment). The resulting dataset enables us to analyze the effect of different treatments at a granular level (i.e. moderating effects of customer/product characteristics).

Results and Discussion

We first check the validity of our randomization. In Table 1 we provide the breakdown of major covariates in the three groups. As shown in the results, there is no significant difference across groups in all covariates (number of past purchases, purchase behaviors across channels, number of units per purchase). The well-balanced sample indicates that our randomization works well.

Q1: Can firms motivate customers to adopt mobile apps, and if so how?

We examine the effect incentive (T1) or information (T2) in motivating mobile app adoption by running a Linear Probability Model (LPM) on full sample, as shown in equation (1),

$$Download_i = \sum \alpha_k * T_{ik} + \varepsilon_i \qquad (1)$$

$Download_i$ is a dummy variable indicating whether the customer i has downloaded the mobile app within a certain time frame. Since customers can check email and respond anytime after receiving the email, we examine the results using different time frames to understand how the effect changes over time (e.g. 1 day, 3 days, 1 week and 2 weeks after the experiment). T_{ik} is the dummy variable of treatment group k that the customer i is randomly assigned to.

The results are presented in Table 2. Both incentive and information lead to a significant increase in customers' mobile app adoptions, and such effects are consistent across different time frames (*1day, 3day, 1week, 2week*). The magnitude of increase is economically significant: providing incentives can lead to an 447% increase in app downloads over that in control group; while providing information leads to an 146% increase over control group (based on downloads within 3 days). The stronger effect of monetary incentive is aligned with findings in previous literature (Dupas et al. 2014). In addition, consistent with the temporary nature of email communication, the increase in mobile app adoption becomes stable within a week after the intervention.

In summary, our results show that firms can effectively motivate customers to adopt mobile apps using external interventions, with monetary incentive performing three times better than pure information. The key question then is whether such app adoptions induced by external interventions can lead to significant changes in customers' purchase behaviors.

Q2: What is the causal effect of induced app adoptions on customers' purchase behaviors?

We are particularly interested in the causal effect of induced mobile adoptions, rather than organic adoptions, on customers' purchase behaviors, because firms' can active influence the level of induced adoption by providing incentives or information. However, it is challenging to disentangle induced adoptions from organic adoptions from the data since both occur simultaneously. Thus, following previous literature (Angrist et al. 1996, 2001), we adopt the

Local Average Treatment Effect (LATE) framework to identify the causal effect of induced adoptions. As described in the Empirical Strategy section, the causal effect of induced adoptions is identified by LATE wherein the exogenous treatment assignment serves as the instrument variable to isolate the induced adoptions from organic adoptions. As discussed above, the effect of both incentives and information on app downloads become stable after one week. Thus, we use the download within the first week after the experiment as our outcome variable in Stage 1 and our instrument in Stage 2. We choose the time frame to include as many induced adoptions as possible and also to exclude organic adoptions to maintain the power in second stage estimation. We also examine download in alternative time windows such as 1day, 3day and 2 weeks, and the results are robust. Thus here we only report results using 1 week as the window.

Here to examine both short-term and long-term effects of mobile adoptions on customers' purchase behaviors, we examine their purchases in two time windows after the experiment -- within 3 months and within 6 months. Since in Treatment 1 a monetary incentive (i.e. 5$ deal bucks) is provided to motivate mobile app adoption, we expect there would be short-run increase in purchases due to the usage of deal bucks. Since the deal bucks expire after three weeks, the correlation between purchase and usage of deal bucks in Treatment group 1 would be strong during the same time window. However, we are interested in the effect of mobile app adoption beyond this short window. Thus, we exclude all the purchases within the first 3 weeks after the experiment for all the measures on purchases. In this way, we are also able to draw causal inferences using LATE, as the first stage instrumental variable (external intervention) is now uncorrelated with the dependent variable in the second stage (purchase).

We present the results from LATE in Table 3. Very interestingly, we find only app adoptions induced by information (T2) lead to a significant increase in purchases in the long run. In

contrast, app adoptions induced by information (T2) have no causal impact on customers' purchase behaviors. The results suggest that the effect of mobile apps heavily depends on how customers are induced to adopt the app in the first place. Though monetary incentives (T1) are effective in driving people to adopt the app, such recruitment approaches do not lead to more purchases from customers after they download the app. There is no sustainable increase in purchases from such adoptions. In contrast, providing information leads to a smaller increase in app adoptions but such adoptions lead a steady increase in customer purchases. These findings show the nuanced tradeoffs between motivating mobile app adoption and appropriating value from such adoption, and provide guidelines to firms on how to encourage app adoption.

Q3: How do the different inducements impact customer purchases and firm profitability?

We run an OLS model on the full sample to examine the effect of two interventions on customer profitability (i.e. number of customers' purchase after experiment) using equation 2.

$$Purchase_i = \sum \gamma_k * T_{ik} + \epsilon_i \qquad (2)$$

$Purch_i$ is the number of purchases within a time frame for customer i. Similar to Q1 and Q2, we use customers' purchases within 3 months and 6 months after the interventions as the outcome measure to investigate short-term effect and long-term effect of our treatments. As displayed in Table 4, providing information (T2) has a positive and significant effect on purchases across different time frames. In contrast, providing incentives does not lead to any significant increase in customer profitability. Such results are consistent with the results from LATE. Overall, our results suggest that providing information may increase customer profitability while monetary incentives may not, though the latter may lead to more app adoptions. Given the lower cost of providing information compared to monetary incentives, our findings indicate that managers should use information provisioning as the main mechanism to encourage mobile app adoption.

Q4: What are the underlying drivers of the differences between the different inducements?

The differential impact of providing monetary incentives (T1) and information (T2) on customers' purchase behaviors might be driven by two processes: 1) consumers induced by T1 are different from the ones induced by T2; 2) such adoptions induced by different interventions in turn, impact the people to use the mobile apps differently. Both processes may be at work at the same time. For instance, providing monetary incentives (T1) may attract those customers who are more price-sensitive leading to a larger but temporal adoption. On the other hand, app adoptions induced by information (T2) could attract customers who download mobile app for its own value - users more likely to sustain using the mobile app in the long run.

We further investigate the underlying mechanism by decomposing the purchase into different channels. There are three channels that customers can use to browse products and make purchases – desktop (PC), mobile web and mobile app. The mobile web channel provides a smaller and customized view of the desktop website to fit the mobile screen. Mobile app offers the same set of products as the desktop and mobile web but presents them in a way that is more convenient for mobile browsing and search.

Our objective here is to understand the causal effect of induced mobile app adoptions on customers' purchases through these different channels. We follow the same empirical approach discussed in Q2 by changing our dependent variable to customer's purchases within each channel, i.e. *Desktop_Purch* for desktop purchases, *MobileApp_Purch* for mobile app purchases and *MobileWeb_Purch* for mobile web purchases. We use the LATE approach and leverage exogenous treatment assignment as the instrument variable for our identification. The results are presented in Table 5. Recalling our results on overall purchases, induced adoptions by information (T1) lead to a positive and significant effect on customers' purchases while those by

incentive (T2) don't. Interestingly, we can gain additional insights by breaking down the above into different channels. Our results show that adoption induced by monetary incentives (T1) has a significant negative impact on *mobile web purchases* while it has a significantly positive impact on *mobile app purchases*. The two channels substitute each other, resulting in a non-significant net effect. In contrast, adoptions induced by information (T2) have a positive and significant impact on purchases through the *desktop channel*. This indicates that the desktop and mobile app channels are complementary to each other in T2, which is aligned with previous literature (Xu et al. 2016, De Haan et al. 2015).

We further investigate the underlying drivers of such complementarity between the mobile app and the desktop channel. The results are displayed in Table 6. First, we find that the mobile app adopters induced by information are much more likely to use the mobile app for browsing than those induced by incentives (indicated by the number of unique items clicked through the mobile app channel, 6.7 items for T2 vs. 3.5 items for T1, difference significant at 0.10 level). Interestingly, the adopters driven by incentives do not lower their purchase through the mobile app, because of their high likelihood of completing transactions in the app, as discussed above. As expected, the mobile app browsing behavior for adopters in control group (i.e. organic adopters) and those induced by information (T2) are similar because both of them are driven by the inherent need of using the app to access more information. However, those induced adopters in T2 are likely to keep browsing on the desktop, while those organic adopters are moving a good portion of their browsing behaviors to the mobile app channel. Thus, information induced adopters on average browse significantly more than organic adopters (29.5 vs. 16.4 items). Second, consistent with the pattern in multichannel purchase behaviors as shown in Table 5, we find strong evidence of complementarity between mobile app adoption and desktop browsing for

customers who are induced by information: they browse more and are more likely to consummate their purchases through the desktop channel (the difference in purchase between T2 and C is significant at p=0.05). We also find that those adopters induced by monetary incentive are likely to browse and purchase more on desktop, indicating the same complementarity (however, the difference in purchase between T1 and C is not significant at p=0.10).

Finally, we further examine the cross-channel purchase behaviors by decomposing the purchases into different price ranges. As displayed in Table 7, we find that customers who start browsing on mobile app channel are more likely to finish the transaction on desktop, as the price of the purchase increases. We also find similar pattern when decomposing the purchases into different deal categories – customers are more likely to finish the transaction on desktop when the product is less standard and more uncertain (e.g. travel, service). The results suggest that the effect of increased browsing using the mobile app and finalizing purchases through the desktop is likely driven by product characteristics and are more significant for deals on product categories that are more expensive and product categories that have greater uncertainty. We are further exploring the browsing data to understand the mechanisms underlying the effect of mobile app adoption.

Conclusion

In summary, our study is among the first to investigate how firms can actively influence customers' adoption of mobile apps and increase profitability. Our field experiment shows that the effect of induced app adoptions may critically depend on *how* customers are motivated. The findings of the study not only provide guidelines for designing interventions to motivate effective mobile app adoption, but also add to our understanding of the role of mobile apps in improving customers' online shopping experience.

References

Angrist, J. D. 2001. Estimation of limited dependent variable models with dummy endogenous regressors. *Journal of Business & Economic Statistics* Vol. 19, No. 1 (Jan., 2001), pp. 2-16

Angrist, J. D., G. W. Imbens, D. B. Rubin. 1996. Identification of causal effects using instrumental variables. *Journal of the American statistical Association* 91(434) 444–455.

Ashraf, N., Berry, J. and Shapiro, J.M., 2010. Can Higher Prices Stimulate Product Use? Evidence from a Field Experiment in Zambia. *American Economic Review*, 100, pp.2383-2413.

Brynjolfsson, E., Hu, Y. and Rahman, M.S., 2009. Battle of the retail channels: How product selection and geography drive cross-channel competition. *Management Science*, 55(11), pp.1755-1765.

Business Insider 2011 "Are Incentivized Downloads A Good Thing?" Accessed at: http://www.businessinsider.com/are-incentivized-downloads-a-good-thing-2011-6

comScore (2014) comScore Reports December 2014 U.S. Smartphone Subscriber Market Share http://www.comscore.com/Insights/Market-Rankings/comScore-Reports-December-2014-US-Smartphone-Subscriber-Market-Share?

Charness, G., & Gneezy, U. 2009. Incentives to exercise. *Econometrica*, 77(3), 909-931.

De Haan E., Kannan PK., Verhoef P., and Wiesel T., 2015 The Role of Mobile Devices in the Online Customer Journey, *Marketing Science Institute Working Paper Series 2015 Report No.15-124*

Dupas, P. (2014). Short-run subsidies and long-run adoption of new health products: Evidence from a field experiment. *Econometrica*, 82(1), 197-228

Einav, L., Levin, J., Popov, I., & Sundaresan, N. (2014). Growth, adoption, and use of mobile e-commerce. *American economic review*, 104(5), 489-494.

Fang, Z., Gu, B., Luo, X., & Xu, Y. 2015. Contemporaneous and delayed sales impact of location-based mobile promotions. *Information Systems Research*, 26(3), 552-564.

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

Ghose, A., Goldfarb, A., & Han, S. P. (2012). How is the mobile Internet different? Search costs and local activities. *Information Systems Research*, 24(3), 613-631.

Jung J., Umyarov A., Bapna R., and Ramaprasad J., 2014. Mobile as a Channel: Evidence from Online Dating, *The 2014 International Conference on Information Systems (ICIS)*, Auckland, New Zealand

Luo, X., Andrews, M., Fang, Z., & Phang, C. W. (2013). Mobile targeting. Management Science, 60(7), 1738-1756.

Miller 2014 "Manage Your Incentivized Mobile Budget for Maximum Volume" Accessed at: http://secretsaucehq.com/blog/mobile-marketing/manage-your-incentivized-mobile-budget-for-maximum-volume/

Montaguti, E., Neslin, S.A. and Valentini, S., 2015. Can marketing campaigns induce multichannel buying and more profitable customers? A field experiment. *Marketing Science*, 35(2), 201-217..

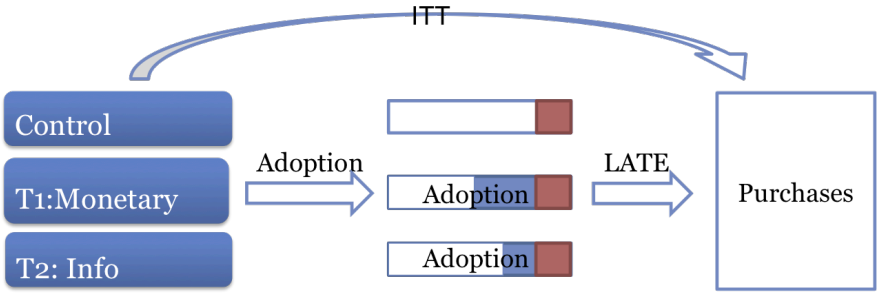
Techcrunch 2015, "What's Better? Incentivized Or Non-Incentivized App-Install Campaigns" Accessed at: http://techcrunch.com/2015/09/10/whats-better-incentivized-or-non-incentivized-app-install-campaigns/

Verhoef, P.C., Lemon, K.N., Parasuraman, A., Roggeveen, A., Tsiros, M. and Schlesinger, L.A., 2009. Customer experience creation: Determinants, dynamics and management strategies. *Journal of Retailing*, 85(1), pp.31-41.

Xu, J., Forman, C., Kim, J.B. and Van Ittersum, K., 2014. News media channels: complements or substitutes? Evidence from mobile phone usage. *Journal of Marketing*, 78(4), pp.97-112.

Xu, K., Chan, J., Ghose, A. and Han, S., 2016. Battle of the Channels: The Impact of Tablets on Digital Commerce. *Management Science*, 2016, Article in Advance

Figure 1: Relationship between Adoption, Causal Effect of Induced Adoption, and ITT (corresponding To the relationships in Q1, Q2 and Q3)



* App adoption consists of organic adoptions (red part) and induced adoptions (blue part). The blue part represents the 'induced adoptions' that would not happen without firm's active intervention. We use 'local average treatment effect' (LATE) approach to identify the causal effect of such 'induced adoptions' (blue part) on customers' purchase behaviors (Q2).

Table 1: Randomization Check & Summary Stats

Pre-Treatment Randomization Check					
Variables	**Stats**	**Control**	**T1**	**T2**	**All Samples**
		(n=139,299)	(n=48,79)	(n=48,840)	(n= 236,936)
Total Number of Purchases	mean	0.000	0.006	0.047	0.011
	sd	3.965	4.103	4.101	4.022
Total Number of Desktop Purchases	mean	0.000	0.014	0.045	0.012
	sd	3.663	3.814	3.811	3.725
Total Number of Mobile Web Purchases	mean	0.000	0.003	0.002	0.001
	sd	0.882	0.854	0.882	0.877
Units of purchases	mean	0.000	-0.002	0.003	0.001
	sd	0.557	0.517	0.691	0.580
Revenue	mean	0.000	0.135	1.508	0.338
	sd	242.161	244.265	244.920	243.166

Post-treatment Summary Statistics				
	Control	**T1**	**T2**	**Total**
Download within 1week	480 (0.34%)	667(1.37%)	350(0.72%)	1,497(0.63%)
Download within 1month	2,006 (1.44%)	1,235(2.53%)	881(1.80%)	4,122(1.74%)
Purchase within 1week	4644(3.33%)	1727(3.54%)	1,683(3.45%)	8,054(3.40%)
Purchase within 2 week	9,565(6.87%)	3,464(7.10%)	3,459(7.08%)	16,488(6.96%)
Purchase within 1month	17,782(12.77%)	6,349(13.01%)	6,338(12.98%)	30,469(12.86%)
Purchase within 3months	39,636 (28.45%)	13,992 (28.67%)	14,115 (28.90%)	67,743(28.59%)

***** The figures provided are demeaned values obtained by subtracting the mean value of treatment groups from that of control group. Demeaning preserves the difference in mean value between test groups as well as the t-test (i.e. randomization check). ****** In the summary stats, we show both the *absolute count* as well as the conversion rate (*percentage* of people who have *downloaded* (within 1week and 1month) or have *purchased* (within 1week, 2week, 1month and 3months)) within each group respectively. The summary statistics of purchases and download using other time windows are qualitatively similar.

Table 2: Effect of Treatments on Mobile App Adoptions (Q 1)

	(1)	(2)	(3)	(4)
VARIABLES	download_1day	download_3day	download_1week	download_2week
Monetary (T1)	**0.00545*** **	**0.00953*** **	**0.0102*** **	**0.0104*** **
	(0.000223)	(0.000361)	(0.000416)	(0.000521)
Information (T2)	**0.00137*** **	**0.00311*** **	**0.00372*** **	**0.00365*** **
	(0.000223)	(0.000360)	(0.000416)	(0.000521)
Constant	0.000395***	0.00213***	0.00345***	0.00702***
	(0.000113)	(0.000184)	(0.000212)	(0.000265)
Observations	236,936	236,936	236,936	236,936
R-squared	0.003	0.003	0.003	0.002

Standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.1

Table 3: Causal Effect of Induced App Adoptions on Purchase Behavior (Q2)

	(1)	(2)
T1	purch_3month	purch_6month
Induced Adoption by T1	-0.193	-0.321
	(0.460)	(0.824)
Constant	0.383***	0.891***
	(0.00348)	(0.00624)
Observations	188,096	188,096
T2	purch_3month	purch_6month
Induced Adoption by T2	**2.835** **	**6.498*** **
	(1.299)	(2.350)
Constant	0.373***	0.867***
	(0.00611)	(0.0111)
Observations	188,139	188,139

Standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.1

*We used different time windows of download within 1day and 3day, and we got qualitatively the same results. Here we report the results using download_1week.

Table 4: Average Estimates of Treatments on Purchases -ITT (Q3)

	(3)	(4)
VARIABLES	purch_3month	purch_6month
Monetary (T1)	0.00104	-0.000262
	(0.00572)	(0.00938)
Information (T2)	**0.0144****	**0.0280*****
	(0.00572)	(0.00938)
Constant	0.499***	1.006***
	(0.00291)	(0.00478)
Observations	236,936	236,936
R-squared	0.000	0.000

Standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.1

Table 5: The Causal Effect of Induced Mobile App Adoptions on Treatment Effect Decomposed by Channel - LATE

	(1)	(2)	(3)
T1	**Desktop**_3Mon	**Mobile App**_3Mon	**Mobile Web**_3Mon
T1 Induced App Adoption	0.372	**0.146***	**-0.580*****
	(0.407)	(0.0876)	(0.198)
Constant	0.410***	0.0172***	0.0972***
	(0.00401)	(0.000865)	(0.00196)
Observations	129,981	129,981	129,981
T2	**Desktop**_3Mon	**Mobile App**_3Mon	**Mobile Web**_3Mon
T2 Induced App Adoption	**3.440*****	0.315	-0.488
	(1.168)	(0.238)	(0.542)
Constant	0.396***	0.0164***	0.0968***
	(0.00713)	(0.00146)	(0.00331)
Observations	130,063	130,063	130,063

Standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.1

* We tested on channel purchases within 1month, 3month and 6month windows and here we report results for the 3-month window. The results are robust across other time windows.

Table 6: Evidence from Browsing Data

	Browsing			Purchases		
	Desktop	**Mobile App**	**Total**	**Desktop**	**Mobile App**	**Total**
Control	8.473	6.655	16.455	1.073	0.491	2.072
T1	16.186	3.579	23.737	1.821	0.551	3.291
T2	16.802	6.709	29.512	1.895	0.651	3.686

*Here we only take into account the users who have downloaded the app during the 1st day after the treatment (n = 426) to minimize the organic adopters included in the samples and to maximize the percentage of induced adopters. The result is based on browsing and purchase behaviors of each user during a period of 30 months after the experiment. We display the behaviors for app adopters in each test group, including a) *the average number of items browsed by each adopter (in total and through* each channel) and b) *the average number of items purchased by each adopter (in total and through* each channel).

Table 7: Mobile App Browsing by Different Price Ranges

Browsing on Mobile App	Purchases on Desktop	Purchases on Mobile App	Total Purchases
0 <Price <10 (11.03%)	69 (5.42%)	1,133 (89.07%)	1,272 (100%)
10 <= Price <20 (31.19%)	280 (7.39%)	3,249 (85.77%)	3,788 (100%)
20 <= Price < 40 (33.76%)	441 (9.92%)	3,728 (83.87%)	4,445 (100%)
40 <= Price < 80 (15.72%)	271 (12.20%)	1,787 (80.46%)	2,221 (100%)