Essays on Mobile Channel User Behavior

by

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ABSTRACT

In two independent and thematically relevant chapters, I empirically investigate consumers' mobile channel usage behaviors. In the first chapter, I examine the impact of mobile use in online higher education. With the prevalence of affordable mobile devices, higher education institutions anticipate that learning facilitated through mobile access can make education more accessible and effective, while some critics of mobile learning worry about the efficacy of small screens and possible distraction factors. I analyze individual-level data from Massive Open Online Courses. To resolve self-selection issues in mobile use, I exploit changes in the number of mobile-friendly, short video lectures in one course ("non-focal course") as an instrumental variable for a learner's mobile intensity in the other course ("focal course"), and vice versa, among learners who have taken both courses during the same semester. Results indicate that high mobile intensity impedes, or at most does not improve course engagement due mainly to mobile distractions from doing activities unrelated to learning. Finally, I discuss practical implications for researchers and higher education institutions to improve the effectiveness of mobile learning. In the second chapter, I investigate the impact of mobile users' popular app adoption on their app usage behaviors. The adoption of popular apps can serve as a barrier to the use of other apps given popular apps' addictive nature and users' limited time resources, while it can stimulate the exploration of other apps by inspiring interest in experimentation with similar technologies. I use individual-level app usage data and develop a joint model of the number of apps used and app usage duration. Results indicate that popular app adoption stimulates users to explore new apps at app stores and allocate more time to them such that it increases both the number of apps used and app usage duration for apps excluding the popular app. Such positive spillover effects are heterogeneous across app categories and user characteristics. I draw insights for app developers, app platforms, and media planners by determining which new apps to release in line with the launch of popular apps, when to release such apps, and to whom distribution should be targeted.

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CHAPTER 1

THE EFFECTS OF MOBILE USE IN ONLINE HIGHER EDUCATION: EVIDENCE FROM MASSIVE OPEN ONLINE COURSES

1.1. Introduction

Mobile technologies have transformed many industries—communication, e-commerce, advertising, healthcare, and education. An expanding academic literature has documented the economic impact of mobile technologies over the past decade. Many of these studies focus on business outcomes and implications that largely pertain to economic transactions, such as mobile promotions (e.g., Andrews et al. 2015, Fang et al. 2015, Fong et al. 2015, Ghose et al. 2013, Luo et al. 2014), mobile advertisements (e.g., Bart et al. 2014), mobile commerce (e.g., Xu et al. 2017), and mobile app download and usage (e.g., Ghose and Han 2014, Han et al. 2016). However, despite the managerial ramifications that would be provided to education service providers and universities, academic studies focusing on the effects of mobile technologies from an educational perspective are relatively rare. This study explores the impact of mobile technologies on learners' course engagement in an online, higher educational context.

A specific link between mobile use and learning engagement remains an important empirical question. On one hand, as an integral part of our daily lives, mobile devices and wireless technologies allow individual learners to easily access online educational resources anywhere and anytime. As a result, they may engage with online courses better. On the other hand, mobile devices have small screens and restricted text entry features, and, due to their ubiquitous nature, learners may use them in a noisy, distracting environment with limited attention being paid to learning materials. This can negatively affect learning efficacy.

This study investigates whether high mobile intensity in usage enhances or impedes learners' course engagement in an empirical setting of Massive Open Online Courses (MOOCs hereinafter). MOOCs are offered for free to the public on the Internet such that learners from a wider range of socioeconomic status (e.g., age, education level, income) can learn anytime and anywhere. I believe that if mobile devices can work as a complementary tool for existing PC-based online learning, higher mobile intensity can enhance overall engagement of learners, but if mobile devices simply substitute the PCs in online learning, an increase in learners' mobile intensity may not improve their learning efficacy. Even worse than such substitutions, it might be harmful to course engagement if increased mobile usage impedes learners from focusing on their courses due to possible distracting mobile activities which are unrelated to learning (e.g., texting, social networking, or gaming). Given the prevalence and merits of mobile technologies, I believe, it is imperative to understand the effects of mobile technologies in online higher education markets. My initial analysis ignoring possible endogeneity issues involved in learners' self-selection into mobile use alludes that higher mobile intensity is associated with higher levels of learners' course engagement, in terms of both the number and the duration of engagement activities such as watching lecture videos, navigating course content, solving problems and assignments, and participating in the online course forum. However, this result must be interpreted with caution.

A case in point is that either highly motivated and interested learners may opt in to use mobile devices in addition to using PCs for learning or mobile-savvy learners who do many non-learning activities also may decide to use mobile devices for learning. If ignored, either case can cause biases in my empirical estimation. Thus, a key empirical challenge in identifying the effect of mobile use on course engagement is to address the potential self-selection bias. To tackle this empirical challenge, I develop an instrumental variable strategy. For identification, I focus on learners who have taken two courses—namely, course *A* and course *B*— during the same semester. I construct an instrumental variable for a learner's time-varying mobile intensity in course *A* ("focal course") at weekly level by utilizing the number of mobile-friendly, short video lectures provided during the same week in course *B* ("non-focal course"). I operationalize the degree of mobile-friendliness of a course during a given week by counting the number of video lectures running less than five minutes as learners tend to watch short videos using mobile channel. As robustness checks, I exploit the number of longer length video lectures (e.g., ten minutes, fifteen minutes) as alternative instrumental variables, and find that the validity of the inclusion restriction weakens as the length of video lectures increases, indicating that the threshold of five minutes is reasonable in my empirical setting.

The proposed instrumental variable for mobile intensity satisfies both inclusion and exclusion restriction conditions. First, an increased (decreased) number of bite-sized, short video lectures in course *B* promotes (discourages) a learner's mobile intensity during the course. Higher (lower) mobile intensity within course *B* is likely to spill over to course *A* because the learner may frequently navigate from a page in course *B* to a page in course *A* within the mobile platform of a MOOC provider. Thus it satisfies the inclusion restriction condition. Second, the number of short video lectures provided in course *B*—an instrumental variable for a learner's mobile intensity in course *A*—cannot be directly related with her motivation to succeed in course *A*. This is because courses *A* and *B* are independently managed by different instructors and thus not coordinated. So, the instrumental variable satisfies the exclusion restriction condition.

After controlling for the self-selection bias by using the instrumental variable approach, I find negative effects of mobile intensity, or at most insignificant effects on learners' course engagement. I demonstrate a possible underlying mechanism of such detrimental or null effects of enhanced mobile intensity. As a possible underlying mechanism, I discover mobile distractions diverting a learner's attention away from their learning activities within a MOOC mobile platform to other mobile activities unrelated to learning (e.g., texting, gaming, or social media). These results imply that the current widespread use of mobile devices in online learning will not automatically guarantee improvement in course engagement beyond and above what PCs alone could do. From these empirical findings, I discuss practical implications for researchers and higher education institutions to improve the efficacy of mobile learning.

1.2. Literature Review

1.2.1. Economic Impact of Mobile Technologies

Current literature on mobile technologies in information systems, marketing, and related fields has mainly focused on the economic impact of mobile technologies. Among the studies that documented how mobile technologies influence firms' economic growth and affect consumer behaviors, scholars have investigated the economic consequences of mobile access in advertisements, promotions, and e-commerce. For example, Bart et al.

(2014) found that mobile display advertisement improves consumer attitudes and purchase intentions but only for high-involvement and utilitarian products. Other studies on the effectiveness of mobile promotions reported that mobile promotions or targeting stimulate the purchase (e.g., Andrews et al. 2015, Fang et al. 2015, Fong et al. 2015, Hui et al. 2013, Luo et al. 2014), influence coupon redemption (e.g., Danaher et al. 2015), and increase click-through (e.g., Ghose et al. 2013). In literature on mobile commerce, the adoption of mobile shopping app (Einav et al. 2014) or tablet PC channel (Xu et al. 2017) enhances the growth of e-commerce market platform. This paper extends the role of mobile technologies from stimuli for accelerating economic growth to potential for a facilitating tool in online higher education. Many educational institutions have paid much attention to investment in mobile technologies surpassing other industries[1]. A better understanding of how to incorporate mobile technologies in learning is timely and important to educational institutions, and could enhance educational productivity and equality.

1.2.2. Impact of ICTs in Education

Scholars from several academic fields (e.g., education, economics, and business) have been interested in the role of emerging information and communication technologies (ICTs) in education. Existing scholarly works in this research stream have investigated the impact of ICTs such as broadband Internet, personal computers, and adaptive learning systems. For example, Machin et al. (2007) reported a positive impact of overall ICT

[1] The education spent a highest share of its IT budget (19.3 %) on mobile technologies among other major industrial sectors in 2012 (Gartner, *Forecast: Enterprise IT Spending by Vertical Industry Market, Worldwide, 2010-2016, 4Q12 Update*, January 2013).

expenditure on student performance in elementary schools because of the efficient use of ICT funding. Fairlie and London (2012) evaluated the effects of financial aid for free personal computers for home use at a large community college in Northern California and found that students who have free computers are better in academic outcomes. Several studies also documented the positive effects of accessing computers at home on student performance such as school enrollment (Fairlie 2005), high school graduation (Beltran et al. 2010), and exam scores (Schmitt and Wadsworth 2006). Recently, Kumar and Mehra (2016) investigated the effectiveness of computer-generated adaptive homework and found that the computer-based group achieved higher scores in final exams than their paper-based group counterparts.

In contrast from aforementioned studies illustrating positive outcomes, other studies documented that there exist null or negative effects of ICT investment and use on student learning. Several studies reported null effect of school computerization (Angrist and Lavy 2002) and Internet investment (Goolsbee and Guryan 2006) on student performance. As possible explanations, the authors argue that computer-aided instruction is no more effective than traditional pedagogical methods, or it takes longer to be proven to be beneficial to students. Even worse, Belo et al. (2014) found that intensive Internet usage in schools can be detrimental for grades on the national exams in Portugal because digital content on the Internet unrelated to learning such as social media, multimedia, music, games interferes with students' concentration in learning. In a similar vein, Vigdor et al. (2014) and Fuchs and Woessmann (2004), respectively, revealed that access to home computer and high-speed Internet lower students' math and reading test scores. Further, several studies ascertained that such detrimental effects of ICT investment and use can be more severe among certain demographic groups, including children in low-income families (Leuven et al 2007) and female students whose parents' education level is low (Malamud and Pop-Eleches 2011).

However, extant literature has paid scant attention to capture the impact of mobile technologies in online higher education. There is an emerging stream of work that examines the impact of mobile podcasts as a learning aid tool (Evans 2008), short message services as a communication channel (Lu 2008, Rau et al. 2008), and tablet PCs as a learning device (Kinash et al. 2012). With few exceptions, most previous research on the role of mobile technologies in online education either has been largely descriptive (e.g., not exploring the impact of mobile use and its underlying mechanism) or has examined their impact on a certain demographic segment (e.g., adolescents, college students). This study not only ascertains the impact of mobile use in online higher education after controlling learners' self-selection into their use of mobile devices and intensity thereof, but also provides the first large-scale empirical study on mobile learning encompassing learners from a wide range of socioeconomic status (e.g., age, income, education level, geography).

1.3. Data and Methodology

1.3.1. Data Description

I examine the effects of mobile use on course engagement for learning in the context of MOOCs. Several features of MOOCs make it an appealing empirical context. First, MOOCs are generally offered for free to a large number of learners of diverse backgrounds. They can reach not only people who already hold university degrees, but also an under-served population who has difficulty in accessing quality education. Hence, MOOCs rather than online classrooms offer a setting in which I am able to recruit a sample who will be more representative of the increasingly online population in higher education. Second, people with a mobile device and Internet connection can easily access the materials on MOOCs anywhere and anytime. So, MOOCs provide a fertile empirical setting in which I collect large-scale behavioral data from mobile learners. With the use of observational data from MOOCs, not only do I investigate the effects of mobile use in learning at scale while being economical (e.g., not giving subjects subsidized mobile devices or/and remuneration for time), but also do I avoid possible ethical questions which possibly can arise from field experiments in my setting (e.g., barring individuals from accessing content through mobile devices).

The data set comes from a leading MOOC platform, edX[2]. I obtain detailed records on MOOC learners' engagement activities at the individual level. I observe, for example, which course(s) each learner registered, when the learner accessed a course, and whether she took quizzes and exams and the scores if taken. For the analyses, I use the data from two courses— "Course *A*: Human Origins" and "Course *B*: Western Civilization"—which were offered to public for free during the same, 7-week semester by a large public university in the United States in Fall 2015. Both courses do not require advanced knowledge or skills as prerequisite, so they are accessible by a wide range of potential learners. For identification purposes, I focus on 411 learners who have taken

[2] edX is a nonprofit online MOOC provider, founded by Harvard University and The Massachusetts Institute of Technology in 2012. It offers over 1300 courses from over 100 universities and institutions to over 10 million learners worldwide.

both courses during the same semester.[3] I construct the 7-week unbalanced panel data which have different number of observations for each user in a given course because learners can register for and terminate from a course at their preferred time. Given this panel consideration, my data have a total of 2,988 observations.

I operationalize the variable of interest, a learner's time-varying "mobile intensity" at weekly level (measured in percentage, %) by computing the ratio of the number of log-ins to a course platform using only mobile devices over the total number of log-ins using both mobile devices and PCs per week. To account for skewness, the dependent variables are log-transformed.

1.3.2. Econometric Model

To empirically examine the impact of mobile intensity on various course engagement activities, I perform the log-linear regression analysis for the number of following engagement activities: video watching, content navigation, problem solving, and forum participation, and all of these. The main model is specified as

$$\ln(Y_{cit}) = \alpha + \beta \cdot P_{cit} + \gamma_c + \delta_i + \tau_t + \varepsilon_{cit} \qquad (1.1)$$

for learner i at week t in course c, where Y_{cit} is the number of engagement activities and P_{cit} is the "mobile intensity" which is measured in percentage (%) and ranged between 0 and 100. α is an intercept, γ_c are course fixed effects that address the unobserved course-specific effects, δ_i are learner fixed effects that control for the unobserved heterogeneity across learners, τ_t are week fixed effects that capture the unobserved temporal effects

[3] This is because the model identification strategy requires information on student activities in multiple courses. I will provide more details in the section '1.3.3. Developing an Instrumental Variable Strategy.'

common to all learners, and ε_{cit} are mean-zero random errors. The coefficient β estimates the effect of mobile intensity on learners' course engagement and is of my main interest.

1.3.3. Developing an Instrumental Variable Strategy

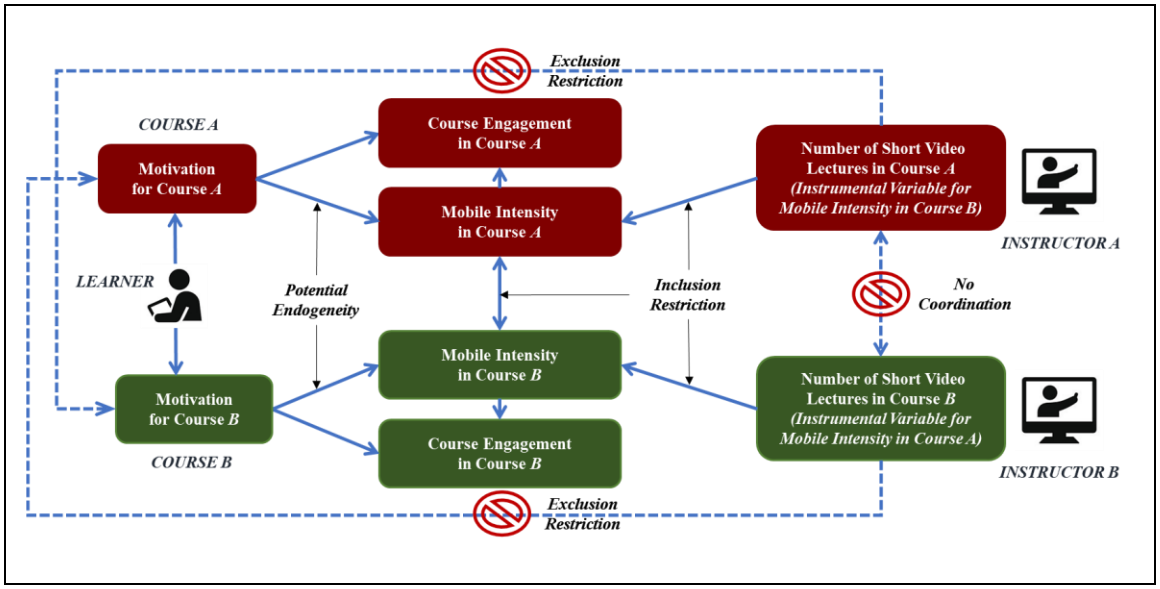
A key empirical challenge in identifying the effect of mobile use on course engagement is that the decision of mobile intensity is determined by learners themselves. This self-selection problem may cause endogeneity biases in empirical estimation if ignored. For example, a learner's interest and motivation to succeed in a course can be critical factors influencing their course engagement. However, these are unobservable to researchers and thus inevitably incorporated into a random error term (ε_{cit} in Equation (1.1)). One example is that a highly motivated and interested learner may prefer to use mobile devices for online learning in addition to PCs. Another example is that mobile-savvy learners who extensively engage in mobile activities unrelated to learning also may decide to use mobile devices for learning. If so, the correlation between the propensity to use mobile devices for learning and the random error can be a source of an endogeneity problem.

Ideally, one might try to address this endogeneity issue by conducting a randomized experiment where learners are randomly assigned to either a control group in which they should use only PCs or a treatment group in which they should use both mobile devices and PCs or only mobile devices for learning. The random assignment of users into treatment and control groups would be a good solution for the endogeneity problem. However, as I alluded earlier, due to economical and ethical considerations, I believe it may not be a viable option to perform a large-scale field experiment in my setting. Furthermore, it is quite difficult to manipulate the level of mobile intensity at an individual learner level either experimentally or ethically, or both. Hence, in my empirical analysis, I rely on using observational data from MOOCs and develop an instrumental variable strategy to establish a causal relationship.

I assume that a valid instrumental variable is related to mobile intensity (P_{cit} in Equation (1.1)) but unrelated to unobserved factors (included in ε_{cit} in Equation (1.1)). To assess the effects of mobile intensity on course engagement, I use an exogenous variation in the level of mobile intensity, which is explained by my instrumental variable, and apply the two-stage least squares estimation approach, which is most commonly used and robust for a linear model with continuous endogenous variables (See pp. 95–102, Cameron and Trivedi (2005) for further information on instrumental variables and two-stage least squares estimation method for continuous endogenous variables).

Below I establish the validity of my instrumental variable for mobile intensity by demonstrating that it satisfies the required two restriction conditions, namely: (1) the instrumental variable should be correlated with the mobile intensity variable (inclusion restriction) but (2) the instrumental variable should not be correlated with unobserved factors included in the error term (exclusion restriction). I assert that changes in the number of mobile-friendly, short video lectures in one course serves as a valid instrumental variable for learners' mobile intensity for learning in the other course, and vice versa, among learners who have taken both courses during the same semester. Figure 1.1 illustrates my identification strategy and I explain the details in the following sections.

Figure 1.1. A Schematic View of Identification Strategy



1.3.3.1. Inclusion Restriction Condition

I develop an instrumental variable for mobile intensity by considering learners who have taken two courses—course *A* ("focal course") and course *B* ("non-focal course")—offered during the same semester. I assert that a valid instrumental variable for mobile intensity in course *A* is the degree of mobile-friendliness of course *B*, and vice versa, for two reasons.

First, people spend more time in watching videos on their mobile devices than on their PCs.[4] As mobile learning grows in popularity, videos, particularly short and bite-size chunks, are becoming one of the most common types of lecture materials on mobile channels. Moreover, smartphone users prefer to watch shorter videos less than five

[4] Available at https://www.recode.net/2017/7/17/15981376/mobile-video-consumption-25-percent-in-2018-online-video-peaks (accessed on January 23, 2018)

minutes.[5] Thus, I speculate that an increased (decreased) number of short video lectures in a certain course (e.g., course *B*) will positively (negatively) affect learners' mobile intensity for learning in that course. Accordingly, I measure the time-varying degree of mobile-friendliness of a course at weekly level by counting the number of short video lectures less than five minutes per week in that course.

Second, I believe that changes in the number of short video lectures in course *B* can also affect the mobile intensity in course *A* for the same learner, and vice versa. This is, in spirit, similar to the cross-course spillover effect of mobile intensity; in other words, a learner is likely to extend her mobile browsing activities to content in course *A* after she navigates increased number of mobile friendly content in course *B*. This cross-course spillover effect is critical in my identification strategy. This is because the association between the number of mobile-friendly video lectures and the mobile intensity within the same course can be subject to potential endogeneity issues resulting from the possibility that learners' low mobile intensity level in the past prompts the course instructor to publish additional mobile-friendly video lectures in her present and future course offering.

In what follows, I demonstrate that my instrumental variable for mobile intensity satisfies the inclusion restriction in my empirical setting such that I do not have a weak instrumental variable problem. In the panel (I) in Table 1.1, the first stage ordinary least squares (OLS) results reveal that the estimated coefficient of my instrumental variable for mobile intensity is significantly positive as 0.392 (p-value < 0.01), indicating that the

[5] Available at http://tubularinsights.com/increase-mobile-video-consumption/ (accessed on January 23, 2018)

instrumental variable is significantly and positively correlated with mobile intensity. In addition, the first-order Granger causality test shows lack of evidence for any reverse causality of mobile intensity on the instrumental variable (p-value = 0.292), suggesting that my instrumental variable explains the variation of mobile intensity well but not the other way around.

As robustness checks, I test two alternative threshold values for short video lectures—ten minutes and fifteen minutes. The Panels (I), (II) and (III) in Table 1.1 show that the estimated coefficients for the instrumental variable are 0.392 for less than five minutes (i.e., current threshold), 0.274 for less than ten minutes, and 0.199 for less than fifteen minutes, respectively. So, the validity of the inclusion restriction weakens as the length of video lectures increases. The Panel (IV) in Table 1.1 further reveals that longer video lectures exceeding fifteen minutes are negatively correlated with the mobile intensity, implying that such longer videos are unlikely watched in mobile devices (i.e., the estimated coefficient = –0.244).

These results altogether lend support to the validity of the inclusion restriction and indicate that the threshold of five minutes in determining mobile-friendly, short video lectures is acceptable in my empirical setting.

Table 1.1. First Stage Estimation Results

Dependent Variable: Mobile Intensity (%)				
Instrumental Variables	**(I)**	**(II)**	**(III)**	**(IV)**
	Number of Video Lectures Less than 5 Minutes	**Number of Video Lectures Less than 10 Minutes**	**Number of Video Lectures Less than 15 Minutes**	**Number of Video Lectures More than 15 Minutes**
Estimated Coefficient (Standard Error)	0.392 (0.019)***	0.274 (0.048)***	0.199 (0.061)***	-0.244 (0.083)**
F-value	16.971***	17.051***	17.047***	16.972***
R^2	0.734	0.735	0.735	0.734
N. Obs.	2,988	2,988	2,988	2,988

*significant at 0.1 level; **significant at 0.05 level; ***significant at 0.01 level
Note: Clustered (by week) standard errors are in parentheses.

1.3.3.2. Exclusion Restriction Condition

To ensure the exclusion restriction condition of my instrumental variable for mobile intensity, I demonstrate below that my instrumental variable cannot be correlated with the error term in my main equation (ε_{cit} in Equation (1.1)), conditional on other covariates.

In my empirical setting, two courses— Course *A* (Human Origins) and Course *B* (Western Civilization)—deal with different topics and are independently managed by different instructors. Thus, it is hard to imagine that the numbers of short video lectures in course *A* determined by instructor *A* are correlated with those in course *B* determined by instructor *B*, and vice versa. Table 1.2 shows results on Chi-square tests on whether the numbers of short video lectures less than five minutes of the two courses are independent to each other, and I find that the two courses are not dependent (*p*-value = 0.307). When two courses are independently coordinated, it implies that the instructor of course *A* creates and manages course *A*'s contents including video lectures, independent of learners' motivation or interest in course *B*, and vice versa. Therefore, an instrumental variable for mobile intensity in course *A* (e.g., the numbers of short video lectures in course *B*) cannot be related with learners' motivation or interest in course *A* which is unobservable to researchers and thus included in the error term, and vice versa. So, my instrumental variable satisfies the exclusion restriction condition.

Table 1.2. Relationship between the Numbers of Short Video Lectures of Course *A* and Course *B*

	Number of Video Lectures Less than 5 Minutes at Course *A* (Human Origins)				
Number of Video Lectures Less than 5 Minutes at Course *B* (Western Civilization)	**Frequency Table**	**1**	**2**	**5**	**Total**
	3	*3*	*0*	*1*	*4*
	4	*1*	*1*	*0*	*2*
	6	*0*	*1*	*0*	*1*
	Total	*4*	*2*	*1*	*7*
χ^2 Test Result	χ^2 = 4.813 (with degrees of freedom 4); *p*-value = 0.307				

Note: During my sample period, the observed numbers of short (< 5 min.) video lectures per week are 1, 2, or 5 in Course *A* (Human Origins) and 3, 4, or 6 in Course *B* (Western Civilization).

1.4. Results

1.4.1. OLS Results Ignoring Self-Selection Biases

I estimate my main model in Equation (1.1) using OLS. The Panel (I) in Table 1.3 reports the OLS results, showing mostly significant and positive coefficients of mobile intensity parameter (i.e., $\hat{\beta}$ = 0.018 for the number of all activities, $\hat{\beta}$ = 0.019 for the number of video watching activities, $\hat{\beta}$ = 0.011 for number of content navigation activities, $\hat{\beta}$ = 0.013 for the number of problem solving activities; *p*-value < 0.01 for all). The estimated coefficients suggest that an increase in learners' mobile intensity increases the volume of various engagement activities. These results, however, should be interpreted with caution, due to possible self-selection bias in mobile intensity decisions by learners.

Table 1.3. Estimation Results of Mobile Intensity

Log-Transformed Number of Course Engagement Activities	Total Number of Engagement Activities	By Activity Type			
		Number of Video Activities	Number of Navigation Activities	Number of Problem Activities	Number of Forum Activities
(I) Ordinary Least Squares Estimation Results for the Number of Engagement Activities[1)]					
Mobile Intensity (%)	0.018 (0.002)***	0.019 (0.002)***	0.011 (0.001)***	0.013 (0.002)***	0.0001 (0.0003)
(II) Instrumental Variable Two-Stage Least Squares Estimation Results for the Number of Engagement Activities[2)]					
Mobile Intensity (%)	-0.210 (0.025)***	-0.209 (0.034)***	-0.124 (0.027)***	-0.144 (0.196)	-0.006 (0.004)
(III) Instrumental Variable Two-Stage Least Squares Estimation Results for the Number of Engagement Activities among Learners Who Have Used Mobile Devices for Learning[2)]					
Mobile Intensity (%)	-0.019 (0.006)**	-0.030 (0.021)	-0.019 (0.007)**	0.037 (0.080)	0.003 (0.001)**
Log-Transformed Duration of Course Engagement Activities	Total Duration of Engagement Activities	By Activity Type			
		Duration of Video Activities	Duration of Navigation Activities	Duration of Problem Activities	Duration of Forum Activities
(IV) Instrumental Variable Two-Stage Least Squares Estimation Results for the Duration of Engagement Activities[2)]					
Mobile Intensity (%)	-0.277 (0.037)***	-0.363 (0.034)***	-0.196 (0.107)	-0.144 (0.290)	-0.005 (0.019)

*significant at 0.1 level; **significant at 0.05 level; ***significant at 0.01 level

1) Heteroscedasticity-consistent standard errors are in parentheses.

2) Clustered (by week) standard errors are in parentheses.

Note: The number of observations for (I), (II), and (IV) is 2,988. The number of observations is 1,335 for (III) after removing the learners who have not used mobile devices during the entire semester.

1.4.2. Two-Stage Least Squares Estimation Results

The Panel (II) in Table 1.3 shows the results of instrumental variable-based two-stage least squares estimation. Most notably, I observe that high mobile intensity reduces the total course engagement level, indicating that increased mobile use disrupts learning and in turn results in less learning activities than without the use of mobile devices. To account for multi-dimensional effects of mobile intensity, I examine how its impact varies by engagement activity type. Results reveal that high mobile intensity reduces the numbers of all engagement activities (i.e., $\hat{\beta}$ = –0.210, *p*-value < 0.01), video watching activities (i.e., $\hat{\beta}$ = –0.209, *p*-value < 0.01) and content navigation activities (i.e., $\hat{\beta}$ = –0.124, *p*-value < 0.01), but it does not affect other course engagement activities such as problem solving (i.e., $\hat{\beta}$ = –0.144, *p*-value > 0.1) and forum participation (i.e., $\hat{\beta}$ = –0.006, *p*-value > 0.1). Specifically, one percentage point increase in learners' mobile intensity decreases the total number of engagement activities by 21%, the number of video activities by 21%, and the number of navigation activities by 12%.

These estimated decreases appear to be large in magnitude at first; this result, however, should be interpreted with caution. In part, this is because more than 55% of learners in my sample have never used mobile devices for learning during the entire semester, so even a small increase in mobile intensity above zero can result in a significant impact on changes in engagement activities. Thus, for sensible interpretation, I re-estimate the main model using learners who have ever engaged with courses through mobile devices. The Panel (III) in Table 1.3 shows the result that the overall impact of mobile intensity is still negative and significant with its marginal effect falling from a 21% decrease down to a 1.9% decrease in the number of all engagement activities, which seems in a reasonable range.

Lastly, the time spent on learning may vary by engagement activity type. The Panel (IV) in Table 1.3 presents the results of the effect of mobile intensity on time spent on different types of engagement activities. I find largely consistent results that high mobile intensity decreases (i.e., $\hat{\beta} = -0.277$ for the duration of all engagement activities, $\hat{\beta} = -0.363$ for the duration of video watching activities; p-value < 0.01 for both) or at best does not increase the duration of certain engagement activities (i.e., $\hat{\beta} = -0.196$ for the duration of content navigation activities, $\hat{\beta} = -0.144$ for the duration of problem solving activities, $\hat{\beta} = -0.005$ for the duration of forum participation activities; p-value > 0.1 for all). Specifically, one percentage point increase in learners' mobile intensity decreases the duration of all engagement activities by 28% and the duration of video watching activities by 36%.

1.4.3. Robustness with Heterogeneous Instrumental Variables

The current instrumental variable for mobile intensity varies by week, but not at the individual learner level. Table 1.4 examines how the main estimates vary with two pre-treatments, individual-learner specific demographics: age and education level both of which are self-reported by learners. Younger and less-educated learners are arguably more likely to use mobile devices for learning: young users are expected to be more proficient at using mobile devices than their old counterparts, and less-educated users might tend to be blue-collar workers who may not sit in front of PCs at work but rely more on mobile devices. So, I expect that young and less-educated learners drive most of the response to increased number of mobile-friendly, short video lectures. To reflect heterogeneous instrumental variables, I use both the current instrumental variable (e.g., the number of less than 5 minutes video lectures) and its interaction with a learner's age variable and an indicator variable for being educated (i.e., having highest degree earned from bachelor or above) as instrumental variables in estimation.

The Panels (I) and (II) in Table 1.4 report estimated coefficients using these instrumental variables, respectively. With the additional age-varying instrumental variable, I find largely consistent results that high mobile intensity impedes course engagement activities (i.e., $\hat{\beta} = -0.129$ for the number of all engagement activities, p-value < 0.05; $\hat{\beta} = -0.080$ for the number of content navigation activities, p-value < 0.01; $\hat{\beta} = -0.012$ for the number of forum participation activities, p-value < 0.1). With the additional education level-varying instrumental variable, I continue to find that high mobile intensity results in decreases in course engagement activities, or at most no changes therein (i.e., $\hat{\beta} = -0.162$ for the number of all engagement activities, p-value < 0.01; $\hat{\beta} = -0.176$ for the number of video watching activities, p-value < 0.05; $\hat{\beta} = -0.105$ for the number of content navigation activities, p-value < 0.05). Thus, the main results in the Panels (II) and (IV) in Table 1.3 are robust with respect to additional use of heterogeneous instrumental variables.

Table 1.4. Robustness Checks with Heterogeneous Instrumental Variables

Log-Transformed Number of Course Engagement Activities	Total Number of Engagement Activities	By Activity Type			
		Number of Video Activities	Number of Navigation Activities	Number of Problem Activities	Number of Forum Activities
(I) Age-Varying Instrumental Variables					
Mobile Intensity (%)	-0.129 (0.039)**	-0.115 (0.076)	-0.080 (0.015)***	-0.161 (0.183)	-0.012 (0.006)*
(II) Education Level-Varying Instrumental Variables					
Mobile Intensity (%)	-0.162 (0.028)***	-0.176 (0.056)**	-0.105 (0.032)**	-0.105 (0.184)	-0.008 (0.008)

*significant at 0.1 level; **significant at 0.05 level; ***significant at 0.01 level

Note 1: Clustered (by week) standard errors are in parentheses.

Note 2: The number of observations is 2,652 for (I) after excluding learners missing their age information; the number of observations is 2,488 for (II) after excluding learners who did not report their educational level information or whose age is less than twenty years old.

1.4.4. Underlying Mechanisms

I explore the following two possible underlying mechanisms through which high mobile intensity induces a negative effect in course engagement activities by learners: mobile distractions (e.g., mobile activities irrelevant to learning such as texting, social networking, or gaming) and small-screen mobile devices. These two mechanisms are not necessarily mutually exclusive but may contribute to clarifying the role of mobile devices in online learning.

1.4.4.1. Evidence Supporting Mobile Distractions

Drawing upon recent studies on the detrimental effects of student phone access on cognitive capacity (Ward et al. 2017) and test scores (Beland and Murphy 2016), I contend that mobile devices' ubiquitous presence effects play an important role by distracting learners, thus luring into mobile activities unrelated to learning (e.g., texting, social networking, or gaming). Hence, if the negative effect of high mobile intensity is driven by mobile distractions, then the number of course engagement activities per *log-in* to the course system should decrease for learners with high mobile intensity. Given the overall negative effect of mobile intensity on course engagement activities, I argue that if the number of *log-ins* increases (or at least does not change) with respect to increases in the mobile intensity level, then I can infer that learners with the high mobile intensity level are mainly distracted away toward aforementioned mobile activities unrelated to learning outside the learning platform. To test this prediction, I estimate the effect of mobile intensity on the number of *log-ins*. Results confirm that an increase in mobile intensity does not change the number of *log-ins* to a course system (i.e., the estimated coefficient = –0.043, *p*-value > 0.1).

Despite the revealed prevalence of mobile distractions, I expect that test stimuli such as quizzes and exams motivate students to remain focused on learning because there is an inherent incentive for the students to do well when they take tests, mitigating the adverse effect of high mobile intensity. To the extent to which a learner complies with the assessment requirements (i.e., taking quizzes or exams), the mobile distractions should be weaker for those who took the tests. In my empirical consideration, the two courses offer quizzes or exams every week. So, to test this conjecture, I examine how the mobile intensity effect varies by whether a learner took a test in a given week. I estimate the time-varying effects of the mobile intensity and its interaction with an indicator variable for having taken tests (e.g., quizzes for week 1–3 and 5–6, a midterm exam for week 4, and a final exam for week 7) on course engagement. The top seven rows in Table 1.5 report the baseline results for learners who did not take any test in a given week, which are in line with my main finding (i.e., the estimated coefficients of mobile intensity are negative ranged between –1.064 and –0.393). The bottom seven rows in the same table show, in general, positive interaction effects between mobile intensity and the indicator for taking a test in a given week (i.e., the estimated interaction coefficients are positive ranged between 0.024 and 0.723). So, I find that taking tests effectively mitigate the adverse effect of high mobile intensity on course engagement.

So far, I find that high levels of mobile use cause distractions for learners, hampering course engagement activities; and test stimuli such as quizzes or exams prevent learners from being distracted to mobile activities unrelated to learning, mitigating the adverse effect of high mobile intensity.

Table 1.5. Evidence Supporting Mobile Distractions

	Log-Transformed Total Number of Engagement Activities
Mobile Intensity (%) at week 1	-0.393 (0.192)*
Mobile Intensity (%) at week 2	-0.599 (0.230)**
Mobile Intensity (%) at week 3	-0.703 (0.258)**
Mobile Intensity (%) at week 4	-0.650 (0.278)*
Mobile Intensity (%) at week 5	-1.064 (0.442)*
Mobile Intensity (%) at week 6	-0.723 (0.308)*
Mobile Intensity (%) at week 7	-0.532 (0.242)*
Mobile Intensity (%) × TT[1)] at week 1	0.024 (0.067)
Mobile Intensity (%) × TT[1)] at week 2	0.231 (0.057)***
Mobile Intensity (%) × TT[1)] at week 3	0.262 (0.103)**
Mobile Intensity (%) × TT[1)] at week 4	0.302 (0.085)**
Mobile Intensity (%) × TT[1)] at week 5	0.723 (0.246)**
Mobile Intensity (%) × TT[1)] at week 6	0.347 (0.113)**
Mobile Intensity (%) × TT[1)] at week 7	0.206 (0.054)***

*significant at 0.1 level; **significant at 0.05 level; ***significant at 0.01 level
[1)] TT (Test Taken) = 1 for learners who have taken a quiz or an exam at the corresponding week; TT = 0, otherwise.
Note 1: Clustered (by week) standard errors are in parentheses.
Note 2: The number of observation is 2,988.

1.4.4.2. Little Evidence of the Impact of Small-Screen Sizes

Small screen sizes on mobile devices increase the search cost to the user of browsing for information (Ghose et al. 2013). Hence, if the negative effect of high mobile intensity arises from limited input/output interfaces associated with screen size, then the adverse effect should be stronger (weaker) for learners who have mobile devices with smaller (larger) screen sizes. To test this conjecture, I estimate the effects of the mobile intensity and its interaction with a screen size variable on the total number of course engagement activities by learners. Results show that the interaction effect is not statistically significant (i.e., the estimated coefficient = –0.310, p-value > 0.1), indicating that the screen size does not significantly change the relationship between mobile intensity and overall course engagement activities. Hence, there is little evidence to suggest that small screen sizes of mobile devices drive the adverse effect of high mobile intensity on learners' engagement activities.

1.5. Discussion

1.5.1. Implications for Researchers

The roles of emerging information communications technologies have been investigated in diverse educational contexts. Nevertheless, extant literature focuses on the impact of broadband Internet connectivity and primarily in the traditional classroom education environment (e.g., Belo et al. 2014, Belo et al. 2016). A few studies, to date, have sought to shed light on online higher education (e.g., Li and Zhang 2016, Baek and Shore 2016). The preceding analysis demonstrates that the increased mobile use induced by additional mobile-friendly video lectures disrupts rather than enhances learning in online higher education. I further document consistent evidence in favor of the distraction effect of the mobile devices in online learning.

This study contributes to an emerging stream of literature on the impact of mobile technologies by being the first study to empirically examine the effects of mobile intensity in usage on course engagement activities in online higher education. Using individual-level data on course engagement, I developed and implemented an identification strategy to distinguish the impact of mobile intensity from potential self-selection. The empirical framework with the suggested identification strategy provides a useful tool for researchers to examine the impact of mobile use in the online higher education context, particularly when mobile device/channel is voluntarily determined to use by learners themselves. Such device/channel self-selection is prevalent in online higher education, rather than enforced by the law which mandates the use of certain devices in learning.

1.5.2. Implications for Education Service Providers

Higher education institutions (e.g., universities, MOOC providers) are increasingly considering blended learning as a critical part of their academic programs. In a broad sense, blended learning is defined as learning that takes place in a mixture of conventional, face-to-face classroom activities and online or mobile environments (Picciano 2006). The present study focuses on blended learning in which mobile devices are used in addition to PCs in online education. Online higher education is pertinent to the discussion of mobile learning because mobile technologies expand opportunities for access to educational content. Mobile devices give learners easy access to much of the same content, information and opportunities as PCs and laptops do (UNESCO 2012).

This study documents empirical evidence from the context of MOOCs that learners' increasing use of mobile devices could impede their course engagement possibly due to the distraction factor. This result suggests that online higher education service providers can enhance the efficacy of mobile use in learning by deterring mobile distractions. To this end, for example, they could consider integrate some precommitment functions into their learning platform to help learners voluntarily block their access to unproductive and distracting apps/sites when they intend to remain focused on accessing the course materials.

1.6. Conclusion

The pervasive penetration of mobile devices has made it possible for learners to access online educational content anywhere and anytime. Several advocates characterize mobile learning as its geographical and temporal flexibility, which is conducive to learning anywhere and anytime. On the other hand, critics express reservations about the efficacy of distraction factors involved in mobile environments.

This study demonstrates that under the current state of mobile learning schemes, its adverse effects overshadow the benefits of using mobile devices in learning in online higher education. Hence, careful design and thorough execution of mobile education appears to be a necessary long-run solution for learning through mobile devices and achieving positive outcomes for learners in the increasing mobile-centric society.

CHAPTER 2

JUMPING ON THE POPULARITY BANDWAGON?

APP USAGE BEHAVIORS AFTER THE ADOPTION OF A POPULAR APP

2.1. Introduction

The rapid adoption of smartphones and tablets, as well as the widespread use of mobile applications ("apps"), continues to fuel the growth of the mobile app economy. A recent industry report states that time spent on mobile media accounts for 62% of total digital media time. Of the time consumed interacting with mobile media, 87% is spent using mobile apps rather than a mobile browser (ComScore 2015). However, consumers do not spend their time equally across apps, leading to a disparity in usage among app categories. As reported by ComScore (2015), the time devoted to business and marketing-related apps (e.g., retail stores and news) account for only 6% of the total time spent on apps, whereas that spent on popular apps (e.g., gaming, social networking, and messaging) account for two-third of the total.

Popular apps are downloaded by a vast majority of consumers and used with great regularity. From a recent popular augmented reality gaming app, Pokémon Go, to previously popular games, such as Candy Crush Saga and Angry Birds, popular gaming apps are progressively becoming a common pastime for many mobile users. These games are targeted toward mass audiences and rank among the most downloaded apps from Apple's App Store and Google's Play Store[6]. For example, Candy Crush Saga has been

[6] Available at http://www.medialiteracycouncil.sg/Lists/Resources/Attachments/200/The%20Attraction%20of%20Casual%20Mobile%20Games.pdf (accessed on September 16, 2017)

downloaded more than 500 million times since its launch in April 2012, outcompeting Twitter in terms of user base and revenues. The remarkable success of casual games is attributed to ease of use as they are easy to learn and do not require special skills. Regardless of category type, from puzzles and adventures to action or arcade games, the rules that govern these “mindless” games are exceedingly simple in principle, involving basic tricks and tasks, such as matching, shooting, racing, and managing time.

However, the enjoyable experience provided by these popular apps can result in a consequent addiction that stems from prolonged exposure. Because popular app adopters are more likely to spend increased time on an adopted popular app, under time constraints, they are less likely to do the same for other apps. Social apps, for example, present strong potential to turn into popular apps and therefore render users vulnerable to addiction. Dependence on social networking apps includes classical biopsychosocial consequences, such as mood modification, salience, tolerance, withdrawal symptoms, conflict, and relapse (Kuss and Griffiths 2011). A recent study by Kwon et al. (2016) showed that two popular social apps (e.g., social networking and social game apps) trigger both myopic and rational addiction. Popular app adoption can also engender inertia in app choice, whereby adopters are more likely to use an adopted popular app than new apps because mobile app users tend to favor apps that they have used as a consequence of increased psychological switching costs, search costs, and learning. Interestingly, the same mechanisms explain consumers’ inertia in brand choice (Dubé, Hitsch, and Rossi 2010).

Contrary to the conventional treatment of popular app adoption as discouraging of the use of other mobile apps, I empirically investigate the potential of popular apps as a catalyst for the adoption and consumption of other apps that would have otherwise been disregarded. To this end, I chose Anipang, a top-ranked mobile-based casual game in South Korea, as a stimulus popular app for my quasi-experiment. I examine how the adoption of the app changes consumers' usage of other apps within the same category (e.g., gaming apps) and across different app categories (e.g., utility apps). For this purpose, I measure the number of apps and the duration of app consumption at an individual level over 15 weeks. I likewise look into the paths through which Anipang increases app usage. To compare the app usage of popular app adopters and non-adopters before and after adoption, I employ the Gaussian copula-based difference-in-differences (DID) framework with propensity score matching. The proposed copula approach simultaneously estimates the number of apps used (discrete variable) and the duration of app usage (continuous variable), thereby allowing for flexible correlation between them.

Findings indicate that popular app adoption increases the number of apps used and duration of app usage not only within the same category (excluding the popular app itself), but also across different categories. Popular app adoption decreases the total usage of apps that had been used before adoption, suggesting that the key sources of positive spillover effects from popular app adoption are increased downloading and usage time of new apps. I find evidence that patronage of app stores, where users search, navigate, and download new apps, significantly increases after the adoption of a popular app.

I perform additional analyses to draw managerial implications that can help various business stakeholders—app platform designers, app developers, and media planners—capitalize on the bandwagon effect of popular apps. Specifically, the analyses were directed toward illuminating the following questions:

- When should new apps be released?
- Which new apps should be launched? and
- To whom should app distribution be targeted?

Results reveal that mobile app developers should coordinate the release schedule of new apps with the lifecycle of popular apps to maximize the discovery and use of their products. This coordinated timing strategy is valid for apps that occupy the same category as a focal popular app and apps belonging to different categories and domains. I also find that app usage increases through the usage of apps that belong to the same platform where a popular app is available. Spillovers among apps offered by the same platform where a popular app is available suggest that mobile platform providers can encourage user engagement with apps by developing and launching such in-demand apps. Further, results also indicate that positive spillover effects of popular app adoption are more pronounced among users with less app experience or low app expertise such as less technologically knowledgeable groups and managerially under-represented target segments (e.g., senior, irregular, occasional, and light app users). The higher spillovers among less tech-savvy users signal that mobile media planners can reach user segments with which they typically have difficulty interacting by scheduling advertising placements in line with the lifecycle of popular apps. All in all, app market stakeholders such as app developers, app platform providers, and media planners, can use popular apps to drive customer engagement thus accelerating performance growth.

2.2. Literature Review

2.2.1. Effects of Increasing Mobile App Usage

Marketing literature has demonstrated that increased usage in mobile apps improves corporate performance. For example, using a branded app increases brand attitude and purchase intention (Bellman et al. 2011) and actual purchase (Kim, Wang, and Malthouse 2015), and firm-generated content in social media increases spending, cross-buying, and customer profitability (Kumar et al. 2016). Furthermore, the adoption of a mobile shopping app is positively associated with immediate and sustained growth in overall purchases on a platform and generates increased sales (Dinner, Van Heerde, and Neslin 2015). To assess return on engagement initiatives (RoEI), Gill, Sridhar, and Grewal (2017) investigated the adoption effect of business-to-business mobile app, which is designed to prompt engagement but not sales. The authors found that the app adoption increases the sales revenues, resulting in positive RoEI. Recent research on the effectiveness of mobile advertising is equally promising. Scholars have investigated the effectiveness of mobile advertising and promotion in various ways, with attention directed particularly toward dimensions such as product characteristics (Bart, Stephen, and Sarvary 2014), location and/or time (Danaher et al. 2015; Fong, Fang, and Luo 2015; Ghose, Goldfarb, and Han 2013; Hui et al. 2013; Luo et al. 2014), and crowdedness (Andrews et al. 2015). In line with this stream of research, the current study probes into the role of popular app adoption as a critical milestone for consumers in enhancing their app consumption behaviors with the specific units of measurement being app usage variety (the number of apps used) and intensity (duration of app usage).

2.2.2. Stimuli for Increased Mobile App Usage

Numerous scholarly works have put forward various stimuli to increase customer purchase. Firm-initiated marketing instruments, such as advertisements and promotions, are designed chiefly to drive customer purchase of a focal advertised product. Several recent studies (e.g., Anderson and Simester 2013; Lewis and Nguyen 2015; Liu, Steenburgh, and Gupta 2015; Sahni 2016; Shapiro 2015) probed into how spillovers from marketing campaigns affect the competitive dynamics among rivals in a product category by focusing on the effects of a focal firm's advertisements and promotion on the sales of its competitors. They revealed that such campaigns produce positive customer purchase for the competing companies instead of the focal firm.

App developers often offer free versions of their paid apps to reduce customer uncertainty about app quality and fit. Arora, Ter Hofstede, and Mahajan (2017) found that this practice of offering free versions of paid apps is negatively associated with the app adoption speed. Releases of new products from a firm may also stimulate customer demand with the firm through positive spillovers on existing products. Xu et al. (2014) found that the release of an app by a major national media company is positively associated with increased demand for the corresponding mobile news website. An important consideration, however, is that the occurrence of positive spillovers depends on product categories or stimulus types. In demonstrating that an online version of a newspaper can cannibalize the sales of its print version, for instance, Gentzkow (2007) discovered the negative spillover effects on demand for existing goods.

The current research expands previous studies on demand spillovers also through an empirical assessment of how such spillovers vary across user preferences and product characteristics. In the empirical work, I quantify the spillover effects of popular app adoption on the usage of other apps by verifying the effectiveness of a popular app. With the exception of Xu et al. (2014), few studies have examined such spillover effects in the mobile context. A noteworthy observation is that prior works, including those presented earlier, generally delved into spillover effects in relation to a single brand/firm or across different brands/firms, but they all extensively centered on spillovers that occur within only a single product category. I extend this research stream by assessing the spillover effects of a popular app on other apps across brands within the same category and across different app categories.

On top of that, recent literature on mobile technologies empirically validated the effectiveness of stimuli – advertisements and promotions, app characteristics, and platform integration that directly aiming at a focal brand. Bart, Stephen, and Sarvary (2014) showed that mobile display advertising improves consumer attitudes toward advertised products and increases purchase intentions but only for high-involvement and utilitarian products. Several other studies found that mobile promotions motivate the purchase of targeted products (e.g., Andrews et al. 2015; Fong, Fang, and Luo 2015; Hui et al. 2013; Luo et al. 2014), influence coupon redemption (e.g., Danaher et al. 2015), and increase click-through (e.g., Ghose, Goldfarb, and Han 2013). Another body of work explored the potential of app characteristics, such as app features and app nature, to increase app demand. Ghose and Han (2014) discovered that app demand increases with the release of in-app purchase features but decreases with the availability of an in-app advertising component that displays advertisements while consumers engage with an app. After analyzing two social apps, Kwon et al. (2016) illustrated that the average social app user rationally adjusts consumption over time to derive optimal utility, albeit the extent of fixation with these apps substantially differs across individuals. Finally, recent work by Li and Agarwal (2016) showed that a social platform's integration of first-party app improves the performance of the first-party app as well as the performance of similar large third-party apps.

The current study contributes to burgeoning research on stimuli for mobile app usage. All the stimuli proposed in previous studies are costly and implemented with the intention to increase usage only with focal apps or platforms. Moreover, the scope of these studies is limited to a small number of apps or a single platform. By contrast, the proposed stimulus (popular app adoption) is a cost-free tool that elevates overall app usage through unintended positive spillovers onto other apps. My large-scale panel data also include all the apps that each panel member accessed during the sample period, thereby greatly enhancing my scope. Table 2.1 summarizes the previous works and compares them with the current study. As shown in the table, my research is the first within the marketing literature to investigate a cost-free stimulus that improves mobile app consumption.

Table 2.1. Stimuli for Enhancing Mobile App Usage

Stimulus types	Costly stimulus?	Spillover effects?	Product categories	Underlying mechanism
Advertising (Anderson and Simester 2013; Lewis and Nguyen 2015; Liu, Steenburgh, and Gupta 2015; Sahni 2016; Shapiro 2015)	Yes	Yes	Within a product category	- Product standards, customer learning, and switching costs (Anderson and Simester 2013) - Consumer memory (Sahni 2016)
New app release (Xu et al. 2014)	Yes	Yes	Within a brand	Content diversity, political propensity, and time constraint (Xu et al. 2014)
Mobile advertising or promotions (Andrews et al. 2015; Bart, Stephen, and Sarvary 2014; Danaher et al. 2015; Fong, Fang, and Luo 2015; Ghose, Goldfarb, and Han 2013; Hui et al. 2013; Luo et al. 2014)	Yes	No	Across product categories	- Mobile immersion (Andrews et al. 2015) - Information processing and persuasion (Bart, Stephen, and Sarvary 2014) - Location, time, and expiration length (Danaher et al. 2015) - Search costs and distance (Ghose, Goldfarb, and Han 2013) - Consumer construal level (Luo et al. 2014)
App feature (Ghose and Han 2014)	Yes	No	Across app categories	In-app purchases and in-app advertising (Ghose and Han 2014)
App nature (Kwon et al. 2016)	No	No	Within an app category	Rational addiction to social apps (Kwon et al. 2016)
Mobile platform integration (Li and Agarwal 2016)	Yes	Yes	Within a brand	Consumer awareness (Li and Agarwal 2016)
Popular app adoption *(the current study)*	*No*	*Yes*	*Across app categories*	*Increased search for and trial of new apps*

2.3. Data and Measures

2.3.1. Data Description

Large-scale panel data that comprise individual users' mobile app and web time-use histories were obtained from Nielsen KoreanClick, a research firm that collects and analyzes information on the Internet and mobile usage of Android users[7]. Android is a dominant operating system of mobile devices worldwide, accounting for 78.3% of the global market in 2013 and 91.4% of the Korean market during my study period[8]. Panel participants of all age groups (teenagers to seniors) were recruited using a stratified sampling method to ensure the representativeness of the population. Nielsen employees who are responsible for panel selection randomly called candidates from the target population and invited them to join the panel[9]. After agreeing to participate, the participants were asked to download and install a tracking app from Nielsen KoreanClick on their mobile devices. After the installation, they were rewarded with incentive points that are redeemable for gift cards. The tracking app ran in the background of the panel member's device and collected information on their use of mobile apps and the mobile web. The tracking app regularly transmitted encrypted log files to a server via a secure cellular connection or Wi-Fi. The data also contain self-reported user demographic information, such as age, gender, monthly income, and educational level.

I note that most of the existing empirical studies on mobile apps and mobile usage

[7] Mobile web is the collective term for websites accessed from mobile devices through browsers. It is thus often used interchangeably with "mobile browser."

[8] Available at http://www.yonhapnews.co.kr/it/2013/12/31/2405000000AKR20131231149900017.HTML (accessed on September 16, 2017)

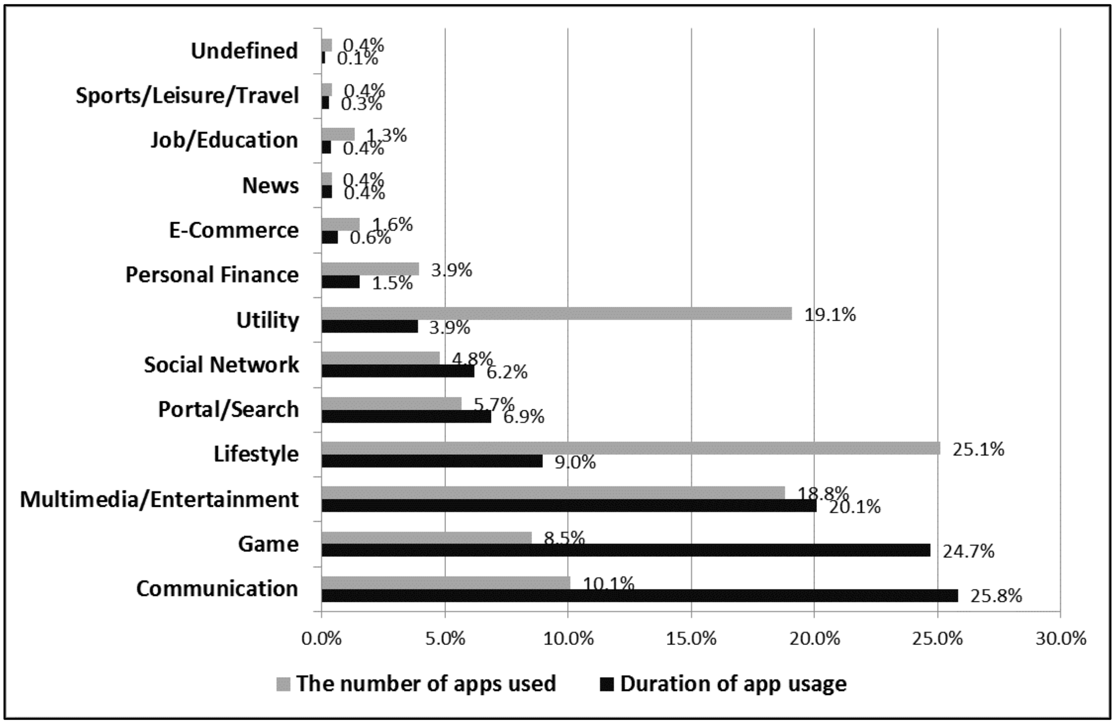
[9] Available at http://www.koreanclick.com/english/solutions/panel_recruiting.html (accessed on September 16, 2017)

are based on app ranking information posted at app stores (e.g., Carare 2012; Garg and Telang 2013), survey data on mobile uses (e.g., Xu et al. 2014), or the number of daily/monthly active users (e.g., Li and Agarwal 2016). These data sets are indirect measures of interest and/or subject to response errors. Compared to these data sets, mine has several advantages. First, it allows me to directly observe what, when, and how much consumers use through mobile channel. Second, it includes all apps and websites subjects use, making it extremely comprehensive. Finally, the tracking app collects information even when mobile devices are not connected to the Internet, and thus, my data provide precise information on mobile use compared to information one might gather from companies' servers.

Between July 23 and November 4, 2012 (15 weeks), the tracking app collected data on 3,156 panel members who used one or more mobile apps every week throughout the sampling period. On a weekly basis, I observed individual access to different mobile apps and visit duration. The smartphone users devoted an average of 1,214 minutes (standard deviation: 818 minutes) every week or 2 hours and 53 minutes per day on average to mobile apps. The panel members accessed an average of 30 different mobile apps each week (standard deviation: 12).

Nielsen KoreanClick classifies mobile apps into 13 broad categories: game, communication, multimedia/entertainment, portal/search, lifestyle, social network, utility, personal finance, e-commerce, news, job/education, sports/leisure/travel, and undefined apps. My empirical analysis adheres to this categorization. Figure 2.1 shows the proportional number of apps used (gray bars) and the proportional duration of app usage (black bars) in each category. Users allocated the largest amount of time (25.8%) to communication apps (e.g., mobile messengers), followed by game apps (24.7%) and multimedia/entertainment apps (e.g., music, video, photo, and book apps) (20.1%). The largest number of apps (25.1%) used were lifestyle apps (e.g., map/navigation, weather, food, and health apps), followed by utility apps (e.g., contact, app stores, clock/alarm, and schedule/memo apps) (19.1%) and multimedia/entertainment apps (18.8%).

Figure 2.1. Variety and Volume of App Usage by App Categories



2.3.2. Choice of Focal Popular App

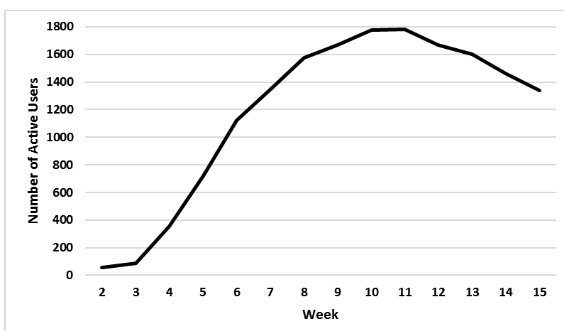
I define the focal popular app as the app which was ranked the highest based on the total usage time among the newly released apps during the sample period. In Table 2.2, the 15 most popular apps (in terms of total usage time) jointly account for 58% of the total app usage. Kakao Talk, a leading communication app in Korea (similar to WhatsApp, WeChat, or Line), is the most frequently used app in my sample. In fact, 98.7% of the panel members used Kakao Talk at least once during the sample period. The average usage time was 242 minutes per week. However, I did not select Kakao Talk as a focal popular app because it was launched in March, 2010, about 2.5 years before my sample period. Anipang is the second most frequently used app in my data. Around 74.6% of the panel members used Anipang at least once during the sample period with average usage time amounting to 246 minutes per week. It was released on July 30, 2012, the second week in my sample period. Thus, I selected Anipang as the focal popular app.

Table 2.2. Top 15 Mobile Apps

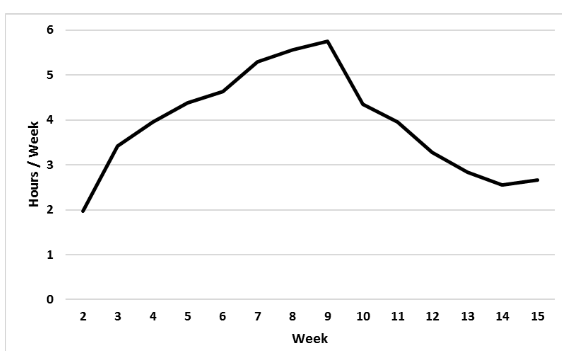
App name	App categories	Total usage time (min.)	Penetration (% of users)
Kakao Talk	Communication	11,016,886	98.7%
Anipang for Kakao	Game	4,066,855	74.6%
Naver	Portal/Search	2,773,975	66.3%
Message	Communication	1,636,667	72.4%
Kakao Story	Social Network	1,591,247	82.7%
Music Player	Multimedia/Entertainment	1,503,870	52.3%
Contact	Utility	1,402,927	98.3%
Dragon Flight for Kakao	Game	1,135,466	51.5%
I Love Coffee for Kakao	Game	950,261	17.0%
Samsung Music Player	Multimedia/Entertainment	843,716	32.6%
Samsung Video Player	Multimedia/Entertainment	779,039	66.6%
Facebook	Social Network	684,416	46.8%
Samsung TV	Multimedia/Entertainment	668,898	56.5%
Daum	Portal/Search	666,109	24.3%
YouTube	Multimedia/Entertainment	645,419	91.7%

Anipang is a timed puzzle game in which players match three or more identical icons to obtain a high score. The game is free to download. To play the game, one has to pay a virtual game token which is automatically generated every 8 minutes, with a maximum storage of 5 free tokens. Players can also purchase additional game tokens within the app. A distinctive feature of this game is that it runs on Kakao Talk's communication platform, thereby leveraging the viral mechanics of messaging platforms. For instance, Anipang players can exchange game tokens through messages on Kakao Talk. A user who has not downloaded the game and clicks on a token is directed to a download page. An Anipang player can likewise be motivated by details regarding leaderboard-based competition displayed in his or her Kakao Talk contact list. Figure 2.2 depicts the number of active Anipang users and the weekly average Anipang usage time per user, respectively. The number of active Anipang users increases in the first 9 weeks after the release of Anipang and decreases afterward, while the weekly average duration of Anipang usage per user increases in the first 7 weeks and then decreases at a faster pace.

Figure 2.2. Lifecycle of Anipang



(a) The number of active Anipang users per week



(b) Weekly average duration of Anipang usage per user

2.4. Empirical Approach

In what follows, I describe my empirical approach to measure the effects of popular app adoption on mobile app usage. I empirically gauged the spillover effects of Anipang adoption on the number of apps accessed and app usage duration. To this end, I conducted a Gaussian copula-based difference-in-differences (DID) analysis. The negative binomial or Poisson regression was used to model the number of apps accessed, and the log-normal regression was employed to model app usage duration. If the two dependent variables have common unobserved factors (to researchers), failure to capture such factors will lead to poor estimation results (Danaher and Smith 2011). Thus, I jointly model the two dependent variables, each with distinct distribution by employing a Gaussian copula function. To control for potential selection biases, I utilized propensity score matching for the treatment group (Anipang adopters) and the corresponding "one-ahead look-forward" control group (Anipang non-adopters who adopted Anipang one week after the treatment group adopted it). I comprehensively discuss the model in the subsequent sub-section.

2.4.1. Gaussian Copula-Based Difference-in-Differences Model

To quantify the spillover effects of popular app adoption on app usage, I used the Gaussian copula-based DID approach which extends the traditional DID model to the multivariate setting. The DID analysis compares a treatment group (TG) to a control group (CG) before and after the adoption of Anipang. I selected the panelists who used apps every week during my 15-week sample period. I identified 3,156 users and noted 47,340 (= 15 weeks × 3,156 users) observations. In my analysis, the TG is a group of

Anipang adopters, whereas the CG comprises Anipang non-adopters.

I used the number of apps used and the log-transformed app usage duration from all the apps (except Anipang) as the outcome variables (dependent variables) in the DID model. The DID model is specified by

$$\begin{cases} \Pr(N_{it} = n) = \frac{\Gamma(\theta + n)}{\Gamma(n+1)\Gamma(\theta)} r_{it}{}^{n}(1 - r_{it})^{\theta},\ r_{it} = \frac{\mu_{it}}{\theta + \mu_{it}} \text{ and } \mu_{it} = \exp(\alpha_i^N + \beta_t^N + \delta I_{it}) \\ T_{it} = \alpha_i^T + \beta_t^T + \gamma I_{it} + \varepsilon_{it} \end{cases} \tag{2.1}$$

for user i (i=1, 2, …, 3,156) at week t (t=1, 2, …, 15). The first equation is the negative binomial regression model for the number of apps used and the second equation is the log-normal regression model for app usage duration. N_{it} denotes the number of apps used and $T_{it} = \ln(1+\text{AppUsageDuration}_{it})$ denotes the log-transformed app usage duration. I exclude Anipang usage in computing N_{it} and T_{it} to focus on the spillover effects of Anipang adoption.

In Equation (2.1), α_i^N and α_i^T are user fixed effects that control for the unobserved heterogeneity across users, β_t^N and β_t^T are week fixed effects that capture the unobserved temporal effects common to all users,

$$I_{it} = \begin{cases} 1, \text{ if } (\text{user } i \in \text{TG}) \text{ and } (t \geq \text{user } i\text{'s Anipang adoption week}) \\ 0, \text{ Otherwise} \end{cases},$$

and ε_{it} are error terms. In the negative binomial regression specification (the first equation in Equation (2.1)), μ_{it} is the expectation of N_{it} and $1/\theta$ (> 0) is a dispersion or heterogeneity parameter. For identification, I set the week fixed effect of the last week to zero. The coefficients of main interest are δ, which estimates the spillover effect of Anipang adoption on number of apps used, and γ, which estimates the spillover effect of Anipang adoption on app usage duration. I note that both δ and γ can be interpreted as percent change in my model specification. I estimated Equation (2.1) using N_{it} and T_{it} based on all app categories and based on each of the eight major app categories: game, communication, multimedia/entertainment, portal/search, lifestyle, social network, utility, and other apps, respectively. I note that I merged the app categories of which usage duration shares are less than 2% (Figure 2.1) into other apps. I also note that in the negative binomial regression model, if $1/\theta$ is equal to zero, then the negative binomial regression model becomes the Poisson regression model. I found that this is the case for all categories except the game app category. Accordingly, I used the Poisson regression to model the number of apps used in these seven app categories.

I jointly estimated the two equations in Equation (2.1) because the two dependent variables of interest, the number of apps used and app usage duration, can all be influenced by common unobserved factors. For example, if a game platform runs a special promotion, users might spend more time playing games and try several new games. Consequently, there might be a potential correlation between unobserved random shocks in the number of apps used and app usage duration in Equation (2.1). I can capture such correlation using a bivariate model. However, I cannot use a regular bivariate model because the number of apps used follows the discrete negative binomial or Poisson distribution while app usage duration follows the continuous log-normal distribution. In this case, a copula model is widely used to construct a joint model of those two distinct marginal distributions. Among many copula functions, the Gaussian copula is known as flexible and robust in many applications in studies and it expresses an explicit correlation between two random variables enabling me to interpret the correlation easily (See Danaher and Smith (2011) and Park and Gupta (2012) for details of copula functions).

Thus, I used the Gaussian copula function to model the correlation between unobserved random shocks in the number of apps used and app usage duration. I first defined a latent standard normal variable ω_{it} which is related to the number of apps used N_{it} as follows,

$$\{N_{it} = n\} \text{ is equivalent to } \{\Pr(N_{it} \leq n - 1) \leq \Phi(\omega_{it}) < \Pr(N_{it} \leq n)\},$$

where $\Phi(\cdot)$ is a standard normal cumulative distribution function. I next used the Gaussian copula to model the correlation between unobserved random shocks in the number of apps used and app usage duration as follows,

$$\begin{bmatrix} \omega_{it} \\ \varepsilon_{it} \end{bmatrix} \sim N\left(\begin{bmatrix} 0 \\ 0 \end{bmatrix}, \begin{bmatrix} 1 & \rho\sigma_{\varepsilon} \\ \rho\sigma_{\varepsilon} & \sigma_{\varepsilon}^2 \end{bmatrix}\right), \tag{2.2}$$

where ω_{it}~$N(0, 1)$ and ε_{it}~$N(0, \sigma_{\varepsilon}^2)$. The coefficient ρ denotes the correlation between unobserved random shocks in the number of apps used and app usage duration. The proposed model is similar to Heckman's (1979) or Lee's (1983) selectivity models in the way that it links a discrete variable to a continuous outcome. For model estimation, I used a two-step estimation procedure as in Heckman (1979) and Lee (1983) (See the Appendix A for details).

2.4.2. Propensity Score Matching

Some unobservable factors (to researchers) may affect both the decision of users to adopt Anipang and the consumption of other apps. For example, a user upgrades her mobile data plan. Subsequently, she downloads several popular apps including Anipang and increases overall mobile usage. Such unobserved factors may cause an endogeneity problem. To tackle this, I used the propensity score matching and the one-ahead look-forward CG along with the Gaussian copula-based DID analysis.

Each week, I selected a one-ahead look-forward CG for analysis. In week 2, for example, the one-ahead look-forward CG corresponding to the TG that adopted Anipang in week 2 is the user group that adopted Anipang in week 3. In week 2, unlike TG, these users had not adopted Anipang but they adopted it in week 3 and thus one-ahead look-forward CG is the closet to TG with respect to the treatment (Anipang adoption) among non-adopters. Because some unobserved factors affect Anipang adoption timing, I posit that Anipang adopters whose adoption timing is close are less likely to have selection bias on unobservables (which are associated with adoption timing of Anipang).

Using the original TG and the corresponding one-ahead look-forward CG in the new sample, I implemented a static one-to-one matching without replacement to pair the adopters and the non-adopters of Anipang, in which the non-adopters are the most similar to the adopters under a caliper size of 0.2 times the standard deviation of the adopters' propensity scores[10] by referring to Rosenbaum and Rubin (1985) and Xu et al. (2017). The propensity scores were calculated using a logit regression model. Specifically, the dependent variable was the indicator for Anipang adoption (i.e., 1 if adopted, 0 otherwise), and the covariates were the previous week's log-transformed app usage time for 15 app categories[11] and 4 categorical demographic variables (age, gender, income, and education). The propensity scores are defined as the predicted probabilities from the logit regression model. My matched sample includes 2,349 users and 33,656 observations. Using several

[10] This was the main sample used for the subsequent data analyses unless otherwise stated.

[11] These 15 app categories are Kakao games (excl. Anipang), other games (excl. Kakao games), Kakao Talk, other communication platforms (excl. Kakao Talk), e-commerce, multimedia/entertainment, personal finance, portal/search, job/education, lifestyle, news, social network, sports/leisure/travel, utility, and undefined app categories.

formal tests, I ensured that TG and CG are comparable in terms of propensity scores (See the Appendix B for details).

2.5. Results

2.5.1. Positive Spillover Effects of Popular App Adoption

In Table 2.3, after comparing the average number of apps used and app usage duration before and after Anipang adoption, I find that after Anipang adoption, the number of apps used in total and in each of app categories increased. Total app usage duration increased, but at the category level, duration increased only in the game and communication app categories. These model-free summary statistics shed light on the positive spillover effects of popular app adoption on both the app usage volume and variety, suggesting the potential of popular apps as a tool that might boost mobile app usage.

Table 2.3. Comparison of App Usage Before and After Anipang Adoption

App categories	Average number of apps used (per week)		Average duration of app usage (minutes per week)	
	Before Anipang adoption	After Anipang adoption	Before Anipang adoption	After Anipang adoption
Total	28.69 (11.52)	32.22 (12.15)	1071.40 (784.99)	1216.52 (777.38)
Game	1.89 (2.69)	2.87 (3.26)	173.79 (430.70)	279.17 (442.22)
Communication	3.07 (1.19)	3.09 (1.15)	286.84 (309.04)	348.12 (340.12)
Multimedia/Entertainment	5.67 (2.96)	6.01 (2.99)	247.65 (364.37)	242.78 (360.02)
Portal/Search	1.71 (1.31)	1.79 (1.32)	89.41 (173.05)	78.90 (151.55)
Lifestyle	7.37 (3.80)	8.11 (4.03)	109.31 (176.56)	104.97 (161.34)
Social Network	1.44 (1.23)	1.59 (1.23)	81.10 (165.27)	80.26 (148.06)
Utility	5.35 (3.14)	6.13 (3.59)	44.40 (123.97)	43.97 (101.86)
Other Apps	2.19 (2.29)	2.61 (2.74)	38.90 (109.89)	38.34 (96.91)

Note: Standard deviations are in parentheses.

I formally verify the above model-free evidence by estimating the Gaussian copula-based DID model (Equations (2.1) and (2.2)) in total and across app categories using each of nine matched samples and two unmatched samples. The results are summarized in Tables 2.4 – 2.6. First, with respect to the number of apps used, the $\hat{\delta}$'s in Tables 2.4 – 2.6 show that the spillover effects of Anipang adoption are statistically significant and positive in total and across all app categories except communication and portal/search app categories. Anipang adoption increases the total number of apps used by 4.2% – 6.6% ($\hat{\delta}$'s in Table 2.4), and it increases the number of game apps used by 20.7% – 25.6% at the highest level ($\hat{\delta}$'s in Tables 2.5 – 2.6). Second, with respect to app usage duration, the $\hat{\gamma}$'s in Table 2.4 illustrate that the spillover effect of Anipang adoption on total app usage duration is significantly positive. Anipang adopters increase their total app usage duration by 8.1% – 12.1%. The effects of Anipang adoption are also significantly positive across different app categories except the multimedia/entertainment app category ($\hat{\gamma}$'s in Tables 2.4 – 2.6). Specifically, Anipang adoption increases the usage time allocated to game and communication apps by 52.8% – 76.2% and 21.2% – 29.2%, respectively. This result indicates that the positive spillover effect of Anipang adoption on app usage duration is pronounced in the game and communication app categories which are closely related to Anipang and its platform, Kakao Talk, respectively.

Table 2.4. Main Estimation Results – Total

Samples	Number of apps used ($\hat{\delta}$)	App usage duration ($\hat{\gamma}$)§	Correlation ($\hat{\rho}$)§	N. Obs.
1-ahead look-forward CG				
Static matching with Caliper size of 0.2 x Std. Dev.				
Without replacement	0.058 (0.005)***	0.104 (0.013)***	0.490 (0.006)***	33,656
With replacement	0.045 (0.005)***	0.111 (0.012)***	0.492 (0.007)***	35,447
Static matching with Caliper size of 0.05 x Std. Dev.				
Without replacement	0.055 (0.005)***	0.097 (0.014)***	0.489 (0.007)***	32,019
With replacement	0.043 (0.005)***	0.109 (0.013)***	0.492 (0.007)***	35,353
Dynamic matching with Caliper size of 0.2 x Std. Dev.				
Without replacement	0.066 (0.005)***	0.102 (0.016)***	0.492 (0.007)***	31,414
With replacement	0.053 (0.005)***	0.121 (0.014)***	0.486 (0.007)***	36,296
Dynamic matching with Caliper size of 0.05 x Std. Dev.				
Without replacement	0.061 (0.005)***	0.107 (0.014)***	0.495 (0.007)***	29,776
With replacement	0.055 (0.005)***	0.121 (0.015)***	0.487 (0.006)***	36,074
No matching				
	0.059 (0.005)***	0.098 (0.012)***	0.492 (0.008)***	35,217
2-ahead look-forward CG				
Static matching with Caliper size of 0.2 x Std. Dev.				
Without replacement	0.059 (0.005)***	0.108 (0.014)***	0.487 (0.007)***	32,696
No look-forward CG				
No matching	0.042 (0.004)***	0.081 (0.010)***	0.473 (0.006)***	47,340

*significant at 0.1 level; **significant at 0.05 level; ***significant at 0.01 level
Note: Standard errors are in parentheses (§ bootstrapped standard errors).

Table 2.5. Main Estimation Results by App Categories (I)

Samples	Game			Communication		
	Number of apps used ($\hat{\delta}$)	App usage duration ($\hat{\gamma}$)[§]	Correlation ($\hat{\rho}$)[§]	Number of apps used ($\hat{\delta}$)	App usage duration ($\hat{\gamma}$)[§]	Correlation ($\hat{\rho}$)[§]
1-ahead look-forward CG						
Static matching with Caliper size of 0.2 x Std. Dev.						
Without replacement	0.237 (0.017)***	0.704 (0.056)***	0.806 (0.006)***	0.023 (0.012)*	0.281 (0.017)***	0.525 (0.012)***
With replacement	0.219 (0.018)***	0.531 (0.064)***	0.794 (0.003)***	0.024 (0.013)*	0.292 (0.017)***	0.529 (0.014)***
Static matching with Caliper size of 0.05 x Std. Dev.						
Without replacement	0.238 (0.018)***	0.697 (0.059)***	0.804 (0.003)***	0.018 (0.013)	0.286 (0.021)***	0.529 (0.014)***
With replacement	0.217 (0.018)***	0.528 (0.064)***	0.795 (0.003)***	0.023 (0.013)*	0.290 (0.018)***	0.530 (0.014)***
Dynamic matching with Caliper size of 0.2 x Std. Dev.						
Without replacement	0.246 (0.018)***	0.714 (0.060)***	0.809 (0.003)***	0.024 (0.013)*	0.281 (0.021)***	0.541 (0.016)***
With replacement	0.220 (0.017)***	0.542 (0.059)***	0.792 (0.003)***	0.020 (0.013)	0.276 (0.018)***	0.549 (0.013)***
Dynamic matching with Caliper size of 0.05 x Std. Dev.						
Without replacement	0.254 (0.019)***	0.687 (0.061)***	0.807 (0.003)***	0.020 (0.013)	0.286 (0.018)***	0.528 (0.014)***
With replacement	0.222 (0.018)***	0.535 (0.059)***	0.792 (0.003)***	0.020 (0.013)	0.279 (0.017)***	0.549 (0.012)***
No matching						
	0.256 (0.017)***	0.748 (0.055)***	0.806 (0.003)***	0.024 (0.012)**	0.275 (0.018)***	0.529 (0.013)***
2-ahead look-forward CG						
Static matching with Caliper size of 0.2 x Std. Dev.						
Without replacement	0.228 (0.018)***	0.675 (0.055)***	0.804 (0.003)***	0.022 (0.012)*	0.291 (0.021)***	0.530 (0.013)***
No look-forward CG						
No matching	0.207 (0.014)***	0.762 (0.042)***	0.838 (0.002)***	0.009 (0.009)	0.212 (0.015)***	0.545 (0.009)***
Samples	**Multimedia/Entertainment**			**Portal/Search**		
	Number of apps used ($\hat{\delta}$)	App usage duration ($\hat{\gamma}$)[§]	Correlation ($\hat{\rho}$)[§]	Number of apps used ($\hat{\delta}$)	App usage duration ($\hat{\gamma}$)[§]	Correlation ($\hat{\rho}$)[§]
1-ahead look-forward CG						
Static matching with Caliper size of 0.2 x Std. Dev.						
Without replacement	0.044 (0.009)***	0.038 (0.029)	0.628 (0.005)***	0.018 (0.016)	0.143 (0.039)***	0.804 (0.003)***
With replacement	0.029 (0.010)***	0.040 (0.032)	0.645 (0.005)***	0.005 (0.017)	0.029 (0.036)	0.812 (0.003)***
Static matching with Caliper size of 0.05 x Std. Dev.						
Without replacement	0.039 (0.009)***	0.009 (0.029)	0.630 (0.005)***	0.020 (0.017)	0.151 (0.041)***	0.806 (0.003)***
With replacement	0.028 (0.010)***	0.038 (0.032)	0.646 (0.005)***	0.003 (0.017)	0.023 (0.040)	0.812 (0.003)***
Dynamic matching with Caliper size of 0.2 x Std. Dev.						
Without replacement	0.046 (0.009)***	0.033 (0.031)	0.635 (0.004)***	0.021 (0.017)	0.131 (0.045)***	0.806 (0.003)***
With replacement	0.042 (0.009)***	0.099 (0.035)***	0.646 (0.004)***	0.036 (0.017)**	0.167 (0.036)***	0.816 (0.003)***
Dynamic matching with Caliper size of 0.05 x Std. Dev.						
Without replacement	0.044 (0.010)***	0.067 (0.033)**	0.640 (0.005)***	0.019 (0.017)	0.114 (0.048)**	0.806 (0.003)***
With replacement	0.043 (0.009)***	0.102 (0.031)***	0.647 (0.004)***	0.039 (0.017)**	0.171 (0.050)***	0.816 (0.003)***
No matching						
	0.038 (0.009)***	0.004 (0.029)	0.628 (0.004)***	0.023 (0.016)	0.159 (0.045)***	0.802 (0.003)***
2-ahead look-forward CG						
Static matching with Caliper size of 0.2 x Std. Dev.						
Without replacement	0.039 (0.009)***	0.020 (0.026)	0.628 (0.005)***	0.022 (0.016)	0.178 (0.033)***	0.803 (0.003)***
No look-forward CG						
No matching	0.013 (0.007)*	−0.028 (0.020)	0.636 (0.004)***	0.022 (0.013)*	0.092 (0.043)**	0.809 (0.002)***

*significant at 0.1 level; **significant at 0.05 level; ***significant at 0.01 level

Note 1: Standard errors are in parentheses (§ bootstrapped standard errors).

Note 2: The number of observation for each sample is given at Table 2.4.

Table 2.6. Main Estimation Results by App Categories (II)

Samples	Lifestyle			Social Network		
	Number of apps used (δ)	App usage duration (γ)§	Correlation (ρ)§	Number of apps used (δ)	App usage duration (γ)§	Correlation (ρ)§
1-ahead look-forward CG						
Static matching with Caliper size of 0.2 x Std. Dev.						
Without replacement	0.047 (0.008)***	0.067 (0.022)***	0.507 (0.006)***	0.058 (0.017)***	0.284 (0.040)***	0.911 (0.002)***
With replacement	0.038 (0.008)***	0.050 (0.023)**	0.523 (0.007)***	0.045 (0.019)**	0.178 (0.039)***	0.912 (0.002)***
Static matching with Caliper size of 0.05 x Std. Dev.						
Without replacement	0.045 (0.008)***	0.061 (0.022)***	0.506 (0.007)***	0.053 (0.018)***	0.270 (0.035)***	0.912 (0.003)***
With replacement	0.036 (0.008)***	0.045 (0.023)*	0.522 (0.006)***	0.044 (0.015)***	0.173 (0.036)***	0.912 (0.002)***
Dynamic matching with Caliper size of 0.2 x Std. Dev.						
Without replacement	0.057 (0.008)***	0.065 (0.025)***	0.506 (0.006)***	0.067 (0.018)***	0.288 (0.034)***	0.915 (0.002)***
With replacement	0.026 (0.008)***	0.091 (0.024)***	0.512 (0.006)***	0.024 (0.018)	0.138 (0.040)***	0.920 (0.002)***
Dynamic matching with Caliper size of 0.05 x Std. Dev.						
Without replacement	0.048 (0.008)***	0.064 (0.023)***	0.506 (0.006)***	0.072 (0.019)***	0.285 (0.041)***	0.916 (0.002)***
With replacement	0.028 (0.008)***	0.091 (0.024)***	0.513 (0.007)***	0.027 (0.018)	0.147 (0.040)***	0.921 (0.002)***
No matching						
	0.049 (0.007)***	0.061 (0.021)***	0.507 (0.006)***	0.054 (0.017)***	0.260 (0.033)***	0.909 (0.003)***
2-ahead look-forward CG						
Static matching with Caliper size of 0.2 x Std. Dev.						
Without replacement	0.051 (0.008)***	0.081 (0.023)***	0.505 (0.006)***	0.065 (0.018)***	0.305 (0.037)***	0.910 (0.003)***
No look-forward CG						
No matching	0.034 (0.006)***	0.033 (0.013)***	0.495 (0.003)***	0.049 (0.014)***	0.187 (0.036)***	0.923 (0.002)***
Samples	**Utility**			**Other Apps**		
	Number of apps used (δ)	**App usage duration (γ)§**	**Correlation (ρ)§**	**Number of apps used (δ)**	**App usage duration (γ)§**	**Correlation (ρ)§**
1-ahead look-forward CG						
Static matching with Caliper size of 0.2 x Std. Dev.						
Without replacement	0.033 (0.009)***	0.113 (0.027)***	0.577 (0.004)***	0.103 (0.014)***	0.159 (0.038)***	0.813 (0.003)***
With replacement	0.010 (0.010)	0.070 (0.027)**	0.579 (0.005)***	0.047 (0.015)***	–0.030 (0.046)	0.825 (0.003)***
Static matching with Caliper size of 0.05 x Std. Dev.						
Without replacement	0.031 (0.009)***	0.114 (0.028)***	0.576 (0.004)***	0.108 (0.014)***	0.173 (0.042)***	0.816 (0.003)***
With replacement	0.009 (0.010)	0.070 (0.024)***	0.578 (0.005)***	0.044 (0.015)***	–0.037 (0.047)	0.825 (0.003)***
Dynamic matching with Caliper size of 0.2 x Std. Dev.						
Without replacement	0.044 (0.009)***	0.128 (0.031)***	0.577 (0.005)***	0.114 (0.014)***	0.196 (0.040)***	0.815 (0.003)***
With replacement	0.052 (0.009)***	0.084 (0.027)***	0.579 (0.005)***	0.046 (0.014)***	–0.061 (0.035)*	0.822 (0.003)***
Dynamic matching with Caliper size of 0.05 x Std. Dev.						
Without replacement	0.039 (0.010)***	0.137 (0.026)***	0.575 (0.005)***	0.095 (0.015)***	0.136 (0.047)***	0.821 (0.003)***
With replacement	0.053 (0.009)***	0.085 (0.025)***	0.580 (0.004)***	0.048 (0.015)***	–0.051 (0.041)	0.822 (0.003)***
No matching						
	0.033 (0.009)***	0.102 (0.028)***	0.574 (0.004)***	0.103 (0.013)***	0.169 (0.041)***	0.811 (0.003)***
2-ahead look-forward CG						
Static matching with Caliper size of 0.2 x Std. Dev.						
Without replacement	0.034 (0.009)***	0.107 (0.022)***	0.576 (0.005)***	0.095 (0.014)***	0.168 (0.043)***	0.814 (0.003)***
No look-forward CG						
No matching	0.020 (0.007)***	0.065 (0.019)***	0.570 (0.004)***	0.061 (0.011)***	0.116 (0.037)***	0.816 (0.002)***

*significant at 0.1 level; **significant at 0.05 level; ***significant at 0.01 level

Note 1: Standard errors are in parentheses (§ bootstrapped standard errors).

Note 2: The number of observation for each sample is given at Table 2.4.

I empirically validated my Gaussian copula-based DID model over the traditional DID model (See the Appendix C for details). Upon verifying the use of the Gaussian copula for my empirical analyses, I omit the estimation results of correlations in subsequent sections.

2.5.2. Robustness Checks

I used a series of alternative matching algorithms to verify the robustness of the results as shown in Tables 2.4 – 2.6. That is, I utilized one-to-one matching with replacement, a smaller caliper size of 0.05, and the two-ahead look-forward CG. I also employed dynamic matching, in which the propensity scores were calculated for the two groups of Anipang adopters: a TG that adopted Anipang between weeks 2 and 6, during which the number of new Anipang adopters increased, as well as a TG that adopted Anipang between weeks 7 and 14, when the number of new Anipang adopters decreased. The dynamic matching accounted for unobserved time-varying factors that may have influenced the trend of Anipang adoption in the matching process. Additionally, I conducted the Gaussian copula-based DID analyses using a sample using the one-ahead look-forward CG but without propensity score matching and another sample without both aforementioned components. The core results remained unchanged in all the different settings[12].

To further improve the robustness of my findings, I used an alternative copula, the Farlie–Gumbel–Morgenstern (FGM) copula other than the Gaussian copula. The FGM copula is one of the most popular copula functions in empirical analyses. I found

[12] I report only the key estimates here but the unreported results are available upon request.

consistent results from the FGM copular-based DID models in Table 2.7.

Table 2.7. Estimation Results on App Usage Duration Using FGM Copula

App categories	App usage duration ($\hat{\gamma}$)
Total	0.121 (0.014)***
Game	0.728 (0.058)***
Communication	0.283 (0.017)***
Multimedia/Entertainment	0.055 (0.030)*
Portal/Search	0.149 (0.040)***
Lifestyle	0.078 (0.022)***
Social Network	0.306 (0.041)***
Utility	0.121 (0.028)***
Other Apps	0.188 (0.041)***

*significant at 0.1 level; **significant at 0.05 level; ***significant at 0.01 level
Note 1: Bootstrapped standard errors are in parentheses.
Note 2: I omit the results on the number of apps used because they are the same as the results using Gaussian copula due to two-step estimation procedure.
Note 3: The number of observation is 33,656.

2.5.3. Uncovering Paths to the Increase in Mobile App Usage

In this section, I shed light on the underlying mechanisms of the positive spillover effect from popular app adoption by leveraging the richness of my data. In particular, I examine increased search for new apps and increased trial of new apps.

2.5.3.1. Search for New Apps

Users search, navigate, and download new apps through app stores. I consider app store usage as a measurement of users' new app search behaviors. In this section, I empirically examine the impact of Anipang adoption on the use of app stores as a proxy measurement for new app downloads or intention to download new apps. I used four major app store apps, namely Google's Play Store, T Store, KT Olleh Market, and LG U+ Store, collectively accounting for 60% of the revenue market share in South Korea in 2012[13] in this analysis. The last three are pre-installed by mobile service providers in South Korea. I found that Anipang adoption increases the number of app store apps used by 6.9% (p-value < 0.01) and the usage duration of app store apps by 44.3% (p-value < 0.01). These results indicate that users visit more app stores and spend more time in those app stores after adopting a popular app. A popular app adoption triggers mobile user to search for new attractive apps to buy and use.

2.5.3.2. Use of New Apps

Upon increased searches for new apps at app stores, users can decide to download new apps and begin to use them. I examine whether the spillover effect I found from my main results is attributable to increased usage in existing apps or new apps. To answer this question, I defined "existing apps" as the apps that have been used in four or more weeks before Anipang adoption and "new apps" as the apps that have never been used during those weeks but have been used after Anipang adoption. To this end, I removed the panel members who adopted Anipang during the first four weeks of sample period. Results in Table 2.8 show that Anipang adoption decreases both the number of apps used and the duration of app usage for existing apps (except for the usage duration of communication apps). Current results on existing apps indicate that increased app usage due to popular app adoption stems from increased usage of new apps, rather than increased usage of existing apps.

[13] Apple's App Store accounts for 30% (source: Korea Mobile Internet Business Association).

Table 2.8. Estimation Results for Existing Apps

App categories	Number of apps used ($\hat{\delta}$)	App usage duration ($\hat{\gamma}$)§
Total	–0.206 (0.006)***	–0.064 (0.019)***
Game	–0.551 (0.022)***	–0.914 (0.054)***
Communication	–0.083 (0.014)***	0.173 (0.025)***
Multimedia/Entertainment	–0.174 (0.011)***	–0.341 (0.035)***
Portal/Search	–0.178 (0.019)***	–0.266 (0.040)***
Lifestyle	–0.182 (0.009)***	–0.148 (0.029)***
Social Network	–0.089 (0.021)***	–0.037 (0.037)
Utility	–0.260 (0.011)***	–0.118 (0.029)***
Other Apps	–0.272 (0.017)***	–0.559 (0.046)***

*significant at 0.1 level; **significant at 0.05 level; ***significant at 0.01 level
Note 1: Standard errors are in parentheses (§ bootstrapped standard errors).
Note 2: The number of observation is 33,656.

Next, I empirically examine the relationship between new app usage and app store usage. To check whether app store usage positively affects new app usage upon the adoption of Anipang, I conducted a simple linear regression analysis and found a significant and positive relationship between app store usage and new app usage after controlling for user and week fixed effects. The estimated regression coefficient of the number of app store apps used on the number of new apps used is 2.772 (p-value < 0.01), and the estimated regression coefficient of app store usage duration on new app usage duration is 0.769 (p-value < 0.01). In summary, the adoption of popular app increases app usage by driving users to visit more app store apps and spend more time on those app store apps and thereby leading them to navigate/download more apps and allocate more time to those new apps.

2.6. Managerial Implications

I empirically validated the potential of popular apps as nonintrusive and cost-effective drivers for increasing app usage. I used Anipang as a popular app and found that it stimulates the adoption and use of new apps. The results highlight several key practical strategies for consideration by mobile app platform providers, media planners, and mobile app developers.

2.6.1. Mobile App Platform Strategies

A noteworthy feature of Anipang is that it runs on Kakao Talk, which has been number one communication app in terms of penetration and usage in South Korea. Leveraging the app's popularity, the makers of Kakao Talk launched Kakao Story, a social networking app, in March 2012 after which they introduced a series of gaming apps, including Anipang. This succession of strategic moves translated to a powerful platform in which users can easily access apps in a variety of categories and exchange information with other users. This background allowed me to tap into the platform aspect of my focal popular app and its spillover effects. Specifically, I measured the spillover effects of Anipang adoption on apps offered within the same platform (Kakao Talk, gaming apps that run on Kakao Talk, and Kakao Story) from which Anipang is available versus apps outside the platform. In other words, I examined whether the spillover effects are contained within the platform where the focal popular app is offered or if they spread to avenues external to the platform. Table 2.9 shows stronger positive spillover effects from Anipang adoption on apps offered within the same platform as that of Anipang than on apps available outside the platform. This result may be due to (1) the stronger sociability of the popular app, (2) the closer proximity of other apps to the popular app within the platform, and/or (3) the higher promotional capabilities of the Anipang platform.

Table 2.9. Estimation Results for Apps Within and Outside the Platform

Within the same platform	Number of apps used ($\hat{\delta}$)	App usage duration ($\hat{\gamma}$)§
Total	0.155 (0.015)***	0.629 (0.026)***
Kakao Talk	0.028 (0.022)	0.566 (0.023)***
Games run on Kakao Talk	1.243 (0.048)***	1.018 (0.048)***
Kakao Story	0.093 (0.026)	0.379 (0.040)***
Outside the platform	**Number of apps used ($\hat{\delta}$)**	**App usage duration ($\hat{\gamma}$)§**
Total	0.052 (0.005)***	0.019 (0.015)
Communication	0.021 (0.015)	0.007 (0.019)
Game	0.163 (0.019)***	0.530 (0.057)***
Social Network	0.033 (0.023)	–0.011 (0.036)

*significant at 0.1 level; **significant at 0.05 level; ***significant at 0.01 level
Note 1: Standard errors are in parentheses (§ bootstrapped standard errors).
Note 2: The number of observation is 33,656.

The stronger positive spillovers from popular app adoption among apps within the platform suggest that mobile app platforms can improve customer engagement by utilizing the bandwagon effect of popular apps. For example, the evolution of new apps into popular products enables the compensation of investments in the purchase or development of new apps or the promotion of newly released apps within the platform (e.g., offering free bonus coupons). A practical example would be Microsoft Windows. With Windows 3.0 and 3.1, Microsoft offered an assortment of games, including Solitaire, Minesweeper, Hearts, and FreeCell, to heighten the aptitude with which users navigate the system (Hunt 2015). These games became extremely popular because of their inherently enjoyable and addictive nature. As stated by Compeau and Higgins (1995), encouragement by others and others' use of the addictive games may have reinforced computer self-efficacy while reducing computer anxiety. As a consequence, the popular games freely available on early Windows versions amplified the appeal of newer variants and fueled their adoption and use. Microsoft's latest upgrade, Windows 10, capitalizes on the popularity of such games to motivate users to access Windows

Store (a core system feature) to download apps other than the pre-installed Solitaire (Hunt 2015). The Windows 10 is also pre-loaded with Candy Crush Saga as a means of boosting system appeal and in-app purchases from Windows Store[14].

2.6.2. Mobile App User Targeting Strategies

The effects of popular app adoption on app usage growth can vary across user groups. Increased app usage due to popular app adoption can be explained by individuals' prior app usage experiences and levels of app expertise. I expect that such effects to be more pronounced among user groups with low app expertise because they are more likely to associate higher perceived switching costs with apps given their lack of experiences and skills in using apps. To empirically verify this assertion, I compared the spillover effects of popular app adoption on app consumption among users with low and high expertise in mobile apps.

Using available demographic and behavioral variables, I selected six user groups with low app expertise and regarded the remaining users in the sample as the high-expertise group. I first chose senior app users—aged 50 years or older— as one of the members of the low expertise group. This group also comprised irregular app users, whose coefficient of variation (CV = mean / standard deviation) in weekly total app usage duration is greater than the overall median; occasional app users, whose average number of apps used per week is less than the overall median; light app users, whose average app usage duration per week is less than the overall median; and mobile game

[14] Available at http://www.idigitaltimes.com/candy-crush-saga-available-windows-10-download-it-here-463418 (accessed on November 28, 2016)

novices, who had never used any game apps during the calibration sample period (April 30, 2012 – July 15, 2012). To this group, I also added late adopters, who adopted Anipang after the first 5 weeks of the app's release. The number of new Anipang adopters increased in the first 5-week period and decreased afterward.

I estimated the spillover effect of Anipang adoption on app usage among users with low app expertise relative to their corresponding users with high app expertise (See the Appendix D for the model specification). Table 2.10 presents the estimation results. I observed that almost all significant estimates are positive. This indicates that the positive effects of popular app adoption pertaining to increase in app usage are more pronounced among user groups with low app expertise, such as less technologically knowledgeable groups (e.g., users aged 50 years or older, mobile game novices, and late adopters of popular app) and managerially under-represented target segments (e.g., users with irregular, occasional, and light app use patterns).

The disproportionately higher positive spillovers among users with low mobile app expertise can be regarded by media planners as an opportunity to reach technologically and managerially marginalized consumers who have been overlooked or underserved. Media planners generally fail to take advantage of such possibilities because advertisement spending on mobile devices is lower than that devoted to other advertising channels, such as television and PCs (Chaffey 2016). This research illuminates ways of reaching potential user segments with whom interaction is typically challenging. One such strategy is the effective scheduling of advertising placements in line with the lifecycle of a popular app. For example, after-release advertising placements and late adopter targeting are particularly cost-effective approaches that media planners can use to extend their customer bases.

Table 2.10. Estimation Results across User Groups

App categories	(1) Senior vs. Young app users		(2) Irregular vs. Regular app users	
	Number of apps used ($\bar{\varphi}$)	App usage duration ($\bar{\tau}$)§	Number of apps used ($\bar{\varphi}$)	App usage duration ($\bar{\tau}$)§
Total	0.045 (0.012)***	0.076 (0.027)***	0.011 (0.006)*	0.057 (0.015)***
Game	0.170 (0.048)***	0.138 (0.131)	–0.007 (0.020)	–0.013 (0.070)
Communication	0.080 (0.029)***	0.222 (0.038)***	0.004 (0.014)	0.126 (0.021)***
Multimedia/Entertainment	0.004 (0.022)	–0.143 (0.075)*	0.014 (0.010)	0.082 (0.035)**
Portal/Search	0.006 (0.038)	0.289 (0.085)***	0.039 (0.019)**	0.153 (0.047)***
Lifestyle	0.042 (0.018)**	–0.051 (0.046)	0.004 (0.009)	0.059 (0.026)**
Social Network	0.167 (0.045)**	0.646 (0.116)***	–0.007 (0.020)	–0.041 (0.047)
Utility	–0.032 (0.022)	0.077 (0.066)	–0.005 (0.010)	0.111 (0.031)***
Other Apps	0.172 (0.034)***	0.098 (0.116)	0.049 (0.016)***	0.027 (0.047)
App categories	**(3) Occasional vs. Frequent app users**		**(4) Light vs. Heavy app users**	
	Number of apps used ($\bar{\varphi}$)	**App usage duration ($\bar{\tau}$)§**	**Number of apps used ($\bar{\varphi}$)**	**App usage duration ($\bar{\tau}$)§**
Total	0.094 (0.006)***	0.191 (0.013)***	0.034 (0.006)***	0.224 (0.014)***
Game	0.243 (0.020)***	0.577 (0.065)***	0.165 (0.020)***	0.332 (0.075)***
Communication	0.032 (0.014)**	0.203 (0.019)***	0.016 (0.014)	0.232 (0.021)***
Multimedia/Entertainment	0.097 (0.010)***	0.185 (0.034)***	0.045 (0.010)***	0.196 (0.031)***
Portal/Search	0.067 (0.019)***	0.344 (0.049)***	0.027 (0.019)	0.359 (0.044)***
Lifestyle	0.095 (0.009)***	0.209 (0.024)***	0.028 (0.009)***	0.072 (0.022)***
Social Network	0.104 (0.021)***	0.320 (0.047)***	0.068 (0.020)***	0.242 (0.049)***
Utility	0.048 (0.011)***	0.241 (0.030)***	–0.023 (0.010)**	0.105 (0.031)***
Other Apps	0.194 (0.017)***	0.319 (0.051)***	0.024 (0.016)	–0.044 (0.049)
App categories	**(5) Mobile game Novices vs. Experiencers**		**(6) Late vs. Early adopters of a popular app**	
	Number of apps used ($\bar{\varphi}$)	**App usage duration ($\bar{\tau}$)§**	**Number of apps used ($\bar{\varphi}$)**	**App usage duration ($\bar{\tau}$)§**
Total	0.053 (0.009)***	0.081 (0.031)***	0.068 (0.006)***	0.055 (0.016)***
Game	1.239 (0.057)***	1.703 (0.115)***	0.185 (0.021)***	0.639 (0.068)***
Communication	0.026 (0.021)	–0.064 (0.045)**	0.044 (0.015)***	0.109 (0.020)***
Multimedia/Entertainment	0.035 (0.016)**	0.215 (0.067)***	0.082 (0.011)***	0.071 (0.034)**
Portal/Search	0.075 (0.029)**	0.132 (0.069)*	0.033 (0.020)*	0.220 (0.052)***
Lifestyle	0.056 (0.014)***	0.075 (0.049)**	0.066 (0.009)***	0.027 (0.024)
Social Network	0.010 (0.031)	0.091 (0.074)	0.020 (0.021)	0.266 (0.045)***
Utility	0.068 (0.017)***	0.160 (0.064)***	0.063 (0.011)***	0.134 (0.036)***
Other Apps	0.076 (0.025)***	0.029 (0.083)	0.067 (0.017)***	–0.024 (0.050)

*significant at 0.1 level; **significant at 0.05 level; ***significant at 0.01 level.

Note 1: Standard errors are in parentheses (§ bootstrapped standard errors).

Note 2: I report only the key estimation results to conserve space but the unreported results are available upon request.

Note 3: The number of observation for (1) and (6) is 33,656,; The number of observation for (2) is 33,375 and the number of observation for (3) – (5) is 33,458 due to missing information during the calibration sample period (April 30, 2012 – July 15, 2012).

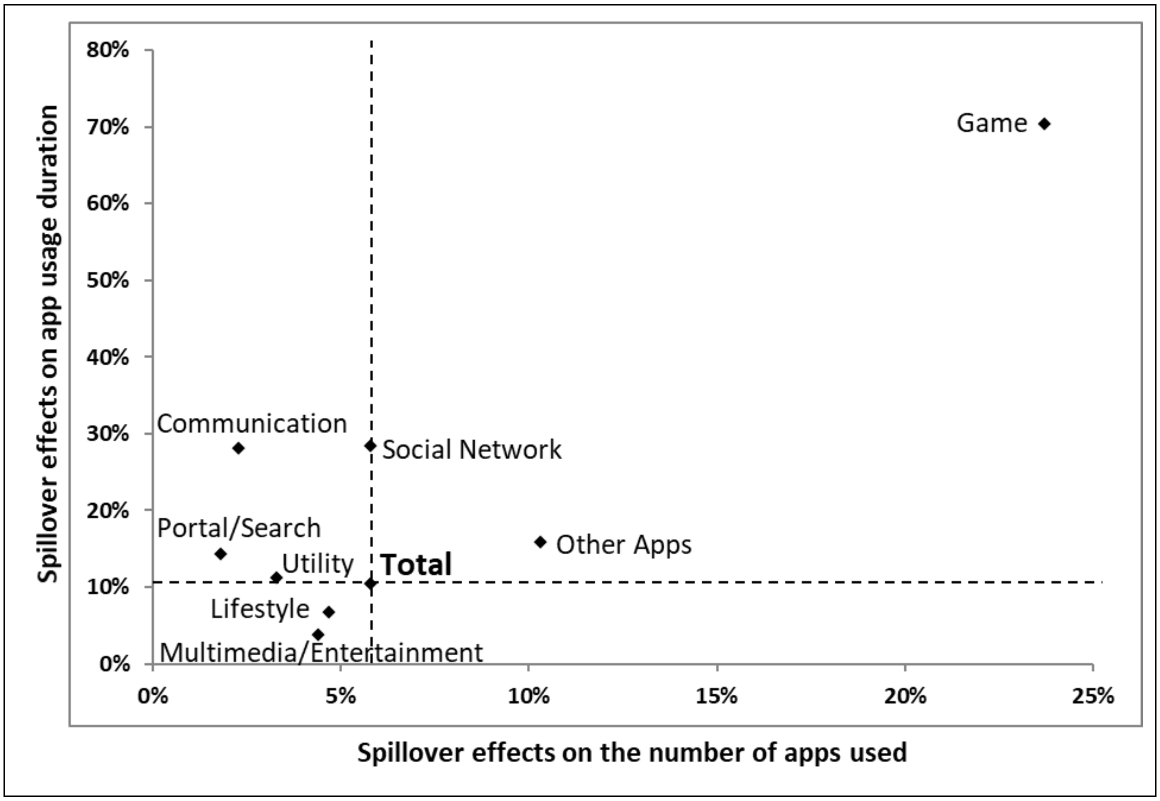
2.6.3. Mobile App Release Strategies

The positive demand spillover effects from the adoption of popular apps indicate that app developers and mobile service providers can augment publicity efforts and sales through effective release strategies. In the competitive mobile app market, determining the category of a new app and accurately timing its release, for instance, is critical in increasing downloads and attracting new users.

2.6.3.1. App Categories to Release

Figure 2.3 visually summarizes the magnitudes of the estimated spillover effects of popular app adoption on app usage variety (x-axis) and time (y-axis) based on the estimation results shown in Tables 2.4 – 2.6. When the magnitudes of spillover effects on total app usage are regarded as baseline effects, the largest increase occurs in the game category, which is the same category to which Anipang belongs. In app categories for social purposes (social networking and communication apps) and utilitarian purposes (portal/search and utility apps), popular app adoption exerts stronger effects on app usage time than app usage variety. That is, users spend more time on social, communication, and utilitarian apps for each app used after they adopt the popular app, suggesting that app developers who produce such genres of apps can improve customer engagement by releasing their new apps in conjunction with the launch of a popular app.

Figure 2.3. Spillover Effects across App Categories



To comprehensively inquire into the positive spillover effects of popular app adoption across app categories, I chose the app categories that are used mainly for utilitarian purposes. This was prompted by the hedonic nature of Anipang as a social casual game app. The utilitarian apps were classified by eight coders, who are graduate students in the Marketing department of a large public university. Table 2.11 presents the positive spillover effects of Anipang adoption on both number of apps used and app usage duration in numerous utilitarian app categories. These findings confirmed that releasing new apps in the app domain that offers contrasting app categories (i.e., utilitarian app domain) can be benefited even when a popular hedonic app is on the market.

Table 2.11. Estimation Results for Utilitarian Apps

Utilitarian app categories		Number of apps used ($\hat{\delta}$)	App usage duration ($\hat{\gamma}$)§
Communication	Messaging / Call	0.034 (0.013)***	0.289 (0.018)***
	Email	–0.041 (0.032)	–0.070 (0.034)**
Portal / Search	Portal	0.040 (0.023)*	0.067 (0.040)*
	Search	–0.008 (0.027)	0.040 (0.030)
	Data Storage	0.021 (0.039)	0.057 (0.035)
Lifestyle	Productivity	0.009 (0.013)	0.059 (0.024)**
	Public Transportation	0.096 (0.027)***	0.197 (0.036)***
	Weather	0.045 (0.041)	0.037 (0.023)
	Business	0.034 (0.030)	0.038 (0.037)
	Maps / Navigation	0.028 (0.024)	0.061 (0.049)
	Coupon / Mileage	0.134 (0.040)***	0.096 (0.032)***
Utility	App Store (All)	0.071 (0.017)***	0.435 (0.036)***
	Security	0.058 (0.027)**	0.081 (0.030)***
	Widget	0.010 (0.025)	–0.008 (0.038)
Other Apps	Finance	0.122 (0.019)***	0.104 (0.041)**
	Job Search / Education	0.035 (0.034)	0.061 (0.032)*

*significant at 0.1 level; **significant at 0.05 level; ***significant at 0.01 level
Note 1: Standard errors are in parentheses (§ bootstrapped standard errors).
Note 2: The number of observation is 33,656.

2.6.3.2. Release Timing

To demonstrate how the scheduling of new app release can be determined, I directed the analysis toward mobile game apps, including Anipang and on which positive spillover effects of popular app adoption are the most considerable. Figure 2.4 illustrates the difference in usage time of other games (black bars) and Anipang (white bars) between the treatment and control groups over weeks before and after the adoption of Anipang. The figure shows that the demand for other game apps after Anipang adoption continues to increase and surpass the demand for Anipang six weeks after the adoption of the focal app. Interestingly, no decrease in the usage of other games was observed with Anipang adoption, indicating that app developers do not need to delay the release of new game apps to prevent competition with the popular app. The results also suggest that game app developers should launch new game apps in line with the release of a popular app because users gradually shift their time resources from a focal popular app to other apps as time progresses. Moreover, managers of popular app platforms can decide on release timing for new apps or promotion timing for new apps by using individual-level information on when their customers adopt a popular app.

Figure 2.4. Difference of Game App Usage Duration between Treatment Group and Control Group Before and After the Adoption Week

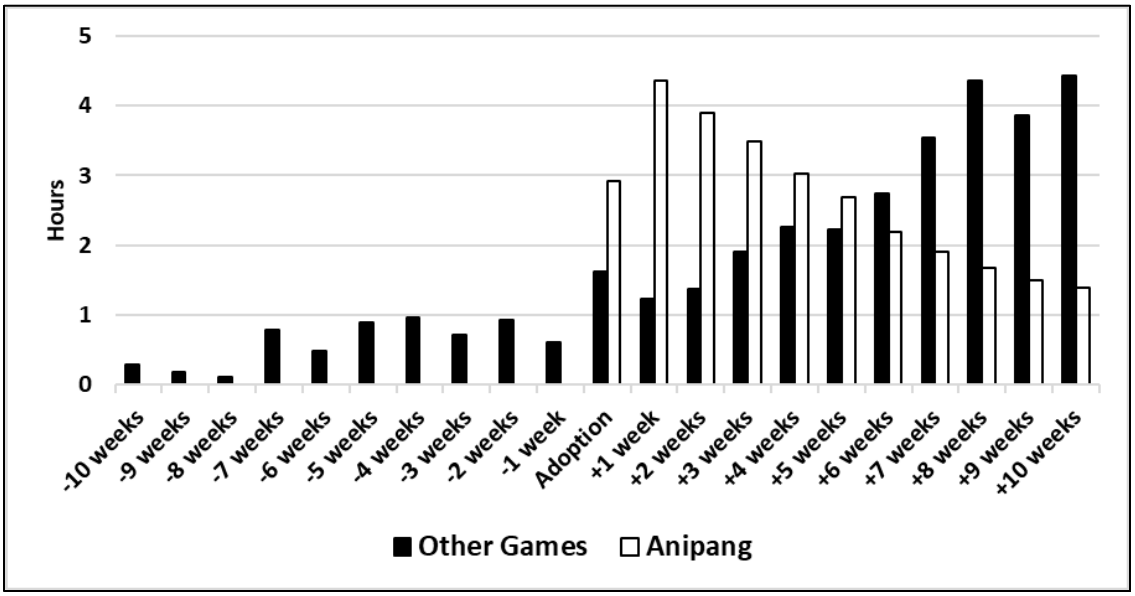


Table 2.12 shows that the positive spillover effects of Anipang adoption are stronger among action, adventure, board, puzzle, and simulation games than among racing, role-playing, shooting, and sports games. Anipang adoption effects are also largest on the puzzle game category to which Anipang belongs, suggesting that Anipang adopters are more likely to play games within the same game category under which Anipang is classified or relatively easy games (such as Anipang) that do not require precise skills or strategic thinking. Mobile game app developers are encouraged to release

new game apps that are similar to popular apps in terms of category and required gaming skills and strategies.

Table 2.12. Estimation Results for Mobile Game Apps

Game app categories	Number of apps used ($\hat{\delta}$)	App usage duration ($\hat{\gamma}$)§
Action	0.157 (0.039)***	0.150 (0.022)***
Adventure	0.324 (0.090)***	0.066 (0.011)***
Board	0.116 (0.055)**	0.079 (0.018)***
Puzzle	0.481 (0.028)***	0.943 (0.034)***
Racing	0.119 (0.081)	0.033 (0.012)***
Role Playing	–0.014 (0.088)	–0.001 (0.014)
Shooting	0.027 (0.069)	–0.219 (0.033)***
Simulation	0.174 (0.030)***	0.325 (0.030)***
Sports	0.049 (0.055)	–0.001 (0.019)

*significant at 0.1 level; **significant at 0.05 level; ***significant at 0.01 level
Note 1: Standard errors are in parentheses (§ bootstrapped standard errors).
Note 2: The number of observation is 33,656.

In summary, mobile app developers can increase customer engagement with their apps and, thus, their revenues by coordinating the release time of their new apps in correspondence with the launch of a popular app. This strategy is effective for apps in categories that are indirectly related to a popular app and apps in the same or similar categories where a popular app belongs. These app release strategies would be more efficient and effective when implemented in cooperation with app stores because mobile app users are known to express readiness in exploring new apps in such establishments and allocate more time to new apps than existing apps after popular app adoption.

2.7. Limitations and Future Research

This study is encumbered by few limitations that can be addressed by future research. I proposed an underlying mechanism for positive spillover effects of popular apps on the usage of other apps: new app usage increase through new app search and navigation. Deeper investigation of popular app adopters' behaviors would provide more insights for mechanisms with which popular app adoption promotes app usage. For example, it would be possible to examine whether watching advertisement of other apps increases after using popular apps or whether communicating with other users increases prior to downloading and using popular apps, if more granular data (e.g., time-stamp data for app usage) are available.

Notwithstanding these limitations, this study offers unique managerial insights into the nonintrusive and cost-efficient nature of popular apps as stimuli for increasing the variety and intensity of apps. These findings suggest that popular app adoption stimulates to adopt and use other apps, increases their search behavior of new apps, as well as their trials of apps. Continuing practical and academic research on mobile app markets, as initiated by the present study, may prompt additional works in this important and emerging field.

2.8. Conclusion

This study empirically validated the potential of well-liked mobile apps as stimuli of app consumption in terms of variety and duration. In serving as drivers of consumption, popular apps produce positive demand spillovers. The results suggest that popular app adoption increases app consumption not only within the same category as the adopted popular app but also across different categories, by increasing new app usage which in turn is driven by the search and download of new apps from app stores. App usage increased through the elevated usage of apps within the same platform as a popular app because apps based on the same platform are characterized by higher promotional possibilities and proximity within the platform. Moreover, the effectiveness of popular apps as stimuli of app usage is more pronounced among users with low app expertise. From a new app launch perspective, popular app release plays a key role to determine the effective timing and categories of new apps in the competitive app market.

As we enter the mobile economy, apps will be poised at the forefront of business transactions and service deliveries, including product ordering, payment, health monitoring, music and film subscription, transportation, and education. Nevertheless, not everyone is engaged with apps, especially consumers who view mobile innovations with suspicion and pessimism. Increasing app usage through popular app adoption has the potential to reach out to such segments. In keeping with the call to increase mobile app usage, app developers and marketers can maximize the potential of popular apps as a driver of customer engagement and growth for the future.

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APPENDIX A

TWO-STEP ESTIMATION (Heckman 1979; Lee 1983)

To jointly estimate the spillover effects of Anipang adoption on both the number of apps used and app usage duration by using the Gaussian copula-based difference-in-differences (DID) approach, I used a two-step estimation procedure for the bivariate selectivity model as in studies by Heckman (1979) and Lee (1983). This empirical approach has been applied to the bivariate selectivity models with various copula functions in previous literature (e.g., Hwang and Park 2015; Prieger 2002; Smith 2003). As the first step, I estimated the negative binomial or Poisson regression model for the number of apps used using maximum likelihood estimation. Next, I added the correction term which deals with correlation between unobserved random shocks in the number of apps used and app usage duration, and then estimated the adjusted log-normal regression model for app usage duration using ordinary least squares (OLS) estimation. The usual OLS standard errors obtained in this step are underestimated. Thus I computed the correct standard errors using a nonparametric bootstrap method with 100 replications (Cameron and Trivedi 2005). The details of my two-step estimation procedure are as follows.

I first define a latent standard normal variable ω_{it} which is related to the number of apps used N_{it} such that

$$\{N_{it} = n\} \text{ is equivalent to } \{\Pr(N_{it} \leq n-1) \leq \Phi(\omega_{it}) < \Pr(N_{it} \leq n)\},$$

where $\Phi(\cdot)$ is a standard normal cumulative distribution function. I next use the Gaussian copula to model the correlation between unobserved random shocks in the number of apps used and app usage duration as follows,

$$\begin{bmatrix} \omega_{it} \\ \varepsilon_{it} \end{bmatrix} \sim N\left(\begin{bmatrix} 0 \\ 0 \end{bmatrix}, \begin{bmatrix} 1 & \rho\sigma_{\varepsilon} \\ \rho\sigma_{\varepsilon} & \sigma_{\varepsilon}^2 \end{bmatrix}\right),$$

where $\omega_{it} \sim N(0, 1)$ and $\varepsilon_{it} \sim N(0, \sigma_{\varepsilon}^2)$ represent unobserved random shocks in the number of apps used and app usage duration, respectively, and ρ is the correlation between them. Then, I can write $\varepsilon_{it} = \rho\sigma_{\varepsilon}\omega_{it} + \sigma_{\varepsilon}\sqrt{1-\rho^2}\epsilon_{it}$ by Cholesky decomposition, given that $\epsilon_{it}{\sim}N(0, 1)$ is not correlated with ω_{it}. Thus, the conditional expectation of ε_{it} given $N_{it} = n$ is

$$
\begin{aligned}
E[\varepsilon_{it}|N_{it} = n] &= E[\varepsilon_{it}|\Phi^{-1}(\Pr(N_{it} \le n-1)) \le \omega_{it} < \Phi^{-1}(\Pr(N_{it} \le n))] \\
&= \rho\sigma_{\varepsilon}E[\omega_{it}|\Phi^{-1}(\Pr(N_{it} \le n-1)) \le \omega_{it} < \Phi^{-1}(\Pr(N_{it} \le n))] \\
&\quad + \sigma_{\varepsilon}\sqrt{1-\rho^2}E[\epsilon_{it}|\Phi^{-1}(\Pr(N_{it} \le n-1)) \le \omega_{it} < \Phi^{-1}(\Pr(N_{it} \le n))] \\
&= -\rho\sigma_{\varepsilon}\frac{\phi(\Phi^{-1}(\Pr(N_{it} \le n))) - \phi(\Phi^{-1}(\Pr(N_{it} \le n-1)))}{\Pr(N_{it} \le n) - \Pr(N_{it} \le n-1)} \\
&\equiv -\rho\sigma_{\varepsilon}\vartheta_{it}(n),
\end{aligned}
$$

where

$$\vartheta_{it}(n) = \{\phi(\Phi^{-1}(\Pr(N_{it} \le n))) - \phi(\Phi^{-1}(\Pr(N_{it} \le n-1)))\} \,/\, \{\Pr(N_{it} \le n) - \Pr(N_{it} \le n-1)\}$$

and $\phi(\cdot)$ is the standard normal density function.

At first, I estimate the negative binomial or Poisson regression model for the number of apps used (the first equation in Equation (2.1)) using maximum likelihood estimation and compute $\vartheta_{it}(n)$. At the second step, I estimate the following model, in which $-\rho\sigma_{\varepsilon}\vartheta_{it}(n)$ is entered as a regressor into the second equation in Equation (2.1) for app usage duration, using OLS estimation,

$$T_{it} = \alpha_i^T + \beta_t^T + \gamma I_{it} - \rho\sigma_{\varepsilon}\vartheta_{it}(n) + \eta_{it}, \tag{A1}$$

where η_{it} are random errors with mean zero. Moreover, as did Heckman (1979), I can estimate σ_{ε} and ρ separately using the following formulas,

$$\widehat{\sigma_{\varepsilon}} = \sqrt{\frac{SSE}{IW} + \frac{\widehat{\rho\sigma_{\varepsilon}}^2}{IW}\sum_{i=1}^{I}\sum_{t=1}^{W_i}\{\pi_{it}(n) + \vartheta_{it}(n)^2\}} \text{ and } \hat{\rho} = \frac{\widehat{\rho\sigma_{\varepsilon}}}{\widehat{\sigma_{\varepsilon}}},$$

where SSE is the sum of squares of residuals computed from Equation (A1), I is the total number of users, $W = \sum_{i=1}^{I} W_i$, W_i is the number of weeks for user i, $\widehat{\rho\sigma_\varepsilon}$ is the estimate obtained from Equation (A1), and

$$\pi_{it}(n) = \frac{\Phi^{-1}(\Pr(N_{it} \leq n))\phi(\Phi^{-1}(\Pr(N_{it} \leq n))) - \Phi^{-1}(\Pr(N_{it} \leq n-1))\phi(\Phi^{-1}(\Pr(N_{it} \leq n-1)))}{\Pr(N_{it} \leq n) - \Pr(N_{it} \leq n-1)}.$$

The standard errors obtained at the second step are underestimated. Thus I compute the correct standard errors using a nonparametric bootstrap method with 100 replications (Cameron and Trivedi 2005).

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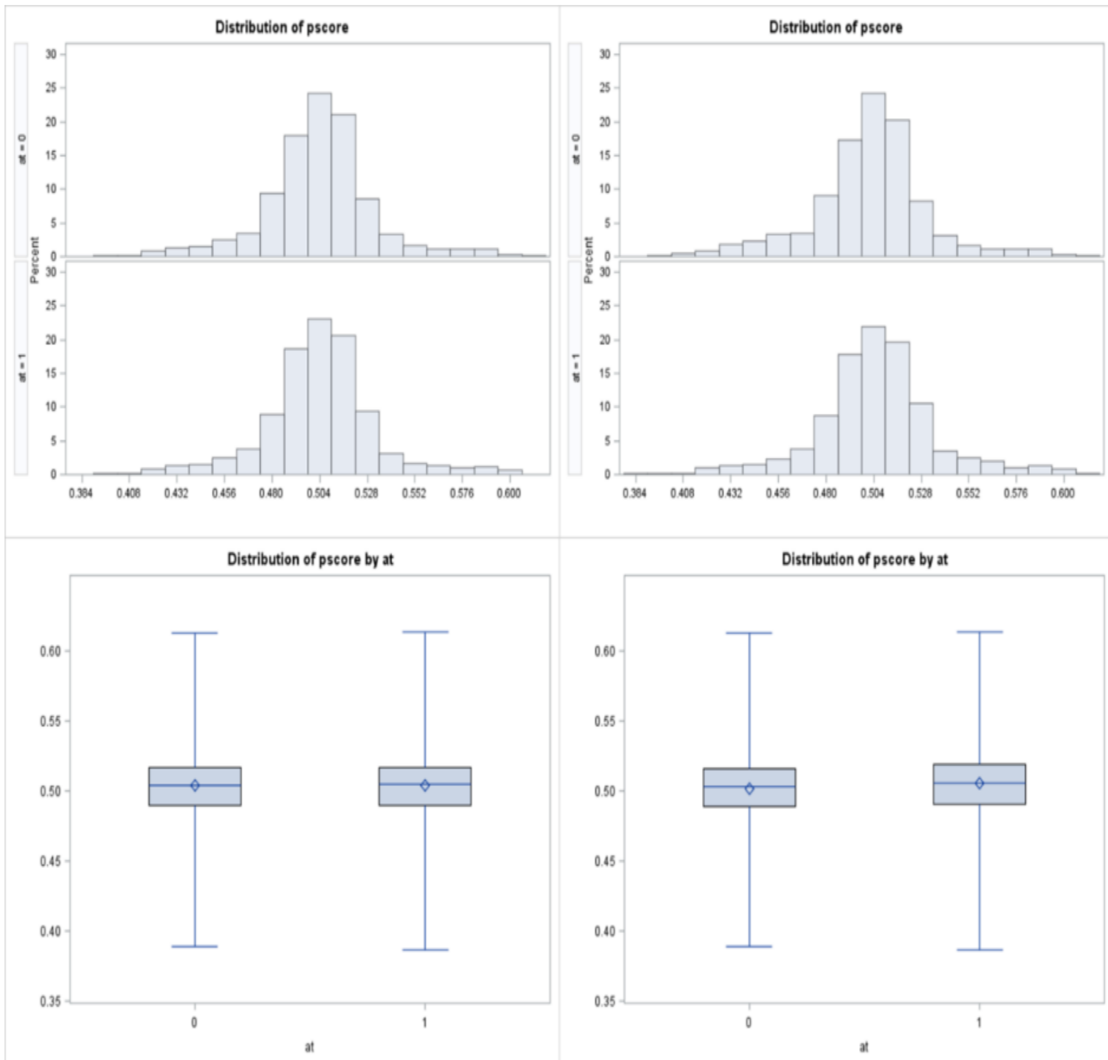
APPENDIX B

RESULTS OF PROPENSITY SCORE MATCHING

To ensure overlap between the Anipang adopters and non-adopters, I verified whether the propensity scores of these groups have a common support. Figure B1 (left column) illustrates the histograms and boxplots of the propensity scores of the two groups in the matched sample. The figure is suggestive of support common to the groups. To assess the quality of the matched sample, I inspected the similarity between the Anipang adopters and non-adopters. I first compared the distribution of the adopters' propensity scores with those of the non-adopters. As expected, the similarity in propensity scores increased with the matching (Figure B1). To formally test this assertion, I performed Kolmogorov–Smirnov tests. The *p*-value of the matched sample was 0.9445, indicating no significant difference between the propensity score distributions of the two groups. By contrast, the *p*-value of the unmatched sample was 0.0018, which reflects significant differences. I also confirmed the differences between the means of the Anipang adopters' and non-adopters' covariates used for the logit regression (to compute the propensity scores) before and after the matching. As indicated in Table B1, no significant t-statistics for the covariates in the matched sample were found, but significant differences existed in the unmatched sample. All in all, my assessments of matching quality support the validity of the matching procedure.

Figure B1. The Distribution of Propensity Scores of Matched and Unmatched Samples



<u>Matched sample</u> **<u>Unmatched sample</u>**

Note 1: pscore: propensity scores
Note 2: at=0: Anipang non-adopters; at=1: Anipang adopters

Table B1. Comparison of Covariates Before and After Matching

Covariates		t-statistic before matching	t-statistic after matching
Age	Age 10s	–0.14	–0.86
	Age 20s	0.32	0.17
	Age 30s	0.24	0.43
	Age 40s	–0.40	–0.04
	Age 50s – 60s	–0.20	–0.17
Gender	Male	0.57	0.15
	Female	–0.57	–0.15
Income	Income < $1000	0.01	–0.09
	Income $1000 – $3000	–0.07	–0.32
	Income $3000 – $5000	0.22	0.76
	Income > $5000	–0.17	–0.49
Education	High School Graduates	0.01	–0.22
	College Graduates	–0.23	0.32
	Undergrad or Grad Students	0.48	0.41
	Elementary, Middle, and High School Students	–0.15	–0.72
App Usage Duration	E-Commerce	0.34	0.04
	Multimedia/Entertainment	–1.19	0.62
	Personal Finance	0.14	0.22
	Portal/Search	–0.53	–0.28
	Job/Education	–0.39	0.24
	Kakao Game	2.28**	–0.10
	Kakao Talk	0.21	0.48
	Lifestyle	–1.20	0.21
	News	–0.27	–0.24
	Other Game (excl. Kakao Game)	0.62	0.35
	Other Communication (excl. Kakao Talk)	–0.86	0.04
	Social Network	–0.49	0.06
	Sports/Leisure/Travel	–2.41**	0.29
	Utility	0.54	0.70
	Other Apps (excl. the above app categories)	–0.04	–0.27

*significant at 0.1 level; **significant at 0.05 level; ***significant at 0.01 level

APPENDIX C

VALIDATION OF GAUSSIAN COPULA-BASED DID MODEL

To empirically validate the proposed Gaussian copula-based DID model over the traditional DID model, I test the presence of correlations between unobserved random shocks in number of apps used and app usage duration. I found consistently significant and positive correlations in both total app and category level analyses ($\hat{\rho}$'s in Tables 2.4 – 2.6). The positive and high (close to 1) correlation means that when unobserved random shocks in number of apps used increase, unobserved random shocks in app usage duration also increase at a high rate. Specifically, social network app category shows the highest correlations (0.909 – 0.923), while lifestyle app category has the lowest (0.495 – 0.523). Highly positive correlations across app categories imply that the proposed Gaussian copula-based DID model is preferred over the traditional DID model which ignores the correlation between unobserved random shocks in number of apps used and app usage duration. From Table C1, I observe that estimates and standard errors are smaller when Gaussian copula is used in the DID model than when no copula is used. For example, in the game category, the estimated spillover effect from popular app adoption decreases by 8.6% and the standard error decreases by 9.7% when Gaussian copula is used. This suggests that the Gaussian copula-based DID approach allows more conservative and efficient estimation and that ignored correlations may result in biases in model estimation.

Table C1. Comparison of Estimation Results on App Usage Duration between Without Copula and With Gaussian Copula

App categories	No copula	Gaussian copula§
Total	0.106 (0.013)***	0.104 (0.013)***
Game	0.770 (0.062)***	0.704 (0.056)***
Communication	0.284 (0.017)***	0.281 (0.017)***
Multimedia/Entertainment	0.045 (0.030)	0.038 (0.029)
Portal/Search	0.155 (0.043)***	0.143 (0.039)***
Lifestyle	0.074 (0.021)***	0.067 (0.022)***
Social Network	0.333 (0.041)***	0.284 (0.040)***
Utility	0.117 (0.026)***	0.113 (0.027)***
Other Apps	0.137 (0.045)***	0.159 (0.038)***

*significant at 0.1 level; **significant at 0.05 level; ***significant at 0.01 level
Note 1: Standard errors are in parentheses (§ bootstrapped standard errors).
Note 2: I omit the results on the number of apps used because they are the same as the results using Gaussian copula due to two-step estimation procedure.
Note 3: The number of observation is 33,656.

APPENDIX D

GAUSSIAN COPULA-BASED DDD MODEL

I used the Gaussian copula-based difference-in-difference-in-differences (DDD) model to quantify the spillover effects of Anipang adoption on app usage among users with low app expertise compared to users with high app expertise. To be more specific, the model includes the two-way interaction between I_{it} defined in Equation (2.1) and a new dummy variable J_i which denotes user i's app expertise group membership. It is formulated as follows:

$$\begin{cases} Pr(N_{it}=n) = \dfrac{\Gamma(\theta+n)}{\Gamma(n+1)\Gamma(\theta)} r_{it}^{\ n}(1-r_{it})^{\theta},\ r_{it}=\dfrac{\mu_{it}}{\theta+\mu_{it}},\ \mu_{it}=\exp(\alpha_i^{ND}+\beta_t^{ND}+\delta^{ND}I_{it}+\varphi I_{it}J_i) \\ T_{it} = \alpha_i^{TD}+\beta_t^{TD}+\gamma^{TD}I_{it}+\tau I_{it}J_i+\varepsilon_{it} \end{cases}$$

for user i (i=1, 2, …, 3,156) and week t (t=1, 2, …, 15). The variables in the above equation are interpreted in the same way as in Equation (2.1). A new dummy variable J_i is defined as follows,

$$J_i = \begin{cases} 1, \text{ if user } i \in \text{ Low app expertise group} \\ 0, \text{ if user } i \in \text{ High app expertise group} \end{cases}.$$

In the above DDD specification, my main interests are the coefficients φ and τ which estimate the difference in spillover effects between low and high app expertise groups. I interpret the significantly positive $\widehat{\varphi}$ and $\hat{\tau}$ as the stronger spillover effects of Anipang adoption among users with low expertise relative to users with high expertise. As in the previous Gaussian copula-based DID estimation, I used the Gaussian copula to capture the correlation between unobserved random shocks in the number of apps used and app usage duration.