Access Affordance of Mobile Technology in e-Commerce: Change of Purchase Time Dispersion

Completed Research Paper

Youngsok Bang
Desautels Faculty of Management
McGill University
Montreal, Quebec, Canada
youngsok.bang@mail.mcgill.ca

Dong-Joo Lee
Division of Management
Hansung University
Seoul, South Korea
djlee@hansung.ac.kr

Kunsoo Han
Desautels Faculty of Management
McGill University
Montreal, Quebec, Canada
kunsoo.han@mcgill.ca

Abstract

The portability of a mobile device and the ubiquity of mobile Internet provide e-market users with more opportunities of access to e-commerce sites throughout a day. In this paper, we examine the access affordance of mobile technologies by analyzing the changes in purchase time dispersion of e-marketplace users after their adoption of mobile channel. By analyzing a large archival dataset including transactions in the mobile and online channels, we find that (1) a user's purchase time becomes more dispersed throughout a day after the mobile channel adoption, and (2) the impact of the mobile channel adoption on the purchase time dispersion is significantly different across different user groups. These findings present strong empirical evidences of access affordance of the mobile channel and how the affordance is realized across e-market users.

Keywords: mobile commerce, affordance, purchase time, dispersion, difference-in-differences, growth mixture model

Introduction

Mobile technologies are transforming e-commerce markets and user behaviors.[1] Statistics show that transactions through mobile channels (m-commerce) as of the second quarter of 2013 account for about 11% of the total e-commerce spending in the U.S. (comScore 2013). eBay recently reported it attracted 6.5 million new mobile customers in the U.S. during the first quarter of 2014 (Rueter 2014). With the proliferation of m-commerce, online retailers or marketplaces are trying to take advantage of m-commerce as a lucrative venue for future growth. Alibaba, for example, announced it will invest heavily on developing a platform to help its retailers' businesses in the mobile channel (Jing 2013).

Compared to a PC, a mobile device is within an easy reach of a user throughout a day due to the mobility and form factor. Further, because most of these mobile devices are Internet-enabled, they allow users to connect to Internet applications such as e-marketplaces regardless of the users' physical locations. Therefore, the mobile channel provides a higher level of spatially flexible access to such applications vis-à-vis the online channel (Bang et al. 2013) and we refer to this as the *ubiquitous access capability* of the mobile channel.[2]

Researchers have enhanced our understanding of the role of mobile channels in e-commerce by focusing on the ubiquitous access capability and its impact on e-market users' behaviors. Bang et al. (2013) link the capability with the time-criticality of transactions and find the mobile channel launch can lead to either cannibalization or synergy effects on the preexisting online channel depending on the extent of time-criticality of transactions. Ghose et al. (2012) show geographical proximity to brands is associated with more searches of the brands on mobile phones. These studies present useful insights into the realization of the ubiquitous access capability, suggesting that it depends on the shopping task a user is engaged in (Bang et al. 2013) or the geographical location of the user (Ghose et al. 2012). The current paper is in line with this emerging stream of research and contributes to it with a different focus from a different perspective. Specifically, drawing on the technology affordance perspective, we examine the change of e-market users' purchase behavior triggered by the ubiquitous access capability of mobile channel with a focus on *purchase time dispersion*, the degree to which an e-commerce user's purchase time is dispersed over twenty-four hours.

Time, the focal behavioral dimension in this study, is an important building block of social actions, promises, and norms. Each of our social behaviors is under a certain social contract or constraint, which is frequently linked with the time. Interestingly, however, despite the importance of the time factor, social science has kept quiet on the role of time in explaining social behaviors (Adam 1994). In e-commerce, it has been proposed that there are peak times for users' shopping and therefore, orders follow a distinct hourly pattern (NetElixir 2011). Whether purchase time is concentrated or dispersed has implications on e-commerce firms' decision on addressing their users. For example, if concentrated, an e-tailer may optimize its advertising impressions and conversions to sales with dayparting on Google AdWords or Facebook advertising, but at a very high cost due to other competing bidders for the limited ads slots. Purchase time is also an important consideration in targeting users to effectively trigger them to visit the e-tailer's site. If dispersed, timing of targeting may as well be dispersed accordingly, and vice versa. Thus, a change in purchase time dispersion with the mobile channel would require e-commerce firms to adapt their existing practices.

Prior studies have addressed user behaviors on digital shopping platforms based on an implicit assumption of deterministic or static relationships between users and channels. The relationships are derived either from invariant channel capabilities enabled by underlying technologies (e.g., Bang et al. 2013; Ghose et al. 2012; Kuruzovich et al. 2008) or from consumer profiling (e.g., Gupta et al. 2004). However, studies on the impact of technology as a socio-technology assemblage have discredited such relationships and shown that users' technology action is, in fact, more situated, flexible, and dynamic (DeSanctis and Poole 1994; Markus and Silver 2008; Orlikowski 2000). From the theoretical lens of *technology affordance*, we view channel usage behaviors as an outcome of flexible and dynamic decisions that can change with the users' usage context and experience. In order to empirically validate the impact

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[1] We use the terms 'user' and 'consumer' interchangeably.

[2] In this paper, the online channel means the traditional e-commerce channel based on the stationary Internet.

of mobile channel on purchase time dispersion, we analyze large-scale archival data from a leading e-marketplace in South Korea. In doing so, this study also contributes to the technology affordance literature, which has employed narrative or case analyses to derive or verify theoretical arguments, thus usually lacking in empirical support for the generalizability of the arguments.

The rest of the paper is organized as follows. We present the theoretical lens of this study, technology affordance, and develop hypotheses. Next, we conduct empirical analyses to test the hypotheses. We conclude by discussing implications, limitations, and directions for future research.

AFFORDANCE OF MOBILE CHANNEL

Technology Affordance

Technology affordances are defined as "the possibilities for goal-oriented action afforded to specified user groups by technical objects" (Markus and Silver 2008, p.622). Affordances are not exclusive properties of user or technology; rather, they are constituted in relations between user and technology. Thus, under this perspective, there is no guarantee that technology features determine a certain type of outcome, but users' (or user groups') technology goals (or intentions) also play an important role in driving the outcomes.

Users come to a technology with diverse goals, and even for the same user, technology goals can differ across various usage contexts. Technology goals can also vary as users' experience with the technology accumulates. With regard to this point, Leonardi (2011) note, "[t]echnologies have material properties, but those material properties afford different possibilities for action based on the contexts in which they are used. Although the material properties of a technology are common to each person who encounters them, the affordances of that artifact are not" (p.153), implying that technology affordance can depend on user, usage context, and usage experience.

Meanwhile, the notion of technology affordance has slightly different nuanced meanings across IS scholars. Markus and Silver (2008) view technology affordance as the necessary condition for IT use given technical objects. According to them, affordance is a function of user goals (intentions) which can differ across user, context, and time, but technical objects exist independent of users' perceptions. On the other hand, another school of thought on technology affordance highlights unexpected, situated and emergent actions (Faraj and Azad 2012). Similarly to the enactment of a technology-in-practice (Orlikowski 2000), they focus on the aspect of technology affordance that allows users to find a new meaning within the context of technology-in-use. Based on the interpretivistic perspective, the same (technical) objects can have different meanings and affordance can be enacted from mutual relations between technical objects and users, therefore, the same technology can exhibit different affordances to different users. Such an enactment can show a different form of usages, compared to what technology implementers (or developers) intended or expected beforehand (Faraj and Azad 2012). Lastly, Leonardi (2011) propose another perspective by incorporating the role of technology designer (or implementer) in the relation between technology and user. Based on the philosophical stance of critical realism, Leonardi (2011)'s affordance is a function of user intention given technical objects, but technical objects can be modified or adapted to users by technology designers based on feedback from users.

Although explanations on the technology use (technology outcome) based on the concept of technology affordance vary across scholars as explained above, their affordance perspectives commonly guide us to look at the mobile channel use in a flexible way in that the affordance can be realized differently across users and contexts, and the realization can be dynamic (i.e., can change over time).

Purchase Time Dispersion and Access Affordance of Mobile Channel

Prior studies distinguish between mobile and online channels with two features: *ubiquity* and *usability* (Clarke 2001; Lee and Benbasat 2003; Venkatesh and Ramesh 2006; Zhang 2007). Small screens and low level of user interface of mobile devices might hamper users' interaction with the devices; however, the ubiquity of mobile network allows users to connect to the Internet regardless of their locations. Based on the ubiquity of mobile channels, Bang et al. (2013) characterize the mobile channel as having *ubiquitous access capability*, while the online channel as having *constrained access capability* in the context of e-commerce.

Users can access the e-market throughout a day; however, their location should be *fixed* to a place that has a PC and Internet connection. Routinized social behaviors, such as going back to work in the morning, restrict us from shopping online anytime. On the other hand, mobile channels, thanks to the ubiquity of mobile Internet and mobility of devices, are free from the constraints that online channels are subject to, and can provide more access possibilities than online channels.

Enhanced access possibilities provided by mobile channels are not only due to the technical aspects of mobile Internet and devices which overcome the geographical limitation and thus time limitation, but also can be enacted through *technology-in-use*. In other words, access affordance of mobile channel can be realized even when the online channel is also available. With regard to this point, the project manager who was in charge of the mobile channel introduction of the e-marketplace from which our data were collected said,

> We figured out significantly large number of mobile transactions are conducted in the middle of night or daybreak. That indicates many of our customers are purchasing products in the mobile channel when they are at home. That is against our prior expectation. We initially thought the mobile channel usages at night would be quite low because we assumed they prefer using PCs to mobile for purchasing products.... Maybe, they accessed our e-market followed by unexpected needs to purchase a product while staying in bed. They probably don't want to bother to boot up their PCs.   – Mr. X, Project Manager.

To sum up, we can shop online when time, space, and situation permit, but these restrictions can be mitigated by the availability of a mobile channel. Therefore, with enhanced access possibilities afforded by the adoption of the mobile channel, we can expect that purchase time of a user would become more dispersed throughout a day. This leads to the following hypothesis:

H1. A user's purchase time becomes more dispersed throughout a day after the mobile channel adoption.

Under the affordance perspective, however, it cannot be assured that such a capability determines a certain purchase behavior for all users. The realization of this *access affordance* will depend on users' shopping goals, which would differ across users, usage context, and usage experience. Since time-related social constraints depend on user groups (e.g., a businessperson might have working hours from 9AM to 6PM, while a professor or a college student might have a more flexible work schedule), the extent of purchase time dispersion induced by the mobile channel adoption could be heterogeneous across user groups. Further, since users' interpretation over technology evolves over time as they interact with the technology, their technology usage pattern would be dynamic. For example, users might find the mobile channel difficult to use at the initial stage, but would make better use of it as they become used to the new channel over time. The above discussion results in the following hypotheses:

H2a. The impact of the mobile channel adoption on purchase time dispersion is heterogeneous across different user groups.

H2b. The impact of the mobile channel adoption on purchase time dispersion is dynamic (i.e., time-varying) as users' experience accumulates in the mobile channel.

Empirical Analysis

Data Description

This study uses two large datasets from a major e-marketplace in South Korea, which introduced the mobile channel on June 1, 2010 to its more than ten million users of the existing online channel.[3] The first dataset contains a random sample of 30,000 users, who did not adopt the mobile channel until one year after the introduction of the mobile channel, and their entire online orders (1.45 million) during more than two years (March 1, 2009-June 1, 2011). The second dataset contains a random sample of 30,000

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[3] The e-marketplace launched its mobile web page on June 1, 2010, which we call the mobile channel launch. Before the launch, users could access the PC version web of the e-marketplace via their feature phones or smartphones. However, from the technology affordance perspective, we do not regard the access mechanism as a mobile channel because it could not afford the users' effective access to the information on the site and execution of their shopping tasks. After the launch of the mobile web page, an access with a mobile device was directed to the mobile web page and any purchase incidents during the access were recorded as transactions in the mobile channel."

Figure 1. Data Composition
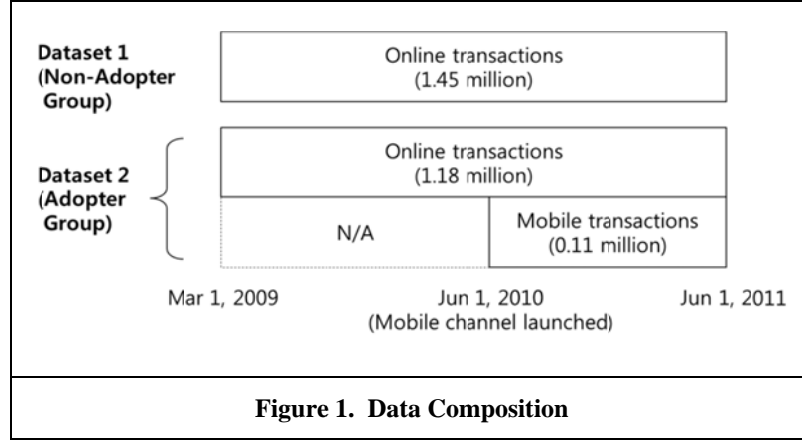
users, who adopted the mobile channel before June 1, 2011 and their entire online orders (1.18 million) and mobile orders (0.11 million) placed during the same period. Figure 1 depicts the composition of our datasets. March 1, 2009 is the beginning of the timespan of the datasets, June 1, 2010 is the time when the e-marketplace launched the mobile channel, and June 1, 2011 is the end of the timespan. Note that the data consists of both mobile channel adopters and non-adopters, and their entire purchase records before and after the mobile channel launch. This unique composition of the data enables us to investigate changes in purchase time dispersion of the adopter group while considering changes in purchase time dispersion of the non-adopter group as the baseline. Accordingly, the first dataset was used for constructing the control group (non-adopters), and the second dataset for the treatment group (adopters).
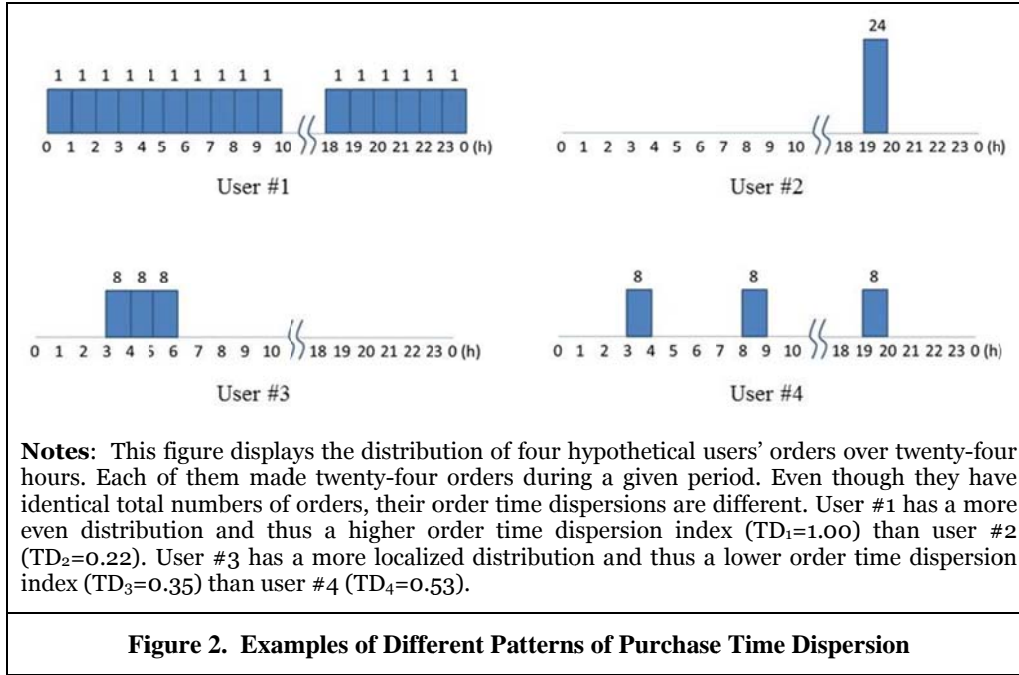
The datasets include a variety of variables related to each order, such as the product category, price, order time, order channel (online or mobile), whether the order was cancelled, whether the product was returned after delivery, and search method used before placing the order (typing in keywords, browsing categories, or clicking on display ads). The datasets also contain user demographics (e.g., age and gender) and e-market use setting (e.g., whether or not a customer used a safer login system).

The focal dependent variable of this study, purchase time dispersion, is a user-level variable. To measure the dispersion, the values of order time need to be aggregated for each user. However, dispersion measures currently available in the literature are not appropriate for this study. The families of Rényi entropy measure, which have been increasingly used for measuring dispersion in social science studies (e.g., Aral et al. 2012; Oh and Jeon 2007), or simple variance of order time are not applicable, since a proper measure of purchase time dispersion needs to capture both the categorical and interval diversities.

Therefore, we developed a measure of purchase time dispersion based on the inverse Simpson index (Simpson 1949). The measure, termed the *revised inverse Simpson index*, is the inverse of the sum of pair-wise multiplications of shares of order hours, weighted by the inverse of the hour gap between pairs. The measure is constructed as follows:

$$TD_i = \frac{N}{\sum_{h_m=0}^{23} \sum_{h_n=0}^{23} s_{ih_m} s_{ih_n}/(\|h_m - h_n\| + 1)}$$

where $h_m(h_n)$ is hour of day, $\|h_m - h_n\|$ is the hour gap between h_m and h_n, e.g., $\|h_m - h_n\| = 2$ if h_m=17h, h_n=19h or h_m=1h, h_n=23h, s_{ih_m} (s_{ih_n}) represents the fraction of individual i's number of orders at $h_m(h_n)$, and N is a normalizing constant (=0.2201) that makes the maximum dispersion be one. Figure 2 describes how purchase time dispersion is calculated.

Notes: This figure displays the distribution of four hypothetical users' orders over twenty-four hours. Each of them made twenty-four orders during a given period. Even though they have identical total numbers of orders, their order time dispersions are different. User #1 has a more even distribution and thus a higher order time dispersion index ($TD_1=1.00$) than user #2 ($TD_2=0.22$). User #3 has a more localized distribution and thus a lower order time dispersion index ($TD_3=0.35$) than user #4 ($TD_4=0.53$).

Figure 2. Examples of Different Patterns of Purchase Time Dispersion

Model Specification

We examine the effect of the mobile channel adoption on the purchase time dispersion with the Difference-in-Differences (DD) technique. By comparing the change in purchase time dispersion after the mobile channel adoption between the treatment group (i.e., mobile channel adopters) and the control group (i.e., mobile channel non-adopters), we can tease out the effect of the mobile channel adoption on the purchase time dispersion (Greene 2003). The DD estimator has the following form:

$$DD_{(before, after)} = \left(\bar{y}^A_{after} - \bar{y}^A_{before}\right) - \left(\bar{y}^{NA}_{after} - \bar{y}^{NA}_{before}\right)$$

where DD is the average treatment effect of the mobile channel adoption on the purchase time dispersion; $\bar{y}^A_{after}$ ($\bar{y}^A_{before}$) is the average purchase time dispersion of the adopter group after (before) the mobile channel adoption; and $\bar{y}^{NA}_{after}$ ($\bar{y}^{NA}_{before}$) is the average purchase time dispersion of the non-adopter group for the same period as the adopter group. In the analysis, we set a three-month time window *after* the adoption from March 2011 to May 2011 (*Window_After*), when there were a sufficient number of mobile channel users, and a time window *before* the adoption from March 2010 to May 2010 (*Window_Before*), that is, just before the channel introduction. We calculated $\bar{y}^i_{after}$ and $\bar{y}^i_{before}$, where i $\in$ {A, NA}, for the two windows, respectively.

It is important to note that the estimator is consistent only when the common trend assumption holds, that is, the adopter and non-adopter groups should not have distinct time trends (Bertrand et al. 2004). The above estimator controls for time-invariant group-specific effects by subtracting the time dispersion *before* the adoption ($\bar{y}^i_{before}$) from the time dispersion *after* the adoption ($\bar{y}^i_{after}$), where i $\in$ {A, NA}, and the common macroeconomic effect is controlled for by subtracting the time dispersion of the *non-adopter* group ($\bar{y}^{NA}_t$) from the time dispersion of the *adopter* group ($\bar{y}^A_t$), where t $\in$ {before, after}; however, group-specific time trends cannot be controlled for by the DD estimator. In our case, there is no guarantee that the adopter group and the non-adopter group have the same time trend, because the two groups are heterogeneous.[4] The DD estimator will overestimate (underestimate) the adoption effect if the last term is positive (negative).

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[4] For example, the treatment group is younger than the control group.

Figure 3. DDD with Distinct Time Trends across Groups
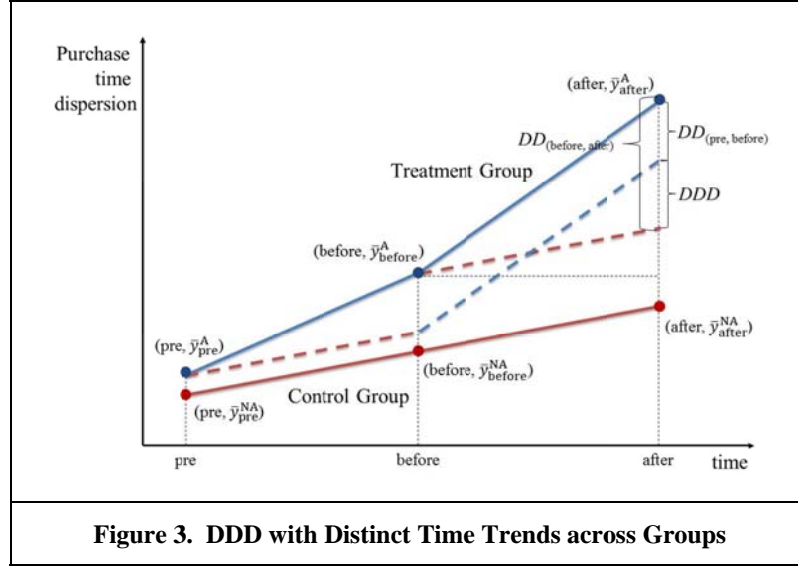
In order to control for a differential trends across the two groups, we use the Difference-in-Differences-in-Differences (DDD) estimator by incorporating the possibility of different time trends for the two groups. We need to select another time window, *Window_Pre*, in such a way that the time interval between Window_Pre and Window_Before is the same as that between Window_Before and Window_After and therefore it can be regarded that similar differential trends have been occurred for the two intervals. So, we set Window_Pre from March 2009 to May 2009. Then, we subtract the DD estimator between Window_Pre and Window_Before ($DD_{(pre,\ before)}$ in Figure 3) from the DD estimator between Window_Before and Window_After ($DD_{(before,\ after)}$ in Figure 3) (Blundell and Costa Dias 2000). Then, the resulting DDD estimator recovers the impact of the mobile channel adoption on purchase time dispersion.

The final confounding factors we need to control for are related to the fact that the mobile channel adoption was not an exogenous treatment to the model (i.e., users made a conscious decision on whether to adopt the mobile channel). So, our data is from an unnatural experimental setting. In this case, the effect estimated from the DDD estimation might be due to other factors such as age of users, which could be associated with the mobile channel adoption. Therefore, we have to control for the factors that potentially drive the mobile channel adoption (Besley and Case 2000). To rule out the endogeneity issue, we employed several control variables, such as search behaviors, privacy-related behaviors, transaction risk-related behaviors, assurance-seeking behaviors, prior transaction density over product categories and days of the week at the online channel and demographics, which were identified as the drivers of mobile channel adoption (Bang et al. 2014). Furthermore, to avoid possible endogeneity issues related to the control variables, we measured the control variables using the data from the period before the mobile channel launch.

To incorporate the control variables in the estimation, we use the following regression model equivalent to the DDD estimation:

$$y_t^i = \beta_0 + \beta_1 \cdot 1(i=A) + \beta_2 \cdot 1(t=after) + \beta_3 \cdot 1(i=A) \cdot 1(t=after) + \beta_4 \cdot 1(t=before) + \beta_5 \cdot 1(i=A) \cdot 1(t=before) + \gamma \cdot X + \varepsilon_t^i,$$

where $1(\cdot)$ is an indicator function, X is a vector of control variables, $\beta = [\beta_0, \beta_1, \dots, \beta_5]$ and γ are vectors of the coefficients, and ε_t^i is an error term. Then, $\beta_3 - 2\beta_5$ should represent the effect of mobile channel adoption on the purchase time dispersion (see Appendix 1).

As stated above, the three-month windows, Window_After, Window_Before, and Window_Pre, are used for deriving $\bar{y}_{after}^i$, $\bar{y}_{before}^i$, and $\bar{y}_{pre}^i$, respectively. For constructing the treatment group from Dataset 2, we eliminated users who joined the e-marketplace after March 1, 2009 (the beginning of Window_Pre) to make sure each user was active over the entire period of the windows. In a similar vein, we also excluded users who adopted the mobile channel after March 1, 2011. Lastly, 16 business users were dropped, since they show significantly different shopping patterns from individual users in terms of purchasing volume

Table 1. Basic Description on Data		
Total Number of Orders		
	Treatment Group	Control Group
Number of orders	**381,256**	**870,708**
Number of orders by hour of day		
00h	22,538	44,577
01h	15,821	30,113
02h	9,137	17,451
03h	5,570	10,354
04h	3,421	6,765
05h	3,009	4,861
06h	3,254	5,260
07h	4,601	7,966
08h	7,172	15,245
09h	12,411	30,893
10h	17,143	45,917
11h	22,935	58,815
12h	20,795	54,128
13h	22,477	59,822
14h	21,988	57,772
15h	21,164	55,944
16h	20,901	55,611
17h	20,274	49,450
18h	16,522	38,190
19h	14,991	32,407
20h	18,327	36,395
21h	22,983	44,911
22h	26,343	51,995
23h	27,479	54,673
Total Subjects	**6,477**	**17,349**
Gender	Female	3,289	10,691
	Male	3,188	6,658
Age	≤ 20	362	626
	21~25	1,592	2,559
	26~30	2,143	4,795
	31~35	1,344	4,547
	36~40	639	2,572
	41~45	245	1,185
	46~50	93	531
	51≤	59	534

and frequency. The remaining dataset consist of 6,477 users and their 381,256 order records. For the control group, we eliminated from Dataset 1 those users who joined the e-marketplace after March 1, 2009, resulting in 17,349 users and their 870,708 records. Table 1 shows the descriptive statistics of the treatment and control groups.

Analysis Result

Table 2 shows the purchase time dispersion by group and time window, and differences of the purchase time dispersion, without the control variables accounted for. Cell (7) shows that the purchase time became more dispersed after the mobile channel adoption, and Cell (11) shows that it is still valid after the common macroeconomic effect influencing both groups are controlled for. Cell (12) shows no difference between the adopter and non-adopter groups in purchase time dispersion changes from Window_Pre to Window_Before. This result partly indicates the common time trends of the two groups. Lastly, Cell (13) implies that the purchase time became more dispersed after the mobile channel adoption after we controlled for the common macroeconomic effect, time-invariant group-specific effects, and group-specific time trends.

Table 2. Purchase Time Dispersion by Panels and Time windows				
Panel A: Adopter group (n^A=6,476)			Differences	
Window_Pre (1)	Window_Before (2)	Window_After (3)	[(3) – (2)] (7)	[(2) – (1)] (8)
.335 (.005)	.392 (.002)	.464 (.004)	.072 (.005)	.057 (.005)
Panel B: Non-adopter group (n^{NA}=17,349)				
Window_Pre (4)	Window_Before (5)	Window_After (6)	[(6) – (5)] (9)	[(5) – (4)] (10)
.355 (.003)	.401 (.002)	.415 (.003)	.015 (.003)	.046 (.003)
Difference-in-differences			[(7) – (9)] (11)	[(8) – (10)] (12)
			.057* (.006)**	**.012 (.007)**
Difference-in-differences-in-differences			[(11) – (12)] (13)	
			.045* (.010)**	

Note: *p<0.05, **p<0.01, ***p<0.001; two-tailed tests.

Table 3. DDD Estimation with Control Variables	
Dependent Variable = Purchase Time Dispersion	
Explanatory Variables	**Coefficients (Std. Err.)**
Constant (β_0)	0.243 (0.030)***
Adopter-group indicator (β_1)	−0.018 (0.006)**
After-period indicator (β_2)	0.077 (0.004)***
Adopter-group indicator × After-period indicator (β_3)	0.059 (0.007)***
Before-period indicator (β_4)	0.066 (0.004)***
Adopter-group indicator × Before-period indicator (β_5)	0.016 (0.007)*
Control Variables	
Search behaviors	
Proportion of orders searched either through keyword typing or category browsing	−0.004 (0.007)
Mean number of product categories per order	−0.008 (0.004)*
Mean display rank of orders	0.001 (0.000)*
Privacy-related behaviors	
Email promotion allowance	0.002 (0.003)
SMS promotion allowance	−0.004 (0.003)
Whether to report personal interests	−0.001 (0.003)
Whether to authorize personal information transfer	0.150 (0.005)***
Transaction risk-related behaviors	
Product return or cancellation ratios	−0.060 (0.010)***
Whether to request e-mail or SMS confirmations for transactions	0.008 (0.005)
Whether to use a safer login system	0.024 (0.013)
Assurance-seeking behaviors	
Ratio of orders with a minimum quality guarantee	−0.023 (0.008)**
Ratio of orders with a price-matching guarantee	−0.180 (0.010)***
Demographics	
Age (years)	0.000 (0.000)*
Gender (0=male, 1=female)	−0.003 (0.004)
Density of orders by day of the week (6 dummies)	χ^2 = 6.43, Prob. > χ^2 = 0.376
Density of orders by product category (37 dummies)	χ^2 = 266.92, Prob. > χ^2 = 0.000

Note: *p<0.05, **p<0.01, ***p<0.001; two-tailed tests. The list of thirty-eight product categories used in the analysis is provided in Appendix 2.

Although the results in Table 2 present evidence of an increase in purchase time dispersion after the mobile channel adoption, it is hasty to conclude that the increase in dispersion was due to the mobile channel adoption since we did not control for those factors that might have affected the mobile channel adoption. Table 3 shows the result after controlling for those factors. $\beta_3 - 2\beta_5$ (=0.027) is positive and significant (p<0.05), demonstrating that the purchase time became more dispersed after the mobile channel adoption even after eliminating the possible confounding effects. This result presents strong evidence of the effect of mobile channel adoption on the purchase time dispersion, thereby supporting H1.

Heterogeneous Impacts of Mobile Channel Adoption across Groups

The technology affordance perspective suggests that the realization of access affordance of mobile channel can be heterogeneous across user groups (H2). Figure 4 shows the histogram of the triple-differences in time-dispersion for each individual user *k* after controlling for the baseline change. The histogram is multimodal, suggesting there might be multiple user segments within the mobile channel adopters that are relatively more homogeneous than others in terms of the effect of the mobile channel adoption on their purchase time dispersion (Hofstede et al. 2002). To formally test for the unimodality, we calculated Hartigan's dip statistic, which is the maximum difference between the empirical distribution function and the unimodal distribution function that minimizes that maximum difference (Hartigan and Hartigan 1985). The Hartigan's dip statistic is 0.0118 with p-value of 0.0013, indicating the null hypothesis of unimodality is rejected at the 1% significance level.

In order to examine the latent user segments, we employed the growth mixture model (GMM). The GMM can capture a subset of users whose growth trajectories are significantly different from others. The random coefficient models are often used to capture the individual heterogeneity through different intercept and slopes, but they are drawn from a single distribution with common parameters. In contrast, the GMM relaxes this assumption and allows for differences in parameters for potential user segments. For the GMM estimation, we focused on users who adopted the mobile channel before Jan/01/2011 (total of 8,818 users) and set the time dispersions for four consecutive 50-day windows, y_t^k, $t \in \{0, 1, 2, 3\}$, as four dependent variables, where y_0^k is the time dispersion during the last 50 days before the user k adopted the mobile channel; y_1^k is the time dispersion during the first 50 days after the adoption; and y_2^k (y_3^k) is the time dispersion during the second (third) 50 days after the adoption. We included all the control variables used in the DDD estimation as the control variables for slopes and intercepts in the GMM estimation. We determined the number of latent classes using the Bayesian Information Criterion (BIC) and Lo-Mendell-Rubin test (Nylund et al. 2007). Both criteria suggest a two-class model is the most appropriate. The entropy of separation (ES) of the two class model was 0.890.
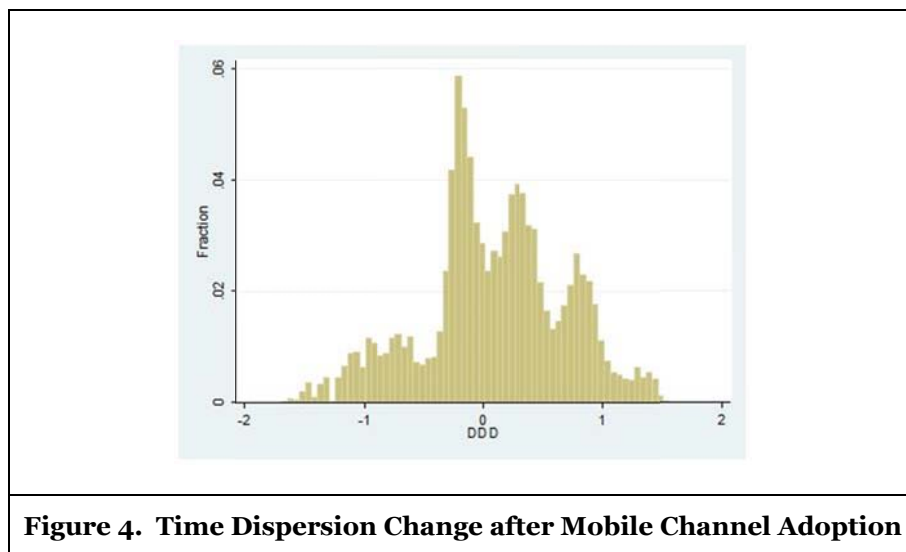

Figure 4. Time Dispersion Change after Mobile Channel Adoption

Among the 8,818 mobile channel adopters, 1,707 users (19.4%) were clustered into Class 1 and 7,111 users (80.6%) into Class 2 based on estimated posterior probabilities (Table 4 and Figure 5). Class 1 is a group of users who showed insignificant changes in the purchase time dispersion, while Class 2 showed an increasingly diversified pattern in their purchase time throughout a day after adopting the mobile channel. The average purchase time dispersion before mobile channel adoption ($t=0$) was much higher for Class 1 than for Class 2, suggesting users in Class 1 might have had a more flexible time table (e.g., college students), and been less subject to time constraints with respect to purchasing products from the e-marketplace, compared to users in Class 2 (e.g., business people). Consequently, there was no impact of mobile channel adoption on their purchase time dispersion. On the other hand, users in Class 2 have received benefits from using the mobile channel. The mobile channel seems to have liberalized their purchase time – they could enjoy anytime shopping by using the channel. The GMM results confirm the existence of user segments and heterogeneous effects of the mobile channel adoption on the purchase time dispersion across the user segments, suggesting access affordance of the mobile technology was realized differently across user segments. Furthermore, the continuous increase in purchase time dispersion of Class 2 (Figure 5) shows the adaptation of the user group to using the mobile channel as their transaction experience in the channel accumulates, indicating the dynamic nature of the realization of access affordance over time. This result is consistent with our early conjecture and supports H2a and H2b.

Table 4	Growth Mixture Model Results		
2-class Model	Class Size	Slope	Intercept
Class 1	n_1=1,707 (19.4%)	0.000 (0.009)	0.457 (0.015)***
Class 2	n_2=7,111 (80.6%)	0.057 (0.009)***	0.221 (0.015)***
Control Variables			
Search Needs			
Proportion of orders searched either through keyword typing or category browsing	0.014 (0.002)***	0.011 (0.004)**	
Mean number of product categories per order	-0.005 (0.001)***	-0.003 (0.002)	
Mean display rank of orders	0.000 (0.000)	0.000 (0.000)	
Privacy Concerns			
Email promotion allowance	0.004 (0.001)**	0.004 (0.002)	
SMS promotion allowance	0.001 (0.001)	−0.002 (0.002)	
Whether to report personal interests	-0.002 (0.001)	0.002 (0.002)	
Whether to authorize personal information transfer	0.002 (0.001)	0.005 (0.002)*	
Transaction risk-related behaviors			
Product return or cancellation ratios	0.016 (0.003)***	0.011 (0.006)	
Whether to request e-mail or SMS confirmations	-0.002 (0.002)	-0.003 (0.003)	
Whether to use a safer login system	-0.020 (0.004)***	0.006 (0.007)	
Assurance-seeking behaviors			
Ratio of orders with a minimum quality guarantee	0.016 (0.003)***	0.009 (0.004)	
Ratio of orders with a price-matching guarantee	0.009 (0.004)*	0.022 (0.006)***	
Demographics			
Age (years)	0.000 (0.000)	0.000 (0.000)	
Gender (0=male, 1=female)	0.003 (0.001)*	0.003 (0.002)	
Preference on Day of Week (6 dummies)	Not shown for expositional brevity		
Preference on Product Categories (37 dummies)			

Note: *$p<0.05$, **$p<0.01$, ***$p<0.001$; two-tailed tests. Class counts and proportions for the latent class patterns are based on estimated posterior probabilities. The list of thirty-eight product categories used in the analysis is provided in Appendix 2.
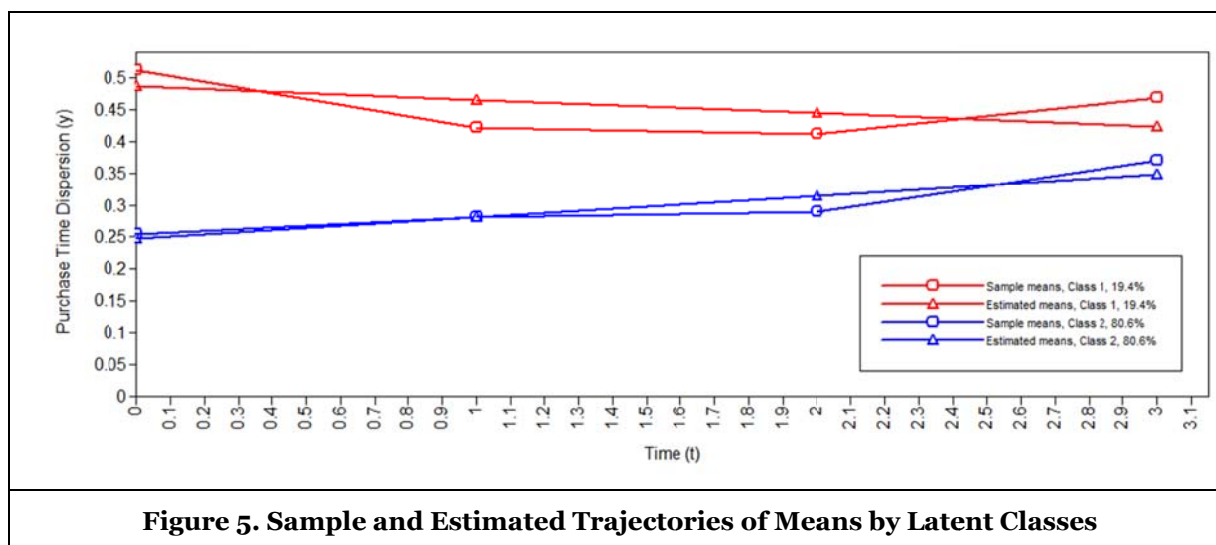
Figure 5. Sample and Estimated Trajectories of Means by Latent Classes

Discussion and Conclusion

In this paper, we empirically examined affordances of mobile technologies. Using a large archival dataset encompassing transactions by mobile channel adopters and non-adopters before and after the mobile channel launch, we analyzed the change of e-commerce users' purchase time dispersion triggered by the access affordance of the mobile channel.

With the portability of a mobile device throughout a day and the ubiquity of mobile Internet, the mobile channel provides e-market users with more opportunities of access to the e-commerce site. Despite the significance of mobile channel and recent calls for research, there is a paucity of empirical studies on m-commerce. Our study contributes to the burgeoning literature on mobile commerce. This is among the first to examine how the mobile channel adoption changes users' behavioral patterns, specifically, in a rarely explored dimension of social and economic behaviors, i.e., time during a day. Our DDD estimation results provide empirical evidence of access affordance of the mobile channel by showing the overall increase in purchase time dispersion throughout a day after the mobile channel adoption. The subsequent GMM analysis results indicate that the effects of the mobile channel adoption on the change of purchase time dispersion vary across two latent user groups. The mobile channel freed those users who wanted to enjoy ubiquitous shopping but couldn't before the mobile channel adoption (Class 2), but had no impact on the purchase time dispersion of the users whose purchase time was already quite dispersed before mobile channel adoption (Class 1).

This study also contributes to the technology affordance literature, which has usually depended on narratives of a few users for empirical evidence of its arguments, by shedding light on the affordance of mobile technologies in the context of e-commerce and verifying heterogeneous and time-varying impacts on technology use. The literature has suggested that the realization of a technology affordance can be different across different user groups, because each user group could have different usage context and technology intention (Markus and Silver 2008). The existence of two distinct user groups found from our GMM analysis supports the argument based on large-scale revealed preference. Another important argument is that the realization could be dynamic as user experience with technology accumulates (Faraj and Azad 2012; Treem 2012). The gradual increase in purchase time dispersion of Class 2 indicates the learning process of the user group in the mobile channel. If there had been no impact of user experience with the mobile channel on the purchase time dispersion, then the increase should have occurred only at the time of the mobile channel adoption.

Our main result, increased purchase time dispersion after mobile channel adoption, provides an important managerial implication to the digital ads market. In the PC-only world, orders are (relatively) concentrated to a few time slots, and advertisers should pay high prices for obtaining the peak time slots from ads platform operators such as Google AdWords, Facebook, or Alibaba-type e-marketplaces. In the

mobile world, however, thanks to the access affordance of mobile channel, e-market users could purchase products anytime they want, resulting in other traditionally non-peak time slots becoming attractive to advertisers. By lowering the advertising costs for advertisers and increasing the time slots the ads platform operators can sell, this purchase time dispersion due to mobile channel adoption can lead to a "win-win" situation for the two parties.

This paper also provides important implications to e-commerce firms. E-commerce users' purchase behavior is not uniform in the time dimension, which has been a rationale behind the suggestion that e-commerce firms should consider time during a day as a decision variable in addressing the users (e.g., dayparting in online advertising). Our results show that the behavioral patterns are subject to changes with adoption of new technologies (i.e., the mobile technology). Further, as the GMM analysis indicates, the same mobile technology does not necessarily lead to changes in purchase time dispersion in similar ways across users; and the change may not be instantaneous but may involve users' adaptation over time. These results imply that e-commerce firms need to monitor and understand users' purchase time patterns continuously, and adjust their practices, including targeting and advertising, accordingly.

Our study has a few limitations. First, our data do not allow us to consider multi-channel usage behaviors. For example, e-marketplace users might search for products in the PC channel, and then purchase the products in the mobile channel which has ubiquitous access capability. Although consumers are likely to purchase at the moment when they have enough information about the product, consumers could exploit the benefits of each channel (Han et al., 2013). Collecting data regarding multi-channel usages and examining the hopping from one channel to another will be an interesting avenue for future research. Second, since our data was obtained from a single e-marketplace, users' experience at other online retailers or marketplaces could not be considered in the analysis. Although the e-marketplace is the largest in terms of revenue in the mobile commerce market in South Korea, users' mobile commerce experience could be accumulated through other competing e-markets as well. Our study can be extended by examining the impact of users' mobile channel experiences at one e-market on their usage behaviors at other e-markets.

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Appendix 1.

$y_t^i = \beta_0 + \beta_1 \cdot 1(i=A) + \beta_2 \cdot 1(t=after) + \beta_3 \cdot 1(i=A) \cdot 1(t=after) + \beta_4 \cdot 1(t=before) + \beta_5 \cdot 1(i=A) \cdot 1(t=before) + \varepsilon_t^i,$

$E[y_t^i \mid i=A, t=after] = \beta_0 + \beta_1 + \beta_2 + \beta_3,\ E[y_t^i \mid i=A, t=before] = \beta_0 + \beta_1 + \beta_4 + \beta_5,\ E[y_t^i \mid i=A, t=pre] = \beta_0 + \beta_1,$

$E[y_t^i \mid i=NA, t=after] = \beta_0 + \beta_2,\ E[y_t^i \mid i=NA, t=before] = \beta_0 + \beta_4,\ E[y_t^i \mid i=NA, t=pre] = \beta_0,$

$DD_{(before,\ after)} = \left(\bar{y}_{after}^A - \bar{y}_{before}^A\right) - \left(\bar{y}_{after}^{NA} - \bar{y}_{before}^{NA}\right),\ \therefore\ E[DD_{(before,\ after)}] = \beta_3 - \beta_5$

$DD_{(pre,\ before)} = \left(\bar{y}_{before}^A - \bar{y}_{pre}^A\right) - \left(\bar{y}_{before}^{NA} - \bar{y}_{pre}^{NA}\right),\ \therefore\ E[DD_{(pre,\ before)}] = \beta_5$

Therefore, $DDD = DD_{(before,\ after)} - DD_{(pre,\ before)} = \beta_3 - 2\beta_5$

Appendix 2. The List of Thirty-eight Product Categories Used in the Analysis

1. Cellphone/Smartphone
2. Digital Camera/DSLR Camera
3. MP3/PMP/Electronic Dictionary
4. Digital Goods (Software, Game)
5. PC-related Peripherals
6. TV/Fridge/Washing Machines
7. e-Coupons/Gift Cards
8. Furniture
9. Bag/Wallet/Fashion Accessories
10. Health/Siler Products
11. Golf Clubs/Supplies
12. Men's Fashions/Apparel/Underwear
13. GPS/Black Box
14. Laptop/Desktop PC
15. Book/Music/DVD
16. Hiking/Outdoor/Camping/Fishing
17. Stationery
18. Baby Products
19. Senior Clothing
20. Daily Supplies
21. Skin Care/Cosmetics
22. Sports Equipment
23. Watches/Jewelry/Fashion Accessories
24. Fresh Goods (Agricultural Products, Marine Products)
25. Flowers
26. Women's Fashions/Apparel/Underwear
27. Shoes
28. Travels/Hotels/Airline Tickets
29. Children's Apparel
30. Sound/Speaker
31. Automobile (Tires, Parts)
32. Toy/Doll
33. Kitchen Appliances/Supplies
34. Confectionary/Processed Food
35. Childbirth/Maternity Dress
36. Bedding/Curtain/Carpet
37. Shopping Abroad
38. Perfume/Hair/Body