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Short Paper

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Abstract

With the introduction of mobile technology, user behavior has been changed. One of the most representative features of mobile channels is that it enables users to access services regardless of time and place. The mobile channel is expected to enhance the flexibility of users. We examine whether there is a difference in purchase behavior between users who adopted mobile channels and those who did not, in a context where purchase time is limited and early purchase gives potential financial merit, using a large dataset from high-speed railway service in Korea. An interesting issue is whether mobile channel makes users purchase earlier and increase the chance to get discounts. Our results using difference-in-differences estimation with propensity score matching show that people who adopted mobile channel purchase tickets later on average and at a higher price than those who did not adopt mobile channel.

Keywords: Mobile channel, flexibility, purchase time, discounted amounts, purchasing behavior

Introduction

Mobile technology has changed our daily lives. From a business perspective, the way people make purchases has undergone many changes due to mobile technology. One of the unique characteristics of mobile channel compared to offline channel and PC channel is that it enable users to access the state-of-the-art services anytime and anywhere (Bang et al. 2013; Xu et al. 2017). Mobile channel is associated with the capability of a channel in offering instant Internet access (Xu et al. 2017). Balasubramanian et al. (2002) argue that time is a precious and limited resource to most people, and the mobile channel has fewer constraints in terms of time and space.

In addition to previous papers on the effects of the traditional online channel (Brynjolfsson et al. 2003, 2009; Choi et al. 2010; Forman et al. 2009), several studies on the impact of mobile channel adoption have been conducted. Ghose et al. (2013) show that the mobile channel has higher ranking effects suggesting higher search costs. In a marketplace, a user's purchase time becomes more dispersed throughout the day after the mobile channel adoption (Bang et al. 2014). Besides, the adoption increases website visits (Xu et al. 2014), spending (Kim et al. 2015), and the number of orders (Wang et al. 2015).

Although prior studies provide useful insights on mobile channel introduction, we found important gaps in the literature. First, previous studies have not investigated the changed purchase timing and the corresponding discounted amounts when there is a time limit. The mobile channel is expected to enhance the flexibility of the customers in the purchase decision process (De Haan et al. 2018; Lee and Benbasat 2004; Okazaki and Mendez 2013; Wang et al. 2015). On the one hand, people can respond more quickly for first-come-first-served purchases, as the mobile channel make them accessible anytime and anywhere. On the other hand, people may not have to make an early purchase because the mobile channel enables them to purchase when they need. Thus, it is unclear whether this enhanced flexibility leads to earlier purchases or delayed purchases in purchase-time limited circumstance. Second, there is a literature gap in the monopoly market. In the previous studies on the marketplace, the existence of numerous substitutes is a typical point of limitation. The monopoly in a marketplace is expected to show better the behavior change of the user according to the new channel adoption.

To fill these gaps, we use a large dataset from a Korean high-speed railway corporate. It has launched the first high-speed railway service in Korea in April 2004 and has become one of the most popular means of transportation. If one makes a reservation for a ticket at the corporate's online homepage or mobile app, one can get a discount opportunity on a first-come-first-served basis. In addition, the railroad service is virtually monopolistic or has relatively limited heterogeneous alternatives compared to the contexts of extant researches.

Our results show that the mobile channel adoption encourages delayed purchases, and thus decreases the discounted amounts on average. This study is in line with this emerging stream on the mobile channel and mobile commerce, and contributes to it with a different context, in respect that consumers in our research are under the circumstances which the purchase time and alternatives are limited.

The rest of this paper is organized as follows. We first provide an overview of our data and describe the empirical approach used in this research. We conclude our paper with the result and future research directions.

Data and Methodology

Data Description

We obtain a large transaction dataset from the database of a dominant railroad corporate in Korea. The dataset contains entire ticketing information including user ID, purchase time, price, departure and arrival information, and the information of the seat during the period from May 2015 to August 2018. We focus on the express train which has the highest demand in the railroad industry.

We are interested in active users to investigate the changed behavior after the mobile channel adoption. So we focus on the users who purchase at least one tickets each year during our observation periods. To examine the impact of mobile channel adoption, we extract the users who did not purchase tickets through the mobile channel for more than 8 months (from May 2015 to December 2015)[1]. The remaining samples contain 105,446 users, including mobile channel adopters who adopt mobile channel from January 2016 and non-adopters, and their 4,594,039 ticketing transactions. Train tickets have static prices based on the departure and arrival station, but the railroad corporate provides a first-come-first-served promotional price on trains. Each ticket starts selling a month before departure. The number of discounted tickets are limited, so the earlier user purchase, the more likely they are to buy tickets cheaper. In our empirical validation, we used a monthly panel dataset, and Table 1 lists the definitions and summary statistics of variables.

Table 1. Variable Definition and Summary Statistics

Variables	Definition	Mean	Std. Dev.
early	Average days purchased earlier than departure date	4.426	6.120
discount	Average discounted amounts (KRW)	2,594.935	5,183.581
rides	Number of purchased tickets	3.096	3.050
hours	Average hours of journey	1.880	0.685
fare	Average paid fare (KRW)	40,828.200	15,715.412
dspstn	The number of unique departure stations	1.843	0.876
arvstn	The number of unique arrival stations	1.874	0.907
rsv_weekend	Proportion of weekend of reservation date	0.310	0.399
rsv_time#	Proportion of time segment at the timing of reservation (0:00~6:00, 6:00~12:00, 12:00~18:00, 18:00~24:00)	0.027 0.312 0.426 0.225	0.136 0.395 0.416 0.356
dpt_weekend	Proportion of weekend of departure date	0.534	0.436
dpt_time#	Proportion of time segment at the timing of departure (0:00~6:00, 6:00~12:00, 12:00~18:00, 18:00~24:00)	0.025 0.361 0.382 0.232	0.124 0.357 0.366 0.321

Empirical Approach

There are potential endogeneity and self-selection problems when we simply compare the adopters and non-adopters to investigate the effects of mobile channel adoption. To mitigate the issue, we use Propensity Score Matching (PSM) to match adopters and non-adopters with propensity scores (Rosenbaum and Rubin 1983). In this paper, we define mobile channel adopters as those who don't have ticketing records through the mobile channel in 2015 but start to purchase tickets through mobile channel after 2015. We also put a strict condition that the adopters use mobile ticketing every year after the adoption. For the matching rule, we employ a logistic regression model to obtain propensity scores and a one-to-one matching with replacement and the caliper size of 0.2 times the standard deviation of the propensity score (Xu et al. 2017).

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[1] We conduct robustness check with a longer period without mobile channel usage (May 2015 ~ December 2016), and the analysis shows the consistent results.

The *t*-tests on our matching variables confirm that the differences between the two groups become insignificant after matching (Table 2).

With the matched samples, we conduct difference-in-differences (DID) estimation (Greenwood and Wattal 2017; Reimers and Xie 2019; Rishika et al. 2013) to compare the relative change in the purchase behaviors of adopters and non-adopters before and after mobile channel adoption. Our DID estimation model for user *i* and month *t* is,

$$\ln DV_{it} = \beta_0 + \beta_1 \times Treatment_i \times Post_{it} + \beta_2 \times Post_{it} + X_{it} + \sigma_i + \tau_t + \varepsilon_{it} \qquad \text{(Eq. 1)}$$

where the DV_{it} is the average days purchased earlier than the departure date (the average discounted amounts), $Treatment_i$ is a dummy variable indicating the treatment group (1=adopter, 0=non-adopter), $Post_{it}$ is a

Table 2. Baseline User Matching Results

Variables	Adopter	Non-Adopter	Matched Non-Adopter	Difference Before Matching	Difference After Matching
ln(early)	1.363	1.419	1.366	-0.055*** (0.006)	-0.003 (0.007)
ln(discount)	4.512	5.243	4.495	-0.731*** (0.025)	0.017 (0.034)
ln(rides)	0.621	0.707	0.620	-0.087*** (0.004)	0.000 (0.005)
ln(hours)	1.055	1.071	1.056	-0.016*** (0.002)	-0.001 (0.002)
ln(fare)	10.577	10.594	10.579	-0.018*** (0.003)	-0.003 (0.004)
ln(dptstn)	0.401	0.458	0.402	-0.058*** (0.002)	-0.002 (0.003)
ln(arvstn)	0.411	0.472	0.412	-0.061*** (0.002)	-0.001 (0.003)
rsv_weekend	0.277	0.275	0.276	0.002 (0.002)	0.001 (0.003)
rsv_time1	0.027	0.018	0.027	0.009*** (0.001)	-0.000 (0.001)
rsv_time2	0.322	0.346	0.324	-0.024*** (0.002)	-0.001 (0.003)
rsv_time3	0.428	0.437	0.427	-0.009*** (0.003)	0.001 (0.003)
rsv_time4	0.223	0.199	0.222	0.024*** (0.002)	0.001 (0.003)
dpt_weekend	0.481	0.460	0.483	0.021*** (0.003)	-0.002 (0.003)
dpt_time1	0.029	0.027	0.030	0.002*** (0.001)	-0.000 (0.001)
dpt_time2	0.393	0.395	0.394	-0.002 (0.002)	-0.001 (0.003)
dpt_time3	0.366	0.384	0.367	-0.018*** (0.002)	-0.001 (0.003)
dpt_time4	0.212	0.194	0.210	0.018*** (0.002)	0.002 (0.002)

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

dummy variable indicating the post-treatment period (1=after adoption, 0=before adoption) for adopters and their matched counterpart, X_{it} are control variables, σ_i is the user fixed effects, τ_t is the time fixed effects, and ε_{it} is the error term clustered by users to allow for a correlation over time (Moulton 1990). The coefficient β_1 for the interaction term represents the comparative effects of mobile channel adoption on the dependent variables for adopters after adoption in comparison to non-adopters.

The coefficients of the interaction term for both dependent variables are negative and statistically significant (Table 3). These results show that users purchase tickets later at a more expensive price after mobile channel adoption. It can be interpreted that users are more likely to purchase tickets right before they get on the train at the expense of catching the promotional price.

For the robustness checks, we replicate our main analysis with a different non-adoption period (May 2015 ~ December 2016), time windows for adoption periods (three, six, nine, and twelve months before and after the adoption), and with a different sample obtained through various matching techniques. We conduct one-to-one matching without replacement and replicate the same matching specification under a caliper size of 0.05 times the standard deviation of propensity scores with common support. We find that the results are consistent with the main results (Table 4).

There are endogeneity issues as we can only match users based on observable features. For an additional robustness check, we restrict our samples to adopters and conduct look-ahead matching, which creates new treatment group with early adopters and control group with late adopters (Datta et al. 2018; Manchanda et al. 2015; Xu et al. 2017). In this analysis, we examine the new treatment and control groups in the period when the late adopters were still non-adopters. We conduct two look-ahead matchings with different adoption periods. First, we set the treatment group as the adopters who started mobile ticketing in 2016, and the control group as the late adopters who made the first purchase through the mobile channel after 2016. Second, we set the treatment group as the users who adopted mobile channel in 2017, and the control group as the adopters who made the first mobile purchase after 2017. We replicate the main analysis, and the results are consistent with our main findings (Table 5).

Table 3. Difference-in-Differences Analysis Results

Variables	Early Purchase	Discounted Amounts
$Treatment_i \times Post_{it}$	-0.132*** (0.003)	-0.160*** (0.013)
Controls	Yes	Yes
User Fixed Effect	Yes	Yes
Time Fixed Effect	Yes	Yes
Number of Observations	1,036,889	1,036,889

Note: Robust standard errors clustered by each user in parentheses. ***$p<0.01$, **$p<0.05$, *$p<0.1$. The results of the control variables are not shown for expositional brevity.

Table 4. Robustness Check Results

	Early Purchase	No. of Obs.	Discounted Amounts	No. of Obs.
Non-adoption period				
One-to-one without replacement	-0.151*** (0.004)	374,781	-0.139*** (0.022)	374,781
No matching	-0.153*** (0.004)	819,936	-0.243*** (0.018)	819,936
Time windows				
Three months	-0.181*** (0.006)	214,278	-0.160*** (0.030)	214,278
Six months	-0.162*** (0.005)	352,247	-0.185*** (0.023)	352,247
Nine months	-0.148*** (0.004)	481,616	-0.174*** (0.019)	481,616
Twelve months	-0.144*** (0.004)	600,496	-0.178*** (0.017)	600,496
Matching techniques				
Caliper size of [0.2*standard deviation]				
One-to-one without replacement	-0.134*** (0.003)	543,672	-0.252*** (0.017)	543,672
With common support and a caliper size of [0.05*standard deviation]				
One-to-one with replacement	-0.132*** (0.003)	1,036,642	-0.161*** (0.013)	1,036,642
One-to-one without replacement	-0.133*** (0.003)	535,603	-0.224*** (0.017)	535,603
No matching	-0.158*** (0.003)	1,483,700	-0.217*** (0.013)	1,483,700

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

Table 5. Look-ahead Matching Results

	Early Purchase	No. of Obs.	Discounted Amounts	No. of Obs.
Cutoff in 2016	-0.149*** (0.004)	407,966	-0.155*** (0.019)	407,966
Cutoff in 2017	-0.166*** (0.005)	259,762	-0.166*** (0.026)	259,762

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

Ticketing behavior could be different between the trains on weekdays and the trains on the weekend. People are more likely to take a train for commuting or business trip on weekdays, but there might be more passengers for leisure or travel on the weekend. The difference purpose of usage can bring difference ticketing time and transacted price. We classify our samples into weekdays (Monday-Thursday) and weekend (Friday- Sunday) based on the departure date, and replicate our panel analysis for two subsamples. The results illustrate that the absolute value of the estimated coefficient on weekdays is slightly bigger than that of the weekend (Table 6). The effects of mobile channel adoption are prevalent when users purchase tickets for trains on weekdays. People might move unplanned on weekdays compared to weekends, and mobile channel further delays ticketing at a higher price on weekdays.

Table 6. Subsample Analysis on Day of the Week

	Early Purchase	No. of Obs.	Discounted Amounts	No. of Obs.
Weekdays	-0.142*** (0.006)	472,547	-0.250*** (0.027)	472,547
Weekend	-0.139*** (0.006)	465,780	-0.197*** (0.029)	465,780

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

Discussion and Future Research Direction

In this study, we empirically examined how the purchase behavior changes as the users adopt the mobile channel represented by the instant access regardless of time and space. As mobile channel further enhances user's flexibility in the purchase process, there is a possible scenario that it would allow users to buy earlier in situations where early purchase brings the chance of financial benefits. Conversely, due to the flexibility, there was another scenario that customers do not make purchases promptly as they are able to make purchases at the time they need.

As the results of our analysis using a large dataset encompassing transactions by mobile channel adopters and non-adopters, how two conflicting scenarios are reflected collectively, the effect of the latter one is stronger. The group of users that adopted the mobile channel is found to have a tendency to delay purchasing (i.e., make a purchase close to the actual date of operation) after the mobile channel adoption and therefore pay a higher price on average than the group of users who did not adopt the mobile channel.

Understanding the changes in user behavior in a mobile environment is increasingly important in a wide variety of industries where the mobile environment has become dominant. This study shed light on how the adoption of a new channel, called mobile channel, reshape the behavior of the users' purchase pattern, especially on their purchase time and transacted price in railroad ticketing.

Future research directions will be a more detailed analysis focusing on the phenomenon that explains users' delayed purchase behavior. We do not expect that the enhanced flexibility enabled by this mobile channel adoption equally applies to all users. As we analyze in more detail considering various heterogeneity, the implication of this study would be more enriched and the mechanism of the results might be explained. We have a plan to add utility model and conduct sub-sample analyses on various attributes including users and discount rates of trains.

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