Mobile Payment Adoption: An Empirical Investigation on Alipay

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The rapid development of mobile technology has introduced a new channel for consumer consumption, in addition to traditional online PC and offline (physical card) payment channels. In this paper, we investigate the determinants and outcomes of mobile channel adoption on consumer consumption behaviors. We utilize a unique data set from one of the largest banks in China, which contains the consumer credit card consumption from PC, offline, and mobile payment channels. The mobile payment channel under study here is from Alipay, which is now the world's largest mobile payment platform. In our work, we find that both higher service demand and higher local penetration are associated with earlier mobile channel adoption. For the post-adoption behavior analysis, we show that the total transaction amount increases by around 2.4% after the Alipay adoption, and the total transaction frequency increases by around 23.5%. The relationship is even stronger for medium income consumers. Furthermore, we find that Alipay channel acts as a substitute for the offline channel, and as a complement for the PC payment channel. Both substitution and complementarity effects increase over time. Finally, we find that the increased credit card transaction activity and profitability are likely to be driven by hedonic shopping behavior with low value items. Our work aims to bring managerial implications for bank and retail managers on multi-channel management.

Key words: Alipay, adoption, mobile payment, channel, PC, offline, online, credit card.

1. INTRODUCTION

With the rapid development of smartphones, mobile payment is becoming more and more popular among consumers and is gradually changing the non-cash commerce around the world. According to the Federal Reserve's study,[1] the amount of mobile transaction in the US reached 1.3 billion in 2015, accounting for 5.6% of the total non-cash payment transactions. In some countries, such as China, mobile payment has already become a counterpart of bank cards. According to the People's Bank of China,[2] mobile transactions have surpassed total transactions made by physical bank cards by 43%. In addition to the amount of transactions, the number of different mobile payment users is also increasing rapidly. For instance, PayPal currently has around 200 million users who have spent US$282 billion in 25 currencies in 202 countries (Farnon (2016)). Also, Apply Pay now has over 87 million users around the world, with more than US$1 million in retail consumption covering major markets, such as the US, Canada, the UK, Italy, France, New Zealand, Australia, Russia, and China (see Statista (2017)). Furthermore, according to Bloomberg,[3] Apple Pay is adding 1 million new consumers per week. The mobile payment channel under study in this paper is Alipay, which is now the largest mobile payment platform in the world[4]. On December 23, 2010, Alipay collaborated with Bank of China to start a new service called "fast payment of credit card,"[5] which simplified the payment process. After the establishment of this innovative service, Alipay officially began its mobile payment

[1] https://www.federalreserve.gov/newsevents/pressreleases/files/2016-payments-study-recent-developments-20170630.pdf

[2] http://www.pbc.gov.cn/goutongjiaoliu/113456/113469/3273108/2017031514423288068.pdf

[3] https://www.bloomberg.com/quicktake/mobile-payments

[4] John Heggestuen (11 February 2014). Alipay Overtakes PayPal As The Largest Mobile Payments Platform In The World. Business Insider. wiki

[5] http://it.sohu.com/20101223/n278474761.shtml

services. As of 2013, Alipay has overtaken PayPal as the largest mobile payment platform in the world. During the fourth quarter of 2016, Alipay had a 54% market share of China's US$5.5 trillion mobile payment market.[6] Because mobile payment has become a new trend for consumer consumption, firms and banks must understand its economic impact.

So far as we know, limited prior work has looked into the new mobile payment channel adoption and the intrinsic interdependencies that are related to mobile, PC, and offline (physical card) payment channels. Therefore, our work aims to take an initial step in understanding the determinants and outcomes of mobile payment adoption. Our ultimate goal is then to bring managerial implications for bank and retail managers on multi-channel management. To do so, we utilize a unique data set from one of the largest banks in China, which contains the consumer credit card transactions from PC, offline, and mobile payment (Alipay) channels. Our focal bank is the first bank in China that collaborated with Alipay, and the collaboration started in December 2010. This data set recorded the transactions of 4,541,583 credit cards issued between 1989 and 2013 from 3,182,237 consumers. Our observed transactions were made between September 2010 and February 2013. With our data set, we are able to identify the specific date each consumer first used Alipay to conduct transactions. We can then exploit the variation among users' Alipay adoption dates, and use our econometric methods to estimate the changes in consumption from the PC channel and physical credit card channel before and after the Alipay adoption.

In the pre-adoption analysis, we conduct survival analysis and find that higher service demand is associated with earlier mobile channel adoption; and the relationship is even stronger for frequent travelers due to channel ubiquity. More specifically, we find that a consumer's time to adopt the mobile payment channel is reduced by around 0.5% with

[6] https://www.ft.com/content/e3477778-2969-11e7-bc4b-5528796fe35c

a one-unit increase in transaction frequency of the month before adoption. Furthermore, we find that if a consumer is a frequent traveler, his time to adopt the mobile payment channel is reduced by at least 0.79% with a one-unit increase in transaction frequency of the month before adoption. Finally, higher local penetration is also associated with earlier mobile channel adoption, and a consumer's time to adopt the mobile payment channel is reduced by around 0.3% with a one-unit increase in local penetration level.

In the post-adoption analysis, we employ the difference-in-differences (DID) methodology coupled with propensity score matching (PSM) to estimate our main results. Controlling for the service demand and local penetration for matched treatment and control groups, we find that the total transaction amount increases by around 2.4% after Alipay adoption, and the total transaction frequency increases by around 23.5%. Therefore, mobile channel adoption is associated with increased credit card transaction activity and profitability, and we further find that the relationship is increasing over time and is even stronger for medium income consumers. We also find that the mobile payment channel acts as a substitute for the offline (physical card) channel and as a complement for the PC payment channel. More specifically, for the PC payment channel, the total transaction amount increases by around 0.3% after the Alipay adoption, the share of the transaction amount increases by around 0.01%, the total transaction frequency increases by around 0.18%, and the share of transaction frequency increases by around 0.016%. On the other hand, for the physical card channel, the total transaction amount decreases by around 3.9% after the Alipay adoption, the share of the transaction amount decreases by around 26.2%, the total transaction frequency decreases by around 9.4%, and the share of transaction frequency decreases by around 39.8%. Moreover, we find both substitution and complementarity effects increase over time. Finally, we find that the increased credit card transaction activity and profitability are likely to be driven by hedonic shopping behavior with low value items. In particular, mobile channel adoption has the largest effect on the groceries category, followed by entertainment, travel, and service categories.

The remainder of the paper is organized as follows. Section 2 provides a literature review. Section 3 discusses our main hypotheses. Section 4 presents the details of our data sources. Section 5 describes our econometric model. Section 6 discusses our empirical results for both pre- and post-adoption, subset analysis, and robustness checks. Section 7 summarizes our results and outlines future research directions.

2. RELATED LITERATURE

In this section, we review three streams of literature that are closely related to our work, namely, (i) PC channel adoption, (ii) features of mobile phone channel, and (iii) interdependencies among different channels.

The first stream of work closely related to ours is on the adoption of the PC channel, which is found to be associated with changes in service consumption, cost to serve, and consumer profitability (see Hitt and Frei (2002) and Campbell and Frei (2010)). In particular, consumers who adopt PC channel are found to be more profitable although the adoption will cause a reduction in short-term consumer profitability (Campbell and Frei (2010)); moreover, consumers who adopt PC channel have a lower propensity to leave the bank (Xue et al. (2011)). Recent work has started looking into the adoption of mobile banking channel, and find that the mobile banking channel serves as a complement to the PC banking channel (Liu et al. (2017)). However, so far limited work has been done on exploring the adoption of mobile payment channel and the associated consequences of mobile payment adoption. In this paper, we want to fill this void by investigating the determinants and outcomes of mobile payment channel adoption on consumer consumption behaviors.

The second stream of literature closely related to our work is on the features of mobile phone consumption. Prior work has looked into the effect of the screen size when analyzing the impact of mobile phone on consumption decisions (see Chae and Kim (2004), Kim et al. (2011), and Ghose et al. (2012)). Recent research has also focused on improving the consumer experience of browsing the web on their smartphones (Adipat et al. (2011)). Portability is also a key feature of mobile phones. Although PCs enable consumers to hold a global perspective when shopping via the computer (Overby and Lee (2006)), the restriction of portability offsets this benefit. Universality, as another essential feature, refers to a channel's ability to provide universal and stable service in space and time. Compared to PCs, mobile channels overcome the constraints of places, which constantly support consumers in activities such as information access or immediate transactions (Jung et al. (2014)). However, the storage limitation of mobile devices constrains the volume of information access and impairs the quality of PC services (Napoli and Obar (2014)). Thus, determining the moderating features associated with mobile channel adoption is crucial for bank and retail managers.

The third stream is the interdependencies among different channels, which has been studied by a significant number of papers in the past few years. In general, findings in these papers provide significant managerial insights into firms' investment-strategies problem of whether to diversify their investments or concentrate on a single retail channel. These papers have looked into the following problems: (1) the effects of substitution and complementarity between PC and offline channels, (i.e., Brynjolfsson et al. (2009), Choi et al. (2008), Ellison and Ellison (2006), Forman et al. (2009), Goolsbee (2001), and Prince (2007)); (2) how offline sales channels could be affected by mobile ads based on location or context (see Hui et al. (2013) and Molitor et al. (2016)); and (3) the interdependencies between the mobile and PC channels (see Bang et al. (2013) and Ghose and Han (2011)). From these papers, we can see that a new channel will probably be established under the condition that it has the ability to provide consumers with extra utility relative to what they have received from the previous channels. For example, when the offline stores enter the market, local consumers will shift away significantly from the previous PC channels (Forman et al. (2009)). Despite the benefits of PC shopping, such as lower prices and a wider area of product selection, the potential reasons why consumers turn to their local offline stores may include lower traveling and shipping costs, as well as the ability to check quality. Moreover, PC and offline channels can complement each other (Luo et al. (2013)), and mobile and PC channels can substitute for and complement each other simultaneously, depending on the product category (Bang et al. (2013)). Finally, the tablet channel acts as a substitute for the PC channel and a complement for the smartphone channel (Xu et al. (2016)). However, so far as we know, limited work has looked into the new mobile payment channel and the intrinsic interdependencies that are related to mobile, PC, and offline (physical card) payment channels. Thus, another goal of this paper is to explore interdependencies among the three channels.

3. HYPOTHESES

A new channel will probably be established under the condition that it has the ability to provide consumers with extra utility relative to what they have received from the previous channels. Random utility theory (McFadden (1974)) shows that consumers adopt the product that provides them with the highest utility given the costs and benefits of the product, and idiosyncratic consumer tastes. In our work, a consumer's direct cost and benefit are captured by the factor of *service demand* and the indirect cost and benefit are mainly captured by the factor of *local penetration*. We discuss how these two factors are associated with consumer mobile channel adoption in Section 3.1. After the mobile channel adoption, the usage of this new channel may change consumers consumption behaviors. We analyze the consumer behavior changes from three perspectives, namely *transaction activities*, *consumer profitability*, and *channel substitution and complementarity*. We study these three aspects in details in Section 3.2.

3.1. Hypotheses: Mobile Channel Adoption

In this subsection, we discuss our two main hypotheses on pre-adoption behavior. We consider two driven factors, namely service demand and local penetration.

Service Demand. Previous research on Internet payment adoption has shown that consumers whose service-interaction demand is high would gain greater overall benefits from any kind of service innovation, and thus they are more likely to adopt Internet payment (see Lee and Lee (2001) and Xue et al. (2011)). Similarly, here those consumers who have high service demand would also be more likely to adopt mobile payment. In our analysis, following Xue et al. (2011), we use the transaction frequency to measure the consumers' service demand. Moreover, previous work has shown that compared to PCs, mobile channels overcome the constraints of places due to channel ubiquity, and constantly support consumers in activities such as information access or immediate transactions (Jung et al. (2014)). This characteristic of channel ubiquity also enables users to enjoy videos to pass the time and mitigate solitude when traveling (O'Hara et al. (2007)). Bang et al. (2013) show that ubiquity is an important feature that measures the channel capability. In our context, similar to Xu et al. (2016), we consider channel ubiquity as the channel's ability to offer instant Internet access wherever and whenever a user wants. Intuitively, the PC channel is constrained by Internet usage and hardware. However, the mobile channel overcomes this limitation by offering ubiquitous Internet access (see Jung et al. (2014)

and Venkatesh et al. (2003)). Therefore, we expect that the relationship between service demand and earlier mobile channel adoption is stronger for consumers in need of channel ubiquity, i.e., frequent travelers. We now summarize our first hypothesis as follows.

HYPOTHESIS 1 **(H1)**. *Higher service demand is associated with earlier mobile channel adoption; and the relationship is even stronger for frequent travelers due to channel ubiquity.*

Local Penetration. Previous product diffusion and network effects literature has shown that the number of compatible products adopters may affect the product demand, see Bass (1969) and Katz and Shapiro (1985). Moreover, the Internet payment adoption literature has shown that local penetration is positively related to faster Internet payment adoption (Xue et al. (2011)). In the mobile payment context, although consumers may not directly interact with each other, following similar two reasons as Xue et al. (2011), we expect local penetration plays an important role in mobile payment adoption. The first reason is the local word-of-mouth effects found in may previous literature for other products such as PC groceries, see Stavins (2001), Goolsbee and Klenow (2002), Forman et al. (2008), Choi et al. (2010). The second reason is the indirect effects such as complementary investments made by service providers who interact with mobile payment channel and want to expand service payment channels, see Xue et al. (2011). Both explanations suggest that one may adopt mobile payment channel faster with more prior adopters in a close area. In our analysis, we use the number of existing Alipay adopters within the same zip code area as the adopter under study to measure the level of local penetration. We specify our hypothesis as follows.

HYPOTHESIS 2 **(H2)**. *Higher local penetration is associated with earlier mobile channel adoption.*

3.2. Hypotheses: Post-adoption Behavior Changes

In this subsection, we discuss our three main hypotheses on post-adoption behavior. We consider three outcomes, i.e., transaction activities, consumer profitability, and channel substitution and complementarity.

Transaction Activities. One key advantage of mobile channel is the convenience of carrying. Compared to mobile phones, devices with larger screens have a negative affect on the convenience of carrying and on usage rates (Kim et al. (2011)). Similarly, although PCs enable consumers to hold a global perspective when shopping via the PC (Overby and Lee (2006)), the restriction of portability offsets this benefit. Therefore, facing the key advantage of convenience, mobile channel adopters are likely to increase the number of transactions they perform. Furthermore, we expect transaction activities to be different across different product values and consumers. For example, low-value products, such as groceries, are generally more likely to be hedonic shopping targets and e-channel appears more attractive to small buyers (Langer et al. (2012)); therefore mobile channel adopters might be more likely to purchase low value products. We next specify our hypothesis on transaction activity as follows.

HYPOTHESIS 3 **(H3)**. *Mobile channel adoption is associated with increased credit card transaction activity, especially for low-value items.*

Consumer Profitability. On one hand, the introduction of mobile payment channel makes consumption much easier, and increased transaction activities are likely to lead to greater consumer profitability. Prior research has shown that the online banking adoption is associated with increasing consumer profitability (Xue et al. (2011)), and multichannel customers are more profitable than they would be if they were not multichannel (Montaguti et al. (2016)). However, on the other hand, if most increased activities are associated with lower value items, then the overall profitability of consumer is not necessarily increasing. Following Xue et al. (2011), we use the monthly transaction amount to measure consumer profitability, and we thus test the following hypothesis.

HYPOTHESIS 4 **(H4)**. *Mobile channel adoption is associated with increased credit card consumer profitability.*

Channel Substitution and Complementarity. Prior research has shown that mobile and PC channels can substitute for and complement each other simultaneously, depending on the product category (Bang et al. (2013)), and the tablet channel acts as a substitute for the PC channel and a complement for the smartphone channel (Xu et al. (2016)). Recent work also finds that the mobile banking channel serves as a complement to the PC channel (Liu et al. (2017)). In the next hypothesis, we want to explore the impact of the mobile payment channel on consumer consumption, and find the intrinsic interdependencies that are related to mobile, PC, and offline payment channels. We test the following hypothesis.

HYPOTHESIS 5 **(H5)**. *Mobile channel serves as substitute of physical card channel; but as complement of PC channel.*

4. DATA

Our credit card data set contains three parts. The first part records 2,016,132 credit card issuances between 1989 and 2013 from one of the largest banks in China[7] to consumers in Jiangsu Province. This issuance data discloses detailed information on the card-issuing date, type of card, annual fee, credit limit, and so on. Here, by knowing the credit card issuance date, we can easily compute the length of the usage of each credit card, which later we use as an important control variable in our model.

[7] Note that the first credit card in China was issued on February 1, 1987.

The second part of our data set contains 1,541,769 consumers' demographic information, for example, age, gender, job position (manager or not), education (graduate degree, bachelor's degree, high school degree, middle high school degree, elementary school degree, and non-educated), marriage status (married or not), living status (rent or own), and so on.

The third part discloses the consumer transaction-level information from September 2010 to February 2013 (29 months), including transaction amount, account balances, transaction date, type of transaction (education, service, healthcare, entertainment, groceries, and travel), interest rate, reward points, and so on. In this part of our data set, we have 159,954,104 observations. By knowing the transaction dates, we can later easily compute the number of transactions (frequency) per month. Moreover, for each transaction observation, we can observe an associated label indicating the payment channel, i.e., online PC, Alipay (mobile channel), offline, etc.[8] Note that the payment here for each transaction is still made through credit card, and each credit card is used through one of the three (online PC, Alipay, and offline) channels. If the payment channel of one transaction is labeled as Alipay, then it means that the credit card used for this transaction is linked to Alipay, and when a consumer makes a payment, he can scan mobile phone codes in restaurants or stores instead of using a physical card. Note that Alipay also allows consumers to make payments or transfers to their friends and relatives (as in Paypal), however our study only focuses on commercial transactions and does not include transactions made to any individual person. Table 1 shows the summary statistics of key variables in our data set.

[8] Note that during our observation period between September 2010 and February 2013, Alipay is the only dominating mobile payment app in China. The second largest mobile payment app, WeChat Pay, was launched in September 2014.

Table 1 Summary Statistics

Variable	Definition	Mean	Sd.	Min	Max	N
		Numerical Variables				
CDT_LMT	Credit limit in RMB	12,878	52,766	0	5,000,000	4,541,583
CDT_LEN	Card usage length in months	25	14	0	192	4,541,583
CDT_TYP	Main (1) or attached (0) card	0.9700	0.1700	0	1.000000	4,500,933
GENDER	Male (1) or female (0)	0.4600	0.5000	0	1.000000	3,181,418
AGE	Age of card holder	29	5.7	12	93	3,181,418
TXN_AMT	Transaction amount per month in RMB	2,239.4	2,133.8	0	4,986,592	159,954,104
TXN_AMT_5	Average transaction amount last 5 months in RMB	2,478.3	2,259.6	0	4,295,375	159,954,104
TXN_CNT	Transaction frequency per month	72.1	69.8	0	1,500.00	28,619,173
ANU_FEE	Annual fee in RMB	3.2100	56.300	0	3,600.000	28,634,369
CDT_BAL	Account credit balances	4,520.2	23,742	0	2,000,000	335,395
		Binary Variables				
JOB_POS	Manager (1) or not (0)	0.35	0.13	0	1	3,179,303
EDU0	Non-educated (1) or not (0)	0.11	0.05	0	1	2,381,090
EDU1	Elementary school (1) or not (0)	0.15	0.06	0	1	2,381,090
EDU2	Middle high school (1) or not (0)	0.16	0.10	0	1	2,381,090
EDU3	High school (1) or not (0)	0.15	0.06	0	1	2,381,090
EDU4	Bachelor (1) or not (0)	0.27	0.17	0	1	2,381,090
EDU5	Graduate (1) or not (0)	0.10	0.05	0	1	2,381,090
MAR_STS	Married (1) or not (0)	0.48	0.27	0	1	2,788,549
LIV_STS	Own (1) or rent (0)	0.44	0.23	0	1	3,154,055

Next, we describe some initial analysis of our data set. First, we find that around 35.14% of the consumers in the data set have used online payment methods, including both PC and mobile channels. Among the online channels, Alipay has 204,547 users, and the PC channel has 244,981 users during our entire observation period. Therefore, we can see that by the end of February 2013, Alipay had almost as many users as the traditional PC payment channel.

Figure 1 shows the number of new consumers who adopted Alipay each month during our observation period. We can see that, starting from December 2010, when our focal bank started to collaborate with Alipay, the number of accumulated new adoptions has been growing steadily. In February 2013, the number of new adoptions had grown to 204,547 (13.3%), which shows that mobile payment has become more and more popular. Figure 2 compares the percentage of the online transaction (including both mobile and PC channels) amount with the percentage of the offline transaction amount made in each month. We can see that the fraction of the online transaction amount has grown steadily over time, especially since October 2010, whereas the offline transaction amount has decreased gradually. Figure 2 shows the initial analysis on the substitution effect of the online channel on the offline channel, and later we will show this effect more rigorously from our DID estimation.

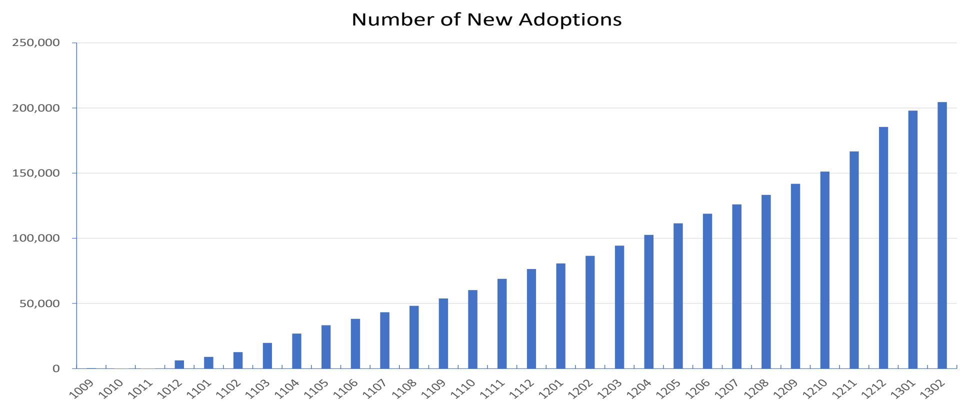

Figure 1 **Number of New Alipay Adoptions**

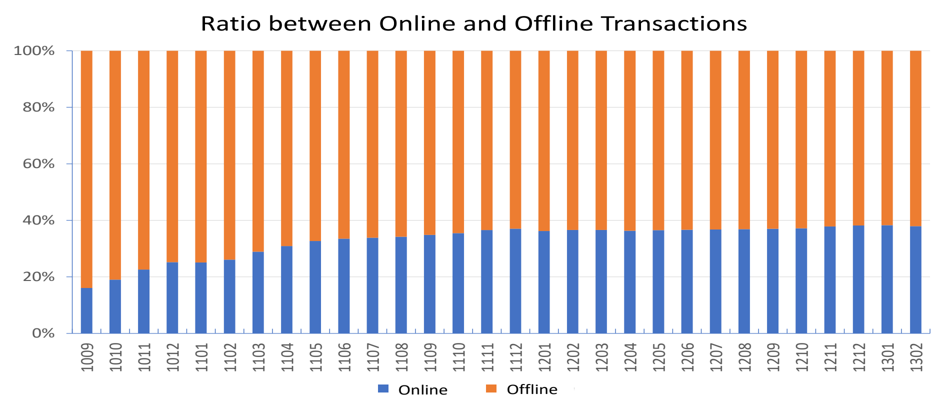

Figure 2 **Ratio between Online (PC and Alipay) and Offline Transaction Amount**

5. ECONOMETRIC MODEL

In this section, we show the econometric models used in both pre- and post-adoption analyses. Section 5.1 describes the survival analysis that we used in the pre-adoption study. Section 5.2 presents the details of our DID method in post-adoption analysis. Section 4.3 discusses our two matching strategies.

5.1. Mobile Channel Adoption Analysis

To understand the determinants of mobile payment adoption, we conduct survival analysis, where a subject leaves the panel when the adoption event happens. Therefore, this approach links the explanatory variables with the time when consumers adopt the mobile payment channel. Note that a number of approaches can be used for survival analysis, for instance, the accelerated failure time (AFT) and proportional hazard (PH) models. Following Tellis et al. (2003) and Xue et al. (2011), we use a log-logistic distribution AFT model, and consider both the regular regression coefficients in the log-time format and the time-ratio coefficient, which is computed as the ratio of fail time to normal time. Note that parametric models have been shown to be more statistically efficient than nonparametric or semi-parametric models in settings where the focus is on the effects of covariates that evolve over time.

We now specify our log-logistic distribution AFT model. Denote t_i as the event time of adoption for consumer i, x_i as a set of covariates, and ϵ_i as the error term. We then have the following regression function:

$$\ln(t_i) = x_i\beta_x + \epsilon_i, \tag{1}$$

where β_x is the set of parameter weights to be estimated. Here, if a regular coefficient is negative or a time ratio coefficient is less than 1, the result implies faster adoption.

To test our two hypotheses on service demand and local penetration, we now define the key measures. We first define two measures to compute service demand. The first measure (denoted as $M1$) is the same as Xue et al. (2011), which computes each consumer's total transaction frequency in the month prior to adoption. As a robustness check, we compute a second measure (denoted as $M2$) that is the monthly average transaction frequency before adoption. Next, to define the frequent and infrequent travelers, we compute the percentage of transactions made in cities other than the focal consumer's residential city. We then compute the sample average of this percentage (0.16 on average). Consumers with values above the sample average are defined as *frequent traveler*, and the ones below the sample average are defined as *infrequent traveler*. Finally, to discuss the impact of local penetration on mobile channel adoption, we use the number of existing Alipay adopters within the same zip code area as the adopter under study to measure the level of local penetration.

5.2. Post-Adoption Analysis: Difference-in-Difference

Following the same approach as Xu et al. (2016), we use DID together with matching to account for unobserved systemic bias. The DID technique is an econometric method traditionally used to measure the treatment effect in a given time period through measuring the difference between a group that received the treatment and a control group that did not (see Meyer (1995)). In our work, the treatment group consists of consumers who use Alipay, and the control group consists of consumers who did not use Alipay during our observation time period. By obtaining the first time the treated group of consumers use Alipay after our focal bank's collaboration with Alipay, our DID approach is able to measure the *average treatment effect* over the treated group. In particular, we measure the impact of the introduction of the mobile payment channel on the overall transaction frequency and amount, as well as the impact on PC payment and offline channels. The central assumption of DID is the parallel trends, i.e., the trends in the outcome variable would have been parallel in the treated and control groups if there had been no treatment. We indeed find the trends to be parallel before the intervention. Note that it is not necessary to have random assignment for the parallel trends assumption to hold, however the assumption might fail if assignment was based on some characteristics of the groups. To further account for potential endogenous assignment bias, we later conduct the synthetic control groups method (see Abadie and Gardeazabal (2003), Abadie et al. (2010), Abadie et al. (2015)) in Section 6.4, and find our results remain consistent.

To make the treatment and control groups comparable, we further adopt matching strategies, which we will discuss in Section 5.3, to derive a sample of treated consumers with similar observed characteristics with a sample of untreated consumers. The idea of our matching strategies is that each Alipay user is paired with a similar non-user in terms of the propensity of being treated. This pair matching allows for a fair comparison between the treatment and control groups (see Heckman et al. (1998) and Aral et al. (2009)). Combining our DID approach with the matching strategy, we can write our estimation equation for consumer i in month t as follows:

$$\begin{aligned} Outcome_{it} =& \beta \times (TreatGroup_i \times AfterTreat_{it}) \\ &+ \alpha \times TreatGroup_i \\ &+ \gamma \times AfterTreat_{it} + X_{it} + \tau_t + \epsilon_{it}, \end{aligned} \tag{2}$$

where the variable $Outcome_{it}$ represents the total transaction amount or total transaction frequency from the PC payment channel, offline channel, or all the three channels combined. Later, we also consider $Outcome_{it}$ as the shares of total transaction amount or total transaction frequency from the PC payment channel and offline channel. Here the variable $TreatGroup_i$ is 1 if consumer i has ever used Alipay for consumption during our observation time period, and 0 otherwise. This binary variable controls for the time-invariant differences between the treatment and control groups. The variable $AfterTreat_{it}$ is also binary, with 1 indicating the post Alipay adoption period for both treatment- and control-group consumers. For example, the first time a consumer used Alipay to purchase products was in December 2012; thus, $AfterTreat_{it}$ will be 1 for this consumer starting from that date, and 0 for those months before. The coefficient β here for the interaction term is the DID estimator that measures how the transaction frequency or amount changes for the treatment group after Alipay adoption as compared to the control group during our observation period. The vector X_{it} here represents the observed characteristics, such as credit card length of usage, card type, card limit, gender, education, marriage, living status, etc. The variable τ_t here is the time dummy, and controls for the time trend. Note that the standard errors ϵ_{it} in our model are clustered by users to account for potential correlation over time (see Moulton (1990)).

As a comparison, we also consider a standard DID model without matching. For this case without matching, the $AfterTreat_{it}$ variable in equation (2) is modified to denote the time period after the release of Alipay, and therefore the interaction term no longer identifies the specific Alipay adoption date for each user, but rather a generic date that affects the entire group of potential adopters through the release of Alipay. The coefficient β then estimates an average treatment effect of Alipay adoption.

5.3. Post-Adoption Analysis: Matching

We now discuss our two main matching strategies, namely, static and dynamic matching. In static matching, treated users are matched with non-adopters who resemble them most closely in terms of their overall propensity scores. Under static matching, the matched control users remain the same for the entire study period; while dynamic matching requires unique propensity scores for Alipay adopters for each time unit, and hence adopters are matched with different non-adopters over time. Following Xu et al. (2016), we here use one month as each time unit. Given the fact that some attributes of users change over time, the dynamic matching procedure is likely to perform better, because it accounts for time-varying factors.

To compute the propensity scores for both strategies, we consider covariates such as age, gender, education, marriage, living status, total transaction amount in the past five months, credit limit, account balances, local penetration and so on, because these factors are likely to affect Alipay adoption and spending behaviors, see Table 2. In particular, to account for the impact of service demand and local penetration on adoption decision, we include these two variables as our covariates in the matching process. We utilize the same set of covariates across all matching procedures. We then adopt different matching algorithms to assess the robustness of the results with respect to different matched samples within two types of matching procedures. We first conduct our baseline matching, that is, to utilize one-to-one matching with replacement to derive the closest matched non-adopter. Under this process, almost all Alipay adopters (92.1%) have been appropriately matched. Next, we conduct one-to-one matching without replacement to assess whether the inclusion of more control users would affect the results. Third, we use nearest-three-neighbors matching as another robustness check. Finally, we conduct matching specifications using the common support requirement and a tighter caliper size to further assess the stability of results under more stringent matching conditions.

To evaluate our matching results, we compare the propensity score distributions of the matched and unmatched samples (Caliendo and Kopeinig (2008); Haviland A. (2007)), as shown in Figures 3 and 4. In general, we find the distributions for control and treated users to be more similar after matching. We also conduct a Kolmogorov-Smirnov test to compare the distributions, and find a strong match between the treated and matched control users.

Following Haviland A. (2007), we next compare the standardized bias before and after matching. We first compute the standardized bias before matching as:

$$SB_{before} = |\mu_{x_t} - \mu_{x_p}| / \sqrt{0.5 \times (s_{x_t}^2 + s_{x_p}^2)}, \tag{3}$$

where μ_{x_t} and $s_{x_t}^2$ are the mean and variance of covariate X for the treated group consumers before matching, and μ_{x_p} and $s_{x_p}^2$ are the mean and variance for unmatched control group consumers. We next calculate the standardized bias after matching as follows:

$$SB_{after} = |\mu_{x_t} - \mu_{x_c}| / \sqrt{0.5 \times (s_{x_t}^2 + s_{x_c}^2)}, \tag{4}$$

where μ_{x_t} and $s_{x_t}^2$ are the mean and variance of covariate X for the treated group consumers after matching, and μ_{x_p} and $s_{x_p}^2$ are the mean and variance for the matched control group consumers. We present the results for the standard bias and the percentage improvement of matching in the following Table 2.

From Table 2, we can see that before matching, the covariates related to purchase behavior via Alipay are quite unbalanced. The biases between the treated and control groups are greatly reduced across most covariates after matching. We further conduct t-test to compare the means of the treatment and control groups after matching, and the results confirm that the means are statistically similar after matching.

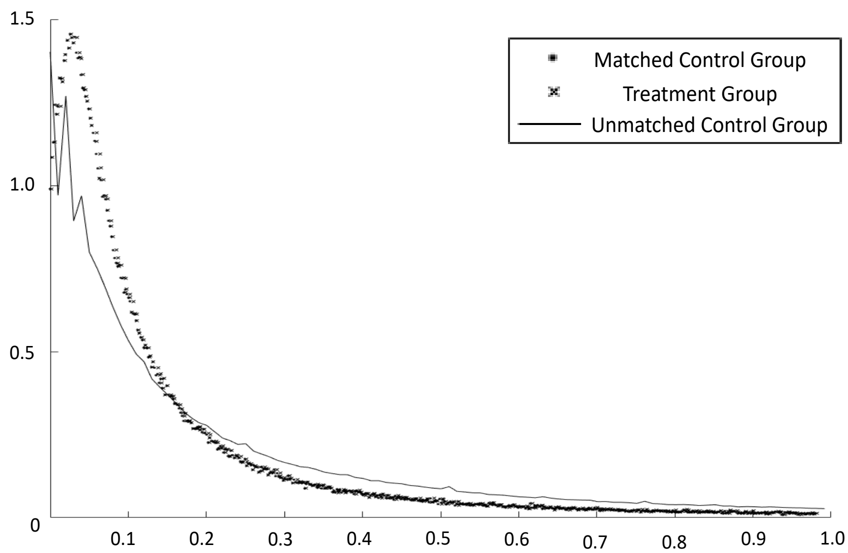

Figure 3 **Estimated Propensity Score for Static Matching**

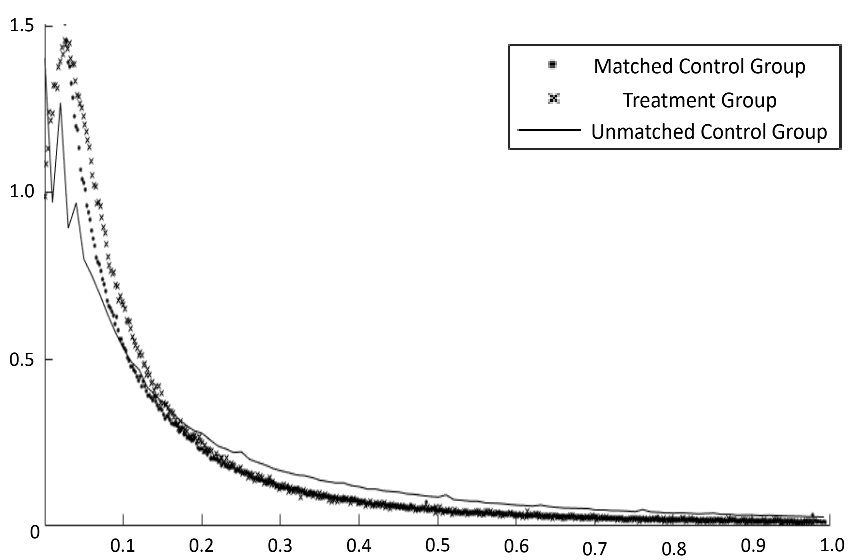

Figure 4 **Estimated Propensity Score for Dynamic Matching**

Table 2 Comparison before and after Matching

	Std. Bias (Before)	Std. Bias (After)	% Improvement
	Static Matching		
log(TXN_AMT)	0.1347	0.0004	99.74
log(TXN_CNT)	0.9707	0.7188	25.95
GEN	0.2661	0.2420	9.07 b
EDU0	0.3517	0.2343	33.37
EDU1	0.0422	0.0474	-12.31
EDU2	0.2819	0.2731	31.32
EDU3	0.1462	0.0820	43.92
EDU4	0.1427	0.1474	-3.29
EDU5	0.0065	0.0071	-8.17
MAR_STS	0.0418	0.0442	-5.69
CDT_LEN	0.0022	0.0022	1.74
CDT_TYP	0.0006	0.000006	99.01
NUM_CDT	0.3179	0.3220	-1.28
CDT_LMT	0.0024	0.0003	87.50
LIV_STS	0.4030	0.3523	12.56
JOB_POS	0.0892	0.0053	94.05
AGE	0.0776	0.0069	91.11
TXN_AMT_5	0.1380	0.0699	49.35
CDT_BAL	0.0685	0.0099	85.55
ANU_FEE	0.0377	0.0084	77.72
PENETRATION	0.0135	0.0079	41.48
	Dynamic Matching		
log(TXN_AMT)	0.1347	0.0026	98.07
log(TXN_CNT)	0.9708	0.7119	26.66
GEN	0.2661	0.2770	-4.09
EDU0	0.3517	0.3037	13.66
EDU1	0.0422	0.0371	12.13
EDU2	0.2819	0.2728	3.61
EDU3	0.1462	0.1254	14.24
EDU4	0.1427	0.1594	-11.66
EDU5	0.0066	0.0074	-13.42
MAR_STS	0.0418	0.0506	-21.07
CDT_LEN	0.0022	0.0021	2.66
CDT_TYP	0.0006	0.0001	83.33
NUM_CDT	0.3179	0.2762	13.11
CDT_LMT	0.0024	0.0024	-0.95
LIV_STS	0.4030	0.4171	-3.51
JOB_POS	0.0892	0.0100	88.73
AGE	0.0776	0.0052	93.30
TXN_AMT_5	0.1380	0.0511	62.97
CDT_BAL	0.0685	0.0094	86.28
ANU_FEE	0.0377	0.0081	78.51
PENETRATION	0.0135	0.0077	42.96

In addition, we apply a look-ahead matching technique as a robustness check, because both static and dynamic matching strategies can only match adopters based on observable factors. In particular, we add an additional restriction in selecting control users under the look-ahead matching procedure: the control candidates have to be non-adopters at the time of matching, but adopters at a future period (see Manchanda et al. (2015)). Therefore, in the look-ahead procedure, we can select late adopters as a control group for early adopters. In this way, we can use control users who bear unobserved attributes inherent in adopters that may simultaneously drive Alipay usage and purchase behavior.

6. EMPIRICAL RESULTS

In this section, we discuss our empirical results. Section 6.1 presents our main estimation results of pre-adoption behavior. Section 6.2 shows post-adoption behavior changes. Section 6.3 provides subset analysis of post-adoption behaviors.

6.1. Mobile Channel Adoption

We can see from Table 3 that both the results for regular and time-ratio coefficients indicate a faster mobile channel adoption. Recall that the first measure $M1$ in Table 3 computes each consumer's total transaction frequency in the month prior to adoption. The second measure $M2$ is the monthly average transaction frequency before adoption. The coefficient of $M1$ ($\beta = -0.005$, $p < 0.01$) shows that a consumer's time to adopt the mobile payment channel is reduced by around 0.5% with a one-unit increase in transaction frequency of the month before adoption. Moreover, the coefficient of $M2$ ($\beta = -0.007$, $p < 0.01$) shows that a consumer's time to adopt the mobile payment channel is reduced by around 0.7% with a one-unit increase in the pre-adoption monthly average transaction frequency. Through this paper, we use $M1$ as our main estimation variable following Xue et al. (2011), and $M2$ serves as a robustness check.

Table 3 Service Demand Impact on Mobile Channel Adoption

	M1		M2	
Variables	Regular	TR	Regular	TR
Service Demand	-0.005***	0.876***	-0.007***	0.903***
	(0.0004)	(0.002)	(0.0006)	(0.004)
Controls	Yes	Yes	Yes	Yes
N	1,541,769	1,541,769	1,541,769	1,541,769
adj. R^2	0.262	0.254	0.264	0.251

Notes. Regular stands for the regular coefficient, and TR stands for the time ratio coefficient. Standard errors in parentheses.
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Next, we consider the impact of service demand for frequent and infrequent travelers separately, and present the results in Table 4. From the results in Table 4, we can see first that both the results for frequent and infrequent travelers show a faster mobile channel adoption. Moreover, if a consumer is a frequent traveler, his time to adopt the mobile payment channel is reduced by at least 0.79% (given $\beta = -0.0079$, $p < 0.01$) with a one-unit increase in the transaction frequency of the month before adoption, and this value decreases to 0.22% if he is an infrequent traveler. To summarize, the results from both Table 3 and 4 confirm our hypothesis 1 that higher service demand is associated with earlier mobile channel adoption; and the relationship is even stronger for frequent travelers due to channel ubiquity.

Table 4 Mobile Channel Adoption of Frequent Travelers

	Frequent Traveler		Infrequent Traveler	
Variables	Regular	TR	Regular	TR
Service Demand	-0.0079***	0.945***	-0.0022***	0.808***
	(0.0005)	(0.003)	(0.0001)	(0.001)
Controls	Yes	Yes	Yes	Yes
N	770,884	770,884	770,885	770,885
adj. R^2	0.282	0.274	0.281	0.272

Notes. Regular stands for the regular coefficient, and TR stands for the time ratio coefficient. Standard errors in parentheses.
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Finally, we discuss the impact of local penetration on mobile channel adoption. The results are presented in Table 5. Recall that we use the number of existing Alipay adopters within the same zip code area as the adopter under study to measure the level of local penetration. From results in Table 5, we find that higher local penetration is associated with earlier mobile channel adoption. More specifically, a consumer's time to adopt the mobile payment channel is reduced by around 0.3% with a one-unit increase in the local penetration level ($\beta = -0.003$, $p < 0.01$ for $M1$).

Table 5 Local Penetration Impact on Mobile Channel Adoption

	M1		M2	
Variables	Regular	TR	Regular	TR
Penetration	-0.003***	0.814***	-0.004***	0.897***
	(0.0002)	(0.001)	(0.0003)	(0.003)
Controls	Yes	Yes	Yes	Yes
N	1,541,769	1,541,769	1,541,769	1,541,769
adj. R^2	0.254	0.242	0.251	0.239

Notes. Regular stands for the regular coefficient, and TR stands for the time ratio coefficient. Standard errors in parentheses.
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

6.2. Post-adoption Behavior Changes

In this subsection, we discuss our empirical findings of post-adoption behavior changes in Table 6. In our main model, we estimate the treatment effect with Alipay adoption over the three channels combined, the PC channel, and the offline channel. We specifically compute the transaction amount and frequency for PC channel and offline channel, because separating these two channels eliminates unobserved purchasing trends that may pertain to these two channels.

From the results in Table 6, first we find our main results suggest both the overall transaction amount and frequency increase after a consumer adopts the Alipay channel. More specifically, from the first two columns of all three channels combined under the static one-to-one matching with replacement in Table 6, we find the total transaction amount increases by around 2.4% after Alipay adoption, and the total transaction frequency increases by around 23.5%. Furthermore, we find that under different matching techniques and algorithms, estimation results from both static and dynamic matching methods remain consistent. Second, we estimate the impact of Alipay adoption on transaction amount and frequency from the PC and offline channels from the third-to-the-last column in Table 6. The estimation results indicate the Alipay channel acts as a substitute for the offline (physical card) channel and as a complement for the PC channel. More specifically, for the PC channel, the total transaction amount increases by around 0.3% after Alipay adoption, the share of the transaction amount increases by around 0.01%, the total transaction frequency increases by around 0.18%, and the share of transaction frequency increases by around 0.016%.

On the other hand, for the offline channel, the total transaction amount decreases by around 3.9% after Alipay adoption, the share of the transaction amount decreases by around 26.2%, the total transaction frequency decreases by around 9.4%, and the share of transaction frequency decreases by around 39.8%. We also present our full estimation results of static and dynamic matching with replacement in Table 7 and 8.

Now we discuss several concerns about our main estimation results. First, we consider the variance from the estimation of the propensity scores. Following Austin and Small (2014), we bootstrap the clustered standard errors in the specifications to account for the variance from the estimation of the propensity scores. Under bootstrapped standard errors, we find the results remain statistically significant, as shown in Table 6. Furthermore, the positive impact of Alipay adoption is present where matching is not employed, and also in matched samples derived under the look-ahead matching process, as shown at the bottom of Table 6. Second, interpreting from the baseline models of one-to-one static and dynamic matching with replacement, we find both the transaction amount and frequency increase after a consumer utilizes the Alipay channel with her credit card purchase. However, given the fact that potential hidden bias might exist, matched individuals with the same observed covariates can have differing probabilities of adopting Alipay, and then can affect the efficacy of the matching procedure. Thus, we further perform the analysis of Rosenbaum (2002) to assess the sensitivity of our main results. Such analysis calculates the magnitude of hidden bias that needs to be present to explain the associations actually observed. The analysis results indicate that to affect the current results, an unobserved bias needs to produce more than a 1.3-fold increase in the odds of Alipay adoption and be a strong predictor of outcome variables. Third, the estimation results may arise due to different pre-existing trends affecting the treatment and control groups. We then check whether the DID estimates are robust to smaller samples derived from shorter time windows before and after the release of Alipay. Specifically, we repeat the regressions using samples that fall within 3, 5, 7, and 9 months before and after the collaboration between our focal bank and Alipay. The results of this check suggest the main results are not affected by long-term differences in pre-existing trends.

Table 6 Main Estimation Results

	All		PC Channel				Offline Channel			
	Amt.	Freq.	Amt.	Amt. Share	Freq.	Freq. share	Amt.	Amt. Share	Freq.	Freq. share
Static Matching										
One-to-One	0.024***	0.235***	0.003***	0.0001***	0.0018**	0.00016***	-0.039***	-0.262***	-0.094***	-0.398***
(with replacement)	(0.00078)	(0.00081)	(0.00082)	(0.000005)	(0.0008)	(0.000006)	(0.00078)	(0.00015)	(0.00081)	(0.00016)
One-to-One	0.024***	0.236***	0.003***	0.0001***	0.0019**	0.00016***	-0.039***	-0.262***	-0.094***	-0.398***
(without replacement)	(0.00078)	(0.00081)	(0.00082)	(0.000005)	(0.0008)	(0.000006)	(0.00078)	(0.00015)	(0.00081)	(0.00016)
Nearest Three Neighbors	0.024***	0.246***	0.002***	0.0001***	0.0019**	0.00014***	-0.038***	-0.262***	-0.096***	-0.397***
(with replacement)	(0.00077)	(0.00080)	(0.00080)	(0.000004)	(0.0008)	(0.0000054)	(0.00077)	(0.00012)	(0.00080)	(0.00014)
With common support and caliper size of 0.05×Std. dev.										
One-to-One	0.021***	0.229***	0.0028***	0.0001***	0.0017**	0.00013***	-0.036***	-0.261***	-0.091***	-0.393***
(with replacement)	(0.00077)	(0.00081)	(0.00081)	(0.000005)	(0.0007)	(0.000006)	(0.00075)	(0.00013)	(0.00081)	(0.00013)
Nearest Three Neighbors	0.020***	0.226***	0.002***	0.0001***	0.0017**	0.00014***	-0.038***	-0.262***	-0.096***	-0.397***
(with replacement)	(0.00075)	(0.00078)	(0.00079)	(0.000004)	(0.0007)	(0.0000051)	(0.00073)	(0.00011)	(0.00080)	(0.00013)
With bootstrapped standard errors										
One-to-One	0.024***	0.234***	0.003***	0.0001***	0.0018**	0.00017***	-0.038***	-0.262***	-0.095***	-0.399***
(with replacement)	(0.00078)	(0.00082)	(0.00082)	(0.000005)	(0.0008)	(0.000006)	(0.00078)	(0.00015)	(0.00081)	(0.00015)
One-to-One	0.024***	0.235***	0.003***	0.0001***	0.0019**	0.00016***	-0.038***	-0.262***	-0.094***	-0.398***
(without replacement)	(0.00077)	(0.00081)	(0.00082)	(0.000005)	(0.0008)	(0.000005)	(0.00079)	(0.00015)	(0.00081)	(0.00016)
Nearest Three Neighbors	0.024***	0.245***	0.002***	0.0001***	0.0018**	0.00014***	-0.039***	-0.262***	-0.097***	-0.397***
(with replacement)	(0.00077)	(0.00080)	(0.00080)	(0.000004)	(0.0008)	(0.0000055)	(0.00077)	(0.00011)	(0.00081)	(0.00014)
Dynamic Matching										
One-to-One	0.018***	0.224***	0.002***	0.0001***	0.0019**	0.00015***	-0.041***	-0.261***	-0.094***	-0.398***
(with replacement)	(0.00078)	(0.00081)	(0.00082)	(0.000005)	(0.0008)	(0.000006)	(0.00078)	(0.00015)	(0.00081)	(0.00016)
One-to-One	0.019***	0.228***	0.003***	0.0001***	0.0018**	0.00013***	-0.039***	-0.265***	-0.096***	-0.392***
(without replacement)	(0.00078)	(0.00081)	(0.00082)	(0.000005)	(0.0008)	(0.000006)	(0.00078)	(0.00015)	(0.00081)	(0.00016)
Nearest Three Neighbors	0.021***	0.231***	0.002***	0.0001***	0.0020**	0.00012***	-0.040***	-0.264***	-0.097***	-0.395***
(with replacement)	(0.00077)	(0.00080)	(0.00080)	(0.000004)	(0.0008)	(0.0000054)	(0.00077)	(0.00012)	(0.00080)	(0.00014)
With common support and caliper size of 0.05×Std. dev.										
One-to-One	0.019***	0.228***	0.0022***	0.0001***	0.0021**	0.00019***	-0.047***	-0.272***	-0.099***	-0.402***
(with replacement)	(0.00079)	(0.00083)	(0.00085)	(0.000006)	(0.0009)	(0.000006)	(0.00079)	(0.00019)	(0.00083)	(0.00015)
Nearest Three Neighbors	0.022***	0.235***	0.0022***	0.0001***	0.0022**	0.00017***	-0.045***	-0.268***	-0.098***	-0.401***
(with replacement)	(0.00079)	(0.00082)	(0.00081)	(0.000006)	(0.0009)	(0.0000055)	(0.00078)	(0.00013)	(0.00082)	(0.00015)
With bootstrapped standard errors										
One-to-One	0.018***	0.225***	0.002***	0.0001***	0.0018**	0.00016***	-0.042***	-0.262***	-0.094***	-0.398***
(with replacement)	(0.00077)	(0.00082)	(0.00083)	(0.000005)	(0.0008)	(0.000006)	(0.00077)	(0.00016)	(0.00082)	(0.00016)
One-to-One	0.019***	0.227***	0.003***	0.0001***	0.0018**	0.00015***	-0.038***	-0.266***	-0.097***	-0.393***
(without replacement)	(0.00079)	(0.00083)	(0.00082)	(0.000005)	(0.0008)	(0.000006)	(0.00077)	(0.00016)	(0.00083)	(0.00017)
Nearest Three Neighbors	0.021***	0.232***	0.002***	0.0001***	0.0021**	0.00013***	-0.041***	-0.265***	-0.096***	-0.396***
(with replacement)	(0.00077)	(0.00080)	(0.00081)	(0.000005)	(0.0008)	(0.0000056)	(0.00075)	(0.00013)	(0.00081)	(0.00015)
Alternative Matching Conditions										
No Matching	0.011***	0.201***	0.0015***	0.00008***	0.0014**	0.00011***	-0.032***	-0.202***	-0.088***	-0.332***
	(0.00078)	(0.00067)	(0.00065)	(0.000005)	(0.0007)	(0.000006)	(0.00073)	(0.00014)	(0.00079)	(0.00014)
Look-Ahead Matching	0.013***	0.214***	0.0018***	0.00009***	0.0015**	0.00013***	-0.036***	-0.214***	-0.090***	-0.347***
One-to-One	(0.00070)	(0.00073)	(0.00076)	(0.000005)	(0.00077)	(0.000005)	(0.00071)	(0.00013)	(0.00078)	(0.00015)
(with replacement)										

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

Table 7 Full Estimation Results for Static Matching With Replacement

	All		PC Channel				Offline Channel			
	Amt.	Freq.	Amt.	Amt. Share	Freq.	Freq. share	Amt.	Amt. Share	Freq.	Freq. share
TreatGroup *AfterTreat	0.024***	0.235***	0.003***	0.0001***	0.0018**	0.00016***	-0.039***	-0.262***	-0.094***	-0.398***
	(0.00078)	(0.00081)	(0.00082)	(0.000005)	(0.0008)	(0.000006)	(0.00078)	(0.00015)	(0.00081)	(0.00016)
TreatGroup	0.0646***	0.0168***	-0.00120	0.0000686***	-0.000753	0.0000864***	-0.0656***	-0.00624***	-0.0648***	-0.00956***
	(0.000725)	(0.000756)	(0.000762)	(0.00000484)	(0.000762)	(0.00000563)	(0.000725)	(0.000139)	(0.000758)	(0.000154)
AfterTreat	0.0088	0.0123	0.0080	0.0045	0.0069	0.00077	0.0159	0.0087	0.0168	0.0072
	(0.0109)	(0.0112)	(0.0108)	(0.0119)	(0.0100)	(0.0113)	(0.0106)	(0.0115)	(0.0106)	(0.0098)
CDT_LEN	0.000587***	0.000595***	0.000284***	-0.00000534***	0.0000921**	-0.00000602***	0.000555***	0.000773***	0.00318***	0.00110***
	(0.0000350)	(0.0000365)	(0.0000368)	(0.000000234)	(0.0000368)	(0.000000272)	(0.0000350)	(0.00000673)	(0.0000366)	(0.00000743)
CDT_TYP	0.000214***	-0.000702***	-0.000422***	-0.00000127***	-0.0000928***	-0.00000200***	0.000265***	-0.0000587***	-0.00157***	-0.0000605***
	(0.0000124)	(0.0000130)	(0.0000131)	(8.32e-08)	(0.0000131)	(9.66e-08)	(0.0000124)	(0.00000239)	(0.0000130)	(0.00000264)
NUM_CDT	0.0264***	0.0195***	0.0224***	0.0000641***	0.00438***	0.0000985***	0.0244***	0.00427***	0.0416***	0.00428***
	(0.000312)	(0.000326)	(0.000328)	(0.00000209)	(0.000328)	(0.00000242)	(0.000312)	(0.0000600)	(0.000326)	(0.0000663)
CDT_LMT	0.293***	0.0206***	-0.00605***	-0.00000326*	-0.00134***	-0.000000685	0.296***	0.00567***	0.0555***	0.00475***
	(0.000283)	(0.000295)	(0.000297)	(0.00000189)	(0.000297)	(0.00000219)	(0.000282)	(0.0000543)	(0.000295)	(0.0000600)
GEN	0.0176***	-0.00842***	0.00202***	0.0000766***	0.000508	0.0000925***	0.0185***	0.0211***	0.0642***	0.0382***
	(0.000527)	(0.000549)	(0.000553)	(0.00000352)	(0.000553)	(0.00000408)	(0.000526)	(0.000101)	(0.000550)	(0.000112)
EDU0	-0.0944***	-0.000938	0.0134**	0.000153***	0.00237	0.000210***	-0.0971***	0.000247	-0.0305***	-0.00548***
	(0.00625)	(0.00651)	(0.00657)	(0.0000418)	(0.00657)	(0.0000485)	(0.00624)	(0.00120)	(0.00653)	(0.00133)
EDU1	-0.152***	-0.0230***	0.0310***	0.000416***	0.00431	0.000518***	-0.156***	0.000730	-0.0546***	-0.000684
	(0.00646)	(0.00673)	(0.00679)	(0.0000432)	(0.00679)	(0.0000501)	(0.00646)	(0.00124)	(0.00675)	(0.00137)
EDU2	-0.114***	-0.0000108	0.0218***	0.000188***	0.00579	0.000266***	-0.118***	-0.0155***	-0.0548***	-0.0237***
	(0.00624)	(0.00650)	(0.00656)	(0.0000417)	(0.00656)	(0.0000484)	(0.00624)	(0.00120)	(0.00652)	(0.00132)
EDU3	-0.115***	0.0217***	0.0182***	0.000152***	0.00305	0.000214***	-0.118***	-0.0114***	-0.00304	-0.0180***
	(0.00624)	(0.00650)	(0.00656)	(0.0000417)	(0.00656)	(0.0000484)	(0.00624)	(0.00120)	(0.00652)	(0.00132)
EDU4	-0.110***	0.0265***	0.0186***	0.000136***	0.00421	0.000197***	-0.113***	-0.00993***	0.0201***	-0.0133***
	(0.00625)	(0.00652)	(0.00657)	(0.0000418)	(0.00657)	(0.0000485)	(0.00625)	(0.00120)	(0.00653)	(0.00133)
EDU5	-0.145***	0.0369	0.0150	0.0000784	0.00230	0.000116	-0.147***	-0.00217	0.103***	0.00462
	(0.0277)	(0.0289)	(0.0291)	(0.000185)	(0.0291)	(0.000215)	(0.0277)	(0.00533)	(0.0290)	(0.00588)
MAR_STS	0.0881***	0.0686***	-0.0200**	-0.000304***	-0.00414	-0.000332***	0.0911***	-0.00295	0.171***	-0.00149
	(0.00961)	(0.0100)	(0.0101)	(0.0000642)	(0.0101)	(0.0000746)	(0.00961)	(0.00185)	(0.0100)	(0.00204)
LIV_STS	-0.0105	0.323*	0.000373	-0.000272	0.000656	-0.000274	-0.0103	-0.0317	0.756***	-0.0381
	(0.177)	(0.184)	(0.186)	(0.00118)	(0.186)	(0.00137)	(0.177)	(0.0340)	(0.185)	(0.0376)
JOB_POS	-0.649***	-0.279	-0.0717	-0.000608	-0.0137	-0.000797	-0.644***	-0.150***	-0.546**	-0.0819*
	(0.208)	(0.217)	(0.218)	(0.00139)	(0.218)	(0.00161)	(0.208)	(0.0399)	(0.217)	(0.0441)
AGE	0.0596***	0.0450***	-0.0186*	-0.000274***	-0.00273	-0.000299***	0.0621***	-0.0131***	0.0887***	-0.0153***
	(0.00931)	(0.00970)	(0.00978)	(0.0000622)	(0.00978)	(0.0000722)	(0.00930)	(0.00179)	(0.00972)	(0.00197)
TXN_AMT_5	0.0422	0.0553	-0.0155	-0.000330	-0.00283	-0.000364	0.0449	-0.0348	0.0688	-0.0412
	(0.130)	(0.135)	(0.136)	(0.000867)	(0.136)	(0.00101)	(0.130)	(0.0249)	(0.136)	(0.0276)
ACT_BAL	0.0255***	0.0634***	-0.0191*	-0.000293***	-0.00466	-0.000324***	0.0294***	-0.0237***	0.151***	-0.0174***
	(0.00931)	(0.00971)	(0.00979)	(0.0000622)	(0.00979)	(0.0000723)	(0.00931)	(0.00179)	(0.00973)	(0.00198)
ANU_FEE	0.00595	0.0418***	-0.0204**	-0.000274***	-0.00415	-0.000308***	0.0102	-0.0323***	0.105***	-0.0303***
	(0.00939)	(0.00979)	(0.00987)	(0.0000627)	(0.00987)	(0.0000729)	(0.00938)	(0.00180)	(0.00981)	(0.00199)
Trend	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	13,415,513	13,415,513	13,415,513	13,415,513	13,415,513	13,415,513	13,415,513	13,415,513	13,415,513	13,415,513
adj. R^2	0.274	0.268	0.258	0.253	0.247	0.245	0.268	0.267	0.252	0.250

Standard errors in parentheses
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$
Note: Trend here refers to the control of time dummies.

Table 8 Full Estimation Results for Dynamic Matching With Replacement

	All		PC Channel				Offline Channel			
	Amt.	Freq.	Amt.	Amt. Share	Freq.	Freq. share	Amt.	Amt. Share	Freq.	Freq. share
TreatGroup *AfterTreat	0.018***	0.224***	0.002***	0.0001***	0.0019**	0.00015***	-0.041***	-0.261***	-0.094***	-0.398***
	(0.00078)	(0.00081)	(0.00082)	(0.000005)	(0.0008)	(0.000006)	(0.00078)	(0.00015)	(0.00081)	(0.00016)
TreatGroup	0.0445***	-0.00431***	-0.00122	0.0000567***	-0.000928	0.0000724***	0.0451***	0.00818***	0.0128***	0.0117***
	(0.000740)	(0.000766)	(0.000771)	(0.00000503)	(0.000772)	(0.00000588)	(0.000740)	(0.000142)	(0.000766)	(0.000157)
AfterTreat	0.0069	0.0117	0.0092	0.0051	0.0073	0.00101	0.0143	0.0089	0.0155	0.0081
	(0.0111)	(0.0113)	(0.0112)	(0.0106)	(0.0109)	(0.0106)	(0.0116)	(0.0108)	(0.0107)	(0.0093)
CDT_LEN	0.000315***	0.000935***	0.000300***	-0.00000625***	0.0000987***	-0.00000704***	0.000286***	0.000792***	0.00413***	0.00113***
	(0.0000359)	(0.0000371)	(0.0000374)	(0.000000244)	(0.0000374)	(0.000000285)	(0.0000359)	(0.00000688)	(0.0000371)	(0.00000760)
CDT_TYP	0.000168***	-0.000694***	-0.000383***	-0.000000971***	-0.0000988***	-0.00000166***	0.000207***	-0.0000238***	-0.00156***	-0.0000244***
	(0.0000122)	(0.0000126)	(0.0000127)	(8.29e-08)	(0.0000127)	(9.68e-08)	(0.0000122)	(0.00000234)	(0.0000126)	(0.00000258)
NUM_CDT	0.0438***	0.0318***	0.0236***	0.0000538***	0.00481***	0.0000905***	0.0423***	0.00307***	0.0739***	0.00305***
	(0.000299)	(0.000310)	(0.000312)	(0.00000204)	(0.000312)	(0.00000238)	(0.000299)	(0.0000574)	(0.000310)	(0.0000634)
CDT_LMT	0.261***	0.0143***	-0.00570***	-0.00000103	-0.00135***	0.00000107	0.264***	0.00495***	0.0403***	0.00415***
	(0.000283)	(0.000293)	(0.000295)	(0.00000192)	(0.000295)	(0.00000225)	(0.000283)	(0.0000542)	(0.000293)	(0.0000599)
GEN	0.0189***	-0.00744***	0.00174***	0.0000802***	0.00176***	0.0000962***	0.0197***	0.0214***	0.0615***	0.0387***
	(0.000534)	(0.000553)	(0.000557)	(0.00000363)	(0.000557)	(0.00000424)	(0.000534)	(0.000102)	(0.000553)	(0.000113)
EDU0	-0.0874***	-0.0242***	0.0170***	0.000144***	0.00551	0.000205***	-0.0900***	0.000849	-0.0948***	-0.00407***
	(0.00595)	(0.00616)	(0.00620)	(0.0000405)	(0.00620)	(0.0000472)	(0.00595)	(0.00114)	(0.00615)	(0.00126)
EDU1	-0.139***	-0.0520***	0.0377***	0.000469***	0.00492	0.000590***	-0.143***	0.000156	-0.135***	-0.000918
	(0.00616)	(0.00638)	(0.00642)	(0.0000419)	(0.00642)	(0.0000489)	(0.00616)	(0.00118)	(0.00637)	(0.00130)
EDU2	-0.111***	-0.0340***	0.0228***	0.000173***	0.00581	0.000252***	-0.114***	-0.0155***	-0.141***	-0.0229***
	(0.00594)	(0.00615)	(0.00619)	(0.0000404)	(0.00619)	(0.0000472)	(0.00594)	(0.00114)	(0.00614)	(0.00126)
EDU3	-0.110***	-0.0146**	0.0183***	0.000134***	0.00321	0.000197***	-0.113***	-0.0117***	-0.0936***	-0.0175***
	(0.00594)	(0.00615)	(0.00619)	(0.0000404)	(0.00619)	(0.0000472)	(0.00594)	(0.00114)	(0.00614)	(0.00126)
EDU4	-0.105***	-0.0109*	0.0196***	0.000121***	0.00351	0.000183***	-0.107***	-0.0102***	-0.0715***	-0.0128***
	(0.00595)	(0.00616)	(0.00620)	(0.0000405)	(0.00620)	(0.0000473)	(0.00595)	(0.00114)	(0.00616)	(0.00126)
EDU5	-0.135***	-0.0195	0.0148	0.0000666	0.00227	0.000103	-0.137***	-0.00190	-0.0356	0.00719
	(0.0281)	(0.0291)	(0.0293)	(0.000191)	(0.0293)	(0.000223)	(0.0281)	(0.00539)	(0.0291)	(0.00595)
MAR_STS	0.0494***	0.0943***	-0.0214**	-0.000274***	-0.00497	-0.000313***	0.0515***	-0.00143	0.246***	-0.00116
	(0.00917)	(0.00949)	(0.00955)	(0.0000623)	(0.00955)	(0.0000728)	(0.00916)	(0.00176)	(0.00948)	(0.00194)
LIV_STS	-0.0628	0.338	-0.00623	-0.000256	-0.00396	-0.000294	-0.0630	-0.0335	0.826***	-0.0405
	(0.248)	(0.257)	(0.258)	(0.00174)	(0.258)	(0.00197)	(0.248)	(0.0492)	(0.256)	(0.0525)
JOB_POS	-0.228	0.0469	-0.0336	-0.000399	-0.00920	-0.000494	-0.227	-0.0793***	0.181	-0.0499*
	(0.142)	(0.147)	(0.148)	(0.000964)	(0.148)	(0.00113)	(0.142)	(0.0272)	(0.147)	(0.0300)
AGE	0.0255***	0.0735***	-0.0193**	-0.000249***	-0.00339	-0.000280***	0.0273***	-0.0118***	0.169***	-0.0153***
	(0.00883)	(0.00914)	(0.00920)	(0.0000600)	(0.00920)	(0.0000701)	(0.00883)	(0.00169)	(0.00913)	(0.00187)
TXN_AMT_5	-0.0940	0.00643	-0.0181	-0.000294	-0.00708	-0.000330	-0.0933	-0.0281	-0.0299	-0.0325
	(0.220)	(0.228)	(0.230)	(0.00150)	(0.230)	(0.00175)	(0.220)	(0.0422)	(0.228)	(0.0467)
ACT_BAL	-0.00921	0.0886***	-0.0200**	-0.000264***	-0.00542	-0.000302***	-0.00630	-0.0229***	0.224***	-0.0176***
	(0.00884)	(0.00915)	(0.00921)	(0.0000601)	(0.00921)	(0.0000702)	(0.00884)	(0.00170)	(0.00915)	(0.00187)
ANU_FEE	-0.0300***	0.0642***	-0.0228**	-0.000253***	-0.00650	-0.000294***	-0.0268***	-0.0308***	0.172***	-0.0301***
	(0.00892)	(0.00923)	(0.00929)	(0.0000606)	(0.00930)	(0.0000708)	(0.00892)	(0.00171)	(0.00923)	(0.00189)
Trend	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	13,302,196	13,302,196	13,302,196	13,302,196	13,302,196	13,302,196	13,302,196	13,302,196	13,302,196	13,302,196
adj. R^2	0.286	0.280	0.272	0.270	0.265	0.262	0.281	0.279	0.272	0.271

Standard errors in parentheses
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$
Note: Trend here refers to the control of time dummies.

6.3. Post-adoption: Subset Analysis

In this subsection, we try to explore the driven forces of the increasing transaction amount and frequency. We conduct subset analysis based on purchasing product category and value, and consumer credit limit level and observation periods.

Product Category. Based on the practice of our focal bank, the credit card department classifies consumer purchasing products into six categories as shown in the following Table 9. We can see that grocery shopping has the highest consumption frequency in our data set, followed by education and entertainment. Intuitively, service, entertainment, groceries, and travel are more related to hedonic shopping. To examine the impact of mobile channel adoption on the consumption for each category, we compute the total consumption amount, frequency, and shares of different channels for each of the six product categories, and then conduct our DID analysis for each category separately and show our results in Table 10. From the results in Table 10, we can see that both the overall consumption amount and frequency increase for groceries, entertainment, travel, and service categories. Second, for these four categories, the complementarity and substitution effects still hold. Third, mobile channel adoption affects the groceries category the most, followed by the entertainment, travel, and service categories. Finally, mobile channel adoption seems unlikely to affect education and healthcare categories, because the estimated coefficients are not statistically significant with our data set.

Table 9 Consumption Categories

Category	Definition	Number	Percentage
Education	School education, professional training, etc.	16,193,466	14.84%
Service	Cleaning, repairing, etc.	1,462,219	1.34%
Healthcare	Hospital service, medicine, etc.	1,002,069	0.92%
Entertainment	Restaurant, gym, etc.	4,326,357	3.96%
Groceries	Supermarket, wholesale, etc.	43,122,235	39.51%
Travel	Flight ticket, hotel rooms, subway, etc.	3,832,095	3.51%

Table 10 Impacts under Different Consumption Categories

	All		PC Channel				Offline Channel			
	Amt.	Freq.	Amt.	Amt. Share	Freq.	Freq. share	Amt.	Amt. Share	Freq.	Freq. share
Education										
Static One-to-One	0.023	0.248	0.007	0.0009	0.0010	0.00022	-0.043	-0.277	-0.091	-0.366
(with replacement)	(0.03289)	(0.27856)	(0.04468)	(0.005497)	(0.04125)	(0.005478)	(0.034879)	(0.26547)	(0.13566)	(0.35811)
Dynamic One-to-One	0.025	0.223	0.012	0.0015	0.0028	0.00014	-0.038	-0.271	-0.088	-0.361
(with replacement)	(0.03256)	(0.25578)	(0.07588)	(0.005469)	(0.04283)	(0.008267)	(0.03167)	(0.34879)	(0.23647)	(0.37945)
Service										
Static One-to-One	0.038**	0.272***	0.002***	0.0005***	0.0013**	0.00011***	-0.022***	-0.233***	-0.064***	-0.375***
(with replacement)	(0.00111)	(0.00105)	(0.00095)	(0.000007)	(0.0011)	(0.000013)	(0.00092)	(0.00015)	(0.00088)	(0.00020)
Dynamic One-to-One	0.033**	0.270***	0.001***	0.0004***	0.0011**	0.00009***	-0.020***	-0.231***	-0.062***	-0.371***
(with replacement)	(0.00113)	(0.00102)	(0.00091)	(0.000005)	(0.0021)	(0.000011)	(0.00087)	(0.00012)	(0.00082)	(0.00017)
Healthcare										
Static One-to-One	0.038	0.257	0.011	0.0013	0.0019	0.00017	-0.042	-0.273	-0.088	-0.355
(with replacement)	(0.03789)	(0.24756)	(0.04257)	(0.005968)	(0.04478)	(0.005649)	(0.034731)	(0.27619)	(0.16791)	(0.36715)
Dynamic One-to-One	0.033	0.249	0.010	0.0012	0.0015	0.00013	-0.031	-0.255	-0.080	-0.352
(with replacement)	(0.03487)	(0.22496)	(0.08472)	(0.006284)	(0.05874)	(0.008964)	(0.03547)	(0.35789)	(0.26478)	(0.34982)
Entertainment										
Static One-to-One	0.049***	0.294***	0.011***	0.0014***	0.0022**	0.00020***	-0.031***	-0.256***	-0.092***	-0.397***
(with replacement)	(0.00102)	(0.00117)	(0.00105)	(0.000012)	(0.0015)	(0.000016)	(0.00096)	(0.00021)	(0.00095)	(0.00021)
Dynamic One-to-One	0.043***	0.281***	0.007***	0.0011***	0.0022**	0.00019***	-0.028***	-0.232***	-0.089***	-0.387***
(with replacement)	(0.00103)	(0.00109)	(0.00108)	(0.000010)	(0.0007)	(0.000019)	(0.00092)	(0.00018)	(0.00087)	(0.00019)
Groceries										
Static One-to-One	0.052***	0.302***	0.012***	0.0018***	0.0027**	0.00024***	-0.033***	-0.271***	-0.099***	-0.402***
(with replacement)	(0.00105)	(0.00121)	(0.00108)	(0.000010)	(0.0012)	(0.000017)	(0.00099)	(0.00022)	(0.00096)	(0.00024)
Dynamic One-to-One	0.047***	0.284***	0.009***	0.0013***	0.0025**	0.00021***	-0.031***	-0.265***	-0.091***	-0.392***
(with replacement)	(0.00101)	(0.00114)	(0.00102)	(0.000009)	(0.0010)	(0.000016)	(0.00094)	(0.00021)	(0.00092)	(0.00022)
Travel										
Static One-to-One	0.041**	0.278***	0.006***	0.0011***	0.0017**	0.00015***	-0.027***	-0.249***	-0.087***	-0.390***
(with replacement)	(0.00108)	(0.00111)	(0.00102)	(0.000009)	(0.0013)	(0.000019)	(0.00099)	(0.00018)	(0.00093)	(0.00025)
Dynamic One-to-One	0.038***	0.277***	0.004***	0.0009***	0.0016**	0.00014***	-0.023***	-0.235***	-0.081***	-0.382***
(with replacement)	(0.00096)	(0.00101)	(0.00112)	(0.000014)	(0.0010)	(0.000023)	(0.00098)	(0.00015)	(0.00089)	(0.00023)

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

Product Value. We next classify the product value into six value categories: less than 100 RMB, 100 to 500 RMB, 500 to 1,000 RMB, 1,000 to 5,000 RMB, 5,000 to 10,000 RMB, and more than 10,000 RMB. Again, to examine the impact of mobile channel adoption on the consumption for different value categories, we compute the total consumption amount, frequency and shares of different channels for each of the six product categories, and then conduct our DID analysis for each value level separately and show our results in Table 11. From the results in Table 11, we can see that both overall consumption amount and frequency increase for products less than 10,000 RMB, and the complementarity and substitution effects still hold for these products. Second, the mobile channel adoption has the greatest effect on low-value items priced at less than 100 RMB, followed by 100 to 500 RMB, and 500 to 1,000 RMB items. The impacts on items with values less than

1,000 to 5,000 RMB and 5,000 to 10,000 RMB seem to be similar. Finally, mobile channel adoption seems unlikely to affect high-value items priced at more than 10,000 RMB, because the estimated coefficients are not statistically significant with our data set. Combining the subset analysis results of product category and value, we find that the increased credit card transaction activity and profitability are likely to be driven by hedonic shopping behavior with low value items.

Table 11 Impacts under Different Product Values

	All		PC Channel				Offline Channel			
	Amt.	Freq.	Amt.	Amt. Share	Freq.	Freq. share	Amt.	Amt. Share	Freq.	Freq. share
Less than 100 RMB										
Static One-to-One	0.055***	0.317***	0.016***	0.0028***	0.0033***	0.00045***	-0.067***	-0.311***	-0.124***	-0.421***
(with replacement)	(0.00102)	(0.00097)	(0.00111)	(0.000022)	(0.0012)	(0.000017)	(0.00099)	(0.00022)	(0.00098)	(0.00033)
Dynamic One-to-One	0.051***	0.312***	0.014***	0.0025***	0.0030***	0.00041***	-0.062***	-0.308***	-0.121***	-0.417***
(with replacement)	(0.00099)	(0.00091)	(0.00102)	(0.000020)	(0.0010)	(0.000011)	(0.00095)	(0.00020)	(0.00091)	(0.00030)
100 to 500 RMB										
Static One-to-One	0.050***	0.311***	0.012***	0.0021***	0.0030***	0.00042***	-0.063***	-0.302***	-0.111***	-0.406***
(with replacement)	(0.00099)	(0.00088)	(0.00103)	(0.000020)	(0.0011)	(0.000014)	(0.00094)	(0.00012)	(0.00090)	(0.00031)
Dynamic One-to-One	0.047***	0.302***	0.010***	0.0017***	0.0028***	0.00039***	-0.060***	-0.297***	-0.106***	-0.398***
(with replacement)	(0.00094)	(0.00081)	(0.00100)	(0.000019)	(0.0009)	(0.000011)	(0.00092)	(0.00010)	(0.00088)	(0.00028)
500 to 1,000 RMB										
Static One-to-One	0.041***	0.297***	0.010***	0.0018***	0.0024***	0.00037***	-0.058***	-0.287***	-0.100***	-0.387***
(with replacement)	(0.00077)	(0.00062)	(0.00087)	(0.000015)	(0.0008)	(0.000010)	(0.00090)	(0.00009)	(0.00081)	(0.00022)
Dynamic One-to-One	0.039***	0.290***	0.009***	0.0016***	0.0021***	0.00035***	-0.053***	-0.284***	-0.098***	-0.380***
(with replacement)	(0.00075)	(0.00060)	(0.00085)	(0.000012)	(0.0007)	(0.000009)	(0.00082)	(0.00008)	(0.00077)	(0.00020)
1,000 to 5,000 RMB										
Static One-to-One	0.028***	0.239***	0.005***	0.0007***	0.0016**	0.00019***	-0.042***	-0.266***	-0.097***	-0.405***
(with replacement)	(0.00098)	(0.00087)	(0.00085)	(0.000009)	(0.0010)	(0.000009)	(0.00083)	(0.00019)	(0.00087)	(0.00018)
Dynamic One-to-One	0.024***	0.235***	0.004***	0.0006***	0.0014**	0.00017***	-0.040***	-0.265***	-0.095***	-0.403***
(with replacement)	(0.00095)	(0.00085)	(0.00084)	(0.000008)	(0.0009)	(0.000007)	(0.00081)	(0.00017)	(0.00085)	(0.00016)
5,000 to 10,000 RMB										
Static One-to-One	0.027***	0.238***	0.005***	0.0006***	0.0016**	0.00018***	-0.041***	-0.265***	-0.093***	-0.397***
(with replacement)	(0.00077)	(0.00079)	(0.00080)	(0.000004)	(0.0006)	(0.000005)	(0.00075)	(0.00014)	(0.00080)	(0.00015)
Dynamic One-to-One	0.019***	0.223***	0.004***	0.0005***	0.0015**	0.00016***	-0.040***	-0.258***	-0.091***	-0.395***
(with replacement)	(0.00074)	(0.00080)	(0.00084)	(0.000007)	(0.0009)	(0.000005)	(0.00075)	(0.00012)	(0.00080)	(0.00014)
More than 10,000 RMB										
Static One-to-One	0.044	0.267	0.005	0.0006	0.0023	0.00019	-0.035	-0.260	-0.090	-0.395
(with replacement)	(0.04268)	(0.27854)	(0.00554)	(0.000789)	(0.0087)	(0.000257)	(0.02478)	(0.25879)	(0.09978)	(0.32568)
Dynamic One-to-One	0.041	0.260	0.002	0.0004	0.0020	0.00015	-0.032	-0.255	-0.081	-0.390
(with replacement)	(0.04546)	(0.29945)	(0.00658)	(0.000812)	(0.0098)	(0.000325)	(0.02587)	(0.25647)	(0.09358)	(0.31578)

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

Credit Limit. Banks normally determine consumers' credit limits based on their consumption ability and income level. Note that here we do not use income data directly because: (i) in China, the income data are generally self-reported and thus not very reliable; and (ii) a lot of consumers choose not to release their income, so we see only a small percentage of consumers' income in our data set. Moreover, under real banking practice in China, the credit limit is a good proxy for consumer income level. We hence separate consumers into different credit-limit percentage categories: bottom 25%, 25% to 50%, 50% to 75%, and top 25%. We show our estimation results in Table 12. Based on the results in Table 12, we find all the effects remain consistent with our main estimation. Furthermore, we find that Alipay adoption has a greater impact on consumers with medium credit-limit levels (i.e., middle 25% to 50% and 50% to 75% categories) than on consumers with the lowest and highest credit-limit levels. Therefore, we would expect that the positive relationship between mobile channel adoption and increased credit card transaction activity and profitability is even stronger for medium income consumers. This subset analysis also checks whether the causal effects are due to actual usage of Alipay or an artifact driven by unobserved characteristics such as disposable income. Although the dynamic matching method that takes into account consumers' behavior over time might alleviate this concern to a certain extent, this subset analysis further reduces this concern.

Table 12 Credit Limit Subsets Analysis

	All		PC Channel				Offline Channel			
	Amt.	Freq.	Amt.	Amt. Share	Freq.	Freq. share	Amt.	Amt. Share	Freq.	Freq. share
Bottom 25%										
Static One-to-One	0.021***	0.230***	0.003***	0.0005***	0.0011**	0.00012***	-0.033***	-0.258***	-0.088***	-0.383***
(with replacement)	(0.00081)	(0.00079)	(0.00078)	(0.000006)	(0.0008)	(0.000006)	(0.00077)	(0.00015)	(0.00081)	(0.00014)
Dynamic One-to-One	0.018***	0.227***	0.002***	0.0004***	0.0009**	0.00011***	-0.031***	-0.256***	-0.085***	-0.381***
(with replacement)	(0.00079)	(0.00073)	(0.00072)	(0.000005)	(0.0007)	(0.000004)	(0.00072)	(0.00011)	(0.00080)	(0.00013)
25% to 50%										
Static One-to-One	0.032***	0.243***	0.009***	0.0012***	0.0019**	0.00021***	-0.047***	-0.278***	-0.106***	-0.408***
(with replacement)	(0.00098)	(0.00095)	(0.00093)	(0.000013)	(0.0017)	(0.000015)	(0.00096)	(0.00029)	(0.00100)	(0.00028)
Dynamic One-to-One	0.030***	0.241***	0.007***	0.0011***	0.0017**	0.00020***	-0.045***	-0.276***	-0.104***	-0.406***
(with replacement)	(0.00091)	(0.00090)	(0.00089)	(0.000011)	(0.0015)	(0.000013)	(0.00092)	(0.00027)	(0.00096)	(0.00024)
50% to 75%										
Static One-to-One	0.040***	0.255**	0.018***	0.0025***	0.0030**	0.00036***	-0.059***	-0.288***	-0.118***	-0.420***
(with replacement)	(0.00105)	(0.00101)	(0.00099)	(0.000024)	(0.0028)	(0.000022)	(0.00100)	(0.00037)	(0.00112)	(0.00043)
Dynamic One-to-One	0.038***	0.251**	0.017***	0.0023***	0.0027**	0.00034***	-0.057***	-0.286***	-0.115***	-0.417***
(with replacement)	(0.00101)	(0.00096)	(0.00093)	(0.000022)	(0.0026)	(0.000020)	(0.00091)	(0.00033)	(0.00108)	(0.00041)
Top 25%										
Static One-to-One	0.025***	0.234***	0.005***	0.0007***	0.0015**	0.00016***	-0.039***	-0.262***	-0.097***	-0.396***
(with replacement)	(0.00089)	(0.00083)	(0.00082)	(0.000009)	(0.0011)	(0.000009)	(0.00085)	(0.00019)	(0.00090)	(0.00018)
Dynamic One-to-One	0.022***	0.231***	0.004***	0.0006***	0.0013**	0.00013***	-0.036***	-0.260***	-0.095***	-0.392***
(with replacement)	(0.00083)	(0.00080)	(0.00079)	(0.000008)	(0.0010)	(0.000007)	(0.00083)	(0.00017)	(0.00088)	(0.00016)

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

Observation Periods. To understand both short- and long-run impact of Alipay adoption, we separate our data set into different observation periods. Recalling that we have 29 months of data, from September 2010 to February 2013, we now classify our data set into the following categories: 1st to 6th month, 6th to 12th month, 13th to 18th month, 19th to 24th month, and 25th to 29th month. We show our estimation results in Table 13. Based on the results in Table 13, we find all the effects remain consistent with our main estimation. Furthermore, we find the impacts of Alipay adoption on both the PC and physical card channels increase over time, and the impact on the physical card channel increases more significantly as time passes as compared to the PC payment channel. Finally, this subset analysis also reduces the concern that our main results might be driven by the improved performance efficiency of the Alipay app and added features in new versions (as a new startup company in China, Alipay has been continuously improving its app functions).

Table 13 Time Periods Subsets Analysis

	All		PC Channel				Offline Channel			
	Amt.	Freq.	Amt.	Amt. Share	Freq.	Freq. share	Amt.	Amt. Share	Freq.	Freq. share
1st to 6th month										
Static One-to-One	0.013***	0.106***	0.009***	0.0011***	0.0012***	0.00018***	-0.029***	-0.108***	-0.087***	-0.177***
(with replacement)	(0.00041)	(0.00072)	(0.00085)	(0.000013)	(0.0009)	(0.000010)	(0.00076)	(0.00014)	(0.00074)	(0.00012)
Dynamic One-to-One	0.011***	0.102***	0.008***	0.0009***	0.0011***	0.00016***	-0.027***	-0.104***	-0.082***	-0.173***
(with replacement)	(0.00040)	(0.00069)	(0.00082)	(0.000011)	(0.0008)	(0.000008)	(0.00072)	(0.00012)	(0.00071)	(0.00011)
6th to 12th month										
Static One-to-One	0.023***	0.120***	0.012***	0.0019***	0.0017***	0.00022***	-0.044***	-0.137***	-0.101***	-0.203***
(with replacement)	(0.00055)	(0.00079)	(0.00089)	(0.000014)	(0.0012)	(0.000011)	(0.00079)	(0.00015)	(0.00077)	(0.00014)
Dynamic One-to-One	0.021***	0.118***	0.011***	0.0017***	0.0015***	0.00020***	-0.042***	-0.135***	-0.100***	-0.199***
(with replacement)	(0.00052)	(0.00075)	(0.00086)	(0.000013)	(0.0012)	(0.000010)	(0.00076)	(0.00014)	(0.00073)	(0.00012)
13th to 18th month										
Static One-to-One	0.032***	0.134***	0.019***	0.0026***	0.0023***	0.00031***	-0.067***	-0.159***	-0.132***	-0.239***
(with replacement)	(0.00072)	(0.00090)	(0.00097)	(0.000025)	(0.0033)	(0.000039)	(0.00091)	(0.00028)	(0.00085)	(0.00029)
Dynamic One-to-One	0.029***	0.130***	0.017***	0.0023***	0.0021***	0.00028***	-0.065***	-0.156***	-0.130***	-0.236***
(with replacement)	(0.00069)	(0.00082)	(0.00088)	(0.000020)	(0.0029)	(0.000033)	(0.00086)	(0.00025)	(0.00082)	(0.00026)
19th to 24th month										
Static One-to-One	0.040***	0.142***	0.027***	0.0039***	0.0039***	0.00041***	-0.106***	-0.199***	-0.189***	-0.310***
(with replacement)	(0.00090)	(0.00108)	(0.00113)	(0.000067)	(0.0049)	(0.000053)	(0.00118)	(0.00045)	(0.00099)	(0.00058)
Dynamic One-to-One	0.040***	0.140***	0.024***	0.0035***	0.0036***	0.00038***	-0.101***	-0.197***	-0.186***	-0.307***
(with replacement)	(0.00082)	(0.00095)	(0.00106)	(0.000061)	(0.0040)	(0.000044)	(0.00102)	(0.00041)	(0.00082)	(0.00049)
25th to 29th month										
Static One-to-One	0.049***	0.148***	0.033***	0.0045***	0.0048***	0.00050***	-0.155***	-0.261***	-0.240***	-0.409***
(with replacement)	(0.00102)	(0.00127)	(0.00122)	(0.000079)	(0.0054)	(0.000068)	(0.00123)	(0.00053)	(0.00107)	(0.00065)
Dynamic One-to-One	0.045***	0.146***	0.030***	0.0041***	0.0042***	0.00047***	-0.152***	-0.259***	-0.238***	-0.401***
(with replacement)	(0.00099)	(0.00123)	(0.00119)	(0.000073)	(0.0051)	(0.000065)	(0.00119)	(0.00048)	(0.00101)	(0.00062)

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

6.4. Robustness and Falsification Checks

In this subsection, we present additional four robustness checks to further validate our main estimation results, then we conduct falsification checks to assess whether the observed effects arise spuriously.

First, the impact of mobile channel adoption in our analysis might be driven by the expansion of Alipay among merchants. Although the monthly dummies introduced in our regression might control for these issues to certain extent, we still want to take a closer look at it. To reduce this concern, we run our analysis separately for different cities in Jiangsu province (13 cities in total), because the expansion among merchants should be different across cities. More developed cities, like Suzhou in Jiangsu province, should have a higher merchant expansion rate, while less developed cities, like Yancheng, should have a lower expansion rate. We find our main results hold consistently across different cities.

Second, we consider the individual specific fixed effect model, to account for the potential correlation between the individual specific effects and the independent variables. To attempt an alternative specification as compared to main estimation model, we estimate the following model:

$$\begin{aligned} Outcome_{it} =& \beta \times (TreatGroup_i \times AfterTreat_{it}) \\ &+ \alpha_i + X_{it} + \tau_t + \epsilon_{it}, \end{aligned} \tag{5}$$

where α_i here characterizes the unobserved time-invariant individual fixed effect. For instance, the innate ability or habit for individuals. We show our estimation results in Table 14. Based on the results in Table 14, we find all the effects remain consistent with our main estimation.

Table 14 Individual Fixed Effect Model

	All		PC Channel				Offline Channel			
	Amt.	Freq.	Amt.	Amt. Share	Freq.	Freq. share	Amt.	Amt. Share	Freq.	Freq. share
Static One-to-One	0.021***	0.224***	0.002***	0.0001***	0.0015**	0.00013***	-0.031***	-0.257***	-0.081***	-0.366***
(with replacement)	(0.00069)	(0.00075)	(0.00077)	(0.000004)	(0.0007)	(0.000005)	(0.00071)	(0.00012)	(0.00071)	(0.00012)
Dynamic One-to-One	0.016***	0.221***	0.001***	0.0001***	0.0017**	0.00012***	-0.038***	-0.255***	-0.0894***	-0.3778***
(with replacement)	(0.00072)	(0.00079)	(0.00075)	(0.000005)	(0.0008)	(0.000004)	(0.00073)	(0.00013)	(0.00074)	(0.00014)

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

Third, in our main model, we treat the outcomes of different channels as independent, i.e., we separately estimate effects on PC and offline purchase amount, frequency, and shares. However, in reality, the outcomes of different channels could influence one another too. To account for the correlation among channels, we consider now a joint analysis that looks at consumption across all three channels at once. We here use the Dirichlet regression which is a model with compositional dependent variables, i.e., fraction of sales allocated to mobile, PC, and offline channels. The Dirichlet model forces the proportions to add up to one in the regression, yet in our main model they occur independently. We show our estimation results in Table 15. Based on the results in Table 15, we find all the effects remain consistent with our main estimation.

Table 15 Dirichlet Regression

	PC Channel		Offline Channel	
	Amt. Share	Freq. share	Amt. Share	Freq. share
Static One-to-One	0.00009***	0.00010***	-0.223***	-0.306***
(with replacement)	(0.000002)	(0.000003)	(0.00009)	(0.00009)
Dynamic One-to-One	0.00007***	0.00009***	-0.231***	-0.302***
(with replacement)	(0.000003)	(0.000004)	(0.00011)	(0.00011)

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

Fourth, we take into account for the potential endogenous assignment bias, we conduct the synthetic control groups method (see Abadie and Gardeazabal (2003), Abadie et al. (2010), Abadie et al. (2015)) to create a synthetic control group that is a weighted average of a number of potential control groups, where the weights are chosen so that the synthetic control group mimics the treatment group in terms of pre-intervention trend and pre-determined covariates as closely as possible. We then conduct our DID analysis again with the synthetic control group, and find our results remain consistent.

Finally, we conduct falsification checks to assess whether the observed effects arise spuriously. We try to see whether the DID estimator produces spurious significant results with outcome variables that are taken from mismatched periods. In particular, we examine the correlation between Alipay adoption and consumption amount and frequency from periods prior to Alipay adoption, because the adoption should not affect the consumption trend before adoption. To perform this check without reducing the number of observations from the original regression, we exchange the outcome variables in the post- and pre-treatment periods. We find the main estimated coefficients are not statistically significant in this falsification test as shown in Table 16, and thus the DID estimator is unlikely to suffer from issues of spurious correlation.

Table 16 Falsification Test - Outcomes with Mismatched Periods.

	All		PC Channel				Offline Channel			
	Amt.	Freq.	Amt.	Amt. Share	Freq.	Freq. share	Amt.	Amt. Share	Freq.	Freq. share
Treated Users After Adopting Alipay	0.055 (0.063)	0.037 (0.045)	-0.008 (0.028)	-0.013 (0.031)	-0.009 (0.022)	-0.011 (0.021)	-0.020 (0.018)	-0.133 (0.092)	-0.075 (0.119)	-0.101 (0.124)

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

7. CONCLUDING REMARKS

Mobile payment is changing consumers' purchasing behaviors in terms of shifting consumers from the physical card payment channel to the mobile payment channel. Although the PC payment channel and physical card channel are still widely used for consumer consumption, the mobile payment channel is gaining prominence. In this paper, we study both pre- and post-adoption consumer behaviors. To do so, we utilize a unique data set from one of the largest banks in China, which contains the consumer credit card transactions from PC, offline, and mobile payment (Alipay) channels. We conduct survival analysis to understand consumer adoption decisions. We then employ the difference-in-differences methodology coupled with propensity score matching to study post-adoption behaviors.

We find that a consumer's time to adopt the mobile payment channel is reduced by around 0.5% with a one-unit increase in transaction frequency of the month before adoption. Furthermore, the positive relationship between service demand and adoption decision is even stronger for frequent travelers due to channel ubiquity. We also find that the level of local penetration also reduces the time to adoption. In the post-adoption behavior analysis, controlling for the service demand and local penetration for matched groups, we find that the total transaction amount increases by around 2.4% after Alipay adoption, and the total transaction frequency increases by around 23.5%.

Therefore, mobile channel adoption is associated with increased credit card transaction activity and profitability. We further find that the positive relationship is increasing over time and is even stronger for medium income consumers. We also find that the mobile payment channel acts as a substitute for the offline (physical card) channel and as a complement for the PC payment channel. Moreover, we find both substitution and complementarity effects increase over time. Finally, we find that the increased credit card transaction activity and profitability are likely to be driven by hedonic shopping behavior with low value items.

As far as we know, our work is the first to explore the determinants and outcomes of mobile payment adoption on traditional PC and offline payment consumption. However, our paper still has a few limitations, and some of them might serve as potential future research directions. First, our data set does not contain consumers' browsing and click-through information, which has been shown in previous IS and marketing literature to be an important driver of consumers' PC and mobile shopping behaviors. Future work might combine consumers' browsing and click-through data with mobile payment consumption to further explore the mechanism behind the increased transaction activities. Moreover, although our analysis brings insights on post-adoption behavior changes, mobile payment adoption might be correlated with other fundamental changes in consumers' consumption behaviors in the long run. For instance, as more and more mobile apps for different product categories become available, such as for healthcare and education, these technologies are changing consumers' fundamental consumption behaviors. A study with longer time periods (say, 5-10 years) might bring further insights into changes in consumer behavior.

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