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The Adoption and Use of Mobile Payment: Determinants and Relationship with Bank Access*

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Abstract

This study aims to answer two questions: What determines the adoption and use of mobile payment? What is the relationship between mobile payment and access to traditional bank services? By using representative survey data in rural China, we apply a hurdle model with 2SLS and find that consumers with better access to bank services are more likely to adopt mobile payment. However, after adoption, the less often the consumers visit banks because of distance or social constraints, the more they use mobile payment to complement bank services. Younger, better educated households with higher income and more smart phones are more likely to adopt and use mobile payment. Among these characteristics, age has the largest marginal effect while income has the least. Households in the agricultural sector are least likely to adopt and use mobile payment. We also find that awareness of neighbors' use of non-cash payment has a substantial positive effect.

JEL Classification: G21, G23, G4
Keywords: Mobile Payment, Financial Inclusion, Banking, FinTech, Consumer Behavior

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1. Introduction

Mobile payment has gained popularity in recent years for making in-person or online payments and money transfers. It lowers transaction costs, boosts business activities, and extends financial services to the under-served consumers and communities. This study conducts empirical research to answer two crucial questions: What determines mobile payment adoption and usage? What is the relationship between mobile payment and bank service access?

Due to a lack of data, most related research had to conduct small-scale online or phone surveys1 with an average of 500 responses. These surveys have technical shortcomings. First, the sample size of these surveys is too small, and the response rate is often too low, which raises doubts over their representativeness. Second, these surveys were conducted online or by phone, limiting the length of questionnaires and constraining the scope of studies. Third, the answers collected online or by phone might be vulnerable to errors and bias.

This study analyzes a large-scale survey of more than 4,000 representative households in rural China. We use the well-designed "Qian Ren Bai Cun" survey conducted by students and faculties of Renmin University of China in summer 2019. It covered 128 villages in 31 provinces in China. Most importantly, the novelty of data is the information about the adoption and perception of mobile payment and access to bank services. Contrary to the existing studies on the adoption of mobile payment, we analyzed a full set of financial and demographic information of households, rather than focusing only on consumer behaviors.

This paper provides two sets of major findings. First, it investigates who are more likely to adopt and use mobile payment. Given abundant zeros in the responses to mobile payment usage, we apply a hurdle model in probit and OLS settings. In this two-part model, first, we treat positive responses as 1 and examine what affects a household's adoption decision.

Subsequently, we focus on positive responses and check the factors that contribute to how much they use it. As expected, we find that when the head of household is younger, better educated, earns higher income, or owns more smart phones, the household is more likely to adopt and use mobile payment. Age plays the largest role: if a head of household is 20 years younger, the probability of adoption and the share of expenditure paid by smart phones would on average increase 18.7 and 8 percentage points respectively. Surprisingly, the marginal effect of increasing family income is modest. For a "typical" household with median values of all characteristics, the effect on adoption of owning one more smart phone is equivalent to that of doubling the household income. After considering occupation, we find that people from several sectors, such as manufacturing and transportation, seem to be more likely to adopt mobile payment, but this effect disappears after controlled for household characteristics, especially family income. One exception is people working in the agricultural sector who are less likely to adopt and use mobile payment, even after including controls. In addition, we hypothesize that people immigrating to urban areas for work (but with Hukou in rural areas) would contribute to higher adoption and more usage of mobile payment by their families staying in rural areas. However, our results do not support this hypothesis. Furthermore, we exploit a survey question about how people perceive the adoption of noncash payment in the neighborhood and find that people who are more sensitive to their neighbor's usage are 16 percentage-points more likely to adopt mobile payment and pay 6 percentage points more of their expenditure by smart phones, confirming the effects of awareness and social externalities in literature on consumer behaviors.

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1 For example, Junger and Mietzner (2020) surveyed 643 households in Germany and received 324 effective responses; Amoah, Korle, and Asiama (2020) gathered data from 733 households in Ghana.

Second, the study finds a both promoting and complementary relationship between mobile payment and bank services. To deal with the endogeneity between the adoption of mobile payment and the frequency of visiting banks (which is a proxy for the access to bank services), we apply two instruments: the distance to the nearest bank branch or ATM and the village average of bank visit frequency (except for the household i). We find that the more often people visit banks, the more likely they are to adopt mobile payment. However, for those who have already adopted mobile payment, their usage would increase if they visit banks less often. A complementary effect could explain this: when people visit banks less often due to distance (the average in our sample is 3–10 km) or social reasons, they tend to switch —using mobile payment to shop, transfer money, or pay bills.

This paper contributes to the literature in three ways. First, it is among the first to investigate mobile payment in relation to bank services. Most of the existing research has focused on FinTech lending and found that FinTech filled the credit gap left by banks and improved financial access, especially for underserved borrowers (e.g., Ahmed et al., 2015;

Chen, Hanson, and Stein, 2017; Schweitzer and Barkley, 2017; Jagtiani and Lemieux, 2018; Buchak et al., 2018). However, Tang (2019) indicated that the credit boom by P2P lenders occurs among those who already have access to bank credit. Our study finds a similar complementary pattern in payment services.

Second, this study is among the pioneers to investigate socio-demographic determinants of mobile payment adoption and use. Previous studies on payment choice have focused on traditional payment methods. A series of Federal Reserve papers investigated customers' choice of payment among cash, check, credit card, and debit card and found that age, education, income, race, and other socio-demographic attributes explained most of the variation (e.g., Schuh and Stavins, 2011; Stavins, 2016; Koulayev et al., 2016; Stavins, 2017). In particular, they found that disadvantaged groups rely more on cash, which is consistent with our results that older, poorer, and less educated people are left behind when adopting new payment technology.

Much of the emerging literature on socio-demographic determinants of mobile payment adoption relied on small survey samples and applied relatively simple analyses. Junger and Mietzner (2020) conducted a principal component analysis on 324 questionnaires in Germany and found that households with lower trust in financial institutions, better financial education, and preference for transparency tend to adopt FinTech. However, their dependent variable is a household's intention to switch from a bank to a FinTech, not actual adoption or usage, and they did not distinguish among the types of FinTech services. Crabbe et al. (2009) analyzed a survey of 271 people in Ghana and suggested that age, education, and banking experience significantly influence mobile banking adoption, while gender, income, and occupation do not affect the adoption but play a significant role in the "sustained usage," which was not specifically defined in the paper. While Crabbe et al. (2009) only conducted ANOVA tests to distinguish differences in those factors between users and non-users, our study contributes to the research by quantifying not only the usage but also the marginal effects in both stages of adoption and use.

For factors contributing to the mobile payment adoption, most studies (e.g., Khalilzadeh,

Ozturk, and Bilgihan, 2017; Kim, Mirusmonov, and Lee, 2010; Schierz, Schilke, and Wirtz, 2010) focus on consumer intentions, not socio-demographic factors. The most commonly applied models are the unified theory of acceptance and use of technology (UTAUT), the technology acceptance model (TAM) (Davis, 1989), and diffusion theory (Rogers, 2010). They focus on user-related factors, such as personal innovativeness, related knowledge, perceived risk and trust, and product-related factors, such as convenience, cost, compatibility, network externalities, and reachability. This paper also extends the results of related studies (e.g., Qasim and Abu-Shanab, 2016; Noor, 2011; Gichuki and Mulu-Mutuku, 2018) by examining the effect of awareness of neighbors' non-cash payment adoption and use, an intersection of customers' awareness and network externalities.

Third, while most research on smart phone technology-enabled money transfer has focused on low-income countries (e.g., Beck et al., 2018; Jack and Suri, 2011; Jack and Suri, 2014), such as Kenya, this study investigates the case in less developed areas in China, a middle income country. Unlike low-income countries that have a large portion of population unbanked, households in rural China have a high rate of bank account ownership. However, their financial needs, especially payment and transfer, remain underserved, partly due to geographic and cultural reasons. Our finding that mobile payment could fulfill consumers' underserved needs for financial payment provides implications for less developed areas in middle-income and even advanced countries.

The rest of the paper is organized as follows. Section 2 introduces the development of mobile payment and the financial inclusion in China. Further, Section 3 describes the data and identification strategy, and Section 4 discusses the results. Finally, Section 5 concludes.

2. Background

2.1 The Rapid Development of Mobile Payment in China

Mobile payment is a broad term for the smart phone-enabled payment method. It refers to the use of mobile devices, such as smart phones, tablets, or laptops, to make in-person or online transactions. To make mobile payments, one needs to first set up a mobile wallet with the user's debit or credit card information. A mobile wallet is a smart device application that stores the user's card information securely. The common mobile wallets in developed economies include Apple Pay, Google Pay, and Samsung Pay. However, in China, 94.4% of the market shares were owned by Wechat Pay and AliPay[2] as of the second quarter of 2020, which leads to several key attributes in the definition of mobile payment in China.

First, the function of mobile payment in China is not limited to paying. Wechat Pay and AliPay are like a combination of Apple/Samsung Pay, Paypal, Venmo/Zelle, and other FinTech applications. They can facilitate not only in-person purchases in supermarkets, restaurants, retail stores, public transportation, etc., but also person-to-person (P2P) transfers, online shopping, utility payments, ticket reservations, money market funds, and other functions. In this paper, banking applications are not included in our definition of mobile payment.

Second, Wechat Pay and AliPay use a different technology to facilitate payment. Apple Pay, Samsung Pay, and others mostly rely on near-field communication or magnetic secure transmission, which facilitates contactless transactions when users bring smart phones close to the point-of-sale devices. Wechat Pay and AliPay use the quick response (QR) code that requires consumers or merchants to scan the counterparty's QR code to complete transactions, either online or in person.

China is the largest market for mobile payment with more than 854 million users in 2020. According to the People's Bank of China (PBoC), financial institutions processed more than 123.22 billion mobile payment transactions with 432.16 trillion CNY in 2020, increasing 21.48%

[2] Based on Alibaba and Taobao, AliPay is the pioneer in mobile payment in China. In 2014, Wechat launched the function of "red pocket" and quickly penetrated the market. In 2016, Apple Pay and Samsung Pay entered the Chinese market, and later Mi Pay and Huawei Pay also joined in the competition. Nevertheless, their market share is small.

and 24.5% from 2019 respectively. According to a survey in It's time for a consumer centred metric: introducing 'return on experience.' (2019), more than 86% of consumers in China have been using mobile payment in their daily consumption. This rapid growth is driven by the increasing ownership of smart mobile phones, declining cost of mobile data plans, fast development of related technologies, and increased spending capacity of consumers. The remaining 14% of non-users are mainly in rural areas, which is why our study focuses on rural residents.

2.2 The Financial Inclusion in Rural China

Mobile payment is an important means of financial inclusion. World Bank defines financial inclusion as "individuals and businesses [having] access to useful and affordable financial products and services that meet their needs – transactions, payments, savings, credit and insurance – delivered in a responsible and sustainable way." However, in the context of rural China, the major obstacle for financial inclusion is the unfulfilled need for payments and transactions, which fundamentally influences the need for credit and other financial services (Bai et al., 2018).

On the one hand, according to the 2017 Global Findex report, about 85%[3] of households in rural China own at least one bank account,[4] which is higher than the average of G20 countries. On the other hand, 15%[5] of respondents who have bank accounts never deposited or withdrew in the previous year, which might be due to a lack of physical accessibility to bank branches, ATMs, or banking agencies in rural China. Although, at an aggregate level, China has more than 126.6 thousand banking outlets in remote areas, according to PBoC as of the end of 2020, the number of banking outlets per capita in China is less than that in many developing countries, such as Kenya, Peru, and Bangladesh. Worse, some banking agencies do not provide certain services, such as opening an account. This issue is also reflected in our survey data: for rural residents, the median frequency of visiting a bank is twice per year, and the average distance to the nearest banking outlet is 3–10 km.

Mobile payment could be influential in solving the problem of financial inclusion in China. First, according to the 2017 Global Findex, 97% of Chinese respondents reported that their household has at least one smart phone, which is the highest among other countries. However, only 70% claimed to have Wi-Fi coverage at home, according to the 2019 Gallup World Poll. This implies that the widespread adoption of smart phones could overcome the obstacle of installing Wi-Fi in remote areas and facilitate easy connection with the Internet that would allow for the use of mobile payment. Second, having a bank account enables rural residents to connect their accounts to Wechat Pay or AliPay to facilitate digital payments or transfers. Furthermore, Zhao, Wu, and Guo (2022) found that mobile payment substantially improves rural household consumption by reducing transaction costs, easing liquidity constraints, and decreasing mental accounting loss.

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3 The percentage of adults owning at least one bank account in rural China is 78%, and 32% of unbanked adults reported that they do not have an account because family members have them. Therefore, we can calculate the percentage of households with at least one bank account.

4 For the households that do not have any bank account, 60% cited the reason as insufficient funds to deposit or transfer, which is more related to poverty than financial inclusion, although financial exclusion would also cause poverty.

5 This percentage reported by the 2017 Global Findex is for urban and rural respondents in total, and the percentage for rural sample only should be higher.

The demand for both credit and insurance is incredibly low in China. According to the 2017 Global Findex, Chinese consumers' demand for borrowing, especially bank loans, is among the lowest in world, with only 8% of rural respondents claiming to have borrowed from a regulated financial institution. The low demand for insurance is partly because approximately 97.6% of rural residents are covered by a social, medical insurance system, according to the Sixth National Health Services Survey in 2021. Therefore, this paper emphasizes the function of payment and money transfer, which is more fundamental in terms of financial inclusion.

The rural residents' lack of interest in applying for loans is also found in our data. In the survey, one question asked about loan application experience, and about half of the respondents did not answer it. Among the effective responses, 70.8% had never considered applying for loans, and 10.5% had considered but never applied. Among 432 households that had applied for loans, 84.7% successfully secured the loans from either commercial banks and credit unions or micro-finance organizations. Surprisingly, regardless of whether households applied for loans, they share similar characteristics, except that those with loan application experience have slightly higher mobile payment adoption rates. Similarly, irrespective of whether the loan was successfully secured, household characteristics are not distinctly different, except for successful loan applicants having relatively higher income, more number of mobile phones, and higher mobile payment adoption rate. Table A.2 summarizes the statistics for each group.

3. Data and Methodology

3.1 Data Sources

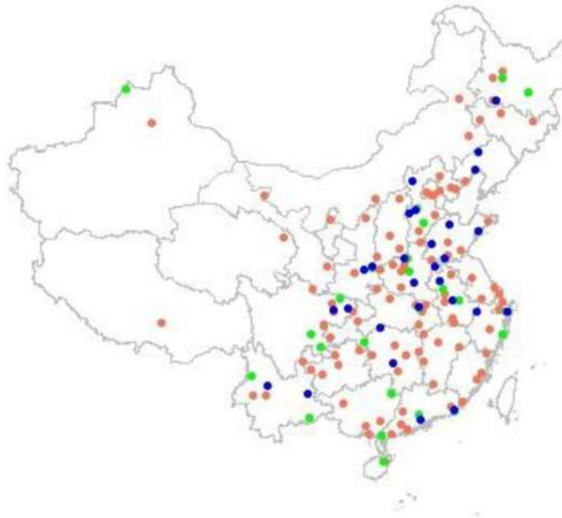
The "Qian Ren Bai Cun" survey has been conducted annually since 2012. Each summer, students and faculties from Renmin University of China visit the sampled villages and collect information concerning agricultural production, land resources, education development, medical services, social organization, and household income and financing.

The survey sampling process was designed adequately to ensure that surveyed households are representative. First, counties were selected based on probability proportional to the size sampling method that uses demographic and economic information to cluster. Second, villages were randomly selected from the pre-selected counties. Finally, three or four students formed a group and selected certain households in a village by applying distance sampling or spot mapping.

The survey used in this study was conducted in summer 2019,[6] which covered 128 villages in 31 provinces, as shown in Figure 1. Although this survey was not originally designed to study mobile payment, the questions covered various aspects of rural life and thus provided useful information to answer our research questions.

6 We cannot construct panel data by adding more surveys from previous years, owing to the changes in survey questions and the concern regarding the rapid growth of mobile payment adoption in rural China.

Figure 1: The Surveyed Villages



Note: The 100 red dots are villages which were selected and actually surveyed; the 41 green dots represent villages which were selected but not surveyed; the 28 blue dots refer to villages which were not selected but actually surveyed. Although the survey teams tried to adhere to the original plan, due to the actual travel and funding constraints, the choice of villages was at the discretion of the survey teams and the alternatives were usually equivalent to the original ones.

On average, residents in rural China paid about 20% of their expenditure by smart phones. However, approximately 60% of respondents did not use mobile payment at all (Figure 2).

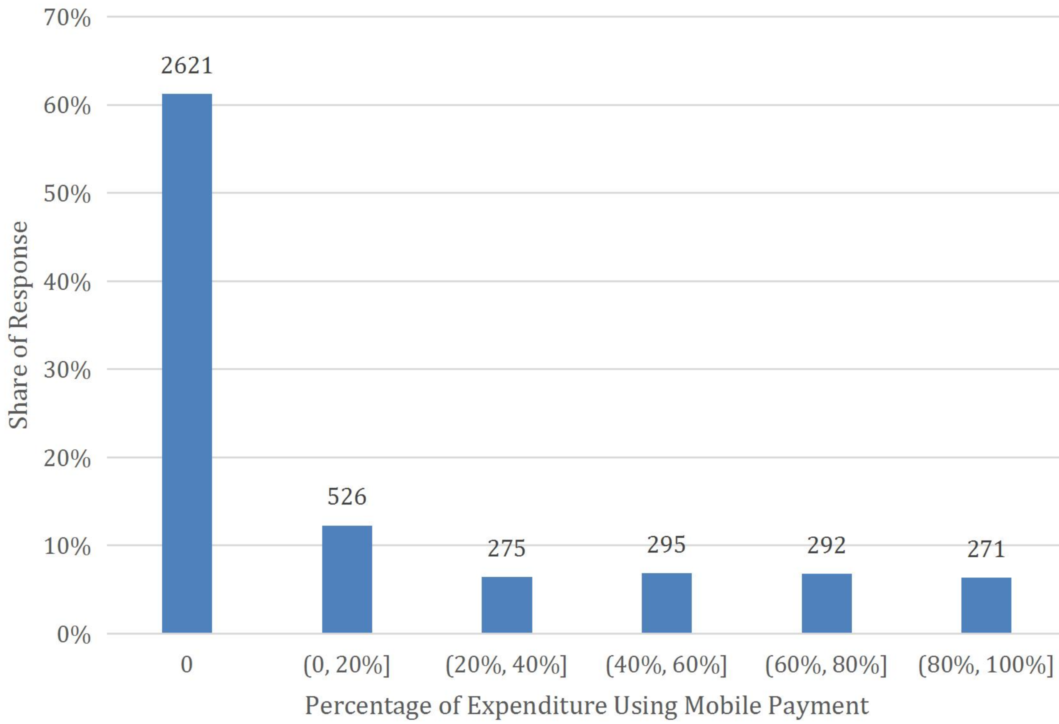
This result is close to the survey results of World Bank: according to the 2017 Global Findex, about 44% of rural respondents in China used online shopping and online bill payment services in the previous year. Therefore, this study uses a two-part Hurdle model to accommodate these zeros.

3.2 Hurdle Model

For data with a large portion of values at zero, "zero-inflated," common solutions are the Tobit model and its less restrictive variation—the Hurdle model (Cragg, 1971 and Duan et al., 1983). We move beyond the Tobit model because it assumes that the adoption and usage decisions are governed by a single mechanism, while the Hurdle model allows different mechanisms[7] which is more suitable for our case. Particularly, our data does not have a sample selection issue because the zeros in the responses are actual values, not censored or missing. In a sample selection environment, the outcome of the selection variable (whether to adopt mobile payment) should not restrict the outcome of response (how much expenditure by mobile payment), which does not hold in our case because not adopting mobile payment would rule out any usage of it. Nevertheless, for comparison, various model specifications and alternative models, such as type II Tobit model, are tested and discussed in the section on robustness check.

7 Wooldridge (2009) provided detailed discussion on this issue.

Figure 2: The Histogram of Percentage of Expenditure Using Mobile Payment



Note: This figure plots the number of responses to the question on what percentage of expenditure was paid by mobile payment in the past month. About 60% of responses in our sample are zeros.

In the first step of the Hurdle model, all positive responses are fixed at 1, and a probit regression is applied to study the factors that influence a household's decision regarding mobile payment adoption. The second part focuses on only positive usage and studies the factors that promote a household's mobile payment usage.

In the first step, we estimate the following probit model on the entire sample for the adoption decision:

$$P(sv,i = 1|Zv,i) = \varphi(Zv,i;\upsilon v), \tag{1}$$

where sv,i is a binary variable equal to 1 if household i at village v has non-zero spending by mobile payment; Zv,i is a vector of household characteristics, including the key variable—access to banks, age, education, family income, number of smart phones, awareness of neighbors' adoption, type of occupation, child's highest education, whether having savings or houses for retirement, and share of medical expenditure.

In the second step, we estimate mobile payment usage, conditioned on mobile payment adoption, by the following OLS regression:

$$yv,i = \upsilon v + \beta Xv,i + \mu v,i, \tag{2}$$

where $y_{v,i}$ is the non-zero percentage of expenditure by mobile payment for household i at village v, $X_{v,i}$ is a vector of household characteristics of users only, and $\mu_{v,i}$ is assumed to have a truncated normal distribution.[8]

Note that we do not need to estimate the inverse Mills ratio as in a Tobit model, therefore the exclusion restriction (i.e., X to be a strict subset of Z.) is not necessary. In spite of that, $x_{v,i}$ includes only the first six factors of $z_{v,i}$ to facilitate an easier comparison with the Tobit results in Table E.9. In both steps, we include the village fixed effect υ_v, and the standard deviations are clustered at the village level.

3.3 Instrumental Variables

To proxy the key variable—access to bank services, we use the frequency of household i in village v visiting a bank branch or ATM. To include this variable in the model, we assume that one who is more exposed to bank services would be more financially educated and thus more likely to adopt new financial technologies. One possible endogeneity problem is reverse causality—how often a household visits banks could also be affected by how much it uses mobile payment. For example, if one family starts using AliPay to pay utility bills, they do not need to visit a bank to pay bills.[9]

To generate sufficient exogenous variation in households' frequency of visiting banks, we use two instruments: the distance to the nearest bank branch or ATM and the average frequency of visiting banks in each village (except for household i). The former seems irrelevant to whether a customer adopts and uses mobile payment, unless by affecting how often they visit banks. The latter can only contribute to one's adoption of mobile payment through influencing one's habit of visiting banks. This can be understood as a cultural or social norm. Therefore, we supplement equation (1) and (2) with the first-stage regression:

$$Frequency_{v,i} = \upsilon_v + \pi Char_{v,i} + \beta_d Distance_{v,i} + \beta_a Average_{v,i} + \omega_{v,i}, \tag{3}$$

where $Distance_{v,i}$ is the distance to the nearest banking outlet from household i in village v, $Average_{v,i}$ is the average frequency of visiting banks in village v except for household i, and $Char_{v,i}$ refers to household characteristics.

3.4 Summary of Statistics

Table 1 and 2 summarize the number of observations and the percentage in each category of demographic factors for mobile payment adopters and all respondents. Except for the percentage of mobile payment usage, total and per person number of mobile phones, the number of family members, and the share of medical expenditure, all other variables are ordinal. Table A.1 provides details about survey questions.

Out of 4,414 effective responses, 2,705 households (about 61%) reported not using mobile payment. These non-users, on average, are older and less educated than mobile payment users and have one or no smart phone and earn about CNY 20,000 or less. However, their bank access, proxied by the distance from their home to the nearest bank and the frequency of visiting banks,

[8] Because the positive part is not over-dispersed. The results from the lognormal model are considerably similar, as shown in Table 7.

[9] A common offline way to pay utility bills is to visit a bank and pay through a bank service.

is not worse than that of mobile payment users. Their awareness of non-cash payment adoption in the neighborhood is also not lower than that of users.

As the relationship between age and the adoption of mobile payment might not be linear, we transform the age data into ordinal. The average age of the survey respondents is about 55 years, which reflects the widely discussed phenomenon that most young people in rural China move to work in urban regions. This fact could explain the abundant zeros in the response for mobile payment usage as the elderly are left behind in rural areas (and responded to the survey), and they are naturally slow to adopt new technologies.

Table 1: Demographic Profile of Mobile Payment Adopters

Demographics	Mobile Payment Adopters		All Respondents	
	Observation	Percentage	Observation	Percentage
	1709	**38.7%**	**4414**	**100%**
Distance to Banks				
0–3 km	767	44.9%	1794	40.6%
3–10 km	736	43.1%	1983	44.9%
10–20 km	134	7.8%	441	10.0%
20–30 km	33	1.9%	102	2.3%
> 30 km	39	2.3%	94	2.1%
Frequency of Visiting Banks*				
Almost never	370	21.7%	1414	32.0%
Once per year	196	11.5%	580	13.1%
Twice per year	324	19.0%	747	16.9%
Once per quarter	359	21.0%	787	17.8%
Once per month	460	26.9%	886	20.1%
Total Number of Smart Phones				
0	0	0	614	13.9%
1	104	6.1%	564	12.8%
2	501	29.3%	1235	28.0%
3	486	28.4%	900	20.4%
4	416	24.3%	703	15.9%
5	120	7.0%	230	5.2%
6	55	3.2%	111	2.5%
> 6	27	1.6%	57	1.3%
Number of Smart Phones p.p.				
0	0	0	614	13.9%
0–1	895	52.4%	2052	46.5%
1	435	25.5%	971	22.0%
1–2	224	13.1%	445	10.1%
2	103	6.0%	197	4.5%
2–3	20	1.2%	45	1.0%
3	19	1.1%	46	1.0%
> 3	13	0.8%	44	1.0%
Number of Family Members				
1	58	3.4%	276	6.3%
2	372	21.8%	1458	33.0%
3	357	20.9%	815	18.5%
4	368	21.5%	744	16.9%
5	273	16.0%	532	12.1%
6	175	10.2%	352	8.0%
> 6	106	6.2%	237	5.4%
Education				
Illiterate	56	3.3%	488	11.1%
Primary school	386	22.6%	1531	34.7%
Middle school	780	45.6%	1669	37.8%
High school	273	16.0%	478	10.8%
Professional high school	104	6.1%	121	2.7%
Three-year college	79	4.6%	91	2.1%
Four-year college	31	1.8%	36	0.8%
Postgraduate	0	0	0	0

*: The original direction of ordering in the frequency of visiting banks is reversed. We deleted 11 households who reported 0 smart phones but at the same time using mobile payment, probably due to misunderstanding the survey question.

Table 2: Demographic Profile of Mobile Payment Adopters (Continued)

	Mobile Payment Adopters		All Respondents	
Demographics	Observation	Percentage	Observation	Percentage
Age	**1709**		**4414**	
< 20	1	0.1%	1	0.0%
20–40	391	22.9%	461	10.4%
40–60	1107	64.8%	2343	53.1%
60–80	200	11.7%	1535	34.8%
> 80	10	0.6%	74	1.7%
Family Income**	**1608**		**4086**	
0–5000 (USD 725)	47	2.9%	333	8.1%
5000–10,000 (USD 1449)	68	4.2%	382	9.3%
10,000–20,000 (USD 2899)	154	9.6%	612	15.0%
20,000–30,000 (USD 4348)	191	11.9%	585	14.3%
30,000–40,000 (USD 5797)	179	11.1%	459	11.2%
40,000–50,000 (USD 7246)	176	10.9%	390	9.5%
50,000–60,000 (USD 8696)	189	11.8%	345	8.4%
60,000–70,000 (USD 10,145)	103	6.4%	176	4.3%
70,000–80,000 (USD 11,594)	85	5.3%	163	4.0%
80,000–90,000 (USD 13,043)	62	3.9%	102	2.5%
90,000–100,000 (USD 14,493)	92	5.7%	144	3.5%
100,000–150,000 (USD 21,739)	150	9.3%	227	5.6%
> 150,000 (USD 21,739)	112	7.0%	168	4.1%
Child Highest Education	**1609**		**4227**	
Illiterate	6	0.4%	20	0.5%
Primary school	222	13.8%	516	12.2%
Middle school	359	22.3%	1353	32.0%
High school	417	25.9%	1020	24.1%
Professional high school	212	13.2%	457	10.8%
Three-year college	352	21.9%	768	18.2%
Four-year college	30	1.9%	72	1.7%
Postgraduate	11	0.7%	21	0.5%
Having Bank Savings for Retirement	**1766**		**4471**	
No	1101	62.3%	3101	69.4%
Yes	665	37.7%	1370	30.6%
Having Real Estate for Retirement	**1766**		**4471**	
No	1688	95.6%	4374	97.8%
Yes	78	4.4%	97	2.2%
Share of Medical Expenditure	**1758**		**4452**	
0	196	11.1%	480	10.8%
1–20%	1189	67.6%	2525	56.7%
21–40%	233	13.3%	797	17.9%
41–60%	96	5.5%	386	8.7%
61–80%	31	1.8%	203	4.6%
81–100%	13	0.7%	61	1.4%
Perception of Non-cash Payment in neighborhood	**1702**		**4159**	
Totally not accepted	12	0.7%	292	7.0%
Generally not accepted	116	6.8%	993	23.9%
Generally accepted	1037	60.9%	2110	50.7%
Totally accepted	537	31.6%	764	18.4%

**: The average exchange rate of CNY to USD in 2019 is around 6.9.

4. Results

4.1 What Affects the Adoption and Usage of Mobile Payment?

In Table 3, panel (a) shows how household characteristics affect a household's mobile payment adoption and panel (b) presents how household characteristics affect how much of spending is paid by smart phones.

A household is more likely to adopt mobile payment and use it more if the head of household is better educated (column 1), younger (column 2), has a strong awareness of neighbors' adoption of non-cash payment (column 4), if the family is richer (column 3) or has more smart phones (column 5). The results are also robust in a multivariate setting (column 8).

4.1.1 Learning Effects

The increasing ownership of smart phones in developing countries has provided poor households more access to online financial services. Our finding also reiterates that the more smart phones a household owns, the more likely they are to adopt mobile payment and to use it. This conclusion holds, especially for adoption decisions, after dividing the total number of smart phones into the number of smart phones per person (column 6) and the number of family members (column 7). The number of smart phones per person is a proxy for the exposure of one person to online information and financing opportunities, while the number of family members represents an effect of learning within a household. The former has larger coefficient for both adoption and usage, implying that exposure to online information is more crucial. The results are also robust in a multivariate setting (column 9).

Table 3: Household Characteristics

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
.Panel A: Adoption Part (Probit Model)									
Dependent variable: whether accepting mobile payment									
Education	0.480***							0.249***	0.250***
	(17.072)							(6.769)	(6.755)
Age		−1.135***						−0.858***	−0.862***
		(−21.086)						(−12.722)	(−12.647)
Family Income			0.127***					0.051***	0.056***
			(12.806)					(4.576)	(5.068)
Awareness				0.878***				0.727***	0.738***
				(15.481)				(10.332)	(10.514)
# Smart Phones					0.259***			0.132***	
					(9.104)			(4.452)	
# Smart Phones p.p.						0.269***			0.197***
						(5.092)			(2.694)
Family Size							0.099***		0.071***
							(5.867)		(3.267)
Constant	−2.556***	2.745***	−1.902***	−3.267***	−1.724***	−1.501***	−1.582***	−1.807***	−1.965***
	(−33.680)	(14.563)	(−38.371)	(−37.086)	(−37.094)	(−44.343)	(−36.301)	(−5.384)	(−5.464)
Controls	N	N	N	N	N	N	N	Y	Y
Village FE	Y	Y	Y	Y	Y	Y	Y	Y	Y
Clustered SE	Y	Y	Y	Y	Y	Y	Y	Y	Y
Observations	4414	4414	4086	4159	4414	4414	4414	3655	3655
Pseudo R^2	0.245	0.315	0.218	0.273	0.220	0.178	0.175	0.417	0.413
Panel B: Usage Part (OLS Model)									
Dependent variable: % of expenditure paid by mobile payment									
Education	4.172***							2.293***	2.250***
	(6.920)							(3.213)	(3.145)
Age		−10.260***						−8.394***	−8.635***
		(−6.952)						(−5.278)	(−5.371)
Family Income			1.294***					0.656**	0.746**
			(4.441)					(2.250)	(2.597)
Awareness				8.447***				5.93***	6.017***
				(5.701)				(3.758)	(3.843)
# Smart phone					2.864***			2.465***	
					(4.482)			(3.969)	
# Mobile/PP						2.380*			6.127***
						(1.857)			(3.804)
Family Size							0.665		1.267**
							(1.463)		(2.364)
Constant	23.692***	68.043***	32.401***	14.020***	30.086***	34.968***	35.262***	30.047***	26.833***
	(12.095)	(15.360)	(29.643)	(3.440)	(18.830)	(28.473)	(25.881)	(4.111)	(3.518)
Village FE	Y	Y	Y	Y	Y	Y	Y	Y	Y
Clustered SE	Y	Y	Y	Y	Y	Y	Y	Y	Y
Observations	1709	1709	1608	1702	1709	1709	1709	1602	1602
$R2$	0.282	0.294	0.281	0.279	0.271	0.261	0.260	0.340	0.339

This table reports the effects of household characteristics on mobile payment adoption and usage decisions. In the adoption part, the specification is a probit model and the dependent variable is an indicator which equals 1 if adopting mobile payment and 0 otherwise. In the usage part, the specification is an OLS model and the dependent variable is the percentage of expenditure paid by mobile payment in the previous month and it only includes positive numbers. The household characteristics include education level, age group, family income, awareness of neighbors' adoption of non-cash payment, total number of smart phone, number of smart phone per person, and number of family members. We control for child's highest education level, savings or house for retirement, and medical expenditure share of total spending in the first part. In both parts, we control for village fixed effect and all standard deviations are clustered at the village level. The *t*-statistics are reported in parentheses. Asterisks denote significance levels (***=1%, **=5%, *=10%).

4.1.2 Awareness of Adoption of Non-cash Payment in the Neighborhood

A unique question in the survey is about the perception of neighbors' adoption of non-cash payment, including mobile payment and credit or debit-card, which asks respondents to rate whether their village "totally accepts," "generally accepts," "generally not accepts," or "totally not accepts" non-cash payment. Using this variable, we can construct a dummy variable—

awareness of adoption—to distinguish "sensitive" and "insensitive" groups. "Sensitive" individuals are those who rated the overall acceptance higher than the actual level. For example, if a respondent rated the neighborhood "totally accepting" of non-cash payment but their village only "generally accepts," then they are classified as "sensitive." As no village 100% accepts or rejects non-cash payments, we define a village as generally accepting if more than 50% of respondents are adopting non-cash payments and as generally not accepting if less than 50% respondents are adopting non-cash payments. The results also hold for grouping under different cutoff points.

In our sample, 2302 respondents (more than 83%) are "sensitive" and 462 are "insensitive". "Sensitive" respondents are more likely to adopt and use mobile payment, as shown previously in Table 3, confirming the results in many consumer behavior studies that consumers' awareness is positively correlated with adoption of new technologies. Moreover, this awareness of neighbors' adoption behavior is a novel intersection of perception and network externalities.

To further investigate the difference between "insensitive" and "sensitive" respondents, we calculate the difference of group mean for key variables, shown in Table 4. The "sensitive" respondents who have more awareness regarding the non-cash payment activities in the neighborhood tend to use smart phones to pay a larger portion of their expenditures. They are younger and better-educated. They have a higher income, own more smart phones and visit banks more often.

However, the distance from home to the nearest banks is not different in the two groups.

This implies that the physical location of financial institutions is less important than the frequency of visiting them, or the actual financial access, in affecting people's awareness of FinTech. Arguably, the number of banking outlets in a community might not be a proper proxy for financial availability, which is commonly used in finance literature.

Table 4: "Sensitive" vs "Insensitive" Respondents

Group	Obs.	Usage of Mobile Payment	Frequency to banks	Distance to banks	# Smart phone	Education	Age	Income
Insensitive	462	3.710	2.434	1.843	1.562	2.418	3.563	4.611
Sensitive	2302	22.877	2.672	1.756	2.661	2.730	3.214	5.874
Difference		−19.167***	−0.238***	0.087*	−1.099***	−0.312***	0.349***	−1.263***
t-test		$t = -12.458$	$t = -2.981$	$t = 1.956$	$t = 13.543$	$t = -5.762$	$t = 10.577$	$t = -7.150$

This table shows the comparison between "sensitive" and "insensitive" households. The definition of "sensitive" is that a respondent's perception of non-cash payment acceptance is higher than the actual level, otherwise "insensitive". Compared variables are the average percentage of expenditure paid by mobile payment, the average frequency of visiting banks, the average distance to banks, the average number of mobile phones in household, the average level of education, the average age group, and the average family income level. The difference between the two group averages is calculated and t-test is conducted to test the null hypothesis of zero differences. Asterisks denote significance levels (***=1%, **=5%, *=10%).

To further present the associated factors, we use a Blinder-Oaxaca decomposition to analyze the extent to which the household characteristics can explain the gap of adoption and usage of mobile payment by the two groups, as shown in Table B.4. The differences in all the listed household characteristics can explain about 60% of higher mobile payment adoption rates by "sensitive" consumers. As to their higher mobile payment usage than "insensitive" consumers, only 25% can be explained by household characteristics, mainly by the younger age of the "sensitive" group.

4.1.3 Farmers Left behind

In Table 5, we complement the previous analysis with information about households' income source: agriculture, working in urban areas, manufacturing, construction, transportation, hotels and restaurants, real estate, and others. Notably, many families have multiple income sources, and most rely on income from agricultural products (63.75%) and salary earned by family members working in urban areas (47.52%). People working in the agriculture sector do not use mobile payment or use less than those in other sectors (row 1). This effect is highly significant even after controlling for household characteristics.

Although people working in manufacturing (row 3), construction (row 4), transportation (row 5), hotels and restaurants (row 6), or urban areas (row 2) seem to be more likely to adopt mobile payment (column 1), the effects are eliminated by controlling for household characteristics (column 2), which is mainly driven by the income level[10].

Generally, we would hypothesize that families with members working in urban areas are more likely to adopt mobile payment, partly because its penetration rate is extremely high in urban areas and partly because the learning effect implies that those who have learned how to use it would like to teach their family members. However, our results (row 2) do not support this hypothesis: after controlling for household characteristics, the coefficients become statistically insignificant (column 2).

Similarly, in the usage part, occupation does not affect how much people use mobile payment (column 3 and 4), except for agriculture (row 1). For a mobile payment user in the agricultural sector, the share of total expenditure paid by smart phone is on average about 6 percentage points lower than that of users in other sectors. In a Blinder-Oaxaca decomposition analysis in Table B.3, we find that the differences in household characteristics can explain about 40% of farmers' lower adoption rate, which is mainly driven by lower income and education level. However, for the lower usage by farmers, the household characteristics can only explain 23% that is solely driven by the lower education level. Some latent factors related to agricultural households prevent them from adopting or using more mobile payments, which requires further research in the future.

10 We also tried to add interaction terms of professions and household characteristics, but they are not statistically significant.

Table 5: Adoption and Usage of Mobile Payment by Occupation

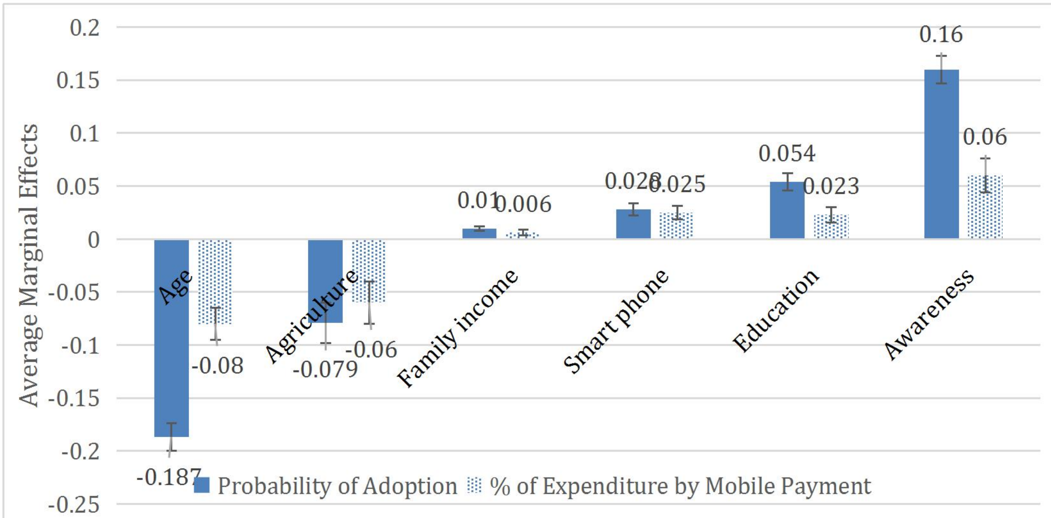
	ADOPTION PART: PROBIT MODEL whether adopt mobile payment			USAGE PART: OLS MODEL % paid by mobile payment		
	%	(1)	(2)	%	(3)	(4)
(1) Agriculture	63.75	−0.337***	−0.360***	55.00	−7.454***	−5.964***
		(−4.551)	(−4.126)		(−3.638)	(−3.032)
(2) Work in urban	47.51	0.247***	−0.002	52.25	−0.715	−2.497
		(3.409)	(−0.018)		(−0.376)	(−1.325)
(3) Manufacturing	2.24	0.381**	−0.039	3.63	7.463*	4.877
		(2.137)	(−0.158)		(1.759)	(1.055)
(4) Construction	2.29	0.374**	−0.080	3.16	4.263	1.936
		(2.287)	(−0.408)		(0.960)	(0.443)
(5) Transportation	2.06	0.576***	0.007	2.75	4.630	−1.116
		(2.876)	(0.309)		(0.933)	(−0.223)
(6) Hotels and restaurants	1.70	0.434**	0.091	2.87	0.483	−2.339
		(2.179)	(0.375)		(0.107)	(−0.544)
(7) Real estate	0.50	0.024	−0.528	0.53	8.411	−1.190
		(0.062)	(−1.639)		(0.751)	(−0.104)
(8) Others	17.54	−0.041	−0.050	17.91	0.718	−1.598
		(−0.416)	(−0.428)		(0.352)	(−0.807)
Education			0.248***			2.208***
			(6.645)			(2.983)
Age			−0.853***			−7.986***
			(−12.641)			(−5.020)
Family income			0.046***			0.613**
			(4.056)			(2.079)
Awareness			0.730***			5.944***
			(10.600)			(3.878)
Smart phones			0.128***			2.530***
			(4.348)			(4.003)
Constant		−1.390***	−1.577**		37.160***	32.362***
		(−17.840)	(−4.507)		(11.800)	(4.254)
Controls		N	Y		N	N
Village FE		Y	Y		Y	Y
Clustered SE		Y	Y		Y	Y
Obs.		4414	3655		1709	1602
(Pseudo) R^2		0.184	0.423		0.273	0.347

This table reports the effects of occupation on mobile payment adoption and usage decisions. In the adoption part, the specification is a probit model and the dependent variable is an indicator which equals 1 if adopting mobile payment and 0 otherwise. In the usage part, the specification is an OLS model and the dependent variable is the percentage of expenditure by mobile payment in the previous month and it only includes positive numbers. The % column shows the percentage of households having income from different sectors. Note that most households have more than one income sources, so the sum exceeds 100%. We control for the household characteristics, including education level, age group, family income, total number of smart phones, and awareness of non-cash payment adoption in column (2) and (4). We also control for child's highest education level, savings or house for retirement, and medical expenditure share of total spending in column (2). We also control for village fixed effect and all standard deviations are clustered at the village level. The t-statistics are reported in parentheses. Asterisks denote significance levels (***=1%, **=5%, *=10%).

4.1.4 Average Marginal Effects

Figure 3 shows the average marginal effects of household characteristics on the adoption and usage of mobile payment, based on results in Table 5. Age affects adoption and usage most, while the awareness of neighborhood's adoption has the second largest influence. For rural residents with strong awareness, they are on average 16 percentage points more

Figure 3: The Average Marginal Effects of Household Characteristics on The Adoption and Usage of Mobile Payment



Note: This graph is calculated from the results in Table 5. The blue solid columns represent the average marginal effects of different household characteristics on the probability of adopting mobile payment, and the blue patterned columns refer to the marginal effects on the percentage of expenditure paid by mobile payment. The *former* is for the entire sample, while the *latter* focuses on mobile payment users only. The 95% confidence intervals are also presented.

likely to adopt mobile payment and, after adopted, would use it to pay 6 percentage points more expenditure than those with weak awareness. As the third largest factor, working in agriculture sector would on average lower the probability of adopting mobile payment by 7.9 percentage points and for adopters, their usage is 6 percentage points less than those of households in other sectors.

To have an intuitive interpretation of the marginal effects of the categorical household characteristics, we consider a "typical" rural household to have an income of 30–40 thousand CNY (USD 5,797), come from agriculture sector (at least partially), own 2 smart phones, have a 40–60-year-old head of household with middle school education, and have strong awareness of non-cash payment usage in the neighborhood. The probability of such a family adopting mobile payment is 23.05% and, once adopted, they would use it to pay 37.75% of the total expenditure.

Age plays a crucial role: if this "typical" head of household is not in their 40–60s but 20 years younger, with other factors unchanged, the adoption probability would more than doubled to 54.81%; if s/he is under 20, the chance would further jump to 83.62%. If this "typical" rural resident is in their 20–40s and adopts mobile payment, then s/he tend to pay almost half (46.14%) of their expenditure by smart phone, and if s/he is under 20, the share would increase to 54.54%.

Education is another key factor. If the "typical" head of household gains a bachelor's degree, this family's probability of adopting mobile payment is 60.21%, and a graduate degree would further boost the chance by more than 9 percentage points. However, for mobile payment users, the impact of education level on usage is relatively limited. Earning one more degree could only expand the share of expenditure paid by smart phone by 2.3 percentage points, similar to the effect of owning one more smart phone (2.5 percentage points).

Surprisingly, the effect of owning more smart phones is stronger than that of improving income. If this “typical” family buys 1 more smart phone to own 3 in total, then the probability of adoption would increase to 27.25%. This effect is similar to that of almost doubling the income of this “typical” household to 60–70 thousand CNY (USD 10,145), which would only improve the chance to 27.91% and grow the usage by about 5 percentage points. If this household buys 3 more smart phone to own 3 in total, then the probability of adoption would boost to 36.65%, equivalent to the effect of more than tripling the income.

4.2 Mobile Payment vs. Access to Bank Services

A key hypothesis of this paper is that mobile payment adoption is affected by access to bank services, proxied by the frequency of visiting banks. However, there is a possibility of reverse causality. To deal with the potential endogeneity issue, we use two instrumental variables: distance to the nearest bank branch or ATM, and the average frequency of visiting banks in each village. A household may visit banks less often because of the long distance to the nearest bank or some social norms in the village.

Table 6 presents 2SLS estimates for frequency of bank visits. We find that the more often a household visits banks, the more likely they would be to adopt mobile payment (column 2). Interestingly, after adopting mobile payment, the less often they visit banks, the more they would use mobile payment (column 4). When deciding whether to adopt mobile payment, visiting banks is a promoting factor. One explanation is that consumers are exposed to financial services and products when they visit banks. Frequent bank visits lead to better financial literacy and more openness to new financial technologies. After adopting mobile payment, there is a complementary effect between bank services and mobile payment. The amount of usage is determined by the level of convenience. When it is not convenient to visit a bank due to either long distance or social norms, consumers use smart phones to buy groceries, transfer money, or pay bills.

The two IVs perform considerably well, although distance to bank is slightly less significant. The exogeneity of frequency of bank visits is rejected for both cases, indicating that inclusion of IVs is necessary. The instruments are jointly highly significant with large F-statistics and therefore they are less likely to be weak instruments. To test the overidentification of IVs, we conduct Amemiya-Lee-Newey and Sargan-Hansen test for adoption and usage respectively. The results imply that we do not reject the null hypothesis of both instruments being exogenous.

Table 6: 2SLS Estimates for Frequency of Bank Visits

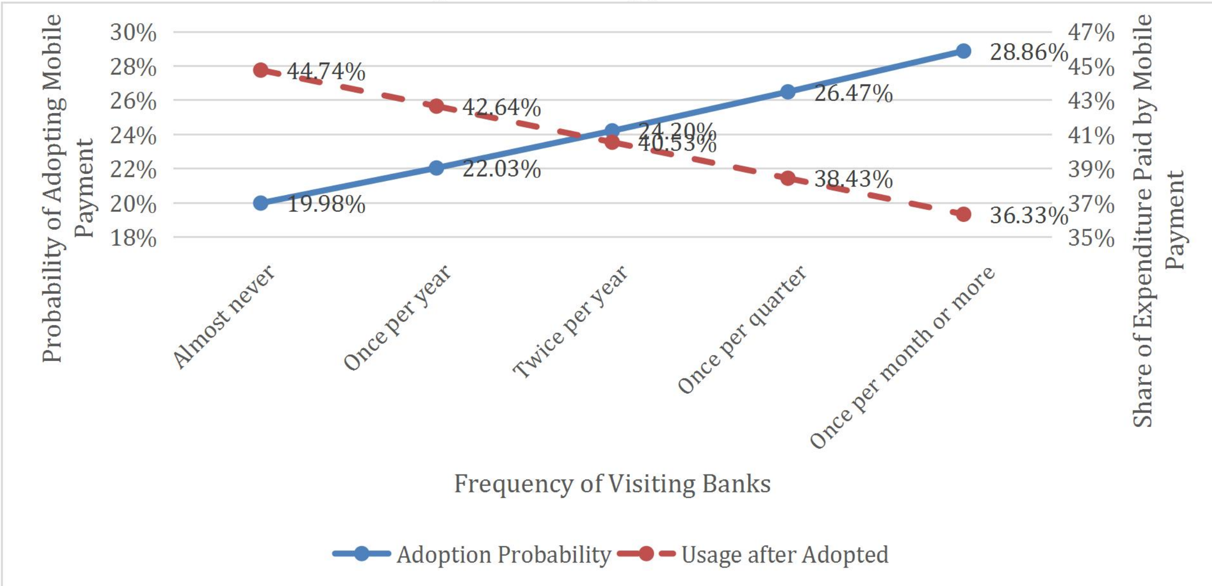
	Adoption		Usage	
	(1) First-stage	(2) Second-stage	(3) First-stage	(4) Second-stage
	Frequency	Whether accepting mobile payment	Frequency	% of expenditure paid by mobile
Frequency of bank visits		0.071***		−2.104***
		(3.498)		(−4.481)
Distance to bank	0.017**		0.019*	
	(2.264)		(1.716)	
Average frequency of bank visits	−32.600***		−32.185***	
(except household i)	(308.497)		(−207.490)	
Education	0.012**	0.234***	0.011*	2.553***
	(2.459)	(7.468)	(1.827)	(4.330)
Age	0.011	−0.864***	0.006	−8.275***
	(1.360)	(−16.090)	(0.527)	(−6.986)
Family income	−0.003	0.047***	−0.001	0.771***
	(−1.592)	(4.757)	(−0.539)	(3.411)
Smart phone	0.005	0.131***	0.002	2.517***
	(1.517)	(6.208)	(0.336)	(4.562)
Awareness	0.0001	0.715***	−0.022*	6.361***
	(−0.021)	(15.050)	(−1.746)	(5.220)
Constant	67.82***	−1.858***	67.67***	36.04***
	(301.308)	(−2.968)	(197.702)	(2.671)
Controls	Y	Y	N	N
Village FE	Y	Y	Y	Y
Clustered SE	Y	Y	Y	Y
Observations	3655	3655	1602	1602
(Pseudo) R^2	0.673	0.419	0.348	0.351
Diagnostic Tests:				
Exogeneity of instrumented: $\chi^2_{(1)}$		18.524(0.000)		241.8(0.000)
Joint significance of IVs: $F_{(2)}$		47,651.47 (0.000)		21,542.322 (0.000)
Overidentification: $\chi^2_{(1)}$		0.016(0.899)		0.571 (0.452)

This table reports both estimated coefficients for probit/OLS and the second-stage of 2SLS on financial access which is proxied by the frequency of visiting banks. Two instruments are the distance from home to the nearest banking outlets and the village-level average frequency of visiting banks except household *i*. In the adoption part, the specification is a probit model and the dependent variable is an indicator which equals 1 if adopting mobile payment and 0 otherwise. In the usage part, the specification is an OLS model and the dependent variable is the percentage of recent expenditure by mobile payment and it only includes positive numbers. We control for household characteristics and village fixed effect and all standard deviations are clustered at the village level. The *t*-statistics are reported in parentheses and asterisks denote significance levels (***=1%, **=5%, *=10%). Diagnostic tests are conducted and test statistics and p-values are reported. For endogeneity of instrumented variable, Durbin-Wu-Hausman test is conducted and the null hypothesis is that frequency of bank visit is exogenous. The null of F test is that IVs are jointly equal to zero. To test overidentification, Amemiya-Lee-Newey/Sargan test are conducted for probit and OLS respectively, and the null hypothesis is that all instruments are exogenous.

4.2.1 Marginal Effects

To demonstrate the marginal effects of access to banks, we again consider a "typical" rural household with an income of 30–40 thousand CNY, 2 mobile phones, a 40–60-year-old head of household with middle school education, strong awareness of non-cash usage in the neighborhood, and visiting a local bank branch or ATM twice a year. Figure 4 shows the marginal effects of access to banks on the adoption and usage of mobile payment for such a "typical" rural household.

Figure 4: The Marginal Effects of Bank Access on The Adoption and Usage of Mobile Payment for A Typical Household



Note: This graph is calculated from the results in Table 6 based on a typical rural household. The blue solid line represents the marginal effects of bank access on the probability of adopting mobile payment (left axis), and the red dash line refers to the marginal effects of bank access on the percentage of expenditure paid by mobile payment (right axis). The *former* is for the entire sample, while the *latter* focuses on mobile payment users only.

For this "typical" household, increasing the frequency of bank visits to once per month or more would raise its probability of adopting mobile payment from 24.2% to 28.86%; for the "typical" user, the percentage of expenditure paid by smart phones would decline from 40.53% to 36.33%.

If this "typical" household almost never visits banks, the adoption probability would drop to 19.98%, but for the "typical" user, the percentage of expenditure paid by smart phones would expand to 44.74%. A complementary effect could explain this: when people visit banks less often due to distance (the average in our sample is 3–10 km) or social reasons, they tend to switch to a more convenient way—using mobile payment to shop, transfer money, or pay bills.

4.3 Robustness Check

We test the exponential type II Tobit model, one version of the Heckman model. Although it is commonly used for missing data or sample selection problems and our data does not have an actual selection issue, we use it to obtain a flexible corner solution. Table E.9 show that ρ is not statistically significantly different from zero which confirms that the inverse Mills ratio is not necessary in the model. Furthermore, Table 7 reports results from a lognormal Hurdle model which are not considerably different either.

Due to the dramatic demographic and economic difference between the east, middle, and west regions11 of China, we run regressions separately to explore the regional heterogeneity and the

[11] Our classification follows that of the National Bureau of Statistics of China. East region includes Hebei, Liaoning, Jiangsu, Zhejiang, Fujian, Shandong, Guangdong, Hainan, Shanghai, Beijing, and Tianjin. Middle region includes Shanxi, Jilin,

results are listed in Table C.5. Although the distribution of mobile payment adoption is similar in the east, middle, and west regions of China: the percentage of zeros in responses is 58%, 65%, and 61%, respectively. Generally, east China enjoys more advanced economic development and higher levels of financial digitalization. East China accommodates the headquarters of both Alibaba and Tencent. Yet, the results are almost the same as those in the aggregated model, except for several insignificant coefficients which might be due to a smaller sample size and reduced variance.

To test whether our results are sensitive to extreme data, we exclude three sets of extreme values and conduct the regressions shown in Table D.6. First, we drop 11% of respondents who are illiterate. Second, we exclude those who are 60 years or older, accounting for 31.7%. Last, we drop data points with extreme family income, either less than USD 700 or more than USD 20,000. The results are consistent with that of the full sample and the coefficients are slightly larger, especially after dropping the elderly respondents, partly because they constitute more than 30% of the sample and partly because the marginal impact of age is

the largest.

Table 7: Log-normal Hurdle Model: Usage of Mobile Payment

Dependent Variable: Positive Percentage Of Household Expenditure Paid By Mobile Payment								
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Education	0.101***					0.047***		0.046***
	(6.309)					(2.562)		(2.376)
Age		−0.284***				−0.240***		−0.231***
		(−7.054)				(−5.463)		(−5.295)
Family Income			0.037***			0.021**		0.020**
			(4.455)			(2.578)		(2.388)
# Smart phones				0.075***		0.062***		0.063***
				(4.118)		(3.412)		(3.439)
Awareness					0.234***	0.169***		0.168***
					(5.820)	(3.894)		(3.933)
Agriculture							−0.178***	−0.138**
							(−3.164)	(−2.483)
Manufacture							0.184*	0.114
							(1.802)	(1.037)
Architecture							0.092	0.045
							(0.763)	(0.378)
Transportation							0.126	−0.0270
							(1.147)	(−0.236)
Hotel And Restaurant							0.105	0.0432
							(0.848)	(0.377)
Real Estate							0.226	0.020
							(0.891)	(0.078)
Work In Urban							0.0001	−0.038
							(0.003)	(−0.760)
Others							0.028	−0.023
							(0.479)	(−0.432)
Constant	3.160***	4.340***	3.350***	3.301***	3.417***		3.470***	3.888***
	(60.62)	(35.960)	(107.513)	(72.385)	(101.629)		(45.891)	(20.343)
Village FE	Y	Y	Y	Y	Y	Y	Y	Y
Clustered SE	Y	Y	Y	Y	Y	Y	Y	Y
Observations	1709	1709	1608	1709	1702	1602	1709	1602
$R2$	0.278	0.296	0.282	0.272	0.263	0.337	0.272	0.342

This table reports the effects of household characteristics on the usage of mobile payment. The specification is an OLS model and the distribution is assumed to be lognormal. The dependent variable is the percentage of recent expenditure by mobile payment and it only includes positive numbers. We control for household characteristics and village fixed effect and all standard deviations are clustered at the village level. The *t*-statistics are reported in parentheses and asterisks denote significance levels (***=1%, **=5%, *=10%).

Heilongjiang, Anhui, Jiangxi, Henan, Hubei, and Hunan. West region includes Inner Mongolia, Guangxi, Sichuan, Guizhou, Yunnan, Tibet, Shaanxi, Gansu, Qinghai, Ningxia, Xinjiang, and Chongqing.

Another concern is regarding households having no smart phone—they are immediately excluded from adopting mobile payment because usage relies on owning a smart phone. Therefore, we exclude these households from our sample and compare the characteristics of these two groups. Subsequently, we run the key regressions again as shown in Table D.7 and find little change to our major results.

For a robustness check, we fit a zero-inflated ordered probit (ZIOP) model.12 ZIOP model considers that zero responses come from two processes which in this paper refers to people who have never used mobile payment and will never use and the ex-users. The zero inflation arises due to the former type of people and ZIOP model could provide insights about which factors contribute to the zero inflation. In unreported results, we find that no variable is significant in affecting zero inflation, except for age. On average, older people are about 11% more likely to be never-users of mobile payment than young people. Therefore, the Hurdle model is more suitable for this paper.

Considering the cases when people did not report their mobile payment usage accurately, we put their responses in five intervals, and the estimated results are similar to the ones reported by us.

5. Conclusion

Mobile payment is witnessing rapid growth in both advanced and developing economies, but there are few empirical studies to investigate its socio-demographic determinants and the relationship with bank access. This study uses large-scale representative survey data in rural China and finds that households with better access to banks are more likely to adopt mobile payment. However, after adoption, the less often consumers visit banks due to distance or social reasons, the more they use mobile payment to complement bank services. This implies that mobile payment could be an important means of financial inclusion, especially for remote areas in developing or developed countries. The households that tend to adopt and use mobile payment share the following characteristics: younger, better-educated, higher income, more number of smart phones, and not in the agricultural sector. This result suggests that the vulnerable groups are slower in the transition to new financial technologies. We also find that more awareness of neighbors' use of non-cash payment has a positive effect on the adoption and usage of mobile payment, suggesting the importance of perception and network externalities.

References

Ahmed, Usman, Thorsten Beck, Christine McDaniel, and Simon Schropp (2015). "Filling the gap: how technology enables access to finance for small-and medium-sized enterprises". In: *Innovations: Technology, Governance, Globalization* 10.3-4, pp. 35–48.

Amoah, Anthony, Kofi Korle, and Rexford Kweku Asiama (2020). "Mobile money as a financial inclusion instrument: what are the determinants?" In: *International Journal of Social Economics*.

Bai, Dangwei, Rundong Jiang, Tiandu Wang, Jennifer Chien, and Douglas Randall (2018). *Toward Universal Financial Inclusion in China: Models, Challenges and Global Lessons*. Tech. rep.

12 For detailed explanations and the comparison between the Hurdle model and the zero-inflated model, see Hofstetter et al. (2016).

Beck, Thorsten, Haki Pamuk, Ravindra Ramrattan, and Burak R Uras (2018). “Payment instruments, finance and development”. In: *Journal of Development Economics* 133, pp. 162–186.

Buchak, Greg, Gregor Matvos, Tomasz Piskorski, and Amit Seru (2018). “Fintech, regulatory arbitrage, and the rise of shadow banks”. In: *Journal of Financial Economics* 130.3, pp. 453–483.

Chen, Brian S, Samuel G Hanson, and Jeremy C Stein (2017). *The decline of big-bank lending to small business: Dynamic impacts on local credit and labor markets*. Tech. rep. National Bureau of Economic Research.

Crabbe, Margaret, Craig Standing, Susan Standing, and Heikki Karjaluoto (2009). “An adoption model for mobile banking in Ghana”. In: *International Journal of Mobile Communications* 7.5, pp. 515–543.

Cragg, John G (1971). “Some statistical models for limited dependent variables with application to the demand for durable goods”. In: *Econometrica: Journal of the Econometric Society*, pp. 829–844.

Davis, Fred D (1989). “Perceived usefulness, perceived ease of use, and user acceptance of information technology”. In: *MIS quarterly*, pp. 319–340.

Duan, Naihua, Willard G Manning, Carl N Morris, and Joseph P Newhouse (1983). “A comparison of alternative models for the demand for medical care”. In: *Journal of business & economic statistics* 1.2, pp. 115–126.

Gichuki, Castro Ngumbu and Milcah Mulu-Mutuku (2018). “Determinants of awareness and adoption of mobile money technologies: Evidence from women micro entrepreneurs in Kenya”. In: *Women’s Studies International Forum*. Vol. 67. Elsevier, pp. 18–22.

Hofstetter, Hedwig, Elise Dusseldorp, Achim Zeileis, and Annemarie A Schuller (2016). “Modeling caries experience: advantages of the use of the hurdle model”. In: *Caries research* 50.6, pp. 517–526.

It’s time for a consumer-centred metric: introducing ‘return on experience.’ (2019). Tech. rep. Global Consumer Insights Survey.

Jack, William and Tavneet Suri (2011). *Mobile money: The economics of M-PESA*. Tech. rep. National Bureau of Economic Research.

— (2014). “Risk sharing and transactions costs: Evidence from Kenya’s mobile money revolution”. In: *American Economic Review* 104.1, pp. 183–223.

Jagtiani, Julapa and Catharine Lemieux (2018). “Do fintech lenders penetrate areas that are underserved by traditional banks?” In: *Journal of Economics and Business* 100, pp. 43– 54.

Junger, Moritz and Mark Mietzner (2020). “Banking goes digital: The adoption of FinTech services by German households”. In: *Finance Research Letters* 34, p. 101260.

Khalilzadeh, Jalayer, Ahmet Bulent Ozturk, and Anil Bilgihan (2017). “Security-related factors in extended UTAUT model for NFC based mobile payment in the restaurant industry”. In: *Computers in Human Behavior* 70, pp. 460–474.

Kim, Changsu, Mirsobit Mirusmonov, and In Lee (2010). “An empirical examination of factors influencing the intention to use mobile payment”. In: *Computers in Human Behavior* 26.3, pp. 310–322.

Koulayev, Sergei, Marc Rysman, Scott Schuh, and Joanna Stavins (2016). “Explaining adoption and use of payment instruments by US consumers”. In: *The RAND Journal of Economics* 47.2, pp. 293–325.

Noor, Maria Mohd (2011). “Determining critical success factors of mobile banking adoption in Malaysia”. In: *Australian Journal of Basic and Applied Sciences* 5.9, pp. 252–265.
Qasim, Huda and Emad Abu-Shanab (2016). “Drivers of mobile payment acceptance: The impact of network externalities”. In: *Information Systems Frontiers* 18.5, pp. 1021–1034. Rogers, Everett M (2010). *Diffusion of innovations*. Simon and Schuster.
Schierz, Paul Gerhardt, Oliver Schilke, and Bernd W Wirtz (2010). “Understanding consumer acceptance of mobile payment services: An empirical analysis”. In: *Electronic commerce research and applications* 9.3, pp. 209–216.
Schuh, Scott D and Joanna Stavins (2011). “How consumers pay: Adoption and use of payments”. In:
Schweitzer, Mark E and Brett Barkley (2017). “Is’ Fintech’Good for Small Business Borrowers? Impacts on Firm Growth and Customer Satisfaction”. In:
Stavins, Joanna (2016). “The effect of demographics on payment behavior: panel data with sample selection”. In:
— (2017). “How do consumers make their payment choices?” In:
Tang, Huan (2019). “Peer-to-peer lenders versus banks: substitutes or complements?” In:
The Review of Financial Studies 32.5, pp. 1900–1938.
Wooldridge, JM (2009). “Hurdle and “selection” models”. In: *IZA Course in Microeconometrics*.
Zhao, Chunkai, Yaqian Wu, and Jianhao Guo (2022). “Mobile payment and Chinese rural household consumption”. In: *China Economic Review* 71, p. 101719.

Appendix A. Survey Questions

Table A.1: Survey Questions

Variable	Question	Options	Note
% of Expenditure Paid by Mobile Payment	What is the percentage of your expenditure paid by mobile payment in the recent month?	%	
Distance to Banks	What is the distance from your home to the nearest bank branch/ATM?	1. 0-3 km; 2. 3-10 km; 3. 10-20 km; 4. 20-30 km; 5. >30 km	
Frequency of Visiting Banks*	How frequent do you visit a bank/ ATM?	1. almost never; 2. Once a year; 3. Twice a year; 4. Once a quarter; 5. Once a month	Reversed the original order in the survey
# Smart phone	How many smart mobile phones in your family?		
Family Size	How many people in your family?		
Education	What is your highest education level?	1. Illiterate; 2. Primary school; 3. Middle school; 4. High school; 5. Professional high school; 6. Three-year college; 7. Four-year college; 8. Graduate school	
Child's Education	What's your child's highest education level?	Same as above.	
Age	What's the age of head of household?	1. under 20; 2. 20–40; 3. 40–60; 4. 60–80; 5. >80	Grouped by authors
Perception of Noncash Payment in neighborhood*	How much do your neighborhood accept non-cash payment methods?	1. Totally not accepted; 2. Generally not accepted; 3. Generally accepted; 4. Totally accepted	Reversed the original order in the survey
Family Income	How much is your total household income in last year?	1. 0–5000; 2. 5000-10,000; 3. 10,000-20,000; 4. 20,000-30,000; 5. 30,000-40,000; 6.40,000-50,000; 7. 50,000-60,000; 8. 60,000-70,000; 9. 70,000-80,000; 10. 80,000-90,000; 11. 90,000–100,000; 12. 100,000-150,000; 13. >150,000	
Savings for Retirement	Do you have bank savings for retirement?	Yes or no.	
Houses for Retirement	Do you have any house for retirement?	Yes or no.	
Share of Medical Expenditure	What is the percentage of medical bills out of total expenditure?	1. 0; 2. 1–20%; 3. 21–40%; 4. 41–60%; 5. 61–80%; 6. 81–100%.	

Table A.2: Summary of Statistics

Variable	Obs	Mean	Median	Std. Dev.	Min.	Max.	Obs	Mean	Median	Std. Dev.	Min.	Max.
Panel A: Whether applied for loans												
	Not Considered or Considered But Not Applied						**Applied**					
% of Expenditure Paid by Mobile Payment	1854	14.66	0	26.53	0	100	429	16.86	0	29.03	0	100
Distance to Banks	1854	1.84	2	0.80	1	5	429	1.82	2	0.82	1	5
Frequency of Visiting Banks*	1854	2.58	2	1.49	1	5	429	2.54	2	1.56	1	5
# Smart phone	1854	2.32	2	1.60	0	10	429	2.71	3	1.43	0	8
# Smart phone/PP	1854	0.77	0.67	0.67	0	6	429	0.83	0.67	0.61	0	5
Family Size	1854	3.46	3	1.74	1	12	429	3.90	4	1.92	1	12
Education	1854	2.61	3	1.02	1	7	429	2.57	3	0.97	1	7
Age	1854	3.30	3	0.63	2	5	429	3.10	3	0.61	2	5
Perception of Non- cash Payment in neighborhood*	1758	2.75	3	0.82	1	4	405	2.86	3	0.71	1	4
Family Income	1745	5.28	5	3.12	1	13	405	5.72	5	3.42	1	13
Panel B: Whether successfully secured loans												
	Denied						**Secured**					
% of Expenditure Paid by Mobile Payment	65	12.78	0	24.56	0	98	364	17.59	0	29.73	0	100
Distance to Banks	65	1.68	2	0.73	1	4	364	1.85	2	0.83	1	5
Frequency of Visiting Banks*	65	2.23	2	1.37	1	5	364	2.59	2	1.58	1	5
# Smart phone	65	2.42	2	1.41	0	6	364	2.76	3	1.43	0	8
# Smart phone/PP	65	0.75	0.67	0.68	0	5	364	0.84	0.67	0.59	0	4
Family Size	65	3.92	4	1.96	1	10	364	3.89	4	1.91	1	12
Education	65	2.65	3	0.74	1	4	364	2.56	3	1.00	1	7
Age	65	3.20	3	0.62	2	4	364	3.08	3	0.60	2	5
% of Non-cash Payment in Neighborhood*	59	2.85	3	0.85	1	4	346	2.86	3	0.69	1	4
Family Income	62	4.23	4	2.68	1	13	343	5.99	5	3.47	1	13

* Note: the original direction of ordering in the frequency of visiting banks is reversed.

Appendix B. Blinder-Oaxaca Decomposition Analysis

Table B.3: Household Income Sources: Agriculture vs. Non-agriculture

	Adoption part				Usage part			
	Coefficient	Std. dev.	z	P > z	Coefficient	Std. dev.	z	P > z
Overall								
Group 1	0.50***	0.03	19.30	0.00	54.09***	1.79	30.20	0.00
Group 2	0.34***	0.02	19.02	0.00	42.19***	1.91	22.11	0.00
Difference	0.16***	0.03	6.19	0.00	11.89***	2.28	5.21	0.00
Endowments	0.07***	0.02	3.69	0.00	2.73***	0.88	3.11	0.00
Coefficients	0.10***	0.02	5.13	0.00	9.25***	2.18	4.24	0.00
Interaction	−0.01	0.01	−1.12	0.26	−0.08	0.72	−0.11	0.91
Endowments								
# Smart phone	0.01**	0.01	2.31	0.02	0.52	0.33	1.57	0.12
Education	0.03***	0.01	3.49	0.00	1.15**	0.55	2.11	0.04
Age	0.01	0.01	0.81	0.42	0.58	0.41	1.41	0.16
Income	0.02***	0.01	3.37	0.00	0.47	0.48	1.00	0.32
Coefficients								
# Smart phone	−0.02	0.03	−0.65	0.52	0.56	3.66	0.15	0.88
Education	−0.06	0.04	−1.52	0.13	−1.25	4.45	−0.28	0.78
Age	−0.21	0.09	−2.35	0.02	−4.17	8.43	−0.49	0.62
Income	0.00	0.03	−0.16	0.87	−0.25	3.29	−0.08	0.94
Interaction								
# Smart phone	0.00	0.00	−0.63	0.53	0.03	0.19	0.15	0.88
Education	−0.01	0.00	−1.42	0.16	−0.15	0.55	−0.28	0.78
Age	0.00	0.00	0.77	0.44	0.09	0.19	0.47	0.64
Income	0.00	0.01	−0.16	0.87	−0.05	0.60	−0.08	0.94
			Obs: 4097				Obs: 1619	
Group 1: Non-agricultural			Group 1 Obs: 1481				Group 1 Obs: 741	
Group 2: Agricultural			Group 2 Obs: 2616				Group 2 Obs: 878	

This table reports the results of Blinder-Oaxaca decomposition on two groups of respondents: group 1 refers to households with income sources other than agriculture and group 2 refers to households having income from agricultural sector. In the adoption part, the dependent variable is an indicator which equals 1 if adopting mobile payment and 0 otherwise. In the usage part, the

dependent variable is the percentage of expenditure in the previous month paid by mobile payment and it only includes positive numbers. All standard deviations are clustered at the village level.
Asterisks denote significance levels (***=1%, **=5%, *=10%).

Table B.4: BO Decomposition: "Sensitive" vs. "Insensitive" Households

	Adoption part				Usage part			
	Coefficient	Std. dev.	z	P > z	Coefficient	Std. dev.	z	P > z
Overall								
Group 1	0.13***	0.02	5.51	0.00	29.61***	4.48	6.61	0.00
Group 2	0.46***	0.02	23.95	0.00	51.25***	1.64	31.21	0.00
Difference	−0.33***	0.03	−11.28	0.00	−21.63***	4.85	−4.46	0.00
Endowments	−0.19***	0.02	−10.30	0.00	−5.50***	1.35	−4.06	0.00
Coefficients	−0.22***	0.04	−5.19	0.00	−16.84***	5.56	−3.03	0.00
Interaction	0.08***	0.02	3.65	0.00	0.71	2.73	0.26	0.79
Endowments								
	−0.05***	0.01	−4.22	0.00	−1.63**	0.72	−2.26	0.02

	Adoption part				Usage part			
	Coefficient	Std. dev.	z	P > z	Coefficient	Std. dev.	z	P > z
# Smart phone								
Education	−0.03***	0.01	−3.75	0.00	−1.32**	0.59	−2.24	0.03
Age	−0.10***	0.01	−7.20	0.00	−2.20**	0.85	−2.58	0.01
Income	−0.02***	0.01	−3.42	0.00	−0.35	0.43	−0.82	0.41
Coefficients								
# Smart phone	0.00	0.04	0.06	0.95	1.16	11.71	0.10	0.92
Education	−0.18***	0.06	−3.10	0.00	−1.99	13.21	−0.15	0.88
Age	0.46***	0.11	4.21	0.00	10.16	19.02	0.53	0.59
Income	−0.03	0.04	−0.87	0.38	4.05	8.35	0.48	0.63
Interaction								
# Smart phone	0.00	0.02	−0.06	0.95	−0.19	1.92	−0.10	0.92
Education	0.02**	0.01	2.50	0.01	0.24	1.60	0.15	0.88
Age	0.05***	0.01	3.74	0.00	0.98	1.86	0.53	0.60
Income	0.01	0.01	0.86	0.39	−0.32	0.75	−0.43	0.67

	Obs: 2557	Obs: 1031
Group 1: Insensitive	Group 1 Obs: 437	Group 1 Obs: 57
Group 2: Sensitive	Group 2 Obs: 2120	Group 2 Obs: 974

This table reports the results of Blinder-Oaxaca decomposition on two groups of respondents: group 1 refers to households not sensitive to the non-cash payment in the neighborhood and group 2 refers to the sensitive households. In the adoption part, the dependent variable is an indicator which equals 1 if adopting mobile payment and 0 otherwise. In the usage part, the dependent variable is the percentage of expenditure by mobile payment and it only includes positive numbers. All standard deviations are clustered at the village level. Asterisks denote significance levels (***=1%, **=5%, *=10%).

Appendix C. Regional Heterogeneity

Due to the dramatic demographic and economic difference between East, Middle, and West part of China, we run regressions separately to explore the regional heterogeneity.

In the adoption part, the sign and magnitude are overall similar to those of the aggregated model. The effect of frequency of bank visit is most significant and largest in middle region. There is little regional difference for education level and age. In the west, family income and the number of smart phones are less likely to increase the probability of adoption. While the impact by the awareness of neighborhood's adoption is highly significant across different regions, it is strongest in the east and weakest in the west.

In the usage part, the regional heterogeneity is larger. Again, the effect of frequency of bank visit is most significant and largest in middle region, and the impact magnitude in the east is only half of that of middle and west region. In the west, family income and education are less likely to increase the usage of mobile payment. Although the impact by age is highly significant across different regions, it is strongest in the east and weakest in the middle. The awareness of neighborhood's adoption affects the usage less in the middle.

Table C.5: Regional Heterogeneity: 2SLS Estimates

	ADOPTION PART: PROBIT whether adopt mobile payment			USAGE PART: OLS % paid by mobile payment		
	(1) East	(2) Middle	(3) West	(1) East	(2) Middle	(3) West
Frequency of bank visit	0.065*	0.103***	0.066*	−1.191*	−2.837***	−2.379**
	(1.802)	(2.771)	(1.905)	(−1.738)	(−3.236)	(−2.509)
Education	0.256***	0.205***	0.234***	2.474***	3.298***	1.974*
	(4.505)	(3.926)	(4.135)	(2.941)	(2.88)	(1.662)
Age	−0.973***	−0.812***	−0.811***	−9.578***	−6.745***	−7.596***
	(−9.756)	(−9.226)	(−8.46)	(−5.559)	(−3.066)	(−3.164)
Family income	0.071***	0.046***	0.03*	0.731**	0.815**	0.79*
	(3.841)	(2.862)	(1.714)	(2.167)	(2.013)	(1.736)
Awareness	0.876***	0.704***	0.608***	7.137***	4.73**	7.408***
	(9.763)	(8.995)	(7.028)	(3.887)	(2.156)	(3.07)
# Smart phone	0.171***	0.189***	0.046	3.327***	1.611	2.406**
	(4.163)	(5.231)	(1.283)	(4.006)	(1.537)	(2.329)
Constant	−1.963**	−1.286***	−1.093**	32.32**	32.35**	27.93**
	(−2.496)	(−2.578)	(−2.004)	(2.205)	(2.396)	(2.032)
Controls	Y	Y	Y	N	N	N
Village FE	Y	Y	Y	Y	Y	Y
Clustered SE	Y	Y	Y	Y	Y	Y
Observations	1342	1252	1061	648	495	459
(Pseudo) R^2	0.523	0.376	0.357	0.371	0.331	0.304
F-test	376.8	371.79	315.62	9666.179	7215.434	5421.019
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)

This table reports the estimated results for east, middle, and west part of rural China. In the adoption part, the specification is a probit model and the dependent variable is an indicator which equals 1 if adopting mobile payment and 0 otherwise. In the usage part, the specification is an OLS model and the dependent variable is the percentage of expenditure by smart phones in the previous month and it only includes positive numbers. For the adoption part, we control for the household characteristics, including education level, age group, family income, total number of smart phones, child's highest education level, savings or house for retirement, and medical expenditure share of total spending. For the usage part, we only control for the first four factors so that the exclusion restriction condition is met. We also control for village fixed effect and all standard deviations are clustered at the village level. The t-statistics are reported in parentheses. Asterisks denote significance levels (***=1%, **=5%, *=10%).

Appendix D. Sensitivity Tests

To test whether our results are sensitive to the outliers, we run regressions by excluding three sets of extreme values, shown below.

First, we drop the illiterate respondents, accounting for 11% of the sample. The estimates are very close to those of the full regression. Second, we exclude the respondents with extreme household income, either higher than CNY 150,000 (USD 21,739) or lower than CNY 5,000 (USD 725), and similarly, the results do not change much. Last, we drop the respondents older than 60 (more than 30% of the sample) and the results are still consistent with those of the full regression, despite the coefficients are slightly larger.

Table D.6: Sensitivity Tests: 2SLS Estimates

	ADOPTION PART: PROBIT whether adopt mobile payment			USAGE PART: OLS % paid by mobile payment		
	Drop illiterate	Drop older	Drop extreme income	Drop illiterate	Drop older	Drop extreme income
Frequency of bank visit	0.072***	0.101***	0.079***	−2.165***	−2.194***	−2.287***
	(3.371)	(4.134)	(3.689)	(−4.512)	(−4.412)	(−4.649)
Education	0.218***	0.277***	0.268***	2.38***	2.448***	2.836***
	(6.154)	(7.048)	(7.956)	(3.831)	(3.949)	(4.531)
Age	−0.863***	−0.933***	−0.845***	−8.92***	−8.34***	−7.682***
	(−15.49)	(−7.413)	(−14.96)	(−7.397)	(−4.862)	(−6.202)
Family income	0.053***	0.039***	0.052***	0.793***	0.877***	0.847***
	(5.142)	(3.214)	(4.47)	(3.458)	(3.587)	(3.226)
Awareness	0.72***	0.781***	0.683***	6.374***	6.681***	6.22***
	(14.56)	(13.46)	(13.74)	(5.117)	(5.114)	(4.883)
# Smart phone	0.13***	0.146***	0.132***	2.366***	3.019***	2.764***
	(5.91)	(5.2)	(5.813)	(4.184)	(4.96)	(4.596)
Constant	−1.795***	−6.382	−1.997***	39.06***	30.14*	33.61**
	(−2.849)	(−0.06)	(−3.129)	(2.879)	(1.951)	(2.494)
Controls	Y	Y	Y	N	N	N
Village FE	Y	Y	Y	Y	Y	Y
Clustered SE	Y	Y	Y	Y	Y	Y
Observations	3290	2341	3245	1550	1414	1443
(Pseudo) R^2	0.407	0.361	0.405	0.348	0.358	0.362

This table reports the estimated results excluding some outliers. In the adoption part, the specification is a probit model and the dependent variable is an indicator which equals 1 if adopting mobile payment and 0 otherwise. In the usage part, the specification is an OLS model and the dependent variable is the percentage of expenditure by smart phones in the previous month and it only includes positive numbers. For the adoption part, we control for the household characteristics, including education level, age group, family income, total number of smart phones, child's highest education level, savings or house for retirement, and medical expenditure share of total spending. For the usage part, we only control for the first four factors so that the exclusion restriction condition is met. We also control for village fixed eff ect and all standard deviations are clustered at the village level. The t-statistics are reported in parentheses. Asterisks denote significance levels (***=1%, **=5%, *=10%).

Table D.7: Summary of Statistics for Households with or without Smart Phones

	Household without smart phone						Households having at least one smart phones					
Variable	Obs	Mean	Median	Std. Dev.	Min.	Max.	Obs	Mean	Median	Std. Dev.	Min.	Max.
% of Expenditure Paid by Mobile Payment	614	99.27	100	5.40	10	100	3800	74.81	100	33.59	0	100
Distance to Banks	614	0.00	0	0.00	0	0	3800	21.55	0	31.22	0	100
Frequency of Visiting Banks*	614	1.89	2	0.89	1	5	3800	1.79	2	0.86	1	5
# Mobile	614	2.38	2	1.52	1	5	3800	2.68	2	1.56	1	5
# Mobile PP	614	0.00	0	0.00	0	0	3800	2.85	3	1.43	1	13
Family Size	614	0.00	0	0.00	0	0	3800	0.94	0.8	0.68	0.09	9
Education	614	2.42	2	1.61	1	22	3800	3.65	3	1.81	1	16
Age	614	2.15	2	0.86	1	7	3800	2.78	3	1.12	1	7
Perception of Non- cash Payment in neighborhood*	614	3.83	4	0.52	2	5	3800	3.19	3	0.64	1	5
Family Income	526	2.16	2	0.85	1	4	3633	2.90	3	0.77	1	4

* Note: the original direction of ordering in the frequency of visiting banks is reversed.

Table D.8: The Adoption of Mobile Payment: Sample without Households Having 0 Smart phone

Dependent Variable: Whether Accepting Mobile Payment								
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Education	0.434***					0.261***		0.241***
	(14.780)					(7.107)		(6.347)
Age		−1.037***				−0.837***		−0.81***
		(−18.430)				(−12.78)		(−11.78)
Income			0.102***			0.051***		0.046***
			(9.786)			(4.398)		(4.067)
# Smart phone				0.143***		0.079***		0.068***
				(5.616)		(2.88)		(2.375)
Awareness					0.833***	0.72***		0.719***
					(13.96)	(10.64)		(10.25)
Agriculture							−0.400***	−0.365***
							(−5.074)	(−4.472)
Manufacture							0.399**	0.039
							(2.217)	(0.170)
Architecture							0.320*	0.061
							(1.824)	(0.290)
Transportation							0.472**	0.232
							(2.363)	(1.047)
Hotel And Restaurant							0.315	0.165
							(1.586)	(0.721)
Finance							1.219**	1.072*
							(2.123)	(1.895)
Real Estate							−0.099	−0.314
							(−0.256)	(−0.950)
Work In Urban							0.073	0.006
							(0.966)	(0.074)
Others							0.056	0.011
							(0.522)	(0.093)
Constant	−2.172***	2.592***	−1.486***	−1.315***	−0.889***	−0.0629	−1.003***	0.156
	(−26.83)	(13.59)	(−28.52)	(−24.79)	(−53.09)	(−0.235)	(−11.97)	(0.542)
Village FE	Y	Y	Y	Y	Y	Y	Y	Y
Clustered SE	Y	Y	Y	Y	Y	Y	Y	Y
Observations	3800	3800	3516	3800	3787	3375	3800	3375
Pseudo R^2	0.229	0.286	0.196	0.17	0.254	0.381	0.18	0.387

This table reports the effects of household characteristics on mobile payment adoption for households having at least one smart phone. The specification is a probit model and the dependent variable is an indicator which equals 1 if adopting mobile payment and 0 otherwise. The household characteristics include education level, age group, family income, total number of smart phones, number of smart phone per person, and number of family members. We control for child's highest education level, savings or house for retirement, and medical expenditure share of total spending in the first part. We also control for village fixed effect and all standard deviations are clustered at the village level. The t-statistics are reported in parentheses. Asterisks denote significance levels (***=1%, **=5%, *=10%).

Appendix E. Alternative Model

Table E.9: Exponential Type II Tobit Model

	ADOPTION PART	USAGE PART
	Probit	Exponential Type II Tobit (log of positive usage)
Frequency of bank visit	0.084***	−0.055***
	(5.38)	(−3.28)
Education	0.276***	0.075**
	(10.81)	(2.49)
Age	−0.788***	−0.196**
	(−18.27)	(−2.21)
Family income	0.053***	0.016*
	(6.79)	(1.85)
Smart phone	0.190***	0.073***
	(11.67)	(2.83)
Constant	0.333*	3.837***
	(1.92)	(22.35)
Controls	Y	N
Village FE	Y	Y
Clustered SE	Y	Y
Observations	3655	1602
Log Pseudo-likelihood		−3628.721
Wald Chi-Sq		39.35
Wald Test (Rho = 0)		0.6 (0.4373)
Rho		−0.138
Sigma		0.800
Lambda		−0.110

This table reports the estimated results in an Exponential Type II Tobit model. In the adoption part, the specification is a probit model and the dependent variable is an indicator which equals 1 if adopting mobile payment and 0 otherwise. In the usage part, the specification is an OLS model and the dependent variable is the logarithm of the percentage of expenditure by mobile payment in the previous month and it only includes positive numbers. For the adoption part, we control for the household characteristics, including education level, age group, family income, total number of smart phones, child's highest education level, savings or house for retirement, and medical expenditure share of total spending. For the usage part, we only control for the first four factors so that the exclusion restriction condition is met. We also control for village fixed effect and all standard deviations are clustered at the village level. The t-statistics are reported in parentheses. Asterisks denote significance levels (***=1%, **=5%, *=10%).