Cashless Payment and Financial Inclusion*

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Abstract

This paper evaluates the impact of mobile cashless payment on credit provision to the underprivileged. Using a representative sample of Alipay users that contains detailed information on their consumption, credit, and investment activities, I exploit a natural experiment to identify the real effects of cashless payment adoption. In this natural experiment, the staggered placement of Alipay-bundled shared bikes across different Chinese cities causes exogenous variations of the payment flow. I find that the use of in-person payment in a month increases the likelihood of gaining access to credit in the same month by 56.3%. Conditional on having credit access, a 1% increase in the in-person payment flow leads to a 0.41% increase in the credit line. Those who have higher in-person payment flow also use their credit lines more. Importantly, the positive effect of in-person payment flow on credit provision mainly exists for the less educated and the older, suggesting that cashless payment particularly benefits those who are traditionally underserved.

Keywords: Cashless Payment, BigTech, Credit Provision, Financial Inclusion, Technology Adoption

JEL Classifications: G21, G23, G51, G53, O33

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"Digital payments also generate real-time data on sellers' businesses, the timing of cash flows, and buyers' purchasing habits, allowing payment providers to offer credit, savings, wealth management, collections, insurance, and other financial services. Where credit was once the way to draw in customers and offer a panoply of financial services, payments may be a safer channel for such upselling."

-- Raghuram G. Rajan (2021). *All Eyes on Digital Payments.*

It has always been hard to provide financial services to the underprivileged, and especially in terms of extending credit access. Overhead costs are high, given the small loan size, and there is wide information asymmetry between lenders and borrowers. Despite these frictions, both the public and private sector have proposed a variety of solutions based on novel mechanisms or new technologies. The microcredit movement, as perhaps the most notable example, has achieved huge impacts but also faces limitations in scalability, cost reduction, and sustainability (Helms et al., 2006). New technologies, including better collection and use of rich data (Agarwal et al., 2021; Berg et al., 2020); more advanced credit risk models (Fuster et al., 2019, 2022); and financial accounts that are more accessible (Ouma et al., 2017) partially mitigate these limitations. However, nothing compares with cashless mobile payment, which makes effective use of a combination of these advancements. [2] Can it serve as a silver bullet and provide new opportunities for lending to the traditionally underserved? If so, how?

I aim to provide causal evidence that more in-person cashless payment flows lead to more credit provision to the previously financially underserved in the real business environment. This is a challenging endeavor, and cannot be directly achieved by performing a predictive exercise using historical data or conducting a field experiment; the former suffers from the manipulation critique of Bjorkegren et al. (2020) and the latter usually involves only a small population and runs for a limited time. To address the empirical challenges, I combine a natural experiment and rich administrative data on a representative sample from the Alipay platform. Alipay is the largest

[2] First, payment records are by-products of daily purchases, which are rich, high frequency, and manipulation-proof. Second, cashless payment providers not only employ the most advanced machine learning and artificial intelligence technologies, but also have access to data that facilitate model training and fully empower predictive credit risk models. Third, mobile phones have been widely adopted globally, which lowers the adoption cost of mobile payment and renders it almost universally accessible.

digital payment services provider in China as of 2020 and has over 1 billion active users. I show that the in-person payment flow has a sizable impact on credit provision on both the extensive and intensive margins. This effect occurs through the channel whereby Alipay makes effective use of creditworthiness information on the payment flow.

My study builds on two observations; the fast development of China's cashless payment system and the rise of consumer lending by FinTech and BigTech[3] companies in China. First, China's cashless payment system and especially in-person mobile payments—achieved remarkable success in less than a decade, during a period in which China was massively shifting from a cash economy to a cashless economy. As of 2019, China's mobile payment system leads in both user penetration rate and income-adjusted annual transaction value per user.[4] Figure 1 shows that from 2012 to 2018, the annual transaction volume of China's mobile payment system increased from 4% of GDP to 302%, while the corresponding measure of US card payments stayed below 34% of GDP. China's mobile payment market provides a unique setting to study the impact of cashless payment and has great implications for other countries and the future. [5] Second, at the same time, China has also become the largest market for both FinTech credit and BigTech credit, in which Alipay is the leading service provider (Cornelli et al., 2020). The *Huabei* credit line, which is a virtual credit card product provided by Alipay, is the largest consumer finance product in China as of 2020. It is also the credit product I will focus on in this study. In a representative sample of Alipay users, I find that 72% have access to a Huabei credit line, of which more than 95% have used it at least once and have an average monthly credit usage of 533 CNY (roughly 80 USD). The credit product is quite inclusive, even among users who do not have a bank-issued credit card on file; of those, 64% have Huabei credit line access.

Despite these observations, establishing a causal relationship between cashless payment and BigTech credit provision is difficult. First, it requires an exogenous shock to cashless payment activity. Second, I need detailed individual-level data on payments, credit, and investments, as

[3] The dominant and largest companies in the information technology (IT) industry such as Alibaba, Alphabet (Google), Amazon, Meta (Facebook) and Tencent.

[4] See the World Economic Forum article by Katharina Buchholz, "China is Fast Becoming the World Leader in Mobile Payment" (May 15, 2019).

[5] There has been a global trend of going cashless in in-person payments, and the pandemic might further speed the process. See the *Forbes* article by Len Covello, "How the Pandemic Made Contactless Payments the New Normal" (April 15, 2021).

well as information on their sociodemographic conditions. Third, in order to focus on the credit supply, I will have to exclude credit demand factors from the observed credit line. I address the first challenge by leveraging a natural experiment that provides exogenous variation of consumers' in-person Alipay payment, which is the staggered placement of Alipay-bundled shared bikes across different Chinese cities. I use the bike placement as an instrument. The usage of shared bikes nudges users to make more in-person cashless payments with Alipay, since both services require consumers to use the same scanning procedure of Alipay.

To address the second challenge, I base my analysis on administrative data from Alipay, which cover a representative sample and contain detailed information on their personal characteristics and daily activities—consumption, credit access and usage, investments, shared-bike usage, and other relevant digital footprints. Linked household behaviors are measured at monthly frequency and recorded as individual-level panel data. A feature of the Huabei credit line enables me to address the third challenge; different from a traditional credit card, it requires no active application and consumers instantly learn their qualification status and approximate credit line. This feature allows me to identify the credit provision effect from the supply side, which is immune from endogenous credit application motives from the demand side (Brown et al., 2011; Han et al., 2009).

I develop multiple tests to show the validity of the staggered placement of Alipay-bundled shared bikes in different cities as the instrument. I show strong supporting evidence that this approach is likely to satisfy both the relevance condition and the exclusion restriction. The relevance condition requires a strong first-stage relationship between city-level bike placement and the in-person payment flow of Alipay users living in the city. Evidence confirms this view. It easily passes the weak instrument criterion proposed by Stock and Yogo (2005) and satisfies the most recent *tF* procedure introduced by Lee et al. (2021). The exclusion restriction condition requires that bike placement affect the credit provision only through in-person cashless payment. I provide evidence to rule out potential concerns about city-level common factors that are correlated with both bike placement and credit provision, the direct credit-revealing effects of bike usage, and the mechanical effects of the bike placement process.

The empirical findings are articulated with respect to three parts of the study. In the first, I show that the exogenous increase in a consumer’s in-person payment flow leads to more digital credit provided by Alipay and more credit take-up by the consumer. On the extensive margin, the

use of in-person payment in a month leads to a 56.3% increase in the probability of getting credit access in the same month. On the intensive margin, for those with credit access, a 1% increase in the in-person cashless payment flow results in a 0.41% increase in the credit line. Given the exponential growth of the digital payment market in China, the accompanying credit expansion should also be enormous. Both the learning-by-doing story and the credit supply mechanism predict that consumers will change their borrowing behaviors. I find that more in-person payment flow leads to more take-up of the credit, in both the in-person and online settings. A 1% increase in the in-person cashless payment flow leads to an increase in the share paid with a digital credit by 0.094% for in-person spending and by 0.030% for online spending.

The second part of the paper investigates the channels through which the in-person cashless payment flow facilitates credit provision. I explore two channels: the information channel and the enforcement channel. I find large differences in the channels relied on by Alipay, a typical BigTech firm, and traditional banks. Since most banks do not have access to payment flow information on daily purchases, they usually rely on credit bureau information on credit usage and repayment or information revealed by the borrower in the application process. Self-reported information is unavailable for Alipay, so it relies heavily on information on payment flow. I show that this channel holds even when information on credit usage and repayment is controlled for. The enforcement channel, which nests collateral channel, arises when users rely more and more on the BigTech platform for daily activities. I use the consumer's assets under management on Alipay as a proxy for collateral, since Alipay can potentially freeze the account if the user does not repay on time. I find that the payment flow information channel still holds when I control for this collateral proxy. Overall, these results suggest that the payment flow contains useful information for credit evaluation.

In the third part of the paper, I investigate the implications of digital payment for financial inclusion. I find that the financially underserved gain more access to credit after the adoption of in-person cashless payment. I use a simple theoretical framework to explain why we should expect this. The traditional view in China is that the less educated and the older tend to be financially underserved. My data confirm this view: these groups have fewer financial activities and lower financial literacy. I find that they also have a higher share of in-person transactions of total

transactions. The exogenous increase in the in-person cashless payment flow results in an increase in credit provision mainly to the less educated and the older segments of the population.

My paper contributes to the literature on the effects of payment technology adoption on consumers. So far, this literature has largely focused on the cost reduction effects of new payment products, but rarely on the value of the payment data accumulated as a result of digitalization. Digital payment products, including debit cards and mobile payments, can reduce transaction costs, monitoring costs, and travel costs, which leads to further changes in consumer banking (Mbiti and Weil, 2015); household savings (P. Bachas et al., 2021); risk-sharing (Jack and Suri, 2014; Riley, 2018); risk-taking (Hong et al., 2020); consumption (Suri and Jack, 2016); crime-related risk (Economides and Jeziorski, 2017); and business growth (Agarwal et al., 2020; Beck et al., 2018). My paper is based on the analysis of a BigTech app, which provides not only payment services but also a large set of data-based financial services and daily-life services. This allows me to study the information value of the payment data, which is a new dimension rarely examined in the literature.

My paper is also the first to take advantage of the nudge effect of digital service usage and employs a natural experiment to solve the endogeneity issues in studying the effects of digital payment adoption. Beshears and Kosowsky (2020) review the literature on nudging and point out that it is crucial to investigate its long-run effects, especially the non-targeted outcomes. My paper adds to this strand of the literature. The results show that the adoption of mobile payment has long-lasting effects on both payment activity and consumer credit. The increased payment flow facilitates consumer credit provision, because it allows a BigTech firm to take advantage of the information contained in the digital payment flow, which goes beyond credit usage, repayment, and assets under management. Thus, my paper is also related to the discussion of data sharing and digital demand (Chen et al., 2021; Cong et al., 2021); the information channel in credit provision (N. Bachas, 2019; Chatterjee et al., 2020; He et al., 2021; Liberti & Petersen, 2019; Tang, 2019); the collateral channel in credit markets (Gambacorta et al., 2020; Kiyotaki & Moore, 1997; Mian & Sufi, 2011); the welfare impacts of information frictions in credit markets (DeFusco et al., 2021; Jansen et al., 2022); and the comparative advantages of FinTech and BigTech lending models (Beaumont et al., 2022; Liu et al., 2021).

My paper also contributes to the literature that investigates the linkage between innovations and financial inclusion. For example, studies have examined the effect of mobile financial services on saving by the poor (Ouma et al., 2017); the use of a secure payments infrastructure to assist the government in implementing antipoverty programs (Muralidharan et al., 2016); and the effects of digital banking on minimum-payment penalties (Choi and Loh, 2019); also see Karlan et al. (2016) for an extensive review. It is widely accepted that having better access to financial services can mean a lot for both consumers and merchants, and especially for disadvantaged groups (Célerier and Matray, 2019; Doornik et al., 2021; Hau et al., 2019; Karlan and Zinman, 2010; Reher and Sokolinski, 2021; Stein and Yannelis, 2020). My paper provides supportive evidence for this argument, whereby cashless payment facilitates credit provision to the underserved and increases credit take-up. An emerging literature uses predictive exercises to demonstrate the wide-ranging potential of digital footprints (Agarwal et al., 2021; Berg et al., 2020) and machine learning models (Di Maggio et al., 2021; Fuster et al., 2022) in credit evaluation and financial inclusion. My paper complements these studies by elucidating the financial inclusion implications of in-person cashless payment in the real business environment.

An emerging literature examines the relationship between digital payment and digital credit. Berg et al. (2021) provide an extensive review of FinTech lending and highlight the importance of studying the role of payment data in the credit market. To my knowledge, this is the first paper to empirically reveal the causal effects of payment flow information on facilitating consumer credit provision. A recent theoretical paper by Parlour et al. (2020) studies a model of competition between financial intermediations for payment processing, in which the premise of the analysis is that payment flow data contain information on the consumer's credit quality. My paper provides evidence that directly supports the paper's premise regarding the informativeness of each consumer's payment flow. Another closely linked paper is by Ghosh et al. (2021), who uncover the synergy between FinTech small-business lending and cashless payments using both theoretical and empirical analyses. In contrast, instead of analyzing lending to firms, my paper focuses on lending to consumers. I show that consumers are less strategic than firms when deciding whether to adopt cashless payment, and even a small nudge toward digital service usage can lead to a large shift in the long-run choice of payment instruments. The difference in setups results in opposite predictions. Ghosh et al. (2021)'s theory suggests that the better firms benefit more from cashless

payment adoption due to the information-revealing effect, whereas my paper suggests that it is the financially underserved who enjoy more credit provision after the adoption of cashless payment.

The paper is organized as follows. Section I provides some institutional background on the Alipay platform and the dockless bike-sharing industry in China. Section II describes the data, and Section III presents the research design and provides evidence on the validity of the instrumental variable. The main empirical results are in Section IV, in which I analyze the relationship between cashless payment flow, credit provision, and financial inclusion. I conclude in Section V.

I. Institutional Background

China is rapidly becoming the world leader in mobile payment, and the path it takes is quite different from most. Unlike the mobile-phone-based payment system that relies on SMS text messages—e.g., M-PESA in Kenya—or card-complementing mobile payment systems, such as Apple Pay or Android Pay, China's mobile payment system is based on so-called "super apps." Among these the most notable are Alipay and TenPay, which provide an all-in-one digital experience to users with both in-house services and integrated third-party services. This paper studies mobile payment in China by analyzing Alipay's proprietary data.

A. The Alipay Platform

Alipay is the largest digital payment services provider as measured by total payment volume in China, which reached RMB 118 trillion from July 2019 to June 2020. It is a third-party mobile and online payment platform launched by the Alibaba Group in China in 2004. As of late 2020, it had over 1 billion users, 80 million merchants, and more than 2,000 partner financial institutions for digital payment and digital financial services, including unsecured consumer credit. Alipay has always been the principal means by which buyers transact with sellers on Alibaba's platforms since its launch. It has grown explosively since 2016, in both the number of users and transaction volume.

China has switched from a cash economy to a cashless economy in less than one decade, during which Alipay has played an important role. Nowadays, consumers in China rarely carry cash. Instead, they use Alipay and TenPay to pay for almost everything, including taxis, bills, e-

commerce purchases, and even purchases from small street vendors. Alipay has become a platform that enables merchants and consumers to complete transactions for almost all online and in-person payments. It also acts as a one-stop shop for digital payment, digital financial services, and a broad range of daily life services. Using Alipay, a consumer can access 1,000 daily life services and more than 2 million mini programs that provide mobility services, local services, municipal services, and many others, without having to download additional apps.

In Figure A1, an illustration from the prospectus of the Ant Group lists the typical use cases available via the Alipay app. From the Ant Group's standpoint, the foundation of all such services is digital payment; the provision of other digital financial services, including consumer credit, wealth management, and insurance, are based on it. Consumers could fund payments for major uses through the e-wallet account balance, the Huabei credit line, and linked bank card accounts. Here, Huabei is a virtual credit card that offers unsecured revolving credit services to qualified Alipay users for daily expenditures. In this paper, I measure Alipay's credit provision based on access to the Huabei credit line. As of late 2020, it is the largest digital consumer credit product by credit balance in China.

Huabei, as a credit line product, is totally virtual and can be accessed only via the Alipay platform. Unlike traditional credit cards, which require completing an application and waiting for the decision on credit access and, if successful, the credit line, Alipay users learn in real time whether they qualify for Huabei and roughly what the credit line is. Once an Alipay user is granted access to Huabei, her credit line is instantly available at the point of sale. The whole process is fully automatic. The minimum credit line is as low as 20 CNY (roughly 3 USD), and Alipay offers consumers an interest-free period of up to 40 days after the corresponding purchase. Consumers have the option to pay in monthly installments over 3 to 12 months after the interest-free period. From July 2019 to June 2020, the majority of Huabei users' daily interest rates were approximately at or below 0.04%, and the average Huabei outstanding balance was around 2,000 CNY.

B. The Dockless Bike-sharing Market in China

The first dockless bike-sharing firm in China was *ofo*, which was founded in 2015 in Beijing. It started as a two-sided platform that enabled students to share their bikes and ride others' bikes

on campus, and later shifted to a one-sided platform supplying GPS-tracked dockless bikes to users of its bike-sharing app (Cao et al., 2018).

Unlike traditional bike-sharing systems that offer rental bikes that are docked in stations, dockless bike-sharing platforms offer users more convenient services. They can use bike-sharing apps or mobile wallet apps to scan the QR code on the bike's smart lock and unlock an available shared bike in seconds. After finishing the trip in any authorized area, they can reset the lock easily; the bike is then available to other users.

Since late 2015, the bike-sharing industry in China has attracted investment from venture capital (VC) funds and BigTech firms, and has undergone exponential growth (Figure A2). According to data from China's transport ministry, there were 23 million shared bikes from 77 companies in hundreds of Chinese cities as of early 2018, when ofo and Mobike accounted for 95% of the market in total.

There were rises and falls among bike-sharing service providers. Although ofo was the first player in the bike-sharing industry and at one time dominated it, it later incurred a large amount of debt it was unable to pay, and had stopped operating bike rentals as of 2020. In contrast, *Hellobike* was a small bike-sharing provider in 2017, but has since become the largest bike-sharing service provider in the world as measured by the number of total rides in 2020.

C. Digital Payment Competition and the Dockless Bike-sharing Market

In 2013, non-cash retail payments in China amounted to less than RMB 50 trillion, and almost all were debit card or credit card transactions. At that time, in-person mobile payment services such as Alipay or TenPay accounted for only a tiny fraction of the non-cash retail transaction volume. The market size of in-person mobile payments grew gradually at first and took off quickly after 2016. As of 2019, non-cash retail payments in China exceeded RMB 350 trillion, with more than RMB 200 trillion attributable to in-person transactions made through mobile payment service providers.

There are two major digital payment service providers in China, Ant Group which offers Alipay, and Tencent which offers TenPay. As of June 2020, Alipay was the largest digital payment

service provider as measured by total transaction volume, with a market share of approximately 55%, and TenPay was the second-largest player in the industry, with a market share of about 40%.

There has always been fierce competition between Alipay and TenPay, and both parties have invested extensive resources and funding to expand market size and gain market share.

A strategic move by mobile wallets has been partnering with bike-sharing companies, since the digital payment system can provide infrastructure for bike-sharing services. The high-frequency usage of bike-sharing services, in turn, can encourage users to adopt mobile wallet use for other payments in daily life.

Because of the synergistic effect between digital payment and bike-sharing services, Alibaba and Ant Group invested more than 0.5 billion dollars in ofo and more than 3 billion dollars in Hellobike; ofo was once the largest player and Hellobike is now the largest player in the bike-sharing industry. In return, these bike-sharing services are deeply bundled with Alipay. By taking advantage of the mini-programs within the Alipay system, Alipay users can unlock shared bikes by scanning the QR code on the bike with Alipay directly, without downloading the specific bike-sharing app or manually entering personal information. This relationship is exclusive; a WeChat user is unable to directly unlock a shared bike operated by Hellobike using TenPay. What is more, for Alipay users who have a high enough credit score in Alipay's credit scoring system, the deposit for using shared bikes can be waived. According to the IPO prospectus of Hello Inc., the company operates Hellobike, "The popularity of our service and our rapid business expansion, in turn, contribute to the prosperity of the ecosystem built upon such payment and digital infrastructure."

From 2016 to 2020, both the bike-sharing market and the mobile payment market experienced booms. This provides a unique setting to study the causal effects of cashless payment since the staggered placement of Alipay-bundled shared bikes across different Chinese cities brought exogenous adoption shocks to Alipay users living in different cities.

II. Data Description

It has always been challenging to obtain a suitable data set to study the relationship between payment flow and consumer lending. It requires granular data with linked payment and credit information. It is even harder to study it in a dynamic setting. I overcome these challenges by using

proprietary panel data at individual and year-month level from Ant Group, which contain detailed information on not only broad payment and credit activities, but also rich personal characteristics.

The main dataset used in the study consists of panel data that include 41,485 randomly selected Alipay users who have at least one in-person transaction in the sample period of May 2017 to September 2020. For each user, I observe both the static characteristics of gender, education, year of birth, and so on, and time-varying measures, such as in-person payment flow, online payment flow, bike-riding activity, credit provision, and credit usage. Another important dataset used in the study consists of city-level panel data on the placement of Alipay-bundled shared bikes.

Table 1 reports a summary of the distribution of the sample in multiple dimensions. The first set of characteristics is at the individual level and covers 41,485 Alipay users. The average user in the sample was born in 1983, with payment activities in 32 months out of the 41 months from May 2017 to September 2020. Roughly 54% of users in the sample are male. About 88% of sampled users do not have a bachelor's or higher degree, and 29% of users used Alipay-bundled shared bikes at least once during the sample period. The second set of measures is at city and year-month level. In the average sampled month, the average city has a log transformed number of placed shared bikes of 7.08. The third set of variables is at individual and year-month level. In the average sampled month, the average user has a 62% probability of having access to Alipay's virtual credit card, a log-transformed credit line of 7.88, a log-transformed in-person Alipay payment amount of 5.70, and a log-transformed online Alipay payment amount of 5.76, where the credit line and payment flows are measured in CNY. For the average user in the average month, 34% of in-person Alipay payments and 33% of online Alipay payments are paid using the virtual credit card, and 3% of in-person Alipay payments and 1% of online Alipay payments are for compulsive spending, including cigarettes, games, lotteries, or live streaming services.

Alipay was widely adopted and intensively used by consumers at the end of my sample period. As of September 2020, the median size of a sampled user's assets under management in Alipay wallet was 8 yuan, and the average size was 5,521 yuan. The median is small since many users do not keep a positive balance on their Alipay accounts and use linked bank cards to make purchases instead. In my data, the median monthly Alipay transaction amount was 238 yuan at the end of the sample period, and the average was 2,628 yuan. As a comparison, the average per capita monthly disposable income in China was 2,682 yuan in 2020.

III. Research Design

Several endogeneity issues arise in addressing the causal relationship between cashless payment and credit provision. For example, simultaneity can arise when there is synergy between the adoption of cashless payment and credit provision by the payment service provider (Ghosh et al., 2021) or other factors that may simultaneously affect payment and credit. Omitted variables that potentially bias the estimates can also be present.

Exogenous variations in digital payment adoption can help address these issues. However, they are in general hard to identify, especially in countries with developed financial systems and widely adopted digital payments. For example, debit and credit cards are already quite popular and accessible in the US, and thus cashless payment activity is endogenously determined; those who use cards for daily purchases are notably different in nature from those who use cash. In contrast, mobile payment is quickly being adopted in China and provides a unique setting to generate exogenous variations in cashless payment adoption across different cities over time. I explain how I address endogeneity issues using an instrumental variable approach in this section.

A. Preliminary Analysis

This subsection provides some direct empirical evidence that supports the story illustrated in Figure 2. I use the placement of Alipay-bundled shared bikes across cities as a novel instrumental variable to solve endogeneity issues. Although Alipay, the mobile payment leader in China, grew rapidly in recent years, there were also staggered placements of Alipay-bundled shared bikes across different cities; this led to exogenous shocks to bike users' adoption of Alipay. When there are more Alipay-bundled shared bikes placed in the city, the bike-sharing service becomes more valuable for bike users, which in turn motivates them to use Alipay more frequently to unlock bikes by scanning the QR code on the bike. This frequent usage of Alipay nudges users to gain trust in Alipay and be comfortable using it not only for bike-related spending but also for other in-person payments. After all, scanning the QR code on a shared bike to unlock it and scanning the QR code of a merchant to make a payment are the same in terms of the procedure.

I provide direct evidence for the logic flow illustrated above, which can be used as a sanity check. First, I show that when more Alipay-bundled shared bikes are placed in a city, individuals

living in that city have higher bike-riding activity. Second, I show that after an individual adopts the use of shared bikes, her in-person payment flows that are unrelated to shared bikes are likely to increase abruptly.

Table 2 presents ordinary least squares (OLS) estimates from regressions that focus on the sample of Alipay users who have used a shared bike at least once in the sample period, and Columns (2) and (3) focus on the months in which bike users use bikes. The results show the positive relationship between the city-level placement of shared bikes and individual-level usage of shared bikes on both the extensive margin and intensive margin. The estimates suggest that on the extensive margin, for sampled bike-riding Alipay users living in city c, having a 1% increase in city-level bike placement in city c in month t increases a user's probability of using shared bikes by 0.028%. On the intensive margin, for bike users in the months they use bikes, the 1% increase in bike placement in month t leads to an increase in the bike user's number of bike rides of 0.082% and an increase in her total distance for bike rides of 0.120% in month t. When more bikes are placed in a city, finding an available shared bike becomes easier for bike users, and they are expected to have higher bike-riding activity. In addition, as Cao et al. (2018) demonstrate, since the dockless bike-sharing system is a one-sided network with positive network effects, there might also exist indirect effects, whereby more bike-riding activity by one user also increases others' bike-riding activity. Both the direct and indirect channels lead to a positive relationship between the city's bike placement and the bike-riding activity of bike users living in the city.

Next, I provide evidence on the nudge effect of shared-bike adoption on in-person payment activity. Table A1 shows the strong correlation between bike usage and in-person cashless payment flow with regressions. This does not evolve in a gradual manner. Figure 3 is a graphical illustration of the effects of bike adoption on in-person payment flow that is unrelated to the use of Alipay-bundled shared bikes. It uses an event study framework, in which the event for individual i is her bike adoption and t corresponds to the number of months after the individual's month of the first use of Alipay-bundled shared bikes. The reference time 0 indicates the end of the month

of each user's bike adoption. The figure plots the β_τ coefficients estimated in the regression:

$$\log(1 + In\ Person\ Non\ Bike\ Payment\ Flow)_{i,t} = \alpha_0 + \sum_{\tau=-5}^{4} \beta_\tau \cdot \mathbb{I}(t = \tau) \cdot \mathbb{I}(\tau \neq -1) + \beta_5 \cdot \mathbb{I}(t \geq 5) + \delta_i + \mu_t + \varepsilon_{i,t} \quad \textbf{(1)}$$

where δ_i represents city fixed effects and μ_t represents year-month fixed effects. For each bike user, the sample only covers periods in which the event time t is not earlier than -5. Compared with the benchmark month, in-person non-bike payment flow increases by more than 80% in the month of shared-bike adoption and stays at a level more than 30% above the benchmark level in the following months. Although the bike-adoption decision itself is endogenous, this sharp contrast of in-person non-bike payment flow before and after shared-bike adoption suggests that it is the use of Alipay-bundled shared bikes that leads to a shift in payment habits. Otherwise, the change should not be so abrupt around the heterogeneous shared-bike adoption date of users, especially with respect to individual and year-month fixed effects. This phenomenon is likely to be caused by switching from paying with cash or other payment instruments to paying with Alipay, rather than by sharply changing the level of consumption after shared-bike adoption. Note that this is not mechanically driven by the people who register for Alipay only to gain access to Alipay-bundled shared bikes. As Figure A3 shows, the vast majority of sampled Alipay users either adopt Alipay-bundled shared bikes after being an Alipay user for more than 1 year or do not use the shared bikes at all in the sample period, and only 1% of users start to use Alipay-bundled shared bikes in their first year of Alipay usage. Thus, the mechanical effect should be negligible.

B. Validity of the Instrumental Variable

In this subsection, I provide empirical evidence that supports the use of city-level bike placement as a valid instrument for individual-level in-person cashless payment that is likely to satisfy both the relevance condition and the exclusion restriction condition. First, I find a strong relationship between bike placement in a city and the in-person cashless payment flow of Alipay users living there. Second, I show that bike placement is likely to affect Alipay credit provision only through in-person cashless payment.

The Relevance Condition

There are concerns that city-level bike placement might not be a strong instrument for individual-level in-person cashless payment flow, especially when granular controls are added. The data show that this relevance condition can be robustly satisfied, and the results suggest that bike placement acts as an exogenous shock to Alipay users' in-person payment through the nudge effect described in the preliminary analysis.

Panel A of Table 3 shows the effects of city-level placement of shared bikes on individual-level in-person payment flow. Column (1) shows that when the bike placement of city c in month t increases by 1%, the in-person payment flow of the individuals living in the city increases by 0.039% on average. The relationship is quite strong, even when both individual and year-month fixed effects are controlled for and when standard errors are double clustered by city and year-month levels. Individual fixed effects can capture the time-invariant determinants of in-person payment activities for everyone—such as financial literacy, digital literacy, and wealth level—while year-month fixed effects can capture the time-varying determinants of in-person payment activity, such as workday effects and holiday effects. Given that the F-statistic is as high as 40.7 and the t-statistic of the coefficient estimate is 3.9, it can easily pass the weak instrument criterion proposed by Stock and Yogo (2005) and satisfy the most recent *tF* procedure introduced by Lee et al. (2021).

A closer look in column (2) reveals that this positive relationship between bike placement and in-person payment flow only exists for bike users, but not for users who have never used Alipay-bundled shared bikes. This result can be regarded as a placebo test that supports the view that it is bike placement that affects Alipay users' in-person payment through bike usage. And it makes sense that for non-bike users—especially those who do not know how to ride a bike—regardless of how many shared bikes are placed around them, their payment activities should not be directly impacted. This test also helps rule out stories whereby the positive relationship is driven by some unobserved common factors that affect the whole population in the local area—e.g., local growth potential or local infrastructure plans—and that simultaneously correlate with the city's bike placement and city residents' in-person payment flow.

Column (3) shows the results of the regression with a specification that further adds city times year-month fixed effects, which remove all unobserved time-varying heterogeneity across cities, such as differences in local business cycles, different levels of local Alipay penetration, different

local trends in bike placement, or aggregate variations that could arise from the placement of shared bikes. Identification of the coefficient relies on comparing the in-person payment flow of bike users in response to bike placement with that of a control group of non-bike users within the same city, with the static characteristics of the individuals controlled for at the same time. For bike users, a 1% increase in bike placement leads to a 0.077% increase in in-person payment flow.

The intensive margin analysis also supports the mechanism whereby bike placement exogenously affects in-person payment flow through bike usage. Differences in the response of in-person payment flow to bike placement not only exist between bike users and non-bike users, but also before and after adoption of Alipay-bundled shared bikes within the same bike user. The corresponding results are shown in column (4) with the specification that focuses on bike users and controls for individual fixed effects and city times year-month fixed effects. Without the variation in bike placement, the bike-adoption decision itself does not have a significant effect on the in-person payment flow, which alleviates concern about selection issues in the endogenous timing of bike adoption. For bike users, after the bike adoption, a 1% increase in bike placement results in a 0.051% increase in the in-person payment flow.

The Exclusion Restriction Condition

The identifying assumption is that bike placement affects digital credit provision only through in-person cashless payment. Four major concerns arise regarding satisfaction of the exclusion restriction by using the bike placement instrument. The first concern is that there exist factors that correlate with bike placement and credit provision at the same time. The second concern is that the use of Alipay-bundled shared bikes can directly reveal the creditworthiness of consumers and affects Alipay's credit provision. The third concern is that bike placement is predictable or clustered within a short time, which renders it not as exogenous as required. The fourth concern is that bike placement affects local economic conditions, which would lead to further changes in digital credit provision. I show that these issues are unlikely to be present.

The first concern is the existence of common factors that are correlated with bike placement and credit provision at the same time. For example, some time-varying growth potential for a city could attract the attention of both bike-sharing companies and Alipay; as a result, the likelihood of bike placement and the level of credit provision would increase at the same time.

Panel B of Table 3 provides reduced-form results on the influence of bike placement on credit provision, and indicates that the positive relationship between bike placement and credit provision is unlikely to be driven by common factors unrelated to the bike-riding channel. Column (1) shows that the higher the bike placement shock in a city, the higher the credit line the individuals living in the city receive. In this setting, individual fixed effects and year-month fixed effects remove static heterogeneity across individuals and time-varying macroeconomic variations.

I further separate Alipay users into bike users and non-bike users and explore the heterogeneous effects of bike placement on their digital credit lines in column (2). It shows that the reduced-form positive effect of bike placement on credit provision only exists for bike users. The fact that bike placement has a positive effect on one group but not on the other group can seem surprising, especially when the difference between the two groups is quite small. In the definition used here, the only difference between a bike user and a non-bike user is whether the person has used Alipay-bundled shared bikes at least once during the whole sample period. The suggested mechanism explains the phenomenon very well, whereby bike placement first leads to more bike usage, then increases in-person payment flow, and finally results in more credit lines. It also helps reject the story whereby some factors correlate with both bike placement and credit provision, since the usual common factors are unlikely to affect bike users and non-bike users in different ways—especially when it is extremely inexpensive for an Alipay user to be a bike user as defined herein. Column (3) shows that the effect of bike placement on the bike user's digital credit line is still positive, despite the weaker significance after city times year-month fixed effects are included in the regression.

Column (4) focuses on bike users and reports results of the regression with individual fixed effects and city times year-month fixed effects. Although the timing of bike adoption is endogenous, the dummy variable that indicates whether the bike user has adopted shared bikes does not imply a higher credit line, which suggests that the timing itself does not play an important role in credit provision. The interaction term of the dummy variable and the bike placement, however, has a significant positive effect on the credit line, and this is consistent with the bike usage channel documented above.

Although the cost to become a bike user is low, one could argue that bike users and non-bike users have very different characteristics, and it is these associated characteristics, instead of bike

usage itself, that lead to the difference in the reduced-form effect of bike placement on credit provision. To rule out this channel, I first screen the personal characteristics that are strongly associated with the bike-user classification, then check the heterogeneous effects of bike placement on credit provision along these dimensions. Table A2 shows the regression results on the relationship between personal characteristics and the choice to become a bike user. Across different specifications, several personal characteristics are indeed correlated with the bike user dummy, including education, age, Alipay experience, gender, and indicators for whether paying with the user's real name or whether using their own account. Table A3 reports the heterogeneous effects of bike placement on in-person payment flow and credit provision. The bike placement variable interacts with both the bike user dummy and the measure of personal characteristics selected from Table A2. Panel A reports the OLS regression results in which the dependent variable is $\log(1 + In\ Person\ Payment\ Flow)_{i,t}$, while Panel B shows the corresponding results in which the dependent variable is $\log(1 + Credit\ Line)_{i,t}$. Each column uses a different personal characteristic measure. Even though personal characteristics such as education, age, and gender all seem to be much harder to change than the status of being a bike user, across all specifications, the heterogeneity mostly arises from the dimension of the bike-user dummy. These results suggest that it is the bike-usage-associated behaviors, instead of the selection issue, that matters most in the effects of bike placement on in-person payment flow and credit provision. It is unlikely that bike users are a special group of individuals who benefit from the shock to the Alipay credit line simply because they have different personal characteristics, especially when everyone can easily join this group.

The second concern is about the direct revelation of creditworthiness by bike usage. Some institutional backgrounds and facts help alleviate this concern. First, Alipay is only a strategic partner with the bike-sharing companies and is unlikely to use third-party data directly as the model input. The bundling also seems to be limited, since the official bike apps support multiple mobile wallets and Alipay is not required for bike usage. Second, the cost of bike usage is very low, which renders the activity easy to manipulate. If the direct effect on credit provision is large and there exist some manipulations, the Alipay company, which is very sophisticated and advanced in technology, will fix those issues in equilibrium. The average cost of bike usage is as low as 0.23 USD for the first 15 minutes and 0.08 USD per 15 minutes after that. The monthly unlimited plan is only 3 USD, which can be regarded as an upper bound for the monthly bike spending of a

rational user. Third, the user base is quite large, given that bike users are unlikely to be very selective. The size of the shared-bike user base in China is as large as 260 million as of late 2019, and Hellobike claimed to have over 400 million registered users as of 2021.

Table 4 furthers shows that bike usage is more like a nudge for payment activity and credit line, instead of a proof of creditworthiness. I separate bike users into two categories: the one-time bike user who has used Alipay-bundled shared bikes only once during the whole sample period, and the repeat bike user who has used the bikes at least twice in the data. Even if bike usage itself reveals some information about creditworthiness in the long run, using the bike once should not be very informative. Columns (1) and (3) show that bike placement has no significant effect on in-person payment flow and the credit line of the non-bike users, but has strong positive effects on in-person payment and credit line of one-time bike users, even though the difference between these two groups is only one bike-riding activity. Moreover, although the effects are stronger for repeat bike users, the difference in the effects between one-time bike users and repeat bike users is relatively small. Columns (2) and (4) indicate that the patterns are very robust, even when city times year-month fixed effects are added to the specification.

The third concern is about the bike placement process. If it is a predictable process or is clustered within a short period for all cities, it is more likely that it will correlate with other factors that are associated with credit provision. From the perspective of bike-sharing companies, it is more beneficial for them to make bike placement a staggered and unpredictable process, and the empirical evidence supports this. There is anecdotal evidence that what bike-sharing companies care most about is local competition and their own operational efficiency, and this could lead to heterogeneous overall strategies. For example, bike-sharing companies such as Mobike and ofo focused mostly on big cities in the beginning and gradually expanded to smaller cities, while Hellobike started bike placement in small cities first to avoid competition and then gradually expanded to larger cities. Regardless of which cities they decide to target first, bike-sharing companies always have an incentive to quickly place their shared bikes in the local market because it helps them build local market power and avoid competitors who may react strategically. Since there are capacity constraints for bike production, it is not feasible to put bikes in all targeted cities within a very short timeframe.

Figure 4 plots the β_τ coefficients estimated in the following regression:

$$Normalized\ Bike\ Placement_{c,t}$$

$$= \alpha_0 + \sum_{\tau=-5}^{4} \beta_\tau \cdot \mathbb{I}(t = \tau) \cdot \mathbb{I}(\tau \neq -1) + \beta_5 \cdot \mathbb{I}(t \geq 5) + \delta_c + \mu_t \quad \textbf{(2)}$$

$$+ \varepsilon_{c,t}$$

In the regression, $Normalized\ Bike\ Placement_{c,t}$ is a measure with a range of [0,1], which is defined as $\frac{Bike\ Placement_{c,t}}{Maximum\ Bike\ Placement\ in\ Sample_c}$, where t corresponds to the number of months after each city's month with the largest bike placement shock. δ_c is city fixed effects, μ_t is year-month fixed effects, and $\varepsilon_{c,t}$ is the error term that varies across cities and over time. The sample period is from May 2017 to January 2020, which avoids later COVID lockdown periods. For each city, the sample only covers periods in which t is not earlier than -5. The figure shows that the magnitude of the largest monthly bike placement shock is large—on average, around 25% of the maximum bike placement of the city during the sample period. Normalized bike placement on average rises by about 10% of the maximum bike placement in the 2 months immediately before the event of the largest monthly bike-placement shock. This pattern of bike placement is consistent with bike-sharing companies' strategic concerns. To address the fierce competition in the bike-sharing industry, once a company decides to enter a city, it is likely to place a lot of bikes in a short period to build up local market power.

At the same time, the timing of the bike placement shock is hard for citizens to predict. Figure 5 shows the monthly time series of the number of cities that are in their month of the largest bike-placement shocks. The critical month for each city's bike placement is distributed broadly over the sample period. This is consistent with the fact that there are capacity constraints on bike production and bike allocation. In that sense, placing shared bikes is like playing chess, in which the players target different cities during different periods. Once they decide on the cities to target, they place many bikes within a very short time frame. Since bike placement is quite staggered and the time of the largest bike placement shock spreads over time, it is hard for citizens of a specific city to predict shocks from the placement of Alipay-bundled shared bikes using only public information.

The fourth concern is about the impact of the bike-placement shock on the local economy. Since dockless shared bikes offer great convenience to users and the number of bike users is large, some might worry that bike placement brings new business opportunities and affects the local

economy or fiscal policy, which further leads to an increase in credit provision. Table A4 shows the relationships between bike placement and the variables associated with local economic conditions. Under city fixed effects and year-month fixed effects, the coefficients for all specifications are small and insignificant, which indicates that bike placement is unlikely to have macroeconomic impacts.

IV. Empirical Results

This section first presents the results of the main specification, which investigates the causal effect of in-person cashless payment flow on BigTech credit provision and consumer take-up of the credit. It then demonstrates the importance of the payment information channel in facilitating BigTech credit provision. Finally, it illustrates the implications of in-person cashless payment flow for financial inclusion, whereby the traditionally financially underserved have a relative advantage in terms of the abundance of in-person cashless payment data, and as a result the causal effects of in-person payment on credit provision mainly hold for this segment.

A. In-Person Cashless Payment Flow and Credit Provision

Causal Effects of In-person Cashless Payment on Credit Provision

To analyze how in-person cashless payment flow affects credit provision by BigTech, I estimate the effect using two-stage least squares regressions. In the first stage, the log-transformed in-person payment flow is instrumented with log-transformed city-level bike placement:

$$g(ipf)_{it} = \alpha_1 + \beta_1 \cdot \log(bp)_{ct} + \delta_{1i} + \theta_{1t} + \varepsilon_{1it} \quad \textbf{(3)}$$

In the second stage, with the instrumented log-transformed in-person payment flow, I estimate its causal effect on credit provision variable using the following specification:

$$\mathrm{Y}_{it} = \alpha_2 + \beta_2 \cdot \widehat{g(ipf)}_{it} + \delta_{2i} + \theta_{2t} + \varepsilon_{2it} \quad \textbf{(4)}$$

And the corresponding ordinary least squares regression performed using the following specification:

$$\mathrm{Y}_{it} = \alpha_0 + \beta_0 \cdot g(ipf)_{it} + \delta_{0i} + \theta_{0t} + \varepsilon_{0it} \quad \textbf{(5)}$$

where $\log(bp)_{ct}$ is log-transformed bike placement in city c at time t; $g(ipf)_{it}$ is the transformed measure of the in-person payment flow of individual i at time t; $g(\widehat{ipf})_{it}$ is the corresponding instrumented variable; Y_{it} is the credit provision variable of individual i at time t; δ_{Ni} $(N = 1,2,3)$ represents individual fixed effects; and θ_{Nt} $(N = 1,2,3)$ represents year-month fixed effects.

Table 5 shows the results of the regressions specified in equations (3), (4), and (5), in which Panel A reports the estimated effects in the second stage of the two-stage least squares (2SLS) regression, Panel B reports the first-stage results of the 2SLS regression, and Panel C reports the OLS estimates. Columns (1), (2), and (3) focus on the extensive margin, where $Credit\ Access_{i,t}$ is a dummy variable that equals 1 if Alipay user i has access to Alipay's virtual credit card at time t and 0 otherwise. Columns (4), (5), and (6) focus on the intensive margin and use only the sample in which users have credit access in the corresponding months, and $\log(Credit\ Line)_{i,t}$ is the log transformed credit line of Alipay user i's virtual credit card at time t. In columns (1) and (4), $g(ipf)_{it}$ is the log(1+x) transformed in-person payment flow, measured in CNY; in columns (2) and (5), it is the dummy variable that indicates whether the in-person payment flow is positive; in columns (3) and (6), it is the log(x) transformed in-person payment flow, which is only available when the in-person payment flow is positive. All specifications include individual and year-month fixed effects. The granular fixed effects tightly control for heterogeneity across individuals, since the effect of bike placement is identified within each Alipay user. Panel A shows that having positive in-person payment flow in a month leads to a 56.3% increase in the likelihood of gaining credit access for an average Alipay user and a 203.3% increase in the credit line for a user who currently has credit access in the same month. Of those who have positive in-person payment flow in the month, a 1% increase in the in-person payment flow leads to a 0.087% increase in the likelihood of gaining credit access for an average Alipay user and a 0.409% increase in the credit line for a user who currently has credit access. Panel B reports both the t-statistic of the estimate in the first stage and the F-statistic of the regression, which indicates that the log-transformed bike placement is a strong instrument and successfully passes the weak instrument tests proposed by Stock and Yogo (2005) and Lee et al. (2020).

Panel C presents the OLS estimates, which are much smaller than the corresponding IV estimates. There are two potential reasons: (1) omitted variables and (2) the non-monotone payment-credit relationship. First, the OLS estimate can have a downward bias due to omitted variables, when people with less credit based on attributes unobservable to econometricians are more likely to make more in-person cashless payments. The econometric analysis of this issue is illustrated in Section A1 of the Appendix. One example of such omitted variables is a negative health shock, which would negatively impact the user's creditworthiness due to a decrease in disposable income and positively affect the in-person payment flow because of spending on treatment and medicine. Second, the non-monotone relationship between credit provision and in-person cashless payment flow can also lead to a downward bias. Below a certain threshold, more payment flow leads to more information acquisition by the BigTech firm, which in turn facilitates credit provision. However, above the threshold, more payment flow can be regarded as overspending, which causes the borrower to seem riskier and leads to a reduction in the BigTech credit provision. Empirical evidence that supports the non-monotone relationship is provided in Figure A4 and Table A5 of the Appendix.

What is more, the patterns illustrated in Table 5 are very robust under various settings. Table A6 presents the results in which city times year-month fixed effects are added, and the interaction between the bike-user indicator and log-transformed bike placement serves as the instrument. It shows that even when unobserved time-varying heterogeneity across cities is removed, the in-person payment flow shock still leads to more credit provision. Table A7 shows that the in-person payment flow also affects future credit provision. Table A8 reports results of regressions that control for the in-person payment flow in the past 1, 2, or 3 months. Table A9 and Table A10 further add bike usage and online payment as controls. The effects of the concurrent in-person payment flow on credit provision are still robust, with similar magnitude across different specifications.

Consumer Take-up of BigTech Credit

The credit access and credit line discussed in the previous section are fully determined by the supply side, since no active application is required for Alipay users to use the virtual credit card, and they directly learn about their credit access and credit line by simply checking the account. The real effects of the changes in credit provision also depend on the demand side—that is,

consumer take-up of BigTech credit. It is natural to anticipate that more in-person payment flow leads to a higher fraction of spending paid for with the virtual credit card, both in-person and online, for two reasons. The first reason is the learning-by-doing channel, whereby people are more likely to use the virtual credit card when they have more knowledge about Alipay and more trust in Alipay. The second reason is the supply-side channel, whereby Alipay users might use the virtual credit card more frequently when they have a higher credit line.

Results in columns (1) and (2) of Table 6 support the above view of consumer credit take-up. With an exogenous increase in the in-person payment flow, the share paid with Alipay's virtual credit card increases for both in-person payment and online payment. The magnitude of the increase is larger for in-person payment.

There are also concerns that consumers use digital payment more for compulsive spending, since more accessible payment methods might also make it easier for people to develop addictions. I find no evidence to support this view. Columns (3) and (4) show that the in-person payment flow does not result in a higher fraction of compulsive spending, in both in-person and online environments.

B. The Payment Information Channel

Channels for Credit Provision

Two main channels facilitate the credit provided by financial intermediation: the information channel and the collateral channel. Both information sharing and the pledge of collateral help mitigate information asymmetry problems in the consumer lending market, including adverse selection and moral hazard. These channels can be further classified as follows.

Information channels include:

- Channel 1.1: Use the information on payment flow.
- Channel 1.2: Use the information on credit usage and repayment.
- Channel 1.3: Use the information on the application form.

Collateral channels include:

- Channel 2.1: Use the asset under management (AUM) in the platform as the collateral.

- Channel 2.2: Explicitly pledge assets as security for loan repayment.

For banks that do not have borrower payment flow information, the payment flow information channel (channel 1.1) is usually not an option. Instead, the information actively provided by borrowers on the credit application form (channel 1.3) plays an important role before the borrower gains the credit access, and the information on credit usage and repayment behaviors (channel 1.2) becomes the most important channel for reducing information asymmetry after the borrower gains credit access. For secured loans such as mortgages, banks usually require borrowers to explicitly pledge the corresponding assets as security for the repayment of loans and forfeit the collateral in the event of default (channel 2.2).

The BigTech company that provides the cashless payment service to borrowers has an advantage in the information flow channel (channel 1.1), whereby the rich information contained in the payment flows reveals valuable information on the borrower's creditworthiness. In the specific setting of Alipay, there no application process is required to access a virtual credit card and the explicit pledge of collateral is not an option; thus channels 1.3 and 2.2 are unlikely to play a role in Alipay's credit provision. Instead, information on credit usage and repayment (channel 1.2) can be important, and the borrower's AUM on Alipay's wealth management (channel 2.1) might serve as collateral to facilitate credit provision, since the borrower might worry that the account could be frozen if they do not repay the credit in time.

In this research, I focus on showing the importance of the payment flow information channel (channel 1.1) for credit provision by Alipay and show that the channel holds strongly, whereas channels 1.3 and 2.2 are unavailable and channels 1.2 and 2.1 are controlled for.

Control for the Credit Use and Repayment Information Channel

With the Alipay app, users have several options to make in-person and online payments. On the Alipay platform, they can use the e-wallet account balance, a liquid money market fund called "Yu'ebao," or Huabei, Alipay's virtual credit card. Although Alipay also supports payments using debit card or credit card accounts for some merchants, most transactions on the Alipay platform are paid for with these within-Alipay payment methods since they are cheap, convenient, and widely accepted. I define "in-person credit payment flow" as the amount of in-person Alipay spending paid for using Alipay's virtual credit card, and this payment flow is directly associated

with credit usage and is highly relevant for the credit repayment flow. All other in-person payment flow is defined as the "in-person noncredit payment flow," which does not have a direct relationship with credit usage and repayment.

Table 7 shows the results of the 2SLS and OLS regressions with specifications similar to those of equations (3), (4), and (5), while replacing in-person payment flow with in-person noncredit payment flow, which excludes in-person Alipay payment flow paid for with the virtual credit card. This exclusion helps eliminate the effects of credit use and repayment on BigTech credit provision. Columns (1) and (3) show that the in-person noncredit payment flow has direct effects on BigTech credit provision, and indicates that even after controlling for the credit usage and repayment information channel (channel 1.2), the payment flow information channel (channel 1.1) still matters. However, there might be concerns that the in-person noncredit payment flow is correlated with the in-person credit payment flow, and the specifications in columns (1) and (3) fail to fully exclude the effects of credit usage and repayment. To alleviate concern about the correlation between payment flows, in the specifications of columns (2) and (4) the in-person credit payment flow is added as a control variable in all regressions. The results are still robust, with very close estimates. Moreover, in the second stage of the 2SLS regressions, the in-person credit payment flow does not seem to have a significant impact on credit provision, on both the extensive margin and the intensive margin. The estimated coefficients of the in-person noncredit payment flow measure are larger than those of the in-person payment flow measure in the analysis in Table 5, which indicates that in-person noncredit payment has larger effects than credit payment. This result is reasonable, since the usage of credit directly leads to a heavier repayment burden and riskier consumer profile, while usage of the account balance does not have a direct implication for the risk faced by the BigTech lender.

Control for the Collateral Channel

Although the explicitly pledged collateral for loan repayment (channel 2.2) is unavailable on the Alipay platform, the user's assets under management in Alipay's wealth management products can partially play the role of collateral, since the Alipay platform has the right to freeze the user's account if she does not repay the loan on time. There is a concern that the BigTech credit provision to a user is largely driven by the size of her AUM instead of the information channels. To deal with this concern, the specifications that control for each user's time-varying AUM are analyzed.

Table 8 shows that the relationship between in-person payment flow and BigTech credit provision is robust to adding the AUM variables as controls. Columns (1) and (3) use the definition of AUM as all assets in Alipay except for the account balance, while columns (2) and (4) use the definition of AUM as all Alipay assets including the account balance. Regardless of which specification is used, the AUM does not have a strong relationship with the credit provision variables, while the in-person payment flow has strong effects on credit provision on both the extensive margin and intensive margin.

C. The Financial Inclusion Implications of In-person Cashless Payment

A Theoretical Illustration of the Effects of a Cashless Payment Shock

From a cash economy to a cashless economy, digitalization of the payment system can result in more information acquisition by the digital payment service provider and further facilitates credit provision. For many developing countries, this could occur in two steps. Banks take the first step by issuing cards and installing point-of-sale (POS) terminals. Since these banks are not very advanced or widely accepted, they usually only serve relatively wealthy customers and relatively large merchants. These customers can easily reveal signals that they are creditworthy and can generate higher expected profits for the banks. Similarly, these merchants have more demand for processing large-volume transactions and can afford the fixed and variable costs of accepting card-based digital payments. The second step is taken by BigTech companies, which have more advanced technology, charge lower intermediation costs, and make it possible to cover a larger population—and especially the previously financially underserved. Wide adoption of the BigTech payment system can be regarded as a positive shock to the information acquired by financial intermediation about each customer in the overall population. This process of payment digitalization can have implications for financial inclusion, which makes it possible for relatively poorer people to gain credit access.

To capture the intuition of how two-step digitalization of the payment system affects credit provision and financial inclusion, I use a theoretical example for illustration.

In the economy, there is a lender and a continuum of borrowers. The type of borrower i follows a uniform distribution between 0 and 1; that is, $\theta_i \sim U[0,1]$. Given the type of borrower θ_i, the lender chooses the optimal lending amount l_i to maximize its expected profit. If the lender decides

not to lend, its profit is zero. When the lending amount is positive, there will be some uncertainties, and the expected profit will be type-dependent. For example, the interest rate will be different for borrowers of different types, and the probability of repayment will depend on the type, the lending amount, and the interest rate. To simplify the specification, I assume that the expected profit function takes the following form:

$$\pi_i(\theta_i, l_i) = \begin{cases} \theta_i + 2 \cdot \theta_i \cdot l_i - l_i^2 - 1 \,, l_i > 0 \\ 0, \;\; l_i = 0 \end{cases} \quad \textbf{(6)}$$

This functional form has three properties. First, given the lending amount, the expected profit monotonically increases with the borrower type. Second, there is an optimal lending amount, below which the expected profit increases with the lending amount and above which the expected profit decreases with the lending amount. Third, given the borrower's type, if the optimal lending amount is nonzero, it strictly increases with the borrower's type. With this specification in Eq. (6), the nonzero lending amount $l^*(\theta_i) = \theta_i$.

Three scenarios with different information provided to the lender are used to represent the cash economy, the card-based cashless economy, and the smartphone-based cashless economy.

In the first scenario, borrower type θ_i is fully unknown to the lender, which can only make the lending decision based on the distribution of borrower types in the population. This captures the feature of the cash economy whereby transactions are not well recorded, and there is a lack of information about the type of each borrower.

In the second scenario, the lender receives a weak signal about the type of borrower, which is specified as $s_i = \mathbb{I}(\theta_i \geq 0.8)$. This scenario captures two facts in the card-based cashless economy. First, it is easier for wealthier individuals to prove their creditworthiness. Second, the digital payment system only covers a small fraction of all transactions, which renders the signal imprecise and unable to further distinguish the exact type of borrower with a positive signal.

In the third scenario, the lender knows the exact type of each borrower. This is a case in which the smartphone-based payment system operated by the BigTech company covers almost all types of customers and merchants, and the recorded cashless transactions render the information about the creditworthiness of everyone quite precise.

The lender makes very different credit-provision decisions in the scenarios with distinct information sets. In the first scenario, it knows only the distribution of the borrower type and will make the same lending decision to every borrower based on the average type of borrowers. Under the above specification, lending a positive amount is always nonprofitable, and the lender will not lend to any borrower in this scenario. In the second scenario, it knows whether each borrower i is the "high type" with $\theta_i \geq 0.8$ or the "low type" with $\theta_i < 0.8$. Intuitively, the lender will not lend to any low-type borrower. For high-type borrowers, it is optimal to lend $l^*(s_i = 1) = 0.9$ to everyone in this group, and this will maximize the expected profit from lending. Comparing the second scenario with the first scenario, the weak signal helps the lender extend more credit, and this effect is concentrated on high-type borrowers. In the third scenario, the intermediation has precise information on each borrower's type, which enables it to make the optimal lending decision for each borrower type separately. In this specification, the optimal lending decision is to not lend to borrowers with type $\theta_i \leq \frac{\sqrt{5}-1}{2}$, and lend $l^*(\theta_i) = \theta_i$ to borrowers with $\theta_i > \frac{\sqrt{5}-1}{2}$. Comparing the third scenario with the second scenario, there are two main differences. The first difference concerns financial inclusion, whereby some of the previously underserved borrowers in the second scenario ($\frac{\sqrt{5}-1}{2} < \theta_i < 0.8$) now gain access to credit in the third scenario. The second difference concerns personalization, whereby previous high-type borrowers get a type-specific lending amount $l^*(\theta_i) = \theta_i$ instead of the same amount, although the average lending amount stays at the level of 0.9.

This simple example yields two general predictions about credit provision in response to the positive information shock caused by the adoption of cashless payment. The first prediction is that with the wide adoption of cashless payment, the credit provided by the lender increases. The second prediction is that the increase in credit provision induced by the adoption shock is more concentrated for borrowers of relatively lower types. That is, the new information from the cashless payment flow is more valuable for the underserved segment with respect to reducing information asymmetry.

The previous section provides empirical evidence that supports the first prediction and shows that the cashless payment flow is likely to contain useful information that facilitates credit

provision. This section shows that the financial inclusion implication highlighted in the second prediction is likely to hold in the data.

The Traditionally Financially Underserved and the Asset of Alternative Data

My data support the traditional view in China that less educated and older people tend to be financially underserved. Since all financial activities of the sampled Alipay users are not observable, which makes it hard to evaluate their overall financial access, I use their level of using Alipay financial services as a proxy for their overall financial access. By analyzing their financial behaviors on the Alipay platform, I find that these groups indeed use financial services for fewer activities.

Columns (1), (2), and (3) in Panel A of Table 9 show the results of cross-sectional regressions that examine the relationship between users' financial activities with Alipay and their personal characteristics. The less educated and the older groups tend to have fewer Alipay financial activities—fewer Alipay-linked debit cards, smaller all-time high Alipay AUM, and shorter Alipay investment experience. This is consistent with the argument that these groups are less financially literate and are less served by financial institutions.

Less educated and older groups also tend to have lower financial literacy (Lyons et al., 2019), which can potentially further worsen the problem of inadequate access to financial services. My data confirm that this is also a problem for Alipay users who are less educated and older.

Columns (4), (5), and (6) show evidence on how sampled users' education and age relate to measures of financial literacy. Less educated and older users tend to have a smaller likelihood of paying while using their real name, using their own accounts instead of others' accounts, and completing their profile information. These behavioral characteristics are detected automatically by machine learning algorithms. Although it is unclear whether these labels are directly used in making consumer lending decisions for borrowers in the Alipay system, they tend to deliver negative signals about the borrowers' creditworthiness, since these behaviors are misaligned with the normal standard.

Rollout of the in-person cashless payment system provides an opportunity for the financially underserved to accumulate payment flow data because of the low barrier of adopting and using cashless payment in the in-person setting. Making cashless payments in the online shopping setting

can be difficult for users with less digital literacy, because it requires users' knowledge about how to search for goods, communicate with strange sellers, and build trust with the multiple parties involved in the process. Instead, once the mobile wallet has been set up, making in-person cashless payments is not very different from, and more convenient than, purchasing goods with cash.

Panel B of Table 9 illustrates the relationship between personal characteristics and payment flow, both in person and online. Although the less educated and the older have both less in-person cashless payment flow and less online cashless payment flow in terms of amount, the gap is much larger for online payment. Thus, the financially underserved have a relative advantage in the in-person fraction of cashless payment flow, and the adoption shock of in-person cashless payment should have a larger impact on them in terms of accumulating data on payment records.

In-person Cashless Payment and Financial Inclusion

Assuming that different types of data can substitute for each other to improve the ability of financial intermediators to evaluate consumers' credit, the rollout of in-person cashless payment can have financial implications for credit provision. The less educated and the older have previously had less alternative data with which to prove their creditworthiness, and thus they have tended to be underserved by financial intermediation. With an exogenous increase in the in-person payment flow by shifting from other payment instruments to Alipay, the marginal increase in the precision of the signal regarding creditworthiness is larger for the previously financially underserved, and it is reasonable to expect that they will benefit more from the shock and gain greater credit access.

Table 10 presents empirical evidence showing the causal relationship between a user's in-person payment flow and the BigTech credit provided to the user, separately for the less and more educated groups and on both the extensive margin and the intensive margin. Panel B shows that, regardless of education group, the first stage is always quite strong. This means that the bike-placement shock consistently increases the in-person cashless payment flow of both the less and more educated. Second-stage results in Panel A reveal that the effects of in-person payment flow on credit provision are quite different for Alipay users with different education levels. The positive relationship only exists for the less educated group and becomes insignificant for the more educated group, on both the extensive margin and the intensive margin. For the less educated group, an increase of in-person payment flow of 1% leads to an increase in the probability of gaining

credit access of 0.095% and an increase in the credit line of 0.335%, conditional on credit access. The corresponding numbers for the more educated groups are 0.027% on the extensive margin and 0.035% on the intensive margin, and both estimates are insignificant.

Similarly, the sample can be grouped by age and be analyzed separately. Table A11 shows the corresponding results. Strong first-stage effects hold for both the older and the younger group. However, in the first stage, there are some differences in the magnitude of effects between age groups. On the extensive margin, the effect of a 1% increase in in-person payment flow on credit access probability is 0.130% for the older group and 0.047% for the younger group, and the former effect is 1.8 times larger. The case is similar on the intensive margin, where the effect of the older group is 1.6 times larger than that of the younger. This is consistent with the previous analysis. The older group has previously been underserved by financial intermediation, and the adoption shock of in-person cashless payment helps them more; thus they end up with larger improvements in credit access.

V. Conclusion

The easy adoption process, high convenience, and low intermediation fee all contribute to the success of the in-person cashless payment in China. Since using cashless payment in the in-person environment is not very different from using cash for daily purchases, the extremely low barrier makes the technology accessible even to those who were previously financially unserved or underserved. In the transition from a cash economy to a cashless economy, users naturally accumulate their payment records while using digital payment services. This paper shows that payment data can serve as valuable digital assets that facilitate credit provision to the relatively disadvantaged.

By using de-identified data from Alipay, the world's leader in mobile payment with 1 billion active users, I document that an exogenous increase in the in-person cashless payment flow leads to more credit provision by financial intermediation. This increase in credit provision results from the useful information for credit evaluation provided by the payment flow. The information goes beyond what is available from credit usage, repayment, and assets under management. I use a novel instrument by taking advantage of the staggered placement of Alipay-bundled dockless

shared bikes across cities to solve endogeneity issues and conduct several tests to confirm the instrument's validity.

I also find that the previously financially underserved benefit more from mobile payment adoption, and I propose a simple theoretical framework to provide insights about the underlying forces that can generate the corresponding predictions. The essential insight is that although the disadvantaged do not have many alternative ways to prove their creditworthiness, they have a relative advantage in revealing their creditworthiness in the in-person cashless payment flow, thanks to the low costs and wide coverage of mobile payments.

These findings have strong policy implications: The prevalence of mobile phone adoption can potentially provide new opportunities for financial inclusion, and mobile payment can support a sustainable business model of lending to the poor. With the remarkably rapid development of mobile payment in China, it is possible that other developing countries can also experience abrupt changes in the cashless payment market in the future. Once that occurs, the digital payment system can function as an infrastructure for credit evaluation and credit provision.

Note that an increase in credit provision to the relatively underserved does not mean that it is optimal for financial intermediation to lend to everyone who has payment data. For instance, it might not be profitable to lend to the extremely disadvantaged. In these cases, the government could potentially subsidize individuals with a fiscal transfer. My work makes a start in studying the implications of digital payments in the consumer credit market. Much more study is necessary to understand the welfare implications of public policies. .

Figures

Figure 1. Transaction Volume of Mobile and Card Payment in China and US

This figure presents the time series of the GDP-adjusted transaction volume of mobile and card payments in China and the US from 2012 to 2018. Data sources are the US Federal Reserve, the People's Bank of China (PBOC), and the World Bank.

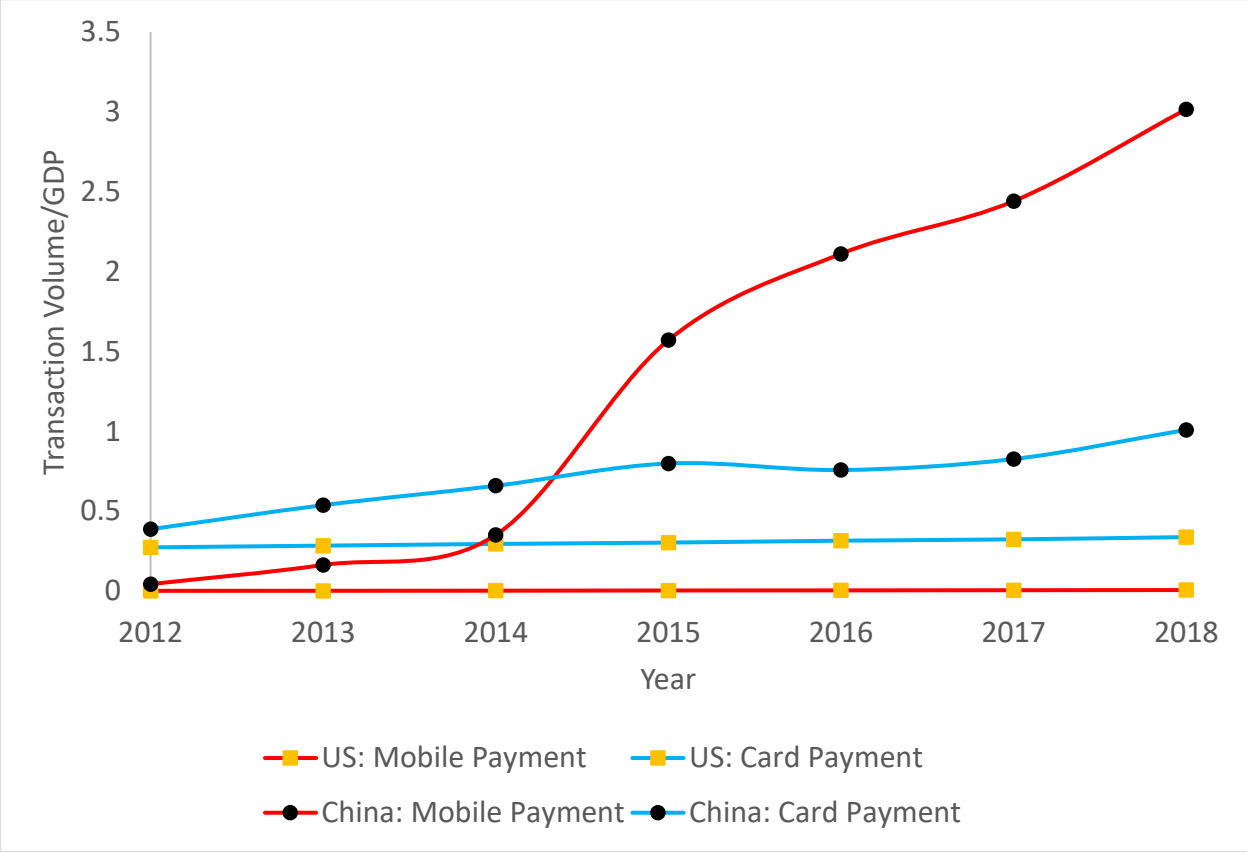


Figure 2. Logic Flow of the Instrumental Variable

This figure presents a graphical illustration of the mechanisms that show how the city-wide placement of Alipay-bundled shared bikes affects the city's residents' in-person Alipay payment at the individual level.

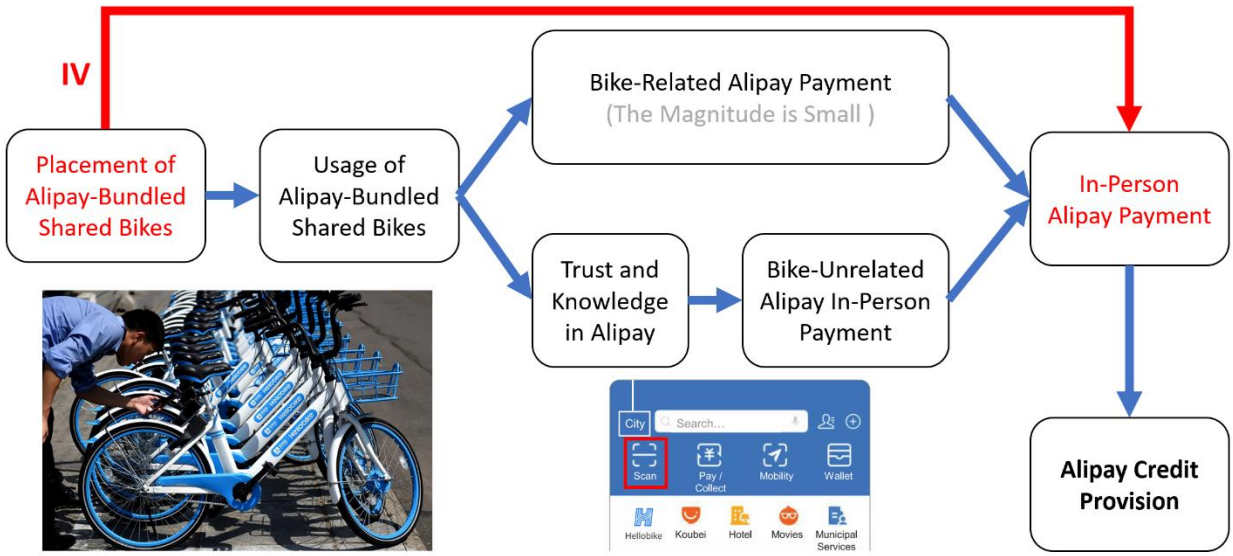


Figure 3. Bike Adoption and Non-bike Payment Flow

This figure plots the β_τ coefficients estimated in the following regression:

$$\log(1 + In\ Person\ Non\ Bike\ Payment\ Flow)_{i,t} = \alpha_0 + \sum_{\tau=-5}^{4} \beta_\tau \cdot \mathbb{I}(t = \tau) \cdot \mathbb{I}(\tau \neq -1) + \beta_5 \cdot \mathbb{I}(t \geq 5) + \delta_i + \mu_t + \varepsilon_{i,t}$$

where $\log(1 + In\ Person\ Non\ Bike\ Payment\ Flow)_{i,t}$ is the log(1+x) transformed amount of in-person payments on purchases not directly related to the usage of shared bikes by individual i at time t using Alipay, t corresponds to the number of months after each individual's month of the first usage of Alipay-bundled shared bikes, δ_i is the individual fixed effects, μ_t is the year-month fixed effects, and $\varepsilon_{i,t}$ is the error term that varies across individuals and over time. The sample covers only users who used the Alipay-bundled shared bikes at least once in the sample period, which is from May 2017 to September 2020. For each bike user, the sample only covers periods in which the t is not earlier than -5.

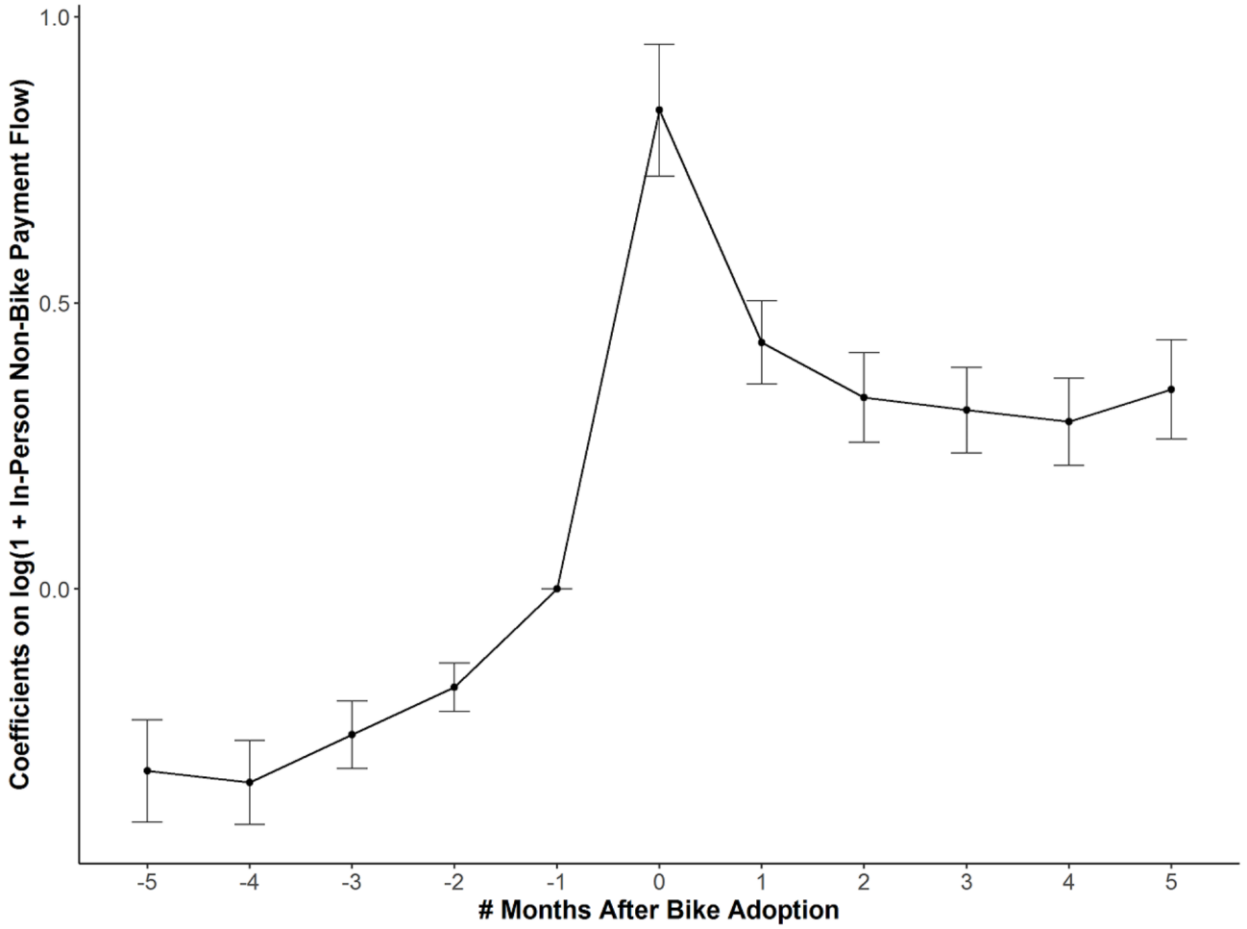


Figure 4. Staggered Placement of Shared Bikes

This figure plots the β_τ coefficients estimated in the following regression:

$$Normalized\ Bike\ Placement_{c,t} = \alpha_0 + \sum_{\tau=-5}^{4} \beta_\tau \cdot \mathbb{I}(t=\tau) \cdot \mathbb{I}(\tau \neq -1) + \beta_5 \cdot \mathbb{I}(t \geq 5) + \delta_c + \mu_t + \varepsilon_{c,t}$$

where $Normalized\ Bike\ Placement_{c,t}$ is defined as $\frac{Bike\ Placement_{c,t}}{Maximum\ Bike\ Placement\ in\ Sample_c}$, which is a measure with a range of [0,1], t corresponds to the number of months after each city's month with the largest bike placement shock, δ_c is the city fixed effects, μ_t is the year-month fixed effects, and $\varepsilon_{c,t}$ is the error term that varies across cities and over time. The sample period is from May 2017 to January 2020, which avoids the later COVID lockdown periods. For each city, the sample only covers periods in which the t is not earlier than -5.

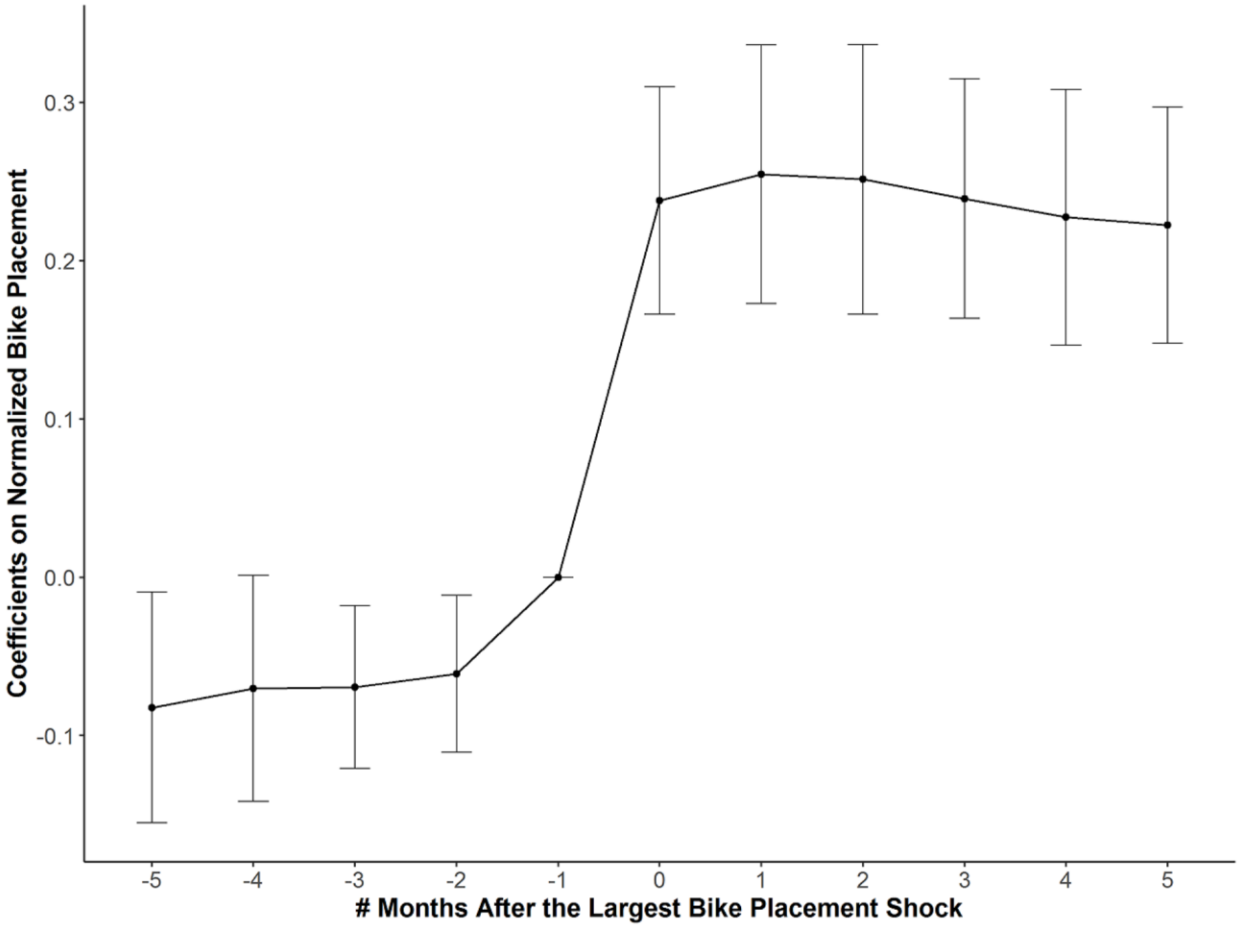


Figure 5. Broad Distribution of Bike-placement Shock

This figure describes the number of cities in the month of their largest bike-placement shock in the period from May 2017 to January 2020, before the later COVID lockdown periods.

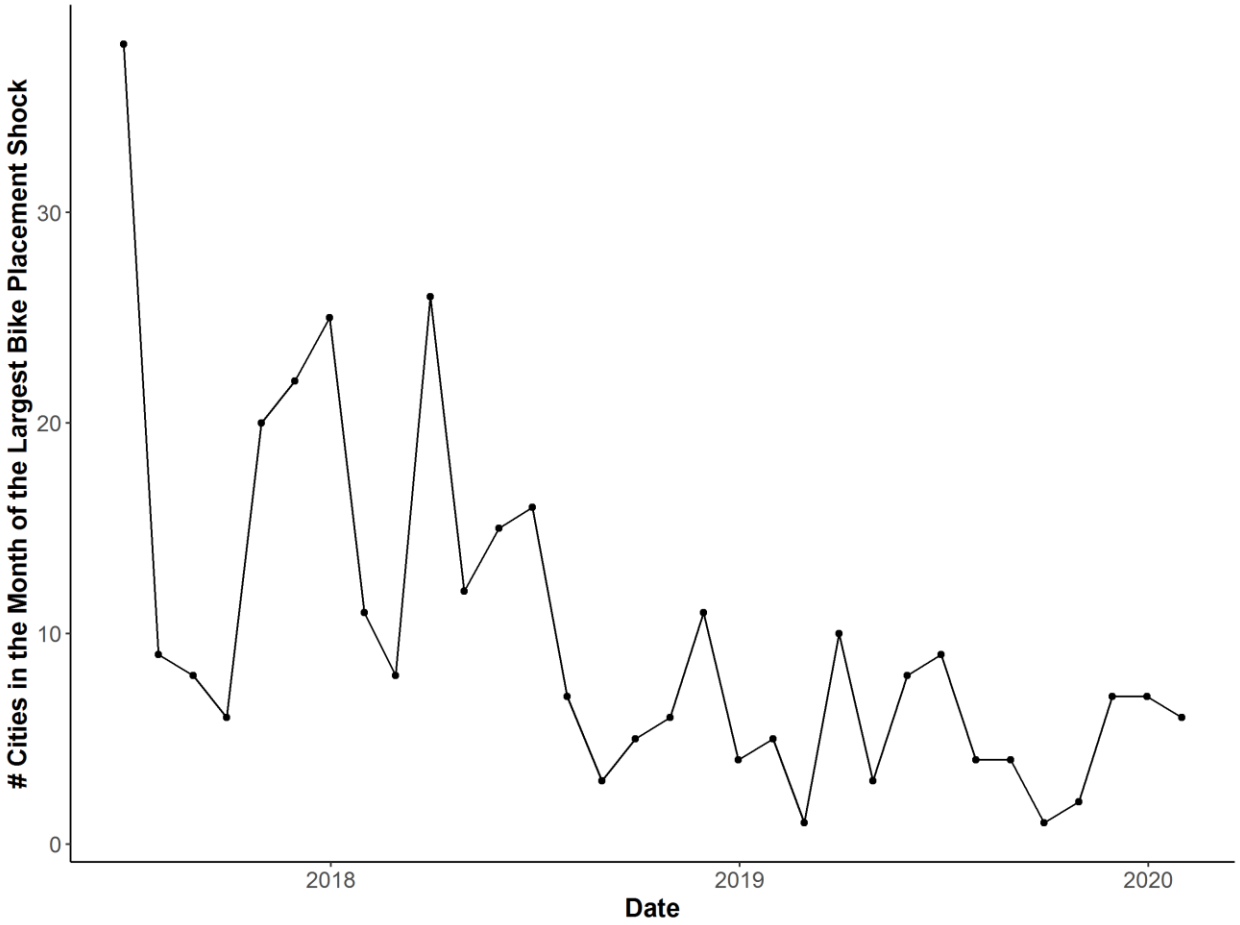
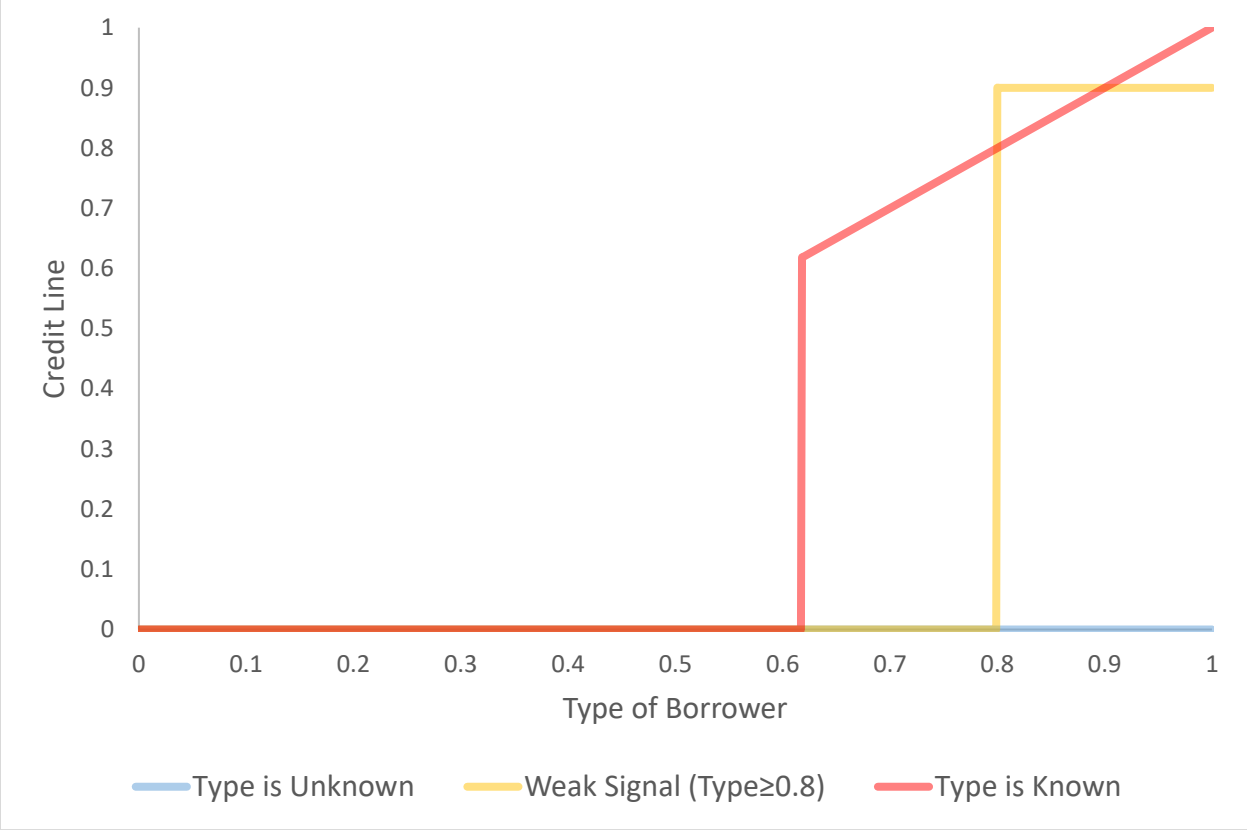


Figure 6. Example of Cashless Payment's Financial Inclusion Implication

This figure presents a graphical illustration of the credit line provided to heterogeneous borrowers in an economy with a lender and a continuum of borrowers. The expected profit of the lender from lending l_i to borrower i if it knows θ_i is:

$$\pi_i(\theta_i, l_i) = \theta_i + 2 \cdot \theta_i \cdot l_i - l_i^2 - 1$$

Given knowledge about the borrower's type, the lender chooses the optimal lending amount to maximize the expected profit if the lending is profitable. There are three scenarios in which the lender has different information sets. In the first scenario, the lender does not observe any information that reveals the type of each borrower, and the relationship between credit line and borrower type is captured by the blue line. In the second scenario, the lender receives only a signal $s(\theta_i) = \mathbb{I}(\theta_i \geq 0.8)$ about the type of each borrower, which corresponds to the yellow line in the figure. In the third scenario, the type of each borrower is precisely known by the lender, and the red line illustrates the relationship between the credit line and the borrower type.



Tables

Table 1. Summary Statistics

This table reports summary statistics of the key variables used in our analysis. The sample covers 41,485 Alipay users over 41 months from May 2017 to September 2020. The table categorizes the variables into three types at different levels. At the individual level, $\#\ Active\ Months_i$ indicates the number of months in which the user has payment activities; $Is\ Male_i$ equals 1 if the individual is male and 0 otherwise; $Low\ Education_i$ equals 1 if the individual does not have a bachelor's degree or above and 0 otherwise; $Birth\ Year_i$ records the individual's year of birth; $Bike\ User_i$ equals 1 if the Alipay user i has used a shared bike at least once during the sample period from May 2017 to September 2020. At the city-month level, $\log(Bike\ Placement)_{c,t}$ is a log transformation of the number of active shared bikes placed in city c at time t. At the individual-month level, $Credit\ Access_{it}$ is a dummy variable that indicates whether individual i is granted access to Alipay's virtual credit card at time t; $\log(Credit\ Line)_{i,t}$ measures the log-transformed credit line of the virtual credit card individual i is granted access to at time t, conditional on $Credit\ Access_{it} = 1$; $\log(In\ Person\ Payment\ Flow)_{i,t}$ is the log-transformed amount of in-person payments made by individual i at time t using Alipay; $\log(Online\ Payment\ Flow)_{i,t}$ is the log-transformed amount of online payments made by individual i at time t using Alipay; $Virtual\ Credit\ Card\ Share\ in\ In\ Person\ Payment_{i,t}$ measures the share of in-person Alipay payments made by individual i at time t using the virtual credit card; $Virtual\ Credit\ Card\ Share\ in\ Online\ Payment_{i,t}$ measures the share of online Alipay payments made by individual i at time t using the virtual credit card; $Compulsive\ Spending\ Share\ in\ In\ Person\ Payment_{i,t}$ measures the share of in-person Alipay payments made by individual i at time t for cigarettes, games, and lotteries; $Compulsive\ Spending\ Share\ in\ Online\ Payment_{i,t}$ measures the share of online Alipay payments made by individual i at time t for cigarettes, games, lotteries, or live streaming services.

	N	Mean	Std	Min	p25	Median	p75	Max
Individual Level								
# Active Months $_i$	41,485	31.86	11.38	1.00	24.00	37.00	41.00	41.00
Is Male $_i$	41,214	0.54	0.50	0.00	0.00	1.00	1.00	1.00
Low Education $_i$	41,459	0.88	0.33	0.00	1.00	1.00	1.00	1.00
Birth Year $_i$	41,214	1983.38	12.75	1930.00	1974.00	1985.00	1993.00	2014.00
Bike User $_i$	41,485	0.29	0.45	0.00	0.00	0.00	1.00	1.00
City-Month Level								
log(Bike Placement) $_{c,t}$	12,665	7.08	3.39	0.00	4.11	7.85	9.91	13.91
Individual-Month Level								
Credit Access $_{i,t}$	1,321,837	0.62	0.49	0.00	0.00	1.00	1.00	1.00
log(Credit Line) $_{i,t}$	819,812	7.88	1.58	3.00	6.91	8.13	9.13	11.02
log(In-Person Payment Flow) $_{i,t}$	688,428	5.70	2.29	-4.61	4.31	6.04	7.27	15.88
log(Online Payment Flow) $_{i,t}$	843,993	5.76	1.80	-4.61	4.70	5.88	6.93	15.74
Virtual Credit Card Share in In-Person Payment $_{i,t}$	688,428	0.34	0.42	0.00	0.00	0.04	0.82	1.00
Virtual Credit Card Share in Online Payment $_{i,t}$	843,993	0.33	0.41	0.00	0.00	0.01	0.80	1.00
Compulsive Spending Share in In-Person Payment $_{i,t}$	688,428	0.03	0.14	0.00	0.00	0.00	0.00	1.00
Compulsive Spending Share in Online Payment $_{i,t}$	843,993	0.01	0.10	0.00	0.00	0.00	0.00	1.00

Table 2. Effects of Bike Placement on Bike Usage

This table reports the effects of city-level placement of shared bikes on individual-level bike-riding activities. $\log(Bike\ Placement)_{c,t}$ is a log transformation of the number of active shared bikes placed in city c at time t. $Use\ Bike_{i,t}$ equals 1 if the Alipay user i uses the shared bike at time t and 0 otherwise. $\log(\#\ Bike\ Rides)_{i,t}$ is the log-transformed number of times individual i rides shared bikes at time t. $\log(Riding\ Distance)_{i,t}$ is the log-transformed total distance individual i rides shared bikes at time t. Column (1) focuses on the sample of bike users, which are Alipay users who have used a shared bike at least once during the sample period from May 2017 to September 2020. Columns (2) and (3) use the sample of bike users during the months they used a bike. The regressions of all columns control for both individual fixed effects and year-month fixed effects. All standard errors are clustered at city and year-month level. ***, **, and * denote the 1%, 5%, and 10% confidence level, respectively. I report standard errors in parentheses.

	$Use\ Bike_{i,t}$	$\log(\#\ Bike\ Rides)_{i,t}$	$\log(Riding\ Distance)_{i,t}$
	(1)	(2)	(3)
	Ordinary Least Squares		
$\log(Bike\ Placement)_{c,t}$	0.028***	0.102***	0.161***
	(0.003)	(0.014)	(0.040)
Individual FE	YES	YES	YES
Year-Month FE	YES	YES	YES
Clustered by City and Year-Month	YES	YES	YES
Sample	Bike Users	Bike Users, Bike Using Months	Bike Users, Bike Using Months
Observations	435,872	69,978	66,048
Adjusted R^2	0.203	0.372	0.306
Note:			*p<0.1; **p<0.05; ***p<0.01

Table 3. Effects of Bike Placement on Payment and Credit

These tables report the effects of city-level placement of shared bikes on the individual-level in-person payment flow and digital credit access. log $(Bike\ Placement)_{c,t}$ is a log transformation of the number of active shared bikes placed in city c at time t. $Bike\ User_i$ equals 1 if the Alipay user i used a shared bike at least once during the sample period from May 2017 to September 2020. $After\ First\ Bike\ Usage_{i,t}$ equals 1 after Alipay user i uses a shared bike for the first time and 0 if the individual i has never used a shared bike. log $(1 + In\ Person\ Payment\ Flow)_{i,t}$ is the log(1+x) transformed total amount of individual i's in-person payment flow through Alipay at time t, with the payment flow measured in CNY. log $(1 + Credit\ Line)_{i,t}$ is the log(1+x) transformed credit line of Alipay user i's virtual credit card at time t, with the credit line measured in CNY. Panel A reports regression results showing the effects of bike placement on in-person payment flow, while Panel B reports results showing the corresponding effects on digital credit line. In both panels, columns (1) and (2) show results for regressions with individual fixed effects and year-month fixed effects. Columns (3) and (4) show regression results that further add city times year-month fixed effects, which nest the year-month fixed effects. Columns (1), (2), and (3) use the full sample, while column (4) focuses on the sample of bike users. All standard errors are clustered at city and year-month level. ***, **, and * denote the 1%, 5%, and 10% confidence level, respectively. I report standard errors in parentheses.

Panel A. Bike Placement and Individual-level In-person Payment Flow

	log(1 + In-Person Payment Flow) $_{i,t}$			
	(1)	(2)	(3)	(4)
	Ordinary Least Squares			
log(Bike Placement) $_{c,t}$	0.041***	0.011		
	(0.010)	(0.009)		
Bike User $_i$ X log(Bike Placement) $_{c,t}$		0.103***	0.077***	
		(0.017)	(0.016)	
After First Bike Usage $_{i,t}$				0.123
				(0.161)
After First Bike Usage $_{i,t}$ X log(Bike Placement) $_{c,t}$				0.049***
				(0.014)
Individual FE	YES	YES	YES	YES
Year-Month FE	YES	YES	-	-
City X Year-Month FE	NO	NO	YES	YES
Clustered by City and Year-Month	YES	YES	YES	YES
Sample	Full Sample	Full Sample	Full Sample	Bike Users
Observations	1,238,309	1,238,309	1,238,309	435,872
F-Statistic	40.4	40.4	31.0	18.4
Adjusted R^2	0.551	0.552	0.555	0.490
Note:				*p<0.1; **p<0.05; ***p<0.01

Panel B. Bike Placement and Individual-level Digital Credit Line

	log(1 + Credit Line) $_{i,t}$			
	(1)	(2)	(3)	(4)
	Ordinary Least Squares			
log(Bike Placement) $_{c,t}$	0.027***	0.009		
	(0.008)	(0.010)		
Bike User $_{i}$ X log(Bike Placement) $_{c,t}$		0.060**	0.039	
		(0.023)	(0.027)	
After First Bike Usage $_{i,t}$				-0.231
				(0.157)
After First Bike Usage $_{i,t}$ X log(Bike Placement) $_{c,t}$				0.070***
				(0.013)
Individual FE	YES	YES	YES	YES
Year-Month FE	YES	YES	-	-
City X Year-Month FE	NO	NO	YES	YES
Clustered by City and Year-Month	YES	YES	YES	YES
Sample	Full Sample	Full Sample	Full Sample	Bike Users
Observations	1,238,309	1,238,309	1,238,309	435,872
Adjusted R^2	0.800	0.800	0.801	0.774
Note:				*p<0.1; **p<0.05; ***p<0.01

Table 4. Bike-usage Intensity and Heterogeneous Bike-placement Effects

This table reports the heterogeneous effects of city-level placement of shared bikes on the individual-level in-person payment flow and digital credit for non-bike users, one-time bike users, and repeat bike users. $\log(Bike\ Placement)_{c,t}$ is a log transformation of the number of active shared bikes placed in city c at time t. $One\ Time\ Bike\ User_i$ equals 1 if the Alipay user i used a shared bike exactly once during the sample period from May 2017 to September 2020. $Repeat\ Bike\ User_i$ equals 1 if the Alipay user i useda shared bike at least two times during the sample period from May 2017 to September 2020. $\log(1 + In\ Person\ Payment\ Flow)_{i,t}$ is the log(1+x) transformed total amount of individual i's in-person payment flow through Alipay at time t, with the payment flow measured in CNY. $\log(1 + Credit\ Line)_{i,t}$ is the log(1+x) transformed credit line of Alipay user i's virtual credit card at time t, with the credit line measured in CNY. Columns (1) and (3) show results for the regressions with individual fixed effects and year-month fixed effects, and columns (2) and (4) show regression results that further add city times year-month fixed effects, which nest the year-month fixed effects. All standard errors are clustered at city and year-month level. ***, **, and * denote the 1%, 5%, and 10% confidence level, respectively. I report standard errors in parentheses.

	log(1 + In-Person Payment Flow)$_{i,t}$		log(1 + Credit Line)$_{i,t}$	
	(1)	(2)	(3)	(4)
	Ordinary Least Squares			
log(Bike Placement)$_{c,t}$	0.011		0.009	
	(0.009)		(0.010)	
One-time Bike User$_i$ X log(Bike Placement)$_{c,t}$	0.088***	0.072***	0.048**	0.035
	(0.020)	(0.019)	(0.023)	(0.025)
Repeat Bike User$_i$ X log(Bike Placement)$_{c,t}$	0.106***	0.078***	0.062**	0.040
	(0.018)	(0.017)	(0.025)	(0.029)
Individual FE	YES	YES	YES	YES
Year-Month FE	YES	-	YES	-
City X Year-Month FE	NO	YES	NO	YES
Clustered by City and Year-Month	YES	YES	YES	YES
Observations	1,238,309	1,238,309	1,238,309	1,238,309
Adjusted R^2	0.552	0.555	0.800	0.801
Note:				*p<0.1; **p<0.05; ***p<0.01

Table 5. In-person Payment Flow and Credit Provision

This table presents empirical evidence showing the robust relationship between a user's in-person payment flow and the BigTech credit provided to the user with different specifications of the key variables, on both the extensive margin and the intensive margin. $Credit\ Access_{i,t}$ is a dummy variable that equals 1 if Alipay user i has access to Alipay's virtual credit card at time t and 0 otherwise. $\log(Credit\ Line)_{i,t}$ is the log-transformed credit line of Alipay user i's virtual credit card at time t, which is assigned a missing value if the measure $Credit\ Line_{i,t}$ is 0. $Measure\ of\ In\ Person\ Payment\ Flow_{i,t}$ is the measure of the total amount of individual i's in-person payment flow through Alipay at time t, which is defined differently in different columns. In columns (1) and (4), it is $\log(1 + In\ Person\ Payment\ Flow)_{i,t}$, where the payment flow is measured in CNY; in columns (2) and (5), it is a dummy variable that equals 1 if $In\ Person\ Payment\ Flow_{i,t}$ is positive and 0 otherwise; in columns (3) and (6), it is $\log(In\ Person\ Payment\ Flow)_{i,t}$, which is assigned a missing value if the measure $In\ Person\ Payment\ Flow_{i,t}$ is 0. $\log(Bike\ Placement)_{c,t}$ is a log transformation of the number of active shared bikes placed in city c at time t, which is assigned a missing value if $Bike\ Placement_{c,t}$ is 0. Panel A reports two-stage least-squares (2SLS) estimates, instrumenting for the individual-level measure of in-person payment flow using the city-level log number of active shared bikes; Panel B reports the corresponding first stage. Panel C reports the coefficient from an OLS regression of the dependent variable against the individual-level measure of the in-person payment flow. All columns show results for the regressions with individual fixed effects and year-month fixed effects. All standard errors are clustered at city and year-month level. ***, **, and * denote the 1%, 5%, and 10% confidence level, respectively. I report standard errors in parentheses.

	Credit Access $_{i,t}$			log(Credit Line) $_{i,t}$		
	(1)	(2)	(3)	(4)	(5)	(6)
Panel A. Two-Stage Least Squares						
Measure of In-Person Payment Flow $_{i,t}$	0.086***	0.563***	0.087**	0.281***	2.033**	0.409***
	(0.024)	(0.175)	(0.043)	(0.085)	(0.766)	(0.132)
Panel B. First Stage for Measure of In-Person Payment Flow $_{i,t}$						
log(Bike Placement) $_{c,t}$	0.041***	0.006***	0.030***	0.043***	0.006***	0.024***
	(0.010)	(0.002)	(0.009)	(0.012)	(0.002)	(0.008)
F-Statistic	40.4	28.9	14.1	31.6	22.5	13.5
Adjusted R^2	0.551	0.465	0.432	0.527	0.439	0.401
Panel C. Ordinary Least Squares						
Measure of In-Person Payment Flow $_{i,t}$	0.010***	0.062***	0.007***	0.022***	0.072***	0.029***
	(0.001)	(0.007)	(0.001)	(0.003)	(0.023)	(0.002)
Adjusted R^2	0.740	0.741	0.700	0.836	0.835	0.841
Form of the IPF Measure	log(1+x)	I (x>0)	log(x)	log(1+x)	I (x>0)	log(x)
Individual FE	YES	YES	YES	YES	YES	YES
Year-Month FE	YES	YES	YES	YES	YES	YES
Clustered by City and Year-Month	YES	YES	YES	YES	YES	YES
Sample	Full Sample	Full Sample	Full Sample	Has Credit Access	Has Credit Access	Has Credit Access
Observations	1,238,309	1,238,309	662,010	779,283	779,283	516,570

Note: *p<0.1; **p<0.05; ***p<0.01

Table 6. In-person Payment Flow and Consumer Behavior

This table presents empirical evidence showing the causal relationship between a user's in-person payment flow and the structure of the payment flows, in both the in-person payment and the online payment settings. $Virtual\ Credit\ Card\ Share_{i,t}$ measures the share of Alipay payments made by individual i at time t using the virtual credit card. $Compulsive\ Share_{i,t}$ measures the share of Alipay payments by individual i at time t on cigarettes, games, lotteries, or live streaming services. $\log\ (1\ +\ In\ Person\ Payment\ Flow)_{i,t}$ is the log(1+x) transformed total amount of individual i's in-person payment flow through Alipay at time t, with the payment flow measured in CNY. $\log\ (Bike\ Placement)_{c,t}$ is a log transformation of the number of active shared bikes placed in city c at time t. Panel A reports 2SLS estimates, instrumenting for individual-level log in-person payment flow using the city-level log number of active shared bikes; Panel B reports the corresponding first stage. Panel C reports the coefficient from an OLS regression of the dependent variable against individual-level log in-person payment flow. All columns show results for regressions with individual fixed effects and year-month fixed effects. All standard errors are clustered at city and year-month level. ***, **, and * denote the 1%, 5%, and 10% confidence level, respectively. I report standard errors in parentheses.

	Virtual Credit Card Share $_{i,t}$		Compulsive Spending Share $_{i,t}$	
	In-Person Payment	Online Payment	In-Person Payment	Online Payment
	(1)	(2)	(3)	(4)
Panel A. Two-Stage Least Squares				
log(1 + In-Person Payment Flow) $_{i,t}$	0.094***	0.030***	0.004	0.002
	(0.034)	(0.011)	(0.010)	(0.002)
Panel B. First Stage for log(1 + In-Person Payment Flow) $_{i,t}$				
log(Bike Placement) $_{c,t}$	0.028***	0.064***	0.028***	0.064***
	(0.009)	(0.014)	(0.009)	(0.014)
F-Statistic	14.2	24.1	14.2	24.1
Adjusted R^2	0.434	0.505	0.434	0.505
Panel C. Ordinary Least Squares				
log(1 + In-Person Payment Flow) $_{i,t}$	-0.009***	0.008***	0.0002	-0.0003***
	(0.002)	(0.001)	(0.000)	(0.000)
Adjusted R^2	0.472	0.480	0.216	0.222
Individual FE	YES	YES	YES	YES
Year-Month FE	YES	YES	YES	YES
Clustered by City and Year-Month	YES	YES	YES	YES
Observations	0.345 (df = 623679)	0.302 (df = 771296)	0.126 (df = 623679)	0.086 (df = 771296)
Note:				*p<0.1; **p<0.05; ***p<0.01

Table 7. In-person Noncredit Payment Flow and Credit Provision

This table presents empirical evidence showing the causal relationship between a user's in-person noncredit payment flow and the BigTech credit provided to the user, on both the extensive margin and the intensive margin. $Credit\ Access_{i,t}$ is a dummy variable that equals 1 if the Alipay user i has access to Alipay's virtual credit card at time t and 0 otherwise. $\log(Credit\ Line)_{i,t}$ is the log-transformed credit line of Alipay user i's virtual credit card at time t, which is assigned a missing value if the measure $Credit\ Line_{i,t}$ is 0. $\log(1 + In\ Person\ Noncredit\ Payment\ Flow)_{i,t}$ is the log(1+x) transformed total amount of individual i's in-person Alipay payment flow that is not paid using the virtual credit card at time t, with the payment flow measured in CNY. $\log(1 + In\ Person\ Credit\ Payment\ Flow)_{i,t}$ is the log(1+x) transformed total amount of individual i's in-person Alipay payment flow that is paid using the virtual credit card at time t, with the payment flow measured in CNY. $\log(Bike\ Placement)_{c,t}$ is a log transformation of the number of active shared bikes placed in city c at time t. Panel A reports 2SLS estimates, instrumenting for individual-level log in-person noncredit payment flow using the city-level log number of active shared bikes; Panel B reports the corresponding first stage. Panel C reports the coefficient from an OLS regression of the dependent variable against individual-level log in-person payment flow. All columns show results for regressions with individual fixed effects and year-month fixed effects. All standard errors are clustered at city and year-month level. ***, **, and * denote the 1%, 5%, and 10% confidence level, respectively. I report standard errors in parentheses.

	Credit Access $_{i,t}$		log(Credit Line) $_{i,t}$	
	(1)	(2)	(3)	(4)
Panel A. Two-Stage Least Squares				
log(1 + In-Person Noncredit Payment Flow) $_{i,t}$	0.094***	0.095***	0.329***	0.358***
	(0.024)	(0.026)	(0.103)	(0.124)
log(1 + In-Person Credit Payment Flow) $_{i,t}$		-0.005		-0.044
		(0.006)		(0.029)
Panel B. First Stage for log(1 + In-Person Noncredit Payment Flow) $_{i,t}$				
log(Bike Placement) $_{c,t}$	0.037***	0.035***	0.037***	0.031***
	(0.009)	(0.009)	(0.010)	(0.009)
log(1 + In-Person Credit Payment Flow) $_{i,t}$		0.218***		0.230***
		(0.009)		(0.007)
F-Statistic	30.0	32.0	24.2	26.4
Adjusted R^2	0.475	0.492	0.457	0.480
Panel C. Ordinary Least Squares				
log(1 + In-Person Noncredit Payment Flow) $_{i,t}$	0.006***	0.004***	0.003	-0.004*
	(0.001)	(0.001)	(0.002)	(0.002)
log(1 + In-Person Credit Payment Flow) $_{i,t}$		0.015***		0.039***
		(0.001)		(0.003)
Adjusted R^2	0.739	0.742	0.835	0.837
Individual FE	YES	YES	YES	YES
Year-Month FE	YES	YES	YES	YES
Clustered by City and Year-Month	YES	YES	YES	YES
Sample	Full Sample	Full Sample	Has Credit Access	Has Credit Access
Observations	1,238,309	1,238,309	779,283	779,283

Note: *p<0.1; **p<0.05; ***p<0.01

Table 8. In-person Payment Flow and Credit Provision, Controlling for the Collateral Proxy

This table presents empirical evidence showing the causal relationship between a user's in-person payment flow and the BigTech credit provided to the user after controlling for the time-varying asset under management (AUM), on both the extensive margin and the intensive margin. $Credit\ Access_{i,t}$ is a dummy variable that equals 1 if the Alipay user i has access to Alipay's virtual credit card at time t and 0 otherwise. $\log(Credit\ Line)_{i,t}$ is the log-transformed credit line of Alipay user i's virtual credit card at time t, which is assigned a missing value if the measure $Credit\ Line_{i,t}$ is 0. $\log(1 + In\ Person\ Payment\ Flow)_{i,t}$ is the log(1+x) transformed total amount of individual i's in-person payment flow through Alipay at time t, with the payment flow measured in CNY. $\log(1 + Asset\ under\ Management)_{i,t}$ is the log(1+x) transformed total amount of individual i's AUM on Alipay's platform at time t, with the amount measured in CNY. $\log(Bike\ Placement)_{c,t}$ is a log transformation of the number of active shared bikes placed in city c at time t. Panel A reports 2SLS estimates, instrumenting for individual-level log in-person payment flow using the city-level log number of active shared bikes; Panel B reports the corresponding first stage. Panel C reports the coefficient from an OLS regression of the dependent variable against individual-level log in-person payment flow. All columns show results for regressions with individual fixed effects and year-month fixed effects. All standard errors are clustered at city and year-month level. In columns (1) and (3) the AUM excludes the account balance of Alipay, while in columns (2) and (4) the AUM includes it. ***, **, and * denote the 1%, 5%, and 10% confidence level, respectively. I report standard errors in parentheses.

	Credit Access $_{i,t}$		log(Credit Line) $_{i,t}$	
	(1)	(2)	(3)	(4)
Panel A. Two-Stage Least Squares				
log(1 + In-Person Payment Flow) $_{i,t}$	0.097***	0.098***	0.280***	0.282***
	(0.025)	(0.026)	(0.085)	(0.086)
log(1 + Asset under Management) $_{i,t}$	-0.005	-0.008	-0.015	-0.026*
	(0.004)	(0.005)	(0.011)	(0.013)
Panel B. First Stage for log(1 + In-Person Payment Flow) $_{i,t}$				
log(Bike Placement) $_{c,t}$	0.038***	0.036***	0.043***	0.043***
	(0.010)	(0.010)	(0.011)	(0.011)
log(1 + Asset under Management) $_{i,t}$	0.147***	0.180***	0.122***	0.152***
	(0.005)	(0.005)	(0.005)	(0.005)
F-Statistic	41.5	42.3	32.4	32.8
Adjusted R^2	0.562	0.566	0.533	0.536
Panel C. Ordinary Least Squares				
log(1 + In-Person Payment Flow) $_{i,t}$	0.009***	0.008***	0.020***	0.020***
	(0.001)	(0.001)	(0.002)	(0.002)
log(1 + Asset under Management) $_{i,t}$	0.008***	0.008***	0.017***	0.014***
	(0.001)	(0.001)	(0.002)	(0.002)
Adjusted R^2	0.741	0.742	0.836	0.836
Whether AUM Include Account Balance	NO	YES	NO	YES
Individual FE	YES	YES	YES	YES
Year-Month FE	YES	YES	YES	YES
Clustered by City and Year-Month	YES	YES	YES	YES
Sample	Full Sample	Full Sample	Has Credit Access	Has Credit Access
Observations	1,220,618	1,220,618	779,283	779,283

Note: *p<0.1; **p<0.05; ***p<0.01

Table 9. Financially Underserved Segments

These tables provide evidence that the less educated and the older tend to be financially underserved in China. $Low\ Education_i$ equals 1 if the Alipay user i does not have a bachelor's degree or above and 0 otherwise. $Older\ than\ Median_i$ is a dummy variable that equals 1 if the Alipay user i is older than more than half of the users included in the sample and 0 otherwise. $\#\ Linked\ Debit\ Cards_i$ is the total number of debit cards linked to user i's Alipay account in April 2021. $\log\ (1\ +\ All\ Time\ High\ AUM)_i$ is the log-transformed highest amount of individual i's assets under management on Alipay's platform from May 2017 to September 2020. $Investment\ Experience_i$ is the number of months since the user first used Alipay's wealth management service till April 2021. $Pay\ with\ Real\ Name_i$ is a dummy variable that equals 1 if the Alipay system labels Alipay user i's account as having passed the real name verification as of April 2021 and 0 otherwise. $Use\ Own\ Account_i$ equals 1 if the Alipay system labels Alipay user i as using her own account instead of others' accounts as of April 2021 and 0 otherwise. $Complete\ Profile_i$ equals 1 if Alipay user i completes all profile information in the Alipay system as of April 2021 and 0 otherwise. $\log\ (1 + In\ Person\ Payment\ Flow)_{i,t}$ is the log(1+x) transformed amount of in-person payments made by individual i at time t using Alipay; $\log\ (1 + Online\ Payment\ Flow)_{i,t}$ is the log(1+x) transformed amount of online payments made by individual i at time t using Alipay; $In\ Person\ Share\ in\ Total\ Payment_{i,t}$ measures the share of Alipay payments made by individual i at time t that are in-person. Panel A reports regression results showing that the less educated and the older tend to have lower financial service usage and lower financial literacy, and Panel B reports regression results showing the relationship between education, age, and payment flows. In both panels, all columns show results for regressions with city fixed effects and gender fixed effects. All standard errors are clustered at the city level. ***, **, and * denote the 1%, 5%, and 10% confidence level, respectively. I report standard errors in parentheses.

Panel A. Education, Age, and Financial Activities

	Financial Service Usage			Financial Literacy		
	# Debit Cards $_i$	log(1 + Max. AUM) $_i$	# Investment Months $_i$	Pay with Real Name $_i$	Use Own Account $_i$	Complete Profile $_i$
	(1)	(2)	(3)	(4)	(5)	(6)
	Ordinary Least Squares					
Low Education $_i$	-0.694***	-1.078***	-3.076***	-0.119***	-0.087***	-0.122***
	(0.046)	(0.075)	(0.282)	(0.006)	(0.008)	(0.008)
Older than Median $_i$	-0.863***	-0.671***	-2.512***	-0.191***	-0.223***	-0.089***
	(0.025)	(0.045)	(0.141)	(0.006)	(0.009)	(0.005)
City FE	YES	YES	YES	YES	YES	YES
Gender FE	YES	YES	YES	YES	YES	YES
Clustered by City	YES	YES	YES	YES	YES	YES
Observations	39,459	39,459	39,459	39,459	39,459	39,459
Adjusted R^2	0.081	0.052	0.036	0.081	0.101	0.046
Note:						*p<0.1; **p<0.05; ***p<0.01

Panel B. Education, Age, and Payment Flows

	log(1 + In-Person Payment Flow) $_{i,t}$ (1)	log(1 + Online Payment Flow) $_{i,t}$ (2)	In-Person Share in Total Payment $_{i,t}$ (3)
	Ordinary Least Squares		
Low Education $_i$	-0.579***	-0.858***	0.049***
	(0.067)	(0.048)	(0.007)
Older than Median $_i$	-0.672***	-1.005***	0.036***
	(0.045)	(0.049)	(0.005)
City FE	YES	YES	YES
Year-Month FE	YES	YES	YES
Gender FE	YES	YES	YES
Clustered by City and Year-Month	YES	YES	YES
Observations	1,315,239	1,315,239	948,334
Adjusted R^2	0.114	0.130	0.091
Note:			*p<0.1; **p<0.05; ***p<0.01

Table 10. Education, In-person Payment Flow, and Credit Provision

This table presents empirical evidence showing the causal relationship between a user's in-person payment flow and the BigTech credit provided to the user, separately for the less educated and more educated groups, on both the extensive margin and the intensive margin. $Credit\ Access_{i,t}$ is a dummy variable that equals 1 if Alipay user i has access to Alipay's virtual credit card at time t and 0 otherwise. $\log(Credit\ Line)_{i,t}$ is the log-transformed credit line of Alipay user i's virtual credit card at time t, which is assigned a missing value if the measure $Credit\ Line_{i,t}$ is 0. $\log(1 + In\ Person\ Payment\ Flow)_{i,t}$ is the log(1+x) transformed total amount of individual i's in-person payment flow through Alipay at time t, with the payment flow measured in CNY. $\log(Bike\ Placement)_{c,t}$ is a log transformation of the number of active shared bikes placed in city c at time t. Panel A reports 2SLS estimates, instrumenting for individual-level log in-person payment flow using the city-level log number of active shared bikes; Panel B reports the corresponding first stage. Panel C reports the coefficient from an OLS regression of the dependent variable against individual-level log in-person payment flow. All columns show results for the regressions with individual fixed effects and year-month fixed effects. Columns (1) and (3) use the subsample of the less educated, who do not have a college degree or above; columns (2) and (4) use the subsample of the more educated, who have a bachelor's degree or above. All standard errors are clustered at city and year-month level. ***, **, and * denote the 1%, 5%, and 10% confidence level, respectively. I report standard errors in parentheses.

	Credit Access $_{i,t}$		log(Credit Line) $_{i,t}$	
	(1)	(2)	(3)	(4)
	Panel A. Two-Stage Least Squares			
log(1 + In-Person Payment Flow) $_{i,t}$	0.093***	0.024	0.334***	0.038
	(0.027)	(0.044)	(0.109)	(0.073)
	Panel B. First Stage for log(1 + In-Person Payment Flow) $_{i,t}$			
log(Bike Placement) $_{c,t}$	0.039***	0.043***	0.039***	0.053***
	(0.010)	(0.013)	(0.011)	(0.014)
F-Statistic	38.8	45.4	31.3	29.1
Adjusted R^2	0.544	0.563	0.528	0.483
	Panel C. Ordinary Least Squares			
log(1 + In-Person Payment Flow) $_{i,t}$	0.009***	0.013***	0.022***	0.013***
	(0.001)	(0.001)	(0.003)	(0.002)
Adjusted R^2	0.741	0.734	0.831	0.893
Individual FE	YES	YES	YES	YES
Year-Month FE	YES	YES	YES	YES
Clustered by City and Year-Month	YES	YES	YES	YES
Sample	Low Education	High Education	Low Education, Has Credit Access	High Education, Has Credit Access
Observations	1,065,769	171,938	657,878	121,194

Note: *p<0.1; **p<0.05; ***p<0.01

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Cashless Payment and Financial Inclusion

Shumiao Ouyang

Online Appendix

A1. Econometric Framework

I use an econometric framework to clarify the economic environment and the assumptions for identification.

There are three parties in the economic environment: the BigTech company that provides both cashless payment services and consumer lending; the consumers who make decisions about making in-person purchases using cashless payment; and the bike-sharing company that makes decisions about when and where to place the shared bikes.

Since the BigTech company provides cashless payment services, it has access to payment flow information and can use it for credit evaluation. Thus, the BigTech credit line provided to a consumer is a function of the consumer's cashless payment flow. For tractability, the BigTech credit provision equation is assumed to take the following form:

$$cl_{i,t} = \alpha_0 + \alpha_1 \cdot ipf_{i,t} + \delta_i + \theta_t + \varepsilon_{i,t}^{OV} + \varepsilon_{i,t}^{EE}$$

where $cl_{i,t}$ is the credit line provided by the BigTech company to individual i at time t, $ipf_{i,t}$ is the in-person payment flow of individual i at time t, δ_i and θ_t are the individual-specific and time-specific characteristics that affect the credit provision, respectively, $\varepsilon_{i,t}^{OV}$ is the omitted variables that affect the credit line of individual i at time t, and $\varepsilon_{i,t}^{EE}$ is an exogenous error term that affects the credit line of individual i at time t.

For consumers, the decision to use in-person cashless payment depends not only on their personal characteristics and the time-specific shocks, but also the credit access provided to them by the BigTech company. With a higher credit line, the individual would have a more relaxed borrowing constraint while using the mobile wallet, which allows her to make a larger amount of cashless payments. Also, if an individual expects that she would get a higher credit line on the BigTech platform by using cashless payment more frequently, she might be encouraged to seek a higher BigTech credit line. For simplicity, the in-person cashless payment decision of individual

i at time t is assumed to have a linear relationship with the credit line, and the corresponding equation is

$$ipf_{i,t} = \beta_0 + \beta_1 \cdot cl_{i,t} + \mu_i + \omega_t + \varphi_{i,t}$$

where μ_i and ω_t are the individual-specific and time-specific characteristics that affect the in-person payment flow decision, respectively. $\varphi_{i,t}$ is an exogenous error term that affects the in-person payment flow of individual i at time t.

Many Alipay-bundled bike-sharing companies could be operating in the same city. In this framework, I model all Alipay-bundled bike-sharing companies as a representative bike-sharing company. This company decides on bike placement in a city in each period by considering the number of bikes already placed in the city in the last period and the average number of times a local shared bike is used in the last period. The first measure captures the local market power in the last period and the latter measure captures the operational efficiency or return on investment (ROI) of the bike placement in the last period. I assume the bike placement decision takes the following linear form:

$$bp_{c,t} = \gamma_0 + \gamma_1 \cdot bp_{c,t-1} + \gamma_2 \cdot oe_{c,t-1} + \pi_c + \sigma_t + \vartheta_{c,t}$$

where $bp_{c,t}$ is the bike placement of the Alipay-bundled bike-sharing company in city c at time t. $oe_{c,t}$ is the operational efficiency of the placed shared bike in city c at time t, which is empirically measured by the average number of times that a shared bike in the city was used in the last period. π_c and σ_t are the city-specific and time-specific characteristics that affect the bike-placement decision, respectively. $\vartheta_{c,t}$ is an exogenous error term that affects the bike placement in city c at time t.

For simplicity, individual-specific, city-specific, and time-specific characteristics are treated as vectors of dimension one. The parameter of interest to estimate is α_1 in the credit provision equation, which captures the direct effect of in-person payment flow on the credit line provided by the BigTech company. Since the BigTech credit provision and in-person cashless payment flow are jointly determined, there are simultaneity issues, and the ordinary least squares (OLS) estimate would be biased. Assuming that $\varepsilon_{i,t}^{EE} \perp \varphi_{i,t}$, the bias of the OLS estimate is captured in the following equation:

$$\hat{\alpha}_1^{OLS} = \frac{Cov(cl_{i,t}, ipf_{i,t})}{Var(ipf_{i,t})} = \alpha_1 + \underbrace{\frac{1}{1-\alpha_1 \cdot \beta_1}}_{A} \cdot [\underbrace{\frac{Var(\delta_i + \theta_t + \varepsilon_{i,t}^{OV} + \varepsilon_{i,t}^{EE})}{Var(ipf_{i,t})} \cdot \beta_1}_{B} + \underbrace{\frac{Cov(\varepsilon_{i,t}^{OV}, \varphi_{i,t})}{Var(ipf_{i,t})}}_{C}]$$

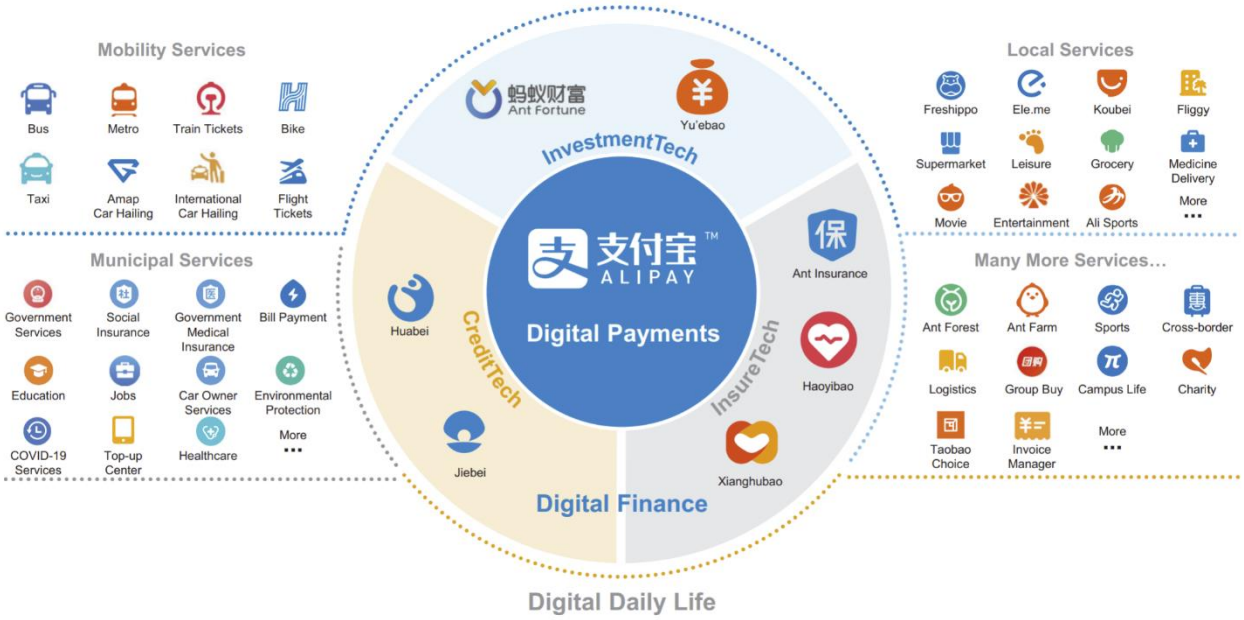
where the bias is captured by $A \cdot (B + C)$, where $A = \frac{1}{1-\alpha_1 \cdot \beta_1}$, $B = \frac{Var(\delta_i + \theta_t + \varepsilon_{i,t}^{OV} + \varepsilon_{i,t}^{EE})}{Var(ipf_{i,t})} \cdot \beta_1$, $C = \frac{Cov(\varepsilon_{i,t}^{OV}, \varphi_{i,t})}{Var(ipf_{i,t})}$.

The econometric model does not provide direct predictions about how the magnitude of the IV estimate compares with the OLS estimate, but it helps to sort out the sources of the difference between the two estimates.

It is reasonable to assume that $0 < \alpha_1 < 1$ and $0 < \beta_1 < 1$, given the synergetic relationship between the cashless payment flow and the BigTech credit provision. With these assumptions, we get $A > 0$ and $B > 0$. The sign of C is determined by the covariance between the omitted variable term in the credit provision equation and the exogenous error term in the in-person cashless payment decision equation, $Cov(\varepsilon_{i,t}^{OV}, \varphi_{i,t})$. This term could either be positive or negative, depending on the types of the omitted variables. For example, if the omitted variable is a negative shock to the individual's health condition, its covariance with the shock in the in-person cashless payment equation should be negative, since the health shock is likely to increase spending on medicine and treatment and decrease the creditworthiness of the individual. On the other hand, if the omitted variable is a positive income shock, the covariance should be positive, since the income shock is likely to increase both the level of payment flow and the magnitude of credit provision.

Figure A1. Typical Use Cases Available via the Alipay App

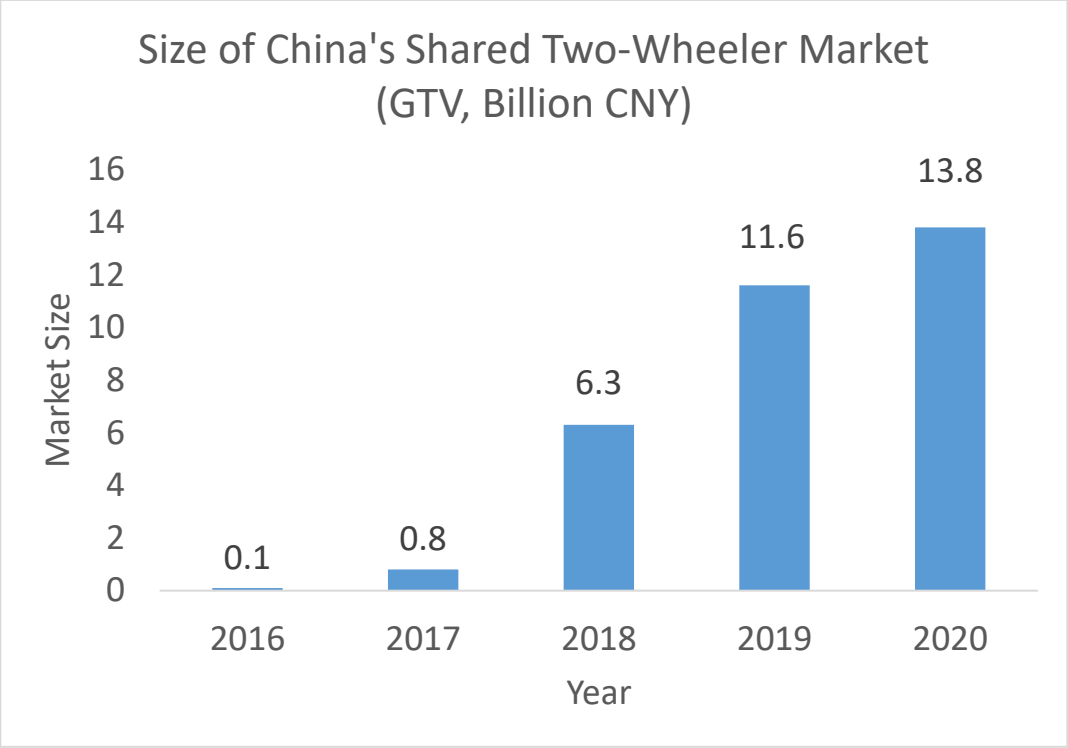
This figure describes the typical use cases that are available via the Alipay app, which cover mobility services, municipal services, local services, and other services. Alipay acts as consumers' one-stop shop for digital payment and digital financial services, including credit, investment, and insurance. There are over 1,000 daily life services and over 2 million mini-programs on Alipay.



Source: IPO Prospectus of the Ant Group, 2020

Figure A2. Development of China's Dockless Bike-sharing Industry

This figure presents the time series of the size of China's shared two-wheeler market from 2016 to 2020. Market size is measured by the gross transaction volume (GTV) in billion CNY.



Source: IPO Prospectus of Hello Inc, 2021; iResearch Report

Figure A3. Alipay Registration and Shared-bike Adoption

This bar plot presents the fraction of sampled users in four groups with different relationships between Alipay registration and bike adoption. $Adopt\ Bike\ in\ 1\ Month$ means that the user starts to use Alipay-bundled shared bikes within 1 month of registering with Alipay; $Adopt\ Bike\ in\ 2\ to\ 12\ Months$ means that the user starts to use Alipay-bundled shared bikes more than 1 month but less than 1 year after registering with Alipay; $Adopt\ Bike\ Later\ than\ 1\ Year$ means that the user starts to use Alipay-bundled shared bikes more than 1 year after registering in Alipay; $Never\ Adopt\ Bike$ means that the Alipay user has never used Alipay-bundled shared bikes during the sample period.

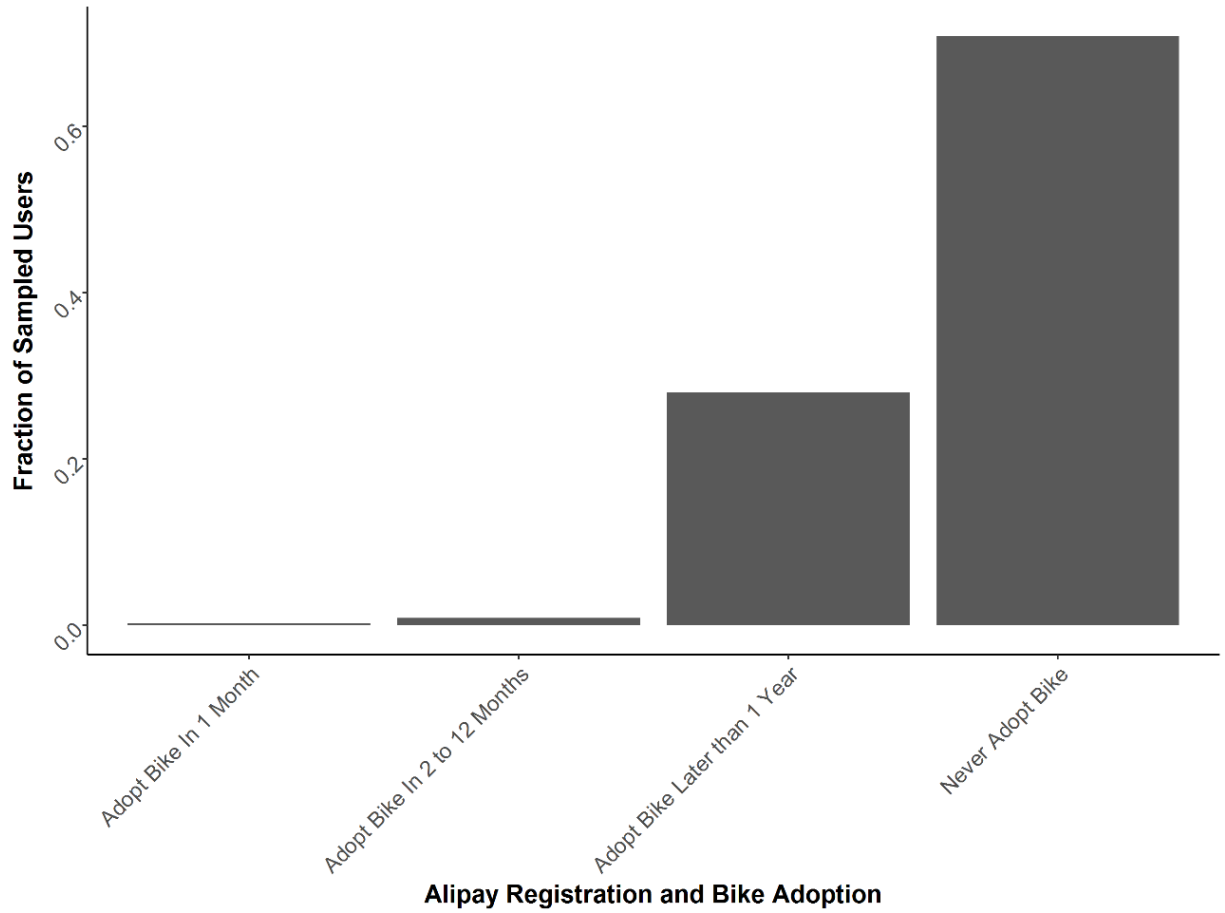


Figure A4. Evidence of the Non-monotone Payment-credit Relationship

This figure presents the fitted linear and quadratic relationship between the normalized credit line and the normalized in-person payment flow.

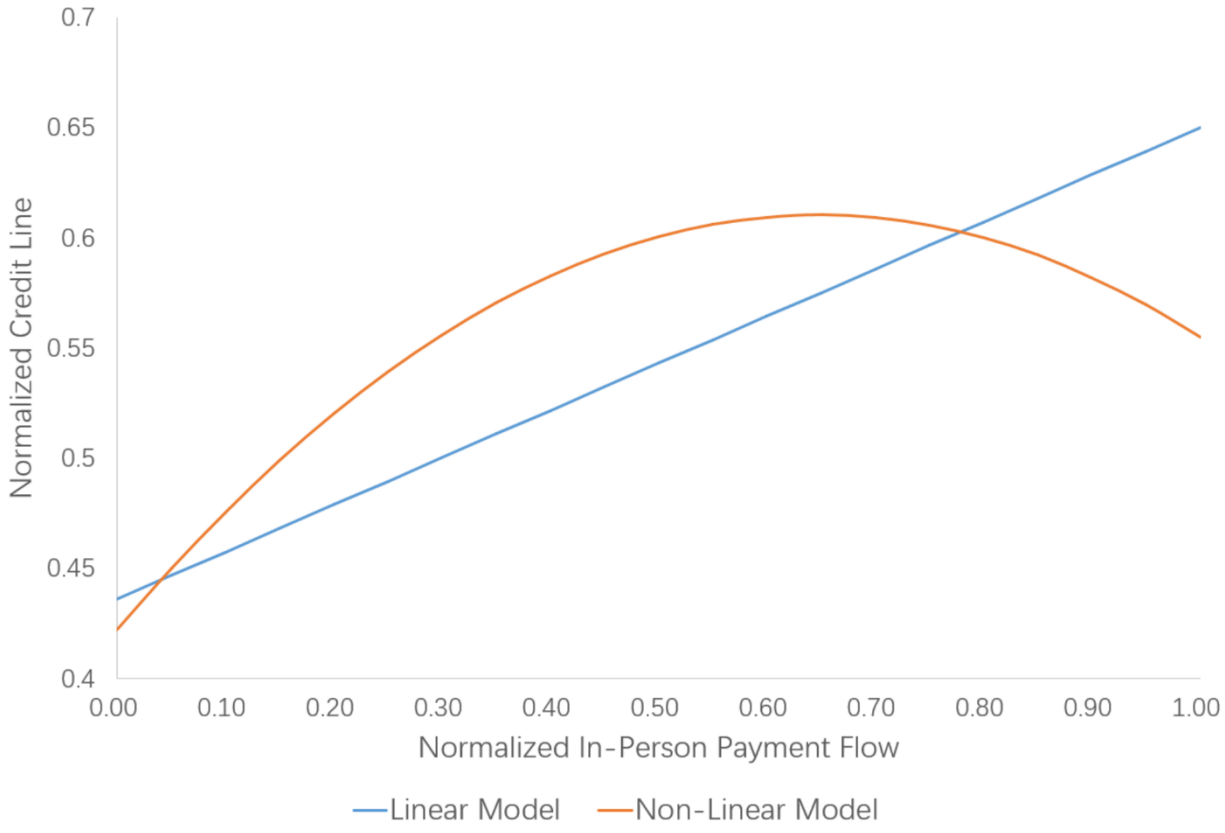


Table A1. Bike-riding Activity and Payment Flow

This table presents empirical evidence showing the relationship between a user's bike-riding activity and her cashless payment flow, both with and without bike-related spending with the cashless payment. $After\ First\ Bike\ Usage_{i,t}$ equals 1 after Alipay user i uses a shared bike for the first time and 0 if the individual i has never used a shared bike. $\log(1 + \#\ Bike\ Rides)_{i,t}$ is the log(1+x) transformed number of times individual i has used a shared bike at time t. $\log(1 + Riding\ Distance)_{i,t}$ is the log(1+x) transformed total distance individual i has traveled using a shared bike at time t, with the distance measured in kilometers. $\log(1 + In\ Person\ Payment\ Flow)_{i,t}$ is the log(1+x) transformed total amount of individual i's in-person payment flow through Alipay at time t, with the payment flow measured in CNY. $\log(1 + In\ Person\ Non\ Bike\ Payment\ Flow)_{i,t}$ is the log(1+x) transformed total amount of individual i's in-person payment flow through Alipay that is not related to spending on Alipay-bundled shared bikes at time t, with the payment flow measured in CNY. Columns (1) and (4) use the sample of users who have used shared bikes at least once and cover all their periods with activities. Columns (2), (3), (5), and (6) use the sample of users who have used shared bikes at least once, and focus on only the periods after they started using shared bikes. Regressions in all columns control for both individual fixed effects and year-month fixed effects. All standard errors are clustered at the city and year-month level. ***, **, and * denote the 1%, 5%, and 10% confidence level, respectively. I report standard errors in parentheses.

	log(1 + In-Person Payment Flow)$_{i,t}$			log(1 + In-Person Non-Bike Payment Flow)$_{i,t}$		
	(1)	(2)	(3)	(4)	(5)	(6)
	Ordinary Least Squares					
After First Bike Usage$_{i,t}$	0.694***			0.638***		
	(0.055)			(0.053)		
log(1 + # Bike Rides)$_{i,t}$		0.347***			0.286***	
		(0.015)			(0.012)	
log(1 + Riding Distance)$_{i,t}$			0.265***			0.211***
			(0.026)			(0.021)
Individual FE	YES	YES	YES	YES	YES	YES
Year-Month FE	YES	YES	YES	YES	YES	YES
Clustered by City and Year-Month	YES	YES	YES	YES	YES	YES
Sample	Bike Users	Bike Users, After First Ride	Bike Users, After First Ride	Bike Users	Bike Users, After First Ride	Bike Users, After First Ride
Observations	449,642	280,435	280,435	449,642	280,435	280,435
Adjusted R^2	0.484	0.528	0.527	0.483	0.526	0.525
Note:						*p<0.1; **p<0.05; ***p<0.01

Table A2. Personal Characteristics of Bike Users

This table reports the relationship between an individual's personal characteristics and the bike user dummy, which indicates whether she has used Alipay-bundled shared bikes at least once. $Low\ Education_i$ equals 1 if the Alipay user i does not have a bachelor's degree or above and 0 otherwise. $Older\ than\ Median_i$ is a dummy variable that equals 1 if the Alipay user i is older than more than half of the users included in the sample and 0 otherwise. $Early\ Alipay\ User_i$ is a dummy variable that equals 1 if the Alipay registration date of user i is earlier than more than half of the users included in the sample and 0 otherwise. $Is\ Male_i$ equals 1 if the individual is male and 0 otherwise. $Pay\ with\ Real\ Name_i$ is a dummy variable that equals 1 if the Alipay system labels Alipay user i's account as having passed the real-name verification test as of April 2021 and 0 otherwise. $Use\ Own\ Account_i$ equals 1 if the Alipay system labels Alipay user i as having used her own account instead of others' accounts as of April 2021 and 0 otherwise. $Complete\ Profile_i$ equals 1 if Alipay user i completes all profile information in the Alipay system as of April 2021 and 0 otherwise. $Bike\ User_i$ equals 1 if Alipay user i used shared bikes at least once during the sample period from May 2017 to September 2020. Column (1) shows the result of simple regression without other control variables, column (2) shows the result of the regression that adds city and occupation fixed effects, and column (3) shows the result of the regression that further controls for Alipay financial activity measures. These measures are $\#\ Linked\ Debit\ Cards_i$, which is the total number of debit cards linked to user i's Alipay account on April 2021, $\log(1 + All\ Time\ High\ AUM)_i$, which is the log(1+x) transformed highest amount of individual i's asset under management in Alipay platform from May 2017 to September 2020, and $Investment\ Experience_i$, which is the number of months since the user first used Alipay's wealth management service till April 2021. All standard errors are clustered at city level. ***, **, and * denote the 1%, 5%, and 10% confidence level, respectively. I report standard errors in parentheses.

	Bike User $_i$		
	(1)	(2)	(3)
	Ordinary Least Squares		
Low Education $_i$	-0.173***	-0.109***	-0.065***
	(0.009)	(0.010)	(0.009)
Older than Median $_i$	-0.095***	-0.110***	-0.096***
	(0.005)	(0.005)	(0.004)
Early Alipay User $_i$	-0.129***	-0.113***	-0.030***
	(0.007)	(0.006)	(0.005)
Is Male $_i$	0.049***	0.059***	0.045***
	(0.004)	(0.004)	(0.004)
Pay with Real Name $_i$	0.088***	0.081***	0.012**
	(0.006)	(0.005)	(0.005)
Use Own Account $_i$	0.076***	0.071***	0.033***
	(0.006)	(0.005)	(0.005)
Complete Profile $_i$	0.012*	0.001	-0.012*
	(0.007)	(0.006)	(0.006)
Constant	0.421***		
	(0.013)		
City FE	NO	YES	YES
Occupation FE	NO	YES	YES
Controls Financial Activity Measures	NO	NO	YES
Clustered by City	YES	YES	YES
Observations	39,459	39,459	39,459
Adjusted R^2	0.123	0.178	0.260
Note:			*p<0.1; **p<0.05; ***p<0.01

Table A3. Analysis of the Heterogeneous Effects of Bike Placement

This table reports the heterogeneous effects of city-level placement of shared bikes on individual-level in-person payment flow and the digital credit provided to the user. $\log(Bike\ Placement)_{c,t}$ is a log transformation of the number of active shared bikes placed in city c at time t. $Bike\ User_i$ equals 1 if Alipay user i has used shared bikes at least once during the sample period from May 2017 to September 2020. $Low\ Education_i$ equals 1 if the Alipay user i does not have a bachelor's degree or above and 0 otherwise. $Older\ than\ Median_i$ is a dummy variable that equals 1 if the Alipay user i is older than more than half of the users included in the sample and 0 otherwise. $Early\ Alipay\ User_i$ is a dummy variable that equals 1 if the Alipay registration date of user i is earlier than more than half of the users included in the sample and 0 otherwise. $Is\ Male_i$ equals 1 if the individual is male and 0 otherwise. $Pay\ with\ Real\ Name_i$ is a dummy variable that equals 1 if the Alipay system labels Alipay user i's account as having passed the real-name verification test as of April 2021 and 0 otherwise. $Use\ Own\ Account_i$ equals 1 if the Alipay system labels Alipay user i as having used her own account instead of others' accounts as of April 2021 and 0 otherwise. $\log(1 + In\ Person\ Payment\ Flow)_{i,t}$ is the log(1+x) transformed total amount of individual i's in-person payment flow through Alipay at time t, with the payment flow measured in CNY. $\log(1 + Credit\ Line)_{i,t}$ is the log(1+x) transformed credit line of Alipay user i's virtual credit card at time t, with the credit line measured in CNY. Panel A reports the results of OLS regressions in which the dependent variable is $\log(1 + In\ Person\ Payment\ Flow)_{i,t}$. Panel B reports the results of OLS regressions in which the dependent variable is $\log(1 + Credit\ Line)_{i,t}$. The $Characteristic\ Measure_i$ in each column is separately specified. Regressions in all columns control for both individual fixed effects and year-month fixed effects. All standard errors are clustered at city and year-month level. ***, **, and * denote the 1%, 5%, and 10% confidence level, respectively. I report standard errors in parentheses.

	Dependent Variable					
	(1)	(2)	(3)	(4)	(5)	(6)
Panel A. Ordinary Least Squares with Dependent Variable: log(1 + In-Person Payment Flow)$_{i,t}$						
log(Bike Placement)$_{c,t}$	-0.022	0.008	0.029**	0.021**	-0.013	-0.01
	(0.014)	(0.010)	(0.011)	(0.009)	(0.015)	(0.010)
Bike User$_i$ X log(Bike Placement)$_{c,t}$	0.139***	0.110***	0.092***	0.099***	0.057**	0.112***
	(0.029)	(0.018)	(0.017)	(0.021)	(0.025)	(0.019)
Characteristic Measure$_i$ X log(Bike Placement)$_{c,t}$	0.036**	0.004	-0.038***	-0.023**	0.033*	0.039***
	(0.017)	(0.013)	(0.012)	(0.008)	(0.019)	(0.013)
Bike User$_i$ X Characteristic Measure$_i$ X log(Bike Placement)$_{c,t}$	-0.04	-0.017	0.009	0.009	0.046**	-0.022
	(0.031)	(0.018)	(0.025)	(0.020)	(0.023)	(0.016)
Adjusted R^2	0.552	0.552	0.552	0.552	0.552	0.552
Panel B. Ordinary Least Squares with Dependent Variable: log(1 + Credit Line)$_{i,t}$						
log(Bike Placement)$_{c,t}$	0.009	0.014	0.02	0.004	-0.008	0.003
	(0.021)	(0.010)	(0.013)	(0.014)	(0.013)	(0.015)
Bike User$_i$ X log(Bike Placement)$_{c,t}$	0.051*	0.053*	0.057*	0.056**	0.049*	0.042**
	(0.030)	(0.026)	(0.029)	(0.025)	(0.029)	(0.020)
Characteristic Measure$_i$ X log(Bike Placement)$_{c,t}$	0.0001	-0.011	-0.023	0.008	0.024*	0.012
	(0.026)	(0.018)	(0.025)	(0.012)	(0.014)	(0.014)
Bike User$_i$ X Characteristic Measure$_i$ X log(Bike Placement)$_{c,t}$	0.012	0.016	-0.008	0.007	0.007	0.022
	(0.025)	(0.028)	(0.046)	(0.019)	(0.037)	(0.034)
Adjusted R^2	0.800	0.799	0.800	0.799	0.800	0.800
Measure of Personal Characteristic	Low Education$_i$	Older than Median$_i$	Early Alipay User$_i$	Is Male$_i$	Pay with Real Name$_i$	Use Own Account$_i$
Individual FE	YES	YES	YES	YES	YES	YES
Year-Month FE	YES	YES	YES	YES	YES	YES
Clustered by City and Year-Month	YES	YES	YES	YES	YES	YES
Observations	1,237,707	1,232,534	1,237,707	1,232,534	1,237,707	1,237,707

Note: *p<0.1; **p<0.05; ***p<0.01

Table A4. Bike Placement and the Local Economy

This table presents empirical evidence showing that conditional on city fixed effects and year-month fixed effects, city-level bike placement does not significantly correlate with key variables that describe local economic conditions. $\log(Bike\ Placement)_{c,t}$ is a log transformation of the number of active shared bikes placed in city c at time t. $\log(GDP)_{c,t}$ is the log of the gross domestic product (GDP) of city c at time t. $\log(GDP\ per\ capita)_{c,t}$ is the log of the GDP per capita in city c at time t. $\text{Fiscal Spending/GDP}_{c,t}$ is the ratio of local fiscal spending over the local GDP in city c at time t. $\text{Fiscal Income/GDP}_{c,t}$ is the ratio of local fiscal spending over the local GDP in city c at time t. All columns show results for the regressions with city fixed effects and year-month fixed effects. All standard errors are clustered at city and year-month level. ***, **, and * denote the 1%, 5%, and 10% confidence level, respectively. I report standard errors in parentheses.

	log(GDP) $_{c,t}$	log(GDP per capita) $_{c,t}$	Fiscal Spending/GDP $_{c,t}$	Fiscal Income/GDP $_{c,t}$
	(1)	(2)	(3)	(4)
	Ordinary Least Squares			
log(Bike Placement) $_{c,t}$	0.002	0.000	-0.001	0.000
	(0.002)	(0.002)	(0.001)	(0.000)
City FE	YES	YES	YES	YES
Year FE	YES	YES	YES	YES
Clustered by City and Year	YES	YES	YES	YES
Observations	895	775	886	891
Adjusted R^2	0.992	0.979	0.957	0.903
Note:				*p<0.1; **p<0.05; ***p<0.01

Table A5. Non-monotone Payment-Credit Relationship

This table reports the non-monotone relationship between the normalized in-person payment flow and the normalized credit line. $Normalized\ In\ Person\ Payment\ Flow_{i,t}$ is the total amount of individual i's in-person payment flow through Alipay at time t, normalized by their highest monthly in-person payment flow. $Normalized\ Credit\ Line_{i,t}$ is the credit line of Alipay user i's virtual credit card at time t, normalized by their highest credit line. Regressions in columns (1) and (2) are simple regressions without control variables, and regressions in columns (3) and (4) control for both individual fixed effects and year-month fixed effects. All standard errors are clustered at city and year-month level. ***, **, and * denote the 1%, 5%, and 10% confidence level, respectively. I report standard errors in parentheses.

	Normalized Credit Line $_{i,t}$			
	(1)	(2)	(3)	(4)
	Ordinary Least Squares			
Normalized In-Person Payment Flow $_{i,t}$	0.214***	0.581***	0.040***	0.105***
	(0.033)	(0.076)	(0.006)	(0.013)
(Normalized In-Person Payment Flow $_{i,t}$)^2		-0.448***		-0.075***
		(0.064)		(0.009)
Constant	0.436***	0.422***		
	(0.042)	(0.043)		
Individual FE	NO	NO	YES	YES
Year-Month FE	NO	NO	YES	YES
Clustered by City and Year-Month	YES	YES	YES	YES
Observations	1,030,678	1,030,678	1,030,678	1,030,678
Adjusted R^2	0.016	0.022	0.767	0.767
Note:				*p<0.1; **p<0.05; ***p<0.01

Table A6. Robustness: In-person Payment Flow and Credit Provision, Controlling for City Times Year-Month Fixed Effects

This table presents empirical evidence showing the causal relationship between a user's in-person payment flow and the BigTech credit provided to the user after controlling for city times year-month fixed effects, on both the extensive margin and the intensive margin. $Credit\ Access_{i,t}$ is a dummy variable that equals 1 if Alipay user i has access to Alipay's virtual credit card at time t and 0 otherwise. log $(Credit\ Line)_{i,t}$ is the log-transformed credit line of Alipay user i's virtual credit card at time t, which is assigned a missing value if the measure $Credit\ Line_{i,t}$ is 0. $\log(1 + In\ Person\ Payment\ Flow)_{i,t}$ is the log(1+x) transformed total amount of individual i's in-person payment flow through Alipay at time t, with the payment flow measured in CNY. log $(Bike\ Placement)_{c,t}$ is a log transformation of the number of active shared bikes placed in city c at time t. $Bike\ User_i$ equals 1 if the Alipay user i has used shared bikes at least once during the sample period from May 2017 to September 2020. Panel A reports 2SLS estimates, instrumenting for individual-level log in-person payment flow using the interaction term of individual-level bike user dummy and city-level log number of active shared bikes; Panel B reports the corresponding first stage. Panel C reports the coefficient from an OLS regression of the dependent variable against individual-level log in-person payment flow. All columns show results for regressions with individual fixed effects and year-month fixed effects. Regressions specified in columns (2) and (4) further control for individual characteristics including gender, education, occupation, and year of birth. All standard errors are clustered at city and year-month level. ***, **, and * denote the 1%, 5%, and 10% confidence level, respectively. I report standard errors in parentheses.

	Credit Access $_{i,t}$		log(Credit Line) $_{i,t}$	
	(1)	(2)	(3)	(4)
Panel A. Two-Stage Least Squares				
log(1 + In-Person Payment Flow) $_{i,t}$	0.115***	0.108***	0.398***	0.418***
	(0.004)	(0.004)	(0.016)	(0.019)
Panel B. First Stage for log(1 + In-Person Payment Flow) $_{i,t}$				
Bike User $_i$ X log(Bike Placement) $_{c,t}$	0.209***	0.178***	0.166***	0.134***
	(0.008)	(0.008)	(0.007)	(0.007)
F-Statistic	20.7	13.3	12.0	8.5
Adjusted R^2	0.168	0.190	0.147	0.173
Panel C. Ordinary Least Squares				
log(1 + In-Person Payment Flow) $_{i,t}$	0.054***	0.047***	0.147***	0.121***
	(0.001)	(0.001)	(0.004)	(0.004)
Adjusted R^2	0.193	0.245	0.181	0.363
City X Year-Month FE	YES	YES	YES	YES
Controls Individual Characteristics	NO	YES	NO	YES
Clustered by City and Year-Month	YES	YES	YES	YES
Sample	Full Sample	Full Sample	Has Credit Access	Has Credit Access
Observations	1,238,309	664,727	779,283	440,418

Note: *p<0.1; **p<0.05; ***p<0.01

Table A7. Robustness: In-person Payment Flow and Future Credit Provision

This table presents empirical evidence showing the persistent relationship between a user's in-person payment flow and the BigTech credit provided to the user, on both the extensive margin and the intensive margin. $Credit\ Access_{i,T}$ is a dummy variable that equals 1 if Alipay user i has access to Alipay's virtual credit card at time T and 0 otherwise, where T takes value of $t+1$, $t+2$, or $t+3$ respectively. $\log(Credit\ Line)_{i,T}$ is the log-transformed credit line of Alipay user i's virtual credit card at time T, which is assigned a missing value if the measure $Credit\ Line_{i,T}$ is 0, where T takes value of $t+1$, $t+2$, or $t+3$ respectively. $\log(1 + In\ Person\ Payment\ Flow)_{i,t}$ is the log(1+x) transformed total amount of individual i's in-person payment flow through Alipay at time t, with the payment flow measured in CNY. $\log(Bike\ Placement)_{c,t}$ is a log transformation of the number of active shared bikes in city c at time t. Panel A reports 2SLS estimates, instrumenting for individual-level log in-person payment flow using city-level log number of active shared bikes; Panel B reports the corresponding first stage. Panel C reports the coefficient from an OLS regression of the dependent variable against individual-level log in-person payment flow. All columns show results for regressions with individual fixed effects and year-month fixed effects. All standard errors are clustered at city and year-month level. ***, **, and * denote the 1%, 5%, and 10% confidence level, respectively. I report standard errors in parentheses.

	Credit Access $_{i,T}$			log(Credit Line) $_{i,T}$		
	t + 1	t + 2	t + 3	t + 1	t + 2	t + 3
	(1)	(2)	(3)	(4)	(5)	(6)
Panel A. Two-Stage Least Squares						
log(1 + In-Person Payment Flow) $_{i,t}$	0.088***	0.085***	0.083***	0.250***	0.242***	0.235***
	(0.023)	(0.024)	(0.024)	(0.071)	(0.069)	(0.064)
Panel B. First Stage for log(1 + In-Person Payment Flow) $_{i,t}$						
log(Bike Placement) $_{c,t}$	0.041***	0.042***	0.042***	0.048***	0.048***	0.049***
	(0.011)	(0.011)	(0.011)	(0.012)	(0.013)	(0.013)
F-Statistic	39.5	38.6	37.7	31.0	30.5	30.0
Adjusted R^2	0.552	0.553	0.554	0.523	0.522	0.521
Panel C. Ordinary Least Squares						
log(1 + In-Person Payment Flow) $_{i,t}$	0.008***	0.007***	0.006***	0.025***	0.026***	0.027***
	(0.001)	(0.001)	(0.001)	(0.003)	(0.003)	(0.003)
Adjusted R^2	0.743	0.750	0.757	0.837	0.839	0.841
Individual FE	YES	YES	YES	YES	YES	YES
Year-Month FE	YES	YES	YES	YES	YES	YES
Clustered by City and Year-Month	YES	YES	YES	YES	YES	YES
Sample	Full Sample	Full Sample	Full Sample	Has Credit Access	Has Credit Access	Has Credit Access
Observations	1,199,746	1,161,435	1,123,295	775,512	763,560	750,694

Note: *p<0.1; **p<0.05; ***p<0.01

Table A8. Robustness: In-person Payment Flow and Credit Provision, Controlling for Past Payment Flows

This table presents empirical evidence showing the relationship between a user's in-person payment flow and the BigTech credit provided to the user after controlling for past in-person payment flows, on both the extensive margin and the intensive margin. $Credit\ Access_{i,t}$ is a dummy variable that equals 1 if Alipay user i has access to Alipay's virtual credit card at time t and 0 otherwise. log $(Credit\ Line)_{i,t}$ is the log-transformed credit line of Alipay user i's virtual credit card at time t, which is assigned a missing value if the measure $Credit\ Line_{i,t}$ is 0. log $(1 + In\ Person\ Payment\ Flow)_{i,t}$ is the log(1+x) transformed total amount of individual i's in-person payment flow through Alipay at time t, with payment flow measured in CNY. log $(Bike\ Placement)_{c,t}$ is a log transformation of the number of active shared bikes placed in city c at time t. Panel A reports 2SLS estimates, instrumenting for individual-level log in-person payment flow using city-level log number of active shared bikes; Panel B reports the corresponding first stage. Panel C reports the coefficient from an OLS regression of the dependent variable against individual-level log in-person payment flow. In columns (1) and (4), all regressions control for the log in-person payment flow in the past period; in columns (2) and (5), all regressions control for the log in-person payment flow in the past two periods; in columns (3) and (6), all regressions control for the log in-person payment flow in the past three periods. All columns show results for regressions with individual fixed effects and year-month fixed effects. All standard errors are clustered at the city and year-month level. ***, **, and * denote the 1%, 5%, and 10% confidence level, respectively. I report standard errors in parentheses.

	Credit Access $_{i,t}$			log(Credit Line) $_{i,t}$		
	(1)	(2)	(3)	(4)	(5)	(6)
Panel A. Two-Stage Least Squares						
log(1 + In-Person Payment Flow) $_{i,t}$	0.139***	0.154***	0.157***	0.388***	0.457***	0.531**
	(0.038)	(0.048)	(0.056)	(0.129)	(0.167)	(0.204)
Panel B. First Stage for log(1 + In-Person Payment Flow) $_{i,t}$						
log(Bike Placement) $_{c,t}$	0.024***	0.019***	0.016***	0.027***	0.022***	0.018***
	(0.006)	(0.005)	(0.005)	(0.007)	(0.006)	(0.005)
F-Statistic	55.5	56.9	56.3	41.5	42.5	42.4
Adjusted R^2	0.636	0.647	0.651	0.596	0.605	0.608
Panel C. Ordinary Least Squares						
log(1 + In-Person Payment Flow) $_{i,t}$	0.007***	0.006***	0.006***	0.015***	0.012***	0.010***
	(0.001)	(0.001)	(0.001)	(0.002)	(0.002)	(0.002)
Adjusted R^2	0.743	0.751	0.759	0.837	0.840	0.842
Controls log(1 + In-Person Payment Flow) $_{i,t-1}$	YES	YES	YES	YES	YES	YES
Controls log(1 + In-Person Payment Flow) $_{i,t-2}$	NO	YES	YES	NO	YES	YES
Controls log(1 + In-Person Payment Flow) $_{i,t-3}$	NO	NO	YES	NO	NO	YES
Individual FE	YES	YES	YES	YES	YES	YES
Year-Month FE	YES	YES	YES	YES	YES	YES
Clustered by City and Year-Month	YES	YES	YES	YES	YES	YES
Sample	Full Sample	Full Sample	Full Sample	Has Credit Access	Has Credit Access	Has Credit Access
Observations	1,199,825	1,161,573	1,123,548	775,601	763,711	750,940

Note: *p<0.1; **p<0.05; ***p<0.01

Table A9. Robustness: In-person Payment Flow and Credit Provision, Controlling for Bike Usage

This table presents empirical evidence showing the relationship between a user's in-person payment flow and the BigTech credit provided to the user after controlling for bike usage, on both the extensive margin and the intensive margin. $Credit\ Access_{i,t}$ is a dummy variable that equals 1 if Alipay user i has access to Alipay's virtual credit card at time t and 0 otherwise. log $(Credit\ Line)_{i,t}$ is the log-transformed credit line of Alipay user i's virtual credit card at time t, which is assigned a missing value if the measure $Credit\ Line_{i,t}$ is 0. log $(1 + In\ Person\ Payment\ Flow)_{i,t}$ is the log(1+x) transformed total amount of individual i's in-person payment flow through Alipay at time t, with the payment flow measured in CNY. log $(Bike\ Placement)_{c,t}$ is a log transformation of the number of active shared bikes placed in city c at time t. Panel A reports 2SLS estimates, instrumenting for individual-level log in-person payment flow using the city-level log number of active shared bikes; Panel B reports the corresponding first stage. Panel C reports the coefficient from an OLS regression of the dependent variable against individual-level log in-person payment flow. All columns show results for regressions with individual fixed effects and year-month fixed effects. All the standard errors are clustered at the city and year-month level. In columns (1) and (3), the measure of bike usage is the number of bike rides, while in columns (2) and (4) it is the riding distance measured in kilometers. ***, **, and * denote the 1%, 5%, and 10% confidence level, respectively. I report standard errors in parentheses.

	Credit Access $_{i,t}$		log(Credit Line) $_{i,t}$	
	(1)	(2)	(3)	(4)
Panel A. Two-Stage Least Squares				
log(1 + In-Person Payment Flow) $_{i,t}$	0.098***	0.097***	0.329***	0.329***
	(0.030)	(0.030)	(0.112)	(0.112)
log(1 + Measure of Bike Usage) $_{i,t}$	-0.034**	-0.028**	-0.112**	-0.094**
	(0.015)	(0.012)	(0.048)	(0.041)
Panel B. First Stage for log(1 + In-Person Payment Flow) $_{i,t}$				
log(Bike Placement) $_{c,t}$	0.034***	0.034***	0.036***	0.036***
	(0.010)	(0.010)	(0.011)	(0.011)
log(1 + Measure of Bike Usage) $_{i,t}$	0.497***	0.391***	0.408***	0.324***
	(0.022)	(0.030)	(0.021)	(0.027)
F-Statistic	40.9	40.8	32.0	31.9
Adjusted R^2	0.554	0.554	0.530	0.529
Panel C. Ordinary Least Squares				
log(1 + In-Person Payment Flow) $_{i,t}$	0.010***	0.010***	0.021***	0.022***
	(0.001)	(0.001)	(0.003)	(0.003)
log(1 + Measure of Bike Usage) $_{i,t}$	0.010***	0.007***	0.015***	0.007*
	(0.002)	(0.001)	(0.005)	(0.004)
Adjusted R^2	0.740	0.740	0.836	0.836
Measure of Bike Usage	# Bike Rides	Riding Distance	# Bike Rides	Riding Distance
Individual FE	YES	YES	YES	YES
Year-Month FE	YES	YES	YES	YES
Clustered by City and Year-Month	YES	YES	YES	YES
Sample	Full Sample	Full Sample	Has Credit Access	Has Credit Access
Observations	1,238,309	1,238,309	779,283	779,283
Note:				*p<0.1; **p<0.05; ***p<0.01

Table A10. Robustness: In-person Payment Flow and Credit Provision, Controlling for Online Payment

This table presents empirical evidence showing the relationship between a user's in-person payment flow and the BigTech credit provided to the user after controlling for online payment, on both the extensive margin and the intensive margin. $Credit\ Access_{i,t}$ is a dummy variable that equals 1 if the Alipay user i has access to Alipay's virtual credit card at time t and 0 otherwise. $\log(Credit\ Line)_{i,t}$ is the log-transformed credit line of Alipay user i's virtual credit card at time t, which is assigned a missing value if the measure $Credit\ Line_{i,t}$ is 0. $\log(1 + In\ Person\ Payment\ Flow)_{i,t}$ is the log(1+x) transformed total amount of individual i's in-person payment flow through Alipay at time t, with the payment flow measured in CNY. $\log(Bike\ Placement)_{c,t}$ is a log transformation of the number of active shared bikes placed in city c at time t. Panel A reports 2SLS estimates, instrumenting for individual-level log in-person payment flow using the city-level log number of active shared bikes; Panel B reports the corresponding first stage. Panel C reports the coefficient from an OLS regression of the dependent variable against individual-level log in-person payment flow. All columns show results for regressions with individual fixed effects and year-month fixed effects. All standard errors are clustered at the city and year-month level. In columns (1) and (3), the measure of online payment is the online payment flow measured in CNY, while in columns (2) and (4) it is the number of online transactions. ***, **, and * denote the 1%, 5%, and 10% confidence level, respectively. I report standard errors in parentheses.

	Credit Access $_{i,t}$		log(Credit Line) $_{i,t}$	
	(1)	(2)	(3)	(4)
Panel A. Two-Stage Least Squares				
log(1 + In-Person Payment Flow) $_{i,t}$	0.086***	0.085***	0.280***	0.277***
	(0.023)	(0.023)	(0.085)	(0.082)
log(1 + Measure of Online Payment) $_{i,t}$	-0.009	-0.028	-0.037*	-0.107*
	(0.006)	(0.017)	(0.021)	(0.054)
Panel B. First Stage for log(1 + In-Person Payment Flow) $_{i,t}$				
log(Bike Placement) $_{c,t}$	0.041***	0.042***	0.043***	0.044***
	(0.010)	(0.010)	(0.012)	(0.012)
log(1 + Measure of Online Payment) $_{i,t}$	0.260***	0.716***	0.246***	0.649***
	(0.007)	(0.015)	(0.008)	(0.018)
F-Statistic	43.8	44.1	33.8	34.0
Adjusted R^2	0.572	0.574	0.544	0.545
Panel C. Ordinary Least Squares				
log(1 + In-Person Payment Flow) $_{i,t}$	0.008***	0.008***	0.018***	0.018***
	(0.001)	(0.001)	(0.002)	(0.002)
log(1 + Measure of Online Payment) $_{i,t}$	0.011***	0.027***	0.027***	0.061***
	(0.001)	(0.002)	(0.003)	(0.007)
Adjusted R^2	0.742	0.742	0.837	0.836
Measure of Bike Usage	Online Payment Flow	# Online Transactions	Online Payment Flow	# Online Transactions
Individual FE	YES	YES	YES	YES
Year-Month FE	YES	YES	YES	YES
Clustered by City and Year-Month	YES	YES	YES	YES
Sample	Full Sample	Full Sample	Has Credit Access	Has Credit Access
Observations	1,238,309	1,238,309	779,283	779,283

Note: *p<0.1; **p<0.05; ***p<0.01

Table A11. Age, In-person Payment Flow, and Credit Provision

This table presents empirical evidence showing the causal relationship between a user's in-person payment flow and the BigTech credit provided to the user, separately for older and younger groups, on both the extensive margin and the intensive margin. $Credit\ Access_{i,t}$ is a dummy variable that equals 1 if the Alipay user i has access to Alipay's virtual credit card at time t and 0 otherwise. log $(Credit\ Line)_{i,t}$ is the log-transformed credit line of Alipay user i's virtual credit card at time t, which is assigned a missing value if the measure $Credit\ Line_{i,t}$ is 0. log $(1 + In\ Person\ Payment\ Flow)_{i,t}$ is the log(1+x) transformed total amount of individual i's in-person payment flow through Alipay at time t, with the payment flow measured in CNY. log $(Bike\ Placement)_{c,t}$ is a log transformation of the number of active shared bikes placed in city c at time t. Panel A reports 2SLS estimates, instrumenting for individual-level log in-person payment flow using the city-level log number of active shared bikes; Panel B reports the corresponding first stage. Panel C reports the coefficient from an OLS regression of the dependent variable against individual-level log in-person payment flow. All columns show results for regressions with individual fixed effects and year-month fixed effects. Columns (1) and (3) use the subsample of older people, who are older than more than half of the individuals in the sample; columns (2) and (4) use the subsample of younger people, who are not older than half of the individuals in the sample. All standard errors are clustered at city and year-month level. ***, **, and * denote the 1%, 5%, and 10% confidence level, respectively. I report standard errors in parentheses.

	Credit Access $_{i,t}$		log(Credit Line) $_{i,t}$	
	(1)	(2)	(3)	(4)
	Panel A. Two-Stage Least Squares			
log(1 + In-Person Payment Flow) $_{i,t}$	0.124***	0.047**	0.440**	0.176**
	(0.041)	(0.020)	(0.177)	(0.065)
	Panel B. First Stage for log(1 + In-Person Payment Flow) $_{i,t}$			
log(Bike Placement) $_{c,t}$	0.032***	0.049***	0.030**	0.054***
	(0.010)	(0.012)	(0.011)	(0.013)
F-Statistic	39.3	39.5	33.4	28.2
Adjusted R^2	0.552	0.539	0.559	0.483
	Panel C. Ordinary Least Squares			
log(1 + In-Person Payment Flow) $_{i,t}$	0.009***	0.011***	0.017***	0.026***
	(0.001)	(0.001)	(0.003)	(0.002)
Adjusted R^2	0.739	0.740	0.833	0.847
Individual FE	YES	YES	YES	YES
Year-Month FE	YES	YES	YES	YES
Clustered by City and Year-Month	YES	YES	YES	YES
Sample	Older than Median	Younger than Median	Older than Median, Has Credit Access	Younger than Median, Has Credit Access
Observations	577,711	654,823	335,670	443,402
Note:				*p<0.1; **p<0.05; ***p<0.01