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 about 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 brings exogenous variations to the payment flow. I find that the use of in-person payment in a month increases the likelihood of getting 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 having 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, especially extending credit access to them. The overhead costs are high compared with the small loan size and the information asymmetry is severe between lenders and borrowers. Despite these frictions, both the public and private sectors have continuously proposed 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 the better collection and usage of rich data (Agarwal et al., 2021; Berg et al., 2020), the more advanced credit risk models (Fuster et al., 2019, 2020), and financial accounts that are more accessible (Ouma et al., 2017), partially solve these limitations. But nothing is like the cashless mobile payment, which naturally makes good use of these advancements altogether. [2] Can it become the silver bullet and bring new opportunities to facilitate lending to the traditionally underserved? If yes, 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 goal is quite challenging, and cannot be directly achieved by doing a prediction exercise with historical data or implementing a field experiment. The former suffers from the manipulation critique raised by Bjorkegren et al. (2020), and the latter usually engages a small population and runs for a limited time. To deal with the empirical challenges, I combine a natural experiment and the rich administrative data of a representative sample on the Alipay platform. Alipay is the largest

[2] First, the payment records are by-products of daily purchases, which are rich, high-frequency, and manipulation-proof. Second, the providers of cashless payment not only master the most advanced machine learning and artificial intelligence technologies but also have the data that help with the model training and fully empower the predictive credit risk models. Third, the mobile phone is being widely adopted globally, lowering the adoption cost of mobile payment, and making it accessible to almost everyone.

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 in both the extensive and the intensive margins. This effect occurs through the channel that Alipay makes good use of the creditworthiness information in the payment flow.

My study builds on two observations, the fast development of China's cashless payment and the rise of consumer lending by FinTech and BigTech companies in China. First, China's cashless payment, especially the in-person mobile payment, achieves its large success in less than a decade, during which period China has drastically shifted from a cash economy to a cashless economy. As of 2019, China's mobile payment leads in both the user penetration rate and the income-adjusted annual transaction value per user.[3] Figure 1 shows that from 2012 to 2018, the annual transaction volume of China's mobile payment increased from 4% of its GDP to 302% of its GDP, while the corresponding measure of the US's card payment stayed below 34% of its 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. [4] Second, at the same time, China has also become the largest market for both FinTech credit and BigTech credit, where Alipay is the leading service provider (Cornelli et al., 2020). *Huabei* credit line, which is a virtual credit card product provided by Alipay, has become 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% of them have access to a *Huabei* credit line, among 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 the users who do not have a bank-issued credit card on file, 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 on the cashless payment activity. Second, I need detailed individual-level data on payment, credit, and investment, as well as information on their sociodemographic conditions. Third, I need to take out the credit demand

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

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

factors from the observed credit line in order to focus on the credit supply. I address the first challenge by leveraging a natural experiment that provides exogenous variation to 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 use the same scanning procedure in Alipay and rely on trusting Alipay. To address the second challenge, I base my analysis on the administrative data from Alipay, which cover a representative sample and contain detailed information about their personal characteristics and their daily activities -- consumption, credit access and usage, investment, shared-bike usage, and other relevant digital footprints. The linked household behaviors are measured in monthly frequency and recorded as individual-level panel data. A feature of the *Huabei* credit line helps me to address the third challenge. Different from a traditional credit card, it requires no active application, and consumers directly know their qualification status and the approximate credit line. This feature allows me to identify the credit provision effect from the supply side, which is immune from the endogenous credit application motives from the demand side (Brown et al., 2011; Han et al., 2009).

I develop multiple tests to confirm the validity of the staggered placement of Alipay-bundled shared bikes in different cities as the instrument. I show that it satisfies both the relevance condition and the restriction exclusion. The relevance condition requires a strong first-stage relationship between the city-level bike placement and the in-person payment flow of Alipay users living in the city. Evidence strongly supports 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 restriction exclusion condition requires that the bike placement affects the credit provision only through the in-person cashless payment. I provide evidence to rule out the potential concerns about the city-level common factors correlated with both the bike placement and the credit provision, the direct credit-revealing effects of the bike usage, and the mechanical effects of the bike placement process.

The empirical findings are articulated around three parts in the study. In the first part, 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. In 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. In 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 accompanied 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. Indeed, I find that more in-person payment flow leads to more take-up of the credit, both in the in-person and the online settings. A 1% increase in the in-person cashless payment flow leads to the increase in the share paid with 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 collateral channel. I find large differences in the channels relied on by Alipay, a typical BigTech firm, and the traditional banks. Since most banks do not have access to the payment flow information of the daily purchases, they usually rely on the credit bureau's information of the credit usage and repayment, or the information revealed by the borrower in the application process. While the self-reported information is unavailable for Alipay, it relies heavily on the information in the payment flow. I show that this channel holds even when the information in the credit usage and repayment is controlled. On the collateral side, banks can offer secured loans with explicitly pledged assets, while this is not an option for Alipay. I use the consumer's asset under management on Alipay as a proxy for the collateral, since Alipay can potentially freeze the account. I find that the payment flow information channel still holds when I control 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 on financial inclusion. I find that the financially underserved get more credit access after the in-person cashless payment adoption. 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. The less educated and the older have fewer financial activities and lower financial literacy. I find that they also have a higher share of in-person transactions in total transactions. The exogenous increase in the in-person cashless payment flow results in an increase in the 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 payment data accumulated in the digitalization. Digital payment products, including debit cards and mobile payments, can reduce transaction costs, monitoring costs, and travel costs, further leading to 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 explored by the literature. My paper is also the first to take advantage of the nudge effect of digital service usage and use 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 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 the consumer credit provision because they allow the BigTech firm to take advantage of the information contained in the digital payment flow, which is beyond what is in credit usage, repayment, and assets under management. Thus, my paper is also related to the discussion in data sharing and digital demand (Chen et al., 2021), information channel in credit provision (N. Bachas, 2019; Chatterjee et al., 2020; He et al., 2021; Liberti & Petersen, 2019; Tang, 2019), and collateral channel in credit market (Gambacorta et al., 2020; Kiyotaki & Moore, 1997; Mian & Sufi, 2011).

My paper also adds to the literature that investigates the linkage between innovations and financial inclusion. For example, studies have looked at the effect of mobile financial services on saving by the poor (Ouma et al., 2017), the use of secure payments infrastructure to help the government implement the antipoverty programs (Muralidharan et al., 2016), and digital banking on the minimum-payment penalties (Choi and Loh, 2019). 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 the consumers and merchants, especially for the 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 shows supportive evidence for this argument, where cashless payment facilitates credit provision to the underserved and increases the credit take-up. An emerging literature use prediction exercises to show the great potentials of digital footprints (Agarwal et al., 2021; Berg et al., 2020) and machine learning models (Di Maggio et al., 2021; Fuster et al., 2020) in credit evaluation and financial inclusion. My paper complements these studies by showing the financial inclusion implications of in-person cashless payment in the real business environment.

There is emerging literature on the relationship between digital payment and digital credit. Berg et al. (2021) provide an extensive review on 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 that empirically shows the causal effects of payment flow information on facilitating consumer credit provision. A recent theoretical paper by Parlour et al. (2020) studies a model on the competition between financial intermediations for payment processing, where the important premise of the analysis is that payment flow data contain information about the credit quality of the consumers. My paper provides evidence that directly supports the paper's premise about the informativeness of each consumer's payment flow. Another closely linked paper is by Ghosh et al. (2021), where they uncover the synergy between FinTech small-business lending and cashless payments with both theoretical and empirical analyses. Instead of analyzing the lending to firms, my paper focuses on lending to consumers. I show that the consumers are less strategic than the firms in the decision of adopting cashless payment, and even a small nudge of digital service usage can lead to a large shift in the long-run choice of payment instruments. The setup difference results in opposite predictions. Their theory suggests that the better firms benefit more from the cashless payment adoption due to the information-revealing effect, while 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 about the Alipay platform and the dockless bike-sharing industry in China. Section II describes the data, and Section III explains the research design and provides evidence about the validity of the instrumental variable. The main empirical results are in Section IV, where I analyze the relationship between cashless payment flow, credit provision, and financial inclusion. I conclude in Section V.

I. Institutional Background

China's mobile payment system is quite different from the mobile-phone-based payment system relying on SMS text messages, like M-PESA, or the card-complementing mobile payment system, such as Apple Pay or Google Pay. It is based on the so-called "super apps," most notably Alipay and WeChat Pay, which provide an all-in-one digital experience to users with both in-house services and integrated third-party services. The research studies mobile payment in China by analyzing the proprietary data of Alipay.

A. The Alipay Platform

Alipay is a third-party mobile and online payment platform launched by Alibaba Group in China in 2004. As of late 2020, it has drawn together over one billion users, 80 million merchants, and over 2,000 partner financial institutions for digital payment and digital financial services, including unsecured consumer credit. 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. Alipay has always been the principal means by which buyers transact with sellers on Alibaba's platforms since its launch. Since 2016, it has grown explosively in both the number of users and the 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 WeChat Pay to pay for almost everything, including taxi, bills, e-commerce purchases, and even purchases from small street vendors. Alipay has become a platform that enables merchants and consumers to complete transactions across almost all online and in-person payment use cases. It also acts as a one-stop-shop for digital payment, digital finance services, and a broad range of daily life services. Using Alipay, a consumer can access over 1,000 daily life services and over two million mini programs that provide mobility services, local services, municipal services, and many other services, without needing to download other apps.

Figure A1 provides a picture that is taken from the prospectus of Ant Group and describes the typical use cases available via the Alipay app. In the eyes of Ant Group, the foundation of all the services is the digital payment. Based on it, other digital financial services, including consumer credit, wealth management, and insurance, are provided to the users. 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 research, I measure Alipay's credit provision with the access to and the credit line of *Huabei*. 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 could be accessed only on the Alipay platform. Unlike the traditional credit card that requires filling out an application form and then waiting for the decision about credit access and a credit line, Alipay users know in real-time whether they qualify for *Huabei* and roughly how high 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 it offers consumers an interest-free period of up to 40 days after the corresponding purchases. Consumers have the option to pay in monthly installments over 3 to 12 months at the purchase or after the interest-free period. From July 2019 to June 2020, the majority of *Huabei* users' daily interest rate was 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 is *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 the GPS-tracked dockless bikes to users of its bike-sharing app (Cao et al., 2018).

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

Since late 2015, the bike-sharing industry in China has attracted investments from venture capital (VC) funds and BigTech firms[5], and has gone through exponential growth (Figure A2). According to the 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 percent of the market in total.

There were rises and falls among the bike-sharing service providers. *ofo* was the first player in the bike-sharing industry and used to dominate the industry, however, it faced a large amount of unpayable debt later, and was no longer operating bike rentals as of 2020. On the other hand, *Hellobike* was a small bike-sharing provider in 2017, but has 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, the size of the non-cash retail payments in China is less than RMB 50 trillion, where almost all of them are debit card or credit card transactions. At that time, in-person mobile payment services like Alipay or WeChat Pay took only a tiny fraction of all the non-cash retail transaction volume. The market size of in-person mobile payments grew gradually at the beginning and took off quickly after 2016. As of 2019, the size of non-cash retail payments in China became greater than 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 WeChat Pay, and both parties have invested lots of resources and money to expand the market size and gain market share.

One strategic move of the mobile wallets is to partner with the bike-sharing companies since the digital payment system can act as the infrastructure of the bike-sharing services. Meanwhile,

[5] The dominant companies in the information technology (IT) industry.

the high-frequency usage of bike-sharing services, in turn, can encourage users to adopt the mobile wallet for other payments in daily life.

Because of the synergistic effect between the digital payment and the bike-sharing services, Alibaba and Ant Group invested more than 0.5 billion dollars in *ofo* and more than 3 billion dollars in Hellobike, where *ofo* was once the largest player and Hellobike is the current largest player in the bike-sharing industry. In return, these bike-sharing services are deeply bundled with Alipay. Taking advantage of the mini-programs within the Alipay system, Alipay users could unlock the shared bikes by scanning the QR code on the bike with Alipay directly, without downloading the specific bike-sharing app or filling in personal information manually to register. This relationship is exclusive -- a WeChat user is unable to unlock a shared bike operated by Hellobike directly with TenPay. What is more, for the Alipay users who have a high enough credit score in Alipay's credit scoring system, the deposit for using the shared bikes could be waived. According to the IPO prospectus of Hello Inc, "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, we see booms in both the bike-sharing market and the mobile payment market. 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 the Alipay users living in different cities.

II. Data Description

It has always been challenging to get 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 the proprietary panel data in the individual and year-month level from Ant Group, which contains detailed information on not only broad activities including payment and credit, but also rich personal characteristics.

The main dataset used in the study is panel data that include randomly selected 41,485 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 the 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 is the city-level panel data of 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 are at the individual level. The sample covers 41,485 Alipay users. The average user in the sample was born in 1983, having 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 the sampled users do not have a bachelor's or higher degree. And 29% of users have rode Alipay-bundled shared bikes at least once in the sample period. The second set of measures are at the city and year-month level. In the average month of the sample, the average city has a log transformed number of placed shared bikes of 7.08. The third set of variables are at the 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, 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 with 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.

III. Research Design

There are several endogeneity issues in addressing the causal relationship between cashless payment and credit provision. For example, simultaneity can arise when there exists a synergy between the adoption of cashless payment and the credit provision by the payment service provider (Ghosh et al., 2021) or some factors that affect the payment and credit at the same time. There can also exist omitted variables that potentially bias the estimates.

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

A. Preliminary Analysis

This subsection provides some direct empirical evidence supporting the story illustrated in Figure 2. I use the placement of Alipay-bundled shared bikes across cities as a novel instrumental variable to solve the endogeneity issues. While Alipay, the mobile payment leader in China, grew fast in the past few years, there were also staggered placements of Alipay-bundled shared bikes across different cities, which brought exogenous shocks to the 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 the bike users, which motivates them to use Alipay more frequently to unlock the bikes by scanning the QR codes on the bikes. This frequent usage of Alipay nudges users to develop trust in Alipay and be comfortable using Alipay 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 procedures.

I provide direct evidence for the logic flow illustrated above, which can be used as sanity checks. First, I show that when more Alipay-bundled shared bikes are placed in the city, individuals living in the city have higher bike riding activity. Second, I show that after an individual adopts the shared bikes, her in-person payment flows, unrelated to the bikes, are likely to increase abruptly.

Table 2 presents OLS estimates from regressions that focus on the sample of Alipay users who have used the shared bike at least once in the sample period, and Columns (2) and (3) focus on the months that the bike users have bike using activity. The results show the positive relationship between the city-level placement of shared bikes and the individual-level usage of shared bikes in both the extensive margin and the intensive margin. The estimates suggest that, in the extensive margin, for the sampled bike-riding Alipay users living in city c, having a 1% increase in the city-level bike placement of city c in month t increases a user's probability of using shared bikes by

0.028%. In the intensive margin, for the bike users in the months with bike using activity, the 1% increase in the bike placement in month t leads to an increase of the bike user's number of bike rides by 0.082% and an increase of her total distance of bike rides by 0.120% in month t. When more bikes are placed in a city, looking for an available shared bike becomes easier for the bike users, and they are expected to have higher bike riding activity. In addition, as Cao et al. (2018) address, since the dockless bike-sharing system is a one-sided network with positive network effects, there might also exist indirect effects, where more bike riding activity of one user also increases others' bike riding activity. Both the direct and indirect channels lead to the 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 bike adoption on the 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 the in-person payment flow that is unrelated to the usage of Alipay-bundled shared bikes. It uses an event study framework, where 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 usage 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:

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

where δ_i represents the city fixed effects and μ_t represents the year-month fixed effects. For each bike user, the sample only covers the periods where its event time t is not earlier than -5. Compared with the benchmark month, the in-person non-bike payment flow increases by more than 80% in the month of the bike adoption and stays at a level above 30% more of 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 the bike adoption suggests that it is the usage of Alipay-bundled shared bikes that leads to a shift in the payment habits. Otherwise, the change should not be so abrupt around the heterogeneous bike adoption date of users, especially under the individual and the 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 caused by sharply changing the level of consumption after the bike adoption. Note that, this is not mechanically driven by the people who register Alipay just to gain access to the Alipay-bundled shared bikes. As Figure A3 shows, the vast majority of the sampled Alipay users either adopt the 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% users start to use the 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 indicating that the city-level bike placement is a valid instrument for the individual-level in-person cashless payment and satisfies both the relevance condition and the exclusion restriction condition. First, I find a strong relationship between the bike placement in a city and the in-person cashless payment flow of the Alipay users living there. Second, I show that the bike placement is likely to affect the Alipay credit provision only through the in-person cashless payment.

The Relevance Condition

There are concerns that the city-level bike placement might not be a strong instrument for the 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 the bike placement acts as an exogenous shock to the Alipay users' in-person payment through the nudge effect mentioned in the preliminary analysis.

Panel A of Table 3 shows the effects of city-level placement of shared bikes on the individual-level in-person payment flow. Column (1) indicates 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 the individual and the year-month fixed effects are controlled and when the standard errors are double clustered by city and year-month levels. The 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 the year-month fixed effects can capture the time-varying determinants of in-person payment activity, such as the workday effects and the holiday effects. With the F-statistic being as high as 40.7 and the t-statistic of the coefficient estimate being 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 the bike placement and in-person payment flow only exists for the bike users, but not for the users who have never used Alipay-bundled shared bikes. This result can be regarded as a placebo test supporting the view that it is the bike placement that affects Alipay users' in-person payment through bike usage. And it makes sense that for the non-bike users, especially those who do not know how to ride a bike, no matter how many shared bikes are placed around them, their payment activities should not be directly impacted. This test also helps rule out the stories that the positive relationship is driven by some unobserved common factors that affect the whole population in the local area, e.g. local growth potentials or local infrastructure plans, that correlate with the city's bike placement and the city residents' in-person payment flow at the same time.

Column (3) shows the results of the regression with a specification that further adds the city times year-month fixed effects, which remove every 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. The identification of the coefficient relies on comparing the in-person payment flow of the bike users in response to the bike placement relative to that of a control group of non-bike users within the same city, with the static characteristics of the individuals controlled at the same time. For the bike users, a 1% increase in bike placement leads to a 0.077% increase in the in-person payment flow.

The intensive margin analysis also supports the mechanism that bike placement exogenously affects in-person payment flow through bike usage. The differences in the response of in-person payment flow to the bike placement do not only exist between the bike users and non-bike users, but also exist before and after the 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 the bike users and controls for the individual fixed effects and the city times year-month fixed effects. Without the variation of bike placement, the bike adoption decision itself does not have a significant effect on the in-person payment flow, which alleviates the concerns about the selection issues in the endogenous timing of the bike adoption. After the bike adoption of the bike users, a 1% increase in the bike placement results in a 0.051% increase in the in-person payment flow.

The Exclusion Restriction Condition

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

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

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

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

Column (4) focuses on the bike users and reports the result of the regression with individual fixed effects and the city times year-month fixed effects. Although the timing of the bike adoption is endogenous, the dummy variable indicating whether the bike user has adopted the shared bikes does not imply a higher credit line, suggesting that the timing itself does not play an important role in the 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 can argue that bike users and non-bike users have very different characteristics, and it is these associated characteristics instead of the bike usage itself that lead to the difference in the reduced-form effect of the bike placement on the credit provision. To rule out this channel, I first screen the personal characteristics strongly associated with the bike user classification, then check the heterogeneous effects of bike placement on the credit provision along these dimensions. Table A2 shows the regression results on the relationship between personal characteristics and the choice of becoming a bike user. Across different specifications, there are indeed several personal characteristics correlated with the bike user dummy, including education, age, Alipay experience, gender, and the indicators of whether paying with the real name or whether using the own account. Table A3 reports the heterogeneous effects of bike placement on the 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 where the dependent variable is $\log(1 + In\ Person\ Payment\ Flow)_{i,t}$, while Panel B shows the corresponding results where 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 the specifications, the heterogeneity mostly comes from the dimension of the bike user dummy. These suggest that it is the bike usage associated behaviors instead of the selection issue that matters most in the effects of bike placement on the in-person payment flow and credit provision. It is unlikely that the bike users are a special group of individuals who benefit from the shock in 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 the 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 necessary for bike usage. Second, the cost of bike usage is very low, which makes 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 these 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 which the group of bike users is unlikely to be very selective. The size of the user base of shared bikes 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 the bike usage is more like a nudge for the payment activity and the credit line, instead of a proof of creditworthiness. I separate the 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 the 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 the bike placement has no significant effect on the in-person payment flow and the credit line of the non-bike users, but has strong positive effects on the payment and credit of the one-time bike users, even though the difference between these two groups is just one bike riding activity. Moreover, although the effects are stronger for the repeat bike users, the difference in the effects between the one-time bike users and the repeat bike users is relatively small. Columns (2) and (4) indicate that the patterns are very robust, even when the city times year-month fixed effects are added in the specification.

The third concern is about the bike placement process. If it is a predictable process or is clustered in a short period for all the cities, it is more likely that it will correlate with other factors that are associated with the credit provision. From the perspectives of the bike-sharing companies, it is more beneficial for them to make the bike placement a staggered and unpredictable process, and the empirical evidence supports this point. There is anecdotal evidence that what the bike-sharing companies care most about are the local competition and their own operational efficiency, and this could lead to their heterogeneous overall strategies. For example, bike-sharing companies such as Mobike and *ofo* focused mostly on the big cities at the beginning and gradually expanded to the smaller cities, while Hellobike started the bike placement in the small cities first to avoid the competition and then gradually expanded to the larger. No matter what cities they decide to target first, bike-sharing companies always have an incentive to quickly place the shared bikes in the local market because it helps them build local market power and avoid the competitors who may react strategically. Since capacity constraints for bike production exist, it is not feasible to put bikes into all the targeted cities in a very short timeframe.

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

$$\begin{aligned} &Normalized\ Bike\ Placement_{c,t} \\ &\quad = \alpha_0 + \sum_{\tau=-5}^{4} \beta_\tau \cdot \mathbb{1}(t=\tau) \cdot \mathbb{1}(\tau \neq -1) + \beta_5 \cdot \mathbb{1}(t \geq 5) + \delta_c + \mu_t \\ &\quad + \varepsilon_{c,t} \end{aligned} \quad \textbf{(2)}$$

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 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, avoiding the later COVID lockdown periods. For each city, the sample only covers the periods where the t is not earlier than -5. The figure shows that the magnitude of the largest monthly bike placement shock is large, which is on average around 25% of the maximum bike placement of the city during the sample period. The normalized bike placement on average rises about 10% of the maximum bike placement in the two months immediately before the event of the largest monthly bike placement shock. This pattern of bike placement is consistent with the strategic concerns of the bike-sharing companies. To deal with the fierce competition in the bike-sharing industry, once a company decides to enter the city, it is likely to place a lot of bikes in a short period to build up the local market power.

At the same time, the timing of the bike placement shock is hard for the 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 of each city's bike placement is distributed broadly over the sample period. This is consistent with the view that there are some capacity constraints of bike production and bike allocation. In that sense, placing shared bikes is like playing chess, where the players target different cities during different periods, and once they decide about the targeted cities, they place lots of bikes in a very short time frame. Since the 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 the shocks of the placement of Alipay-bundled shared bikes using just the public information.

The fourth concern is about the impact of bike placement shock on the local economy. Since dockless shared bikes bring lots of convenience to the users and the number of bike users is large, some might worry that the bike placement brings new business opportunities and affect the local economy or fiscal policy, which further leads to the increase in the credit provision. Table A4 shows the relationships between the bike placement and the variables associated with the local economic condition. Under the city fixed effects and the year-month fixed effects, the coefficients for all the specifications are small and insignificant, indicating that bike placement is unlikely to have some macroeconomic impacts.

IV. Empirical Results

This section first presents the results of the main specification that investigates the causal effect of in-person cashless payment flow on the BigTech credit provision and the consumer take-up of the credit. Then, it shows the importance of the payment information channel in facilitating the BigTech credit provision. Finally, it illustrates the implications of in-person cashless payment flow for financial inclusion, where the traditionally financially underserved has some relative advantage in 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 the credit provision from the BigTech, I estimate the effect with the two-stage least squares regressions. In the first stage, the log-transformed in-person payment flow is instrumented with the log-transformed city-level bike placement:

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

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

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

And the corresponding ordinary least squares regression is with the following specification:

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

where $\log(bp)_{ct}$ is the log-transformed bike placement in city c at time t, $g(ipf)_{it}$ is the transformed measure of 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), where Panel A reports the estimated effects in the second stage of the 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 which equals 1 if the Alipay user i has access to Alipay's virtual credit card at time t, and equals 0 otherwise. Columns (4), (5), and (6) focus on the intensive margin and use only the sample where the 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, which is measured in CNY; in columns (2) and (5), it is the dummy variable indicating whether the in-person payment flow is positive; in column (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 the specifications include the individual and year-month fixed effects. The granular fixed effects tightly control for heterogeneity across individuals as the effect of the 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 getting credit access for an average Alipay user and a 203.3% increase in the credit line for a user currently with credit access in the same month. Among 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 getting credit access for an average Alipay user and a 0.409% increase in the credit line for a user currently with 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 in Stock & 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) the 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 affects the in-person payment flow because of the treatment and medicine spending. Second, the non-monotone relationship between the credit provision and the in-person cashless payment flow can also lead to the 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 makes the borrower seem riskier and leads to a reduction of the BigTech credit provision. Empirical evidence supporting 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 where the city times year-month fixed effects are added, and the interaction between bike user indicator and log-transformed bike placement is used as the instrument. It shows that even when the unobserved time-varying heterogeneity across cities is removed, the in-person payment flow shock still leads to more credit provision. Table A7 illustrates that the in-person payment flow also affects future credit provision. Table A8 reports results of the regressions controlling for the in-person payment flow in the past one, two, or three 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 the credit provision are still robust with similar magnitude across different specifications.

Consumer Take-Up of the BigTech Credit

The credit access and the credit line discussed in the previous section are fully determined by the supply side since no active application is required for the Alipay users to use the virtual credit card, and they know directly about the credit access and credit line by checking the account. The real effects of the changes of credit provision also depend on the demand side, that is, the consumer take-up of the BigTech credit. It is natural to anticipate that more in-person payment flow leads to a higher fraction of spending paid with the virtual credit card, both in-person and online, for two reasons. The first reason is the learning-by-doing channel, where people are more likely to use the virtual credit card when they have more knowledge about Alipay and more trust with Alipay. The second reason is the supply-side channel, where 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 about the consumer credit take-up. With an exogenous increase in the in-person payment flow, the share that is paid with

Alipay's virtual credit card increases for both the in-person payment and the online payment. The magnitude of the increase is larger for the in-person payment.

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

B. The Payment Information Channel

Channels for Credit Provision

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

The information channels include:

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

The 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 the borrowers in the credit application form (channel 1.3) plays an important role before the borrower gets the credit access, and the information in the credit usage and repayment behaviors (channel 1.2) becomes the most important channel for reducing information asymmetry after the borrower gets the credit access. For secured loans such as the mortgage, 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 a default (channel 2.2).

The BigTech company that provides the cashless payment service to the borrowers has some advantage in the information flow channel (channel 1.1), where the rich information in the payment flows reveal valuable information about the borrower's creditworthiness. In the specific setting of Alipay, there is no application process required for accessing the virtual credit card and the explicit pledge of collateral is not an option, thus channels 1.3 and 2.2 are unlikely to contribute to Alipay's credit provision. Instead, the information in the credit usage and repayment (channel 1.2) can be important, and the borrower's AUM in the wealth management platform of Alipay (channel 2.1) might act like collateral to facilitate credit provision since the borrower might worry that there are some account freezes 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 the credit provision by Alipay and show that the channel holds strongly while channels 1.3 and 2.2 are unavailable and channels 1.2 and 2.1 are controlled.

Control for the Credit Use and Repayment Information Channel

With the Alipay app, the users have several options to make in-person and online payments. Within the Alipay platform, they can use the e-wallet account balance, a liquid money market fund called "Yu'ebao," or the virtual credit card called "Huabei." Although Alipay also supports payments using debit card or credit card accounts for some of the merchants, most of the transactions in the Alipay platform are paid 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 using the Alipay virtual credit card, and this payment flow is directly associated with credit usage and is highly relevant for the credit repayment flow. All the other in-person payment flow is defined as the "in-person noncredit payment flow," which does not have direct relationships with credit usage and repayment.

Table 7 shows the results of the 2SLS and OLS regressions with similar specifications of equations (3), (4), and (5) while replacing the in-person payment flow with the in-person noncredit payment flow, which excludes the in-person Alipay payment flow paid with the virtual credit card. This exclusion helps get rid of the effects of credit use and repayment on the BigTech credit provision. Columns (1) and (3) show that the in-person noncredit payment flow has direct effects on the BigTech credit provision, indicating 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 the credit usage and repayment. To alleviate the 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 the 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 the credit provision, both in 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, indicating that the in-person noncredit payment has larger effects than the credit payment. This result is reasonable since the usage of credit directly leads to a heavier repayment burden and riskier consumer profile, while the usage of 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 in the Alipay platform, the user's asset 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 in 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 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 the assets in Alipay except for the account balance, while columns (2) and (4) use the definition as all Alipay assets including the account balance. No matter in which specification, the AUM does not have a strong relationship with the credit provision variables, while the in-person payment flow has strong effects on the credit provision in both the extensive margin and the intensive margin.

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

A Theoretical Illustration of the Effects of Cashless Payment Shock

From a cash economy to a cashless economy, the digitalization of the payment system can result in more information acquisition by the digital payment service provider and further facilitates credit provision. For many of the developing countries, it might happen in two steps. The banks lead the first step by issuing cards and installing point-of-sale (POS) terminals. Since these banks are not very advanced and 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 led by the BigTech companies, which have more advanced technology, charge lower intermediation costs, and make it possible to cover a larger population, especially the previously financially underserved. The wide adoption of the BigTech payment system can be regarded as a positive shock to information acquired by financial intermediation about each customer in the overall population. This process of payment digitalization can have financial inclusion implications, making it possible for relatively poorer people to have credit access.

To capture the intuition of how the 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 the borrower i follows a uniform distribution between 0 and 1, that is, $\theta_i \sim U[0,1]$. Given the type of the 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 paying back will depend on the type, the lending amount, and the interest rate. To simplify the specification, I assume that the expected profit function has 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, while above which the expected profit decreases with the lending amount. Third, given the borrower type, if the optimal lending amount is nonzero, it strictly increases with the borrower type. With this specific 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 type in the population. This captures the feature of the cash economy that the transactions are not well-recorded, and there is a lack of information about the type of each borrower.

In the second scenario, the lender knows a weak signal of 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, making the signal imprecise and unable to further distinguish the exact type of borrowers with a positive signal.

In the third scenario, the lender knows the exact type of each borrower. This is a case where the smartphone-based payment system operated by the BigTech company covers almost all types of customers and merchants, and the recorded cashless transactions make 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 the 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 the 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 of the lending. Comparing the second scenario with the first scenario, the weak signal helps the lender extend more credit, and this effect is concentrated on the high-type borrowers. In the third scenario, the intermediation has the precise information of each borrower's type, which enables it to make the optimal lending for each borrower type separately. In this specification, the optimal lending decision is to not lend to the borrowers with type $\theta_i \leq \frac{\sqrt{5}-1}{2}$, and lend $l^*(\theta_i) = \theta_i$ to the 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 is about financial inclusion, where some of the previously underserved borrowers in the second scenario ($\frac{\sqrt{5}-1}{2} < \theta_i < 0.8$) now get access to the credit in the third scenario. The second difference is about personalization, where the 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 gives two general predictions about the credit provision in response to the positive information shock brought 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 the credit provision induced by the adoption shock is more concentrated for the borrowers with relatively lower types. That is, the new information from the cashless payment flow is more valuable for the underserved segment to reduce the information asymmetry.

The previous section provides empirical evidence supporting 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 the complete financial activities of the sampled Alipay users are not observable, making it hard to evaluate their overall financial access, I use their activeness in using Alipay financial services as a proxy for their overall financial access. By analyzing their financial behaviors in 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 results of the cross-sectional regressions exploring the relationship between users' financial activities in Alipay and their personal characteristics. The less educated and the older groups tend to have less Alipay financial activities. They have 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 about how sampled users' education and age relate to the measures of financial literacy. Less educated and older users tend to have a smaller likelihood of paying with their real names, using their own accounts instead of the 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 the consumer lending decisions of the borrowers in the Alipay system, they tend to deliver negative signals about the borrowers' creditworthiness since these behaviors are aligned with the normal standard.

The 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 the cashless payment in the in-person setting. Making cashless payments in the online shopping setting can be difficult for users with less digital literacy, and it requires users' knowledge about searching for goods, communicating with strange sellers, and building trust with the multiple parties involved in the process. Instead, once the mobile wallets have been set up, making in-person cashless payments are not very different from, if not more convenient than, purchasing goods with cash.

Panel B of Table 9 illustrates the relationship between personal characteristics and the 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 the online part. Thus, the financially underserved have some 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 of 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 the credit provision. The less educated and the older previously have had fewer alternative data to prove their creditworthiness, 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 about people's creditworthiness is larger for the previously financially underserved, and it is reasonable to expect that they will benefit more from the shock and get more 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, both in the extensive margin and the intensive margin. Panel B shows that, no matter for which education group, the first stage is always quite strong, meaning the bike placement shock consistently increases the in-person cashless payment flow of both the less and more educated. The second stage results in Panel A reveal that the effects of in-person payment flow on the credit provision are quite different for the Alipay users with different educational levels. The positive relationship only exists for the less educated group and becomes insignificant for the more educated group, both in the extensive margin and the intensive margin. For the less educated group, an increase of in-person payment flow by 1% leads to an increase of probability to get the credit access by 0.095% and an increase of the credit line by 0.335% conditional on the credit access. The corresponding numbers for the more educated groups are 0.027% in the extensive margin and 0.035% in 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 the age groups. In 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, where the former effect is 1.8 times larger. The case is similar in the intensive margin, where the effect of the order group is 1.6 times larger than that of the younger. This is consistent with the previous analysis. The older group is previously underserved by the financial intermediation, and the adoption shock of in-person cashless payment helps them more, and 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 to even the ones who are previously financially unserved or underserved. In the transition from a cash economy to a cashless economy, the users naturally accumulate their payment records while using digital payment services. This paper shows that the payment data can become 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 the endogeneity issues and provide several tests to prove the instrument's validity.

I also find that the previously financially underserved benefit more from mobile payment adoption and 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 some relative advantage in revealing their creditworthiness in the in-person cashless payment flow, thanks to the low costs and wide coverage of the mobile payment.

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 development of mobile payment being so fast in China, it is possible that other developing countries can see abrupt changes in the cashless payment market in the future. Once that happens, the digital payment system can function as an infrastructure for credit evaluation and credit provision.

Note that an increase in the credit provision to the relatively underserved does not mean it is optimal for financial intermediation to lend to everyone who has payment data. 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 on studying the implication 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. The sources of the data include the US Federal Reserve, the People's Bank of China (PBOC), and the World Bank.

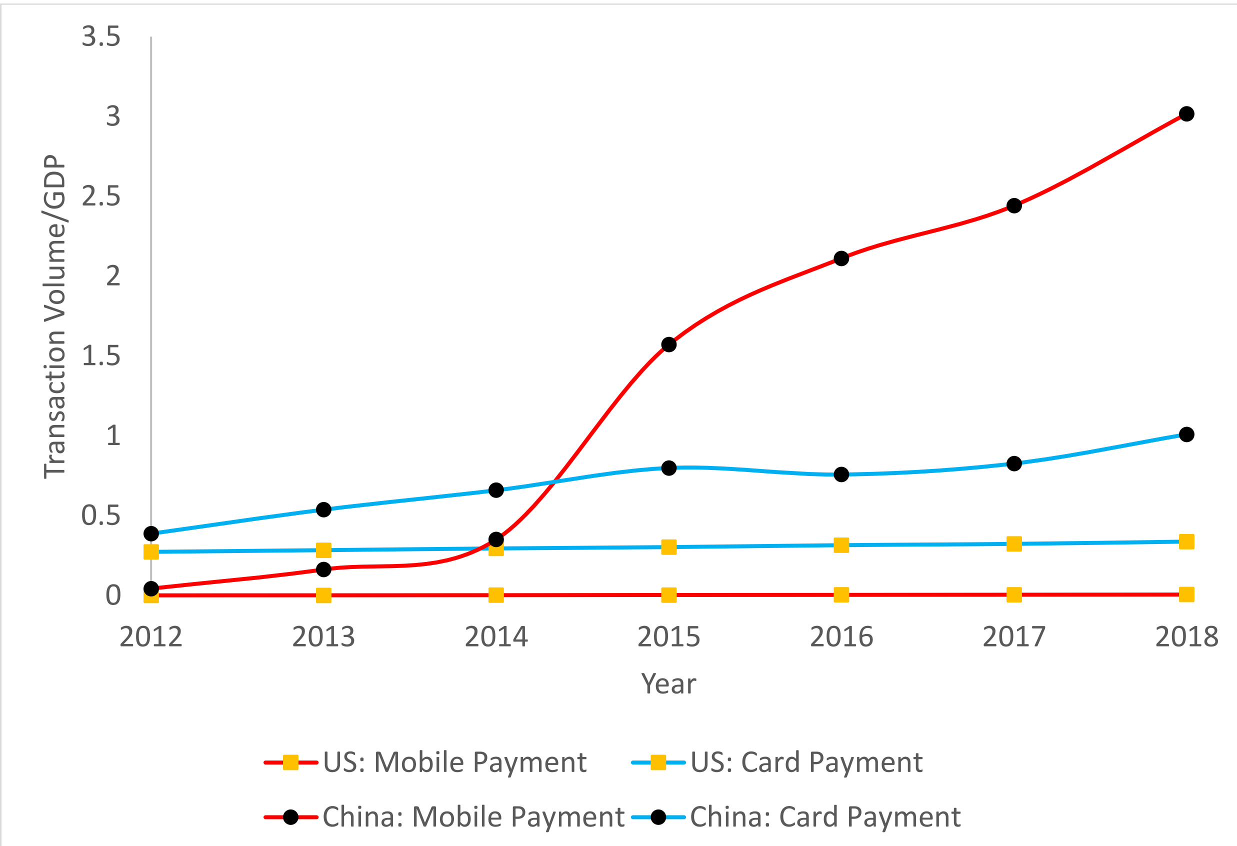


Figure 2. Logic Flow of the Instrumental Variable

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.

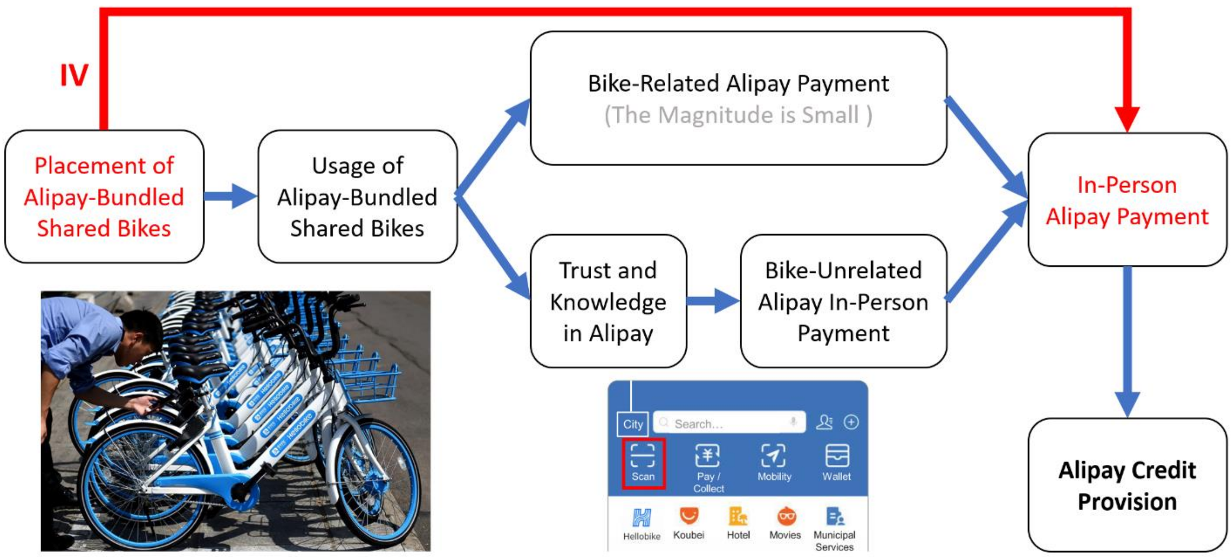


Figure 3. Bike Adoption and Non-Bike Payment Flow

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 made 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 the users who have 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 the periods where the t is not earlier than -5.

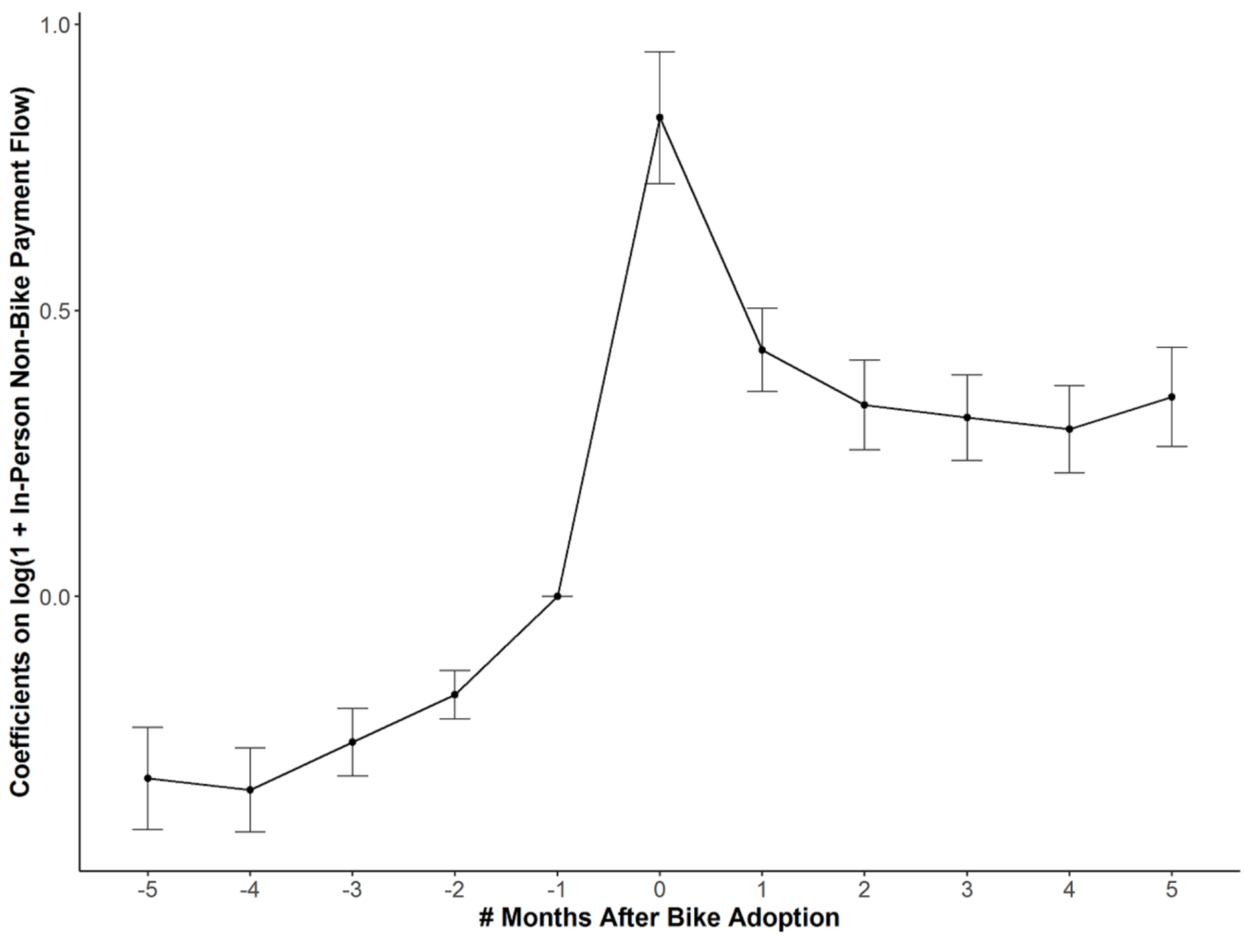


Figure 4. Staggered Placement of Shared Bikes

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

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

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, avoiding the later COVID lockdown periods. For each city, the sample only covers the periods where the t is not earlier than -5.

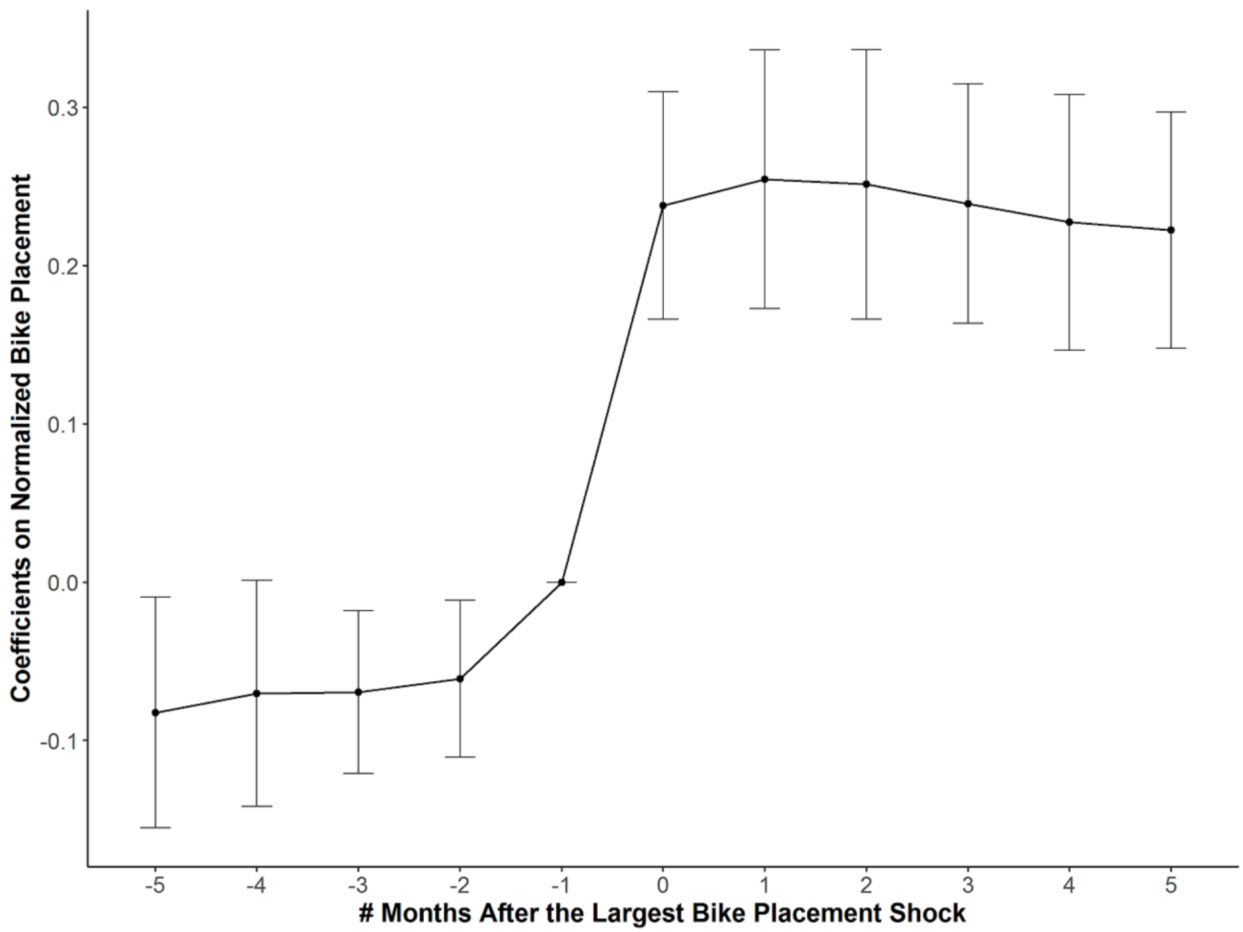


Figure 5. Broad Distribution of Bike Placement Shock

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

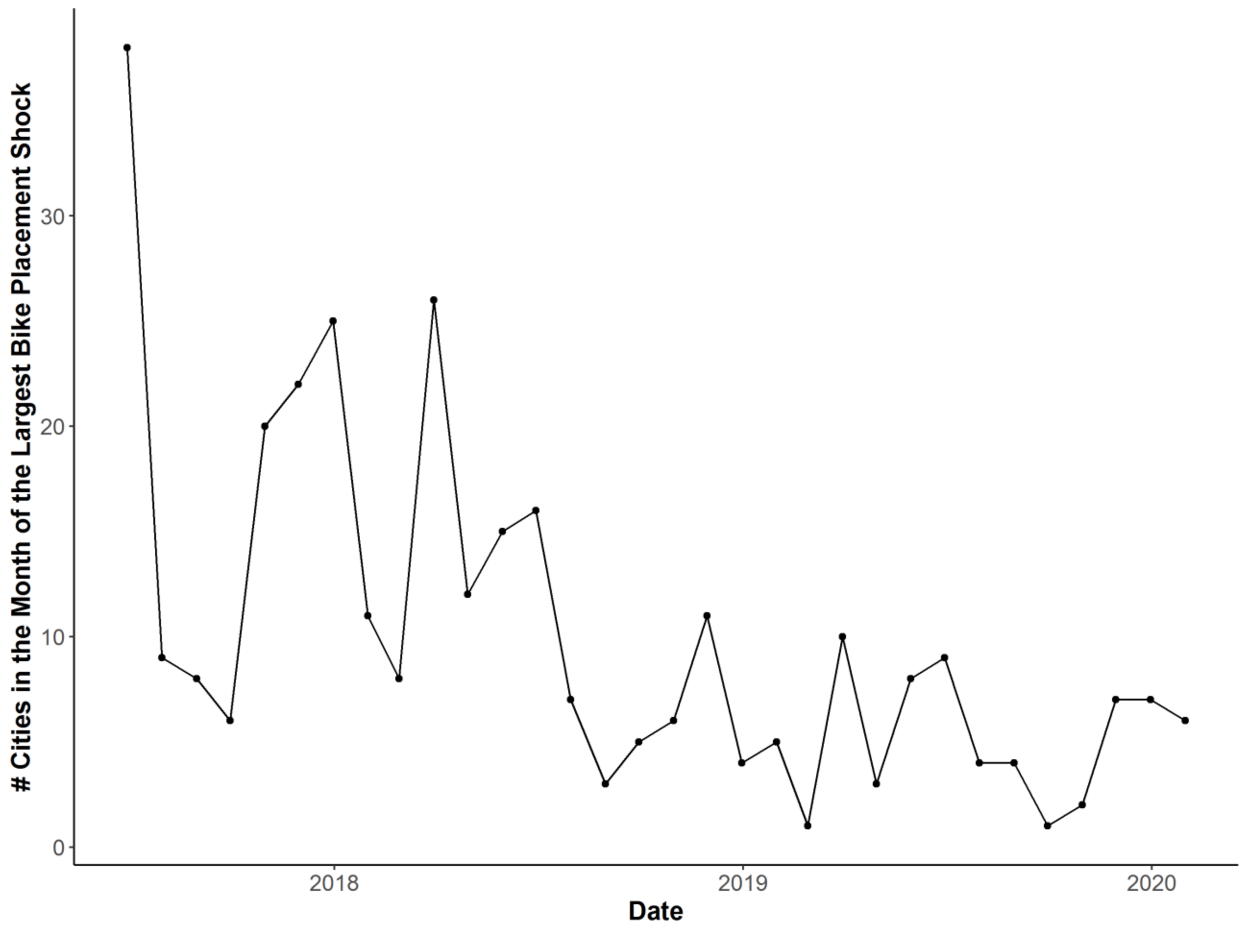
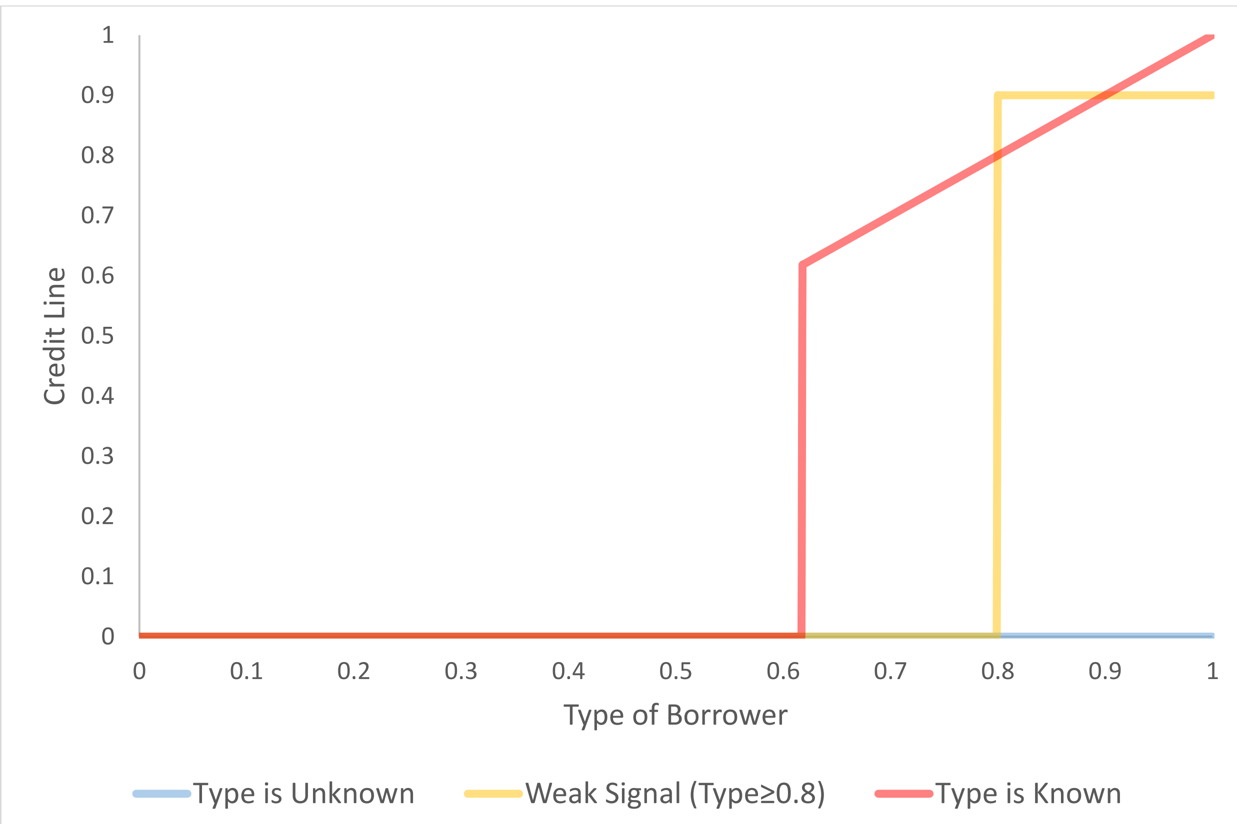


Figure 6. Example of Cashless Payment's Financial Inclusion Implication

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 the knowledge about the borrower type, the lender chooses the optimal lending amount to maximize the expected profit if the lending is profitable. There are three scenarios where the lender has different information sets. The first scenario is that the lender does not observe any information revealing the type of each borrower, and the relationship between the credit line and the borrower type is captured by the blue line. The second scenario is that 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. The third scenario is that 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 of different levels. In the individual level, $\# \, Active\ Months_i$ indicates the number of months that 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 degree of bachelor 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 rode shared bikes 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 indicating 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 granted access to individual i at time t, conditional on that $Credit\ Access_{it} = 1$; $\log(In\ Person\ Payment\ Flow)_{i,t}$ 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 that is paid with 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 that is paid with the virtual credit card; $Compulsive\ Spending\ Share\ in\ In\ Person\ Payment_{i,t}$ measures the share of in-person Alipay payments spent by individual i at time t that is on cigarettes, games, and lotteries; $Compulsive\ Spending\ Share\ in\ Online\ Payment_{i,t}$ measures the share of online Alipay payments spent by individual i at time t that is on 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 that the individual i rides shared bikes at time t. $\log(Riding\ Distance)_{i,t}$ is the log transformed total distance that the individual i rides shared bikes at time t. Column (1) focuses on the sample of bike users, which are the Alipay users who have rode shared bikes 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 that they have bike using activities. The regressions of all the columns control both individual fixed effects and year-month fixed effects. All the standard errors are clustered at the city and year-month level. I denote ***, **, and * as the 1%, 5%, and 10% confidence levels, respectively. I report standard errors in parentheses.

	$\text{Use Bike}_{i,t}$	$\log(\text{\# Bike Rides})_{i,t}$	$\log(\text{Riding Distance})_{i,t}$
	(1)	(2)	(3)
	Ordinary Least Squares		
$\log(\text{Bike Placement})_{c,t}$	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 has rode shared bikes at least once during the sample period from May 2017 to September 2020. $After\ First\ Bike\ Usage_{i,t}$ equals 1 after an Alipay user i uses the 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 the 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 the standard errors are clustered at the city and year-month level. I denote ***, **, and * as the 1%, 5%, and 10% confidence levels, respectively. I report standard errors in parentheses.

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

	$\log(1 + \text{In-Person Payment Flow})_{i,t}$			
	(1)	(2)	(3)	(4)
	Ordinary Least Squares			
$\log(\text{Bike Placement})_{c,t}$	0.041***	0.011		
	(0.010)	(0.009)		
$\text{Bike User}_i \times \log(\text{Bike Placement})_{c,t}$		0.103***	0.077***	
		(0.017)	(0.016)	
$\text{After First Bike Usage}_{i,t}$				0.123
				(0.161)
$\text{After First Bike Usage}_{i,t} \times \log(\text{Bike Placement})_{c,t}$				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 has rode shared bikes exactly once during the sample period from May 2017 to September 2020. $Repeat\ Bike\ User_i$ equals 1 if the Alipay user i has rode shared bikes 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, columns (2) and (4) show regression results that further add city times year-month fixed effects, which nest the year-month fixed effects. All the standard errors are clustered at the city and year-month level. I denote ***, **, and * as the 1%, 5%, and 10% confidence levels, respectively. I report standard errors in parentheses.

	$\log(1 + \text{In-Person Payment Flow})_{i,t}$		$\log(1 + \text{Credit Line})_{i,t}$	
	(1)	(2)	(3)	(4)
	Ordinary Least Squares			
$\log(\text{Bike Placement})_{c,t}$	0.011		0.009	
	(0.009)		(0.010)	
One-time Bike User $_i$ X $\log(\text{Bike Placement})_{c,t}$	0.088***	0.072***	0.048**	0.035
	(0.020)	(0.019)	(0.023)	(0.025)
Repeat Bike User $_i$ X $\log(\text{Bike Placement})_{c,t}$	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, both in the extensive margin and the intensive margin. $Credit\ Access_{i,t}$ is a dummy variable which equals 1 if the Alipay user i has access to Alipay's virtual credit card at time t, and equals 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 the two-stage least-squares estimates, instrumenting for the individual-level measure of 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 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 the standard errors are clustered at the city and year-month level. I denote ***, **, and * as the 1%, 5%, and 10% confidence levels, 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, both in the in-person payment and the online payment settings. $Virtual\ Credit\ Card\ Share_{i,t}$ measures the share of Alipay payment made by individual i at time t that is paid with the virtual credit card. $Compulsive\ Share_{i,t}$ measures the share of Alipay payment spent 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 the two-stage least-squares 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 the regressions with individual fixed effects and year-month fixed effects. All the standard errors are clustered at the city and year-month level. I denote ***, **, and * as the 1%, 5%, and 10% confidence levels, 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, both in the extensive margin and the intensive margin. $Credit\ Access_{i,t}$ is a dummy variable which equals 1 if the Alipay user i has access to Alipay's virtual credit card at time t, and equals 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 with 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 with 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 the two-stage least-squares estimates, instrumenting for individual-level log in-person noncredit 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 the regressions with individual fixed effects and year-month fixed effects. All the standard errors are clustered at the city and year-month level. I denote ***, **, and * as the 1%, 5%, and 10% confidence levels, 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), both in the extensive margin and the intensive margin. $Credit\ Access_{i,t}$ is a dummy variable which equals 1 if the Alipay user i has access to Alipay's virtual credit card at time t, and equals 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 in Alipay 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 the two-stage least-squares 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 the 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 AUM excludes the account balance of Alipay, while in columns (2) and (4), the AUM includes it. I denote ***, **, and * as the 1%, 5%, and 10% confidence levels, 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. The Financially Underserved Segments

These tables provide evidence that the less educated and the older users tend to be financially underserved in China. $Low\ Education_i$ equals 1 if the Alipay user i does not have a degree of bachelor 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 that are linked to user i's Alipay account on April 2021. $\log\,(1 + All\ Time\ High\ AUM)_i$ is the log transformed highest amount of individual i's asset under management in Alipay platform from May 2017 to September 2020. $Investment\ Experience_i$ is the number of months since the user firstly uses 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 that the Alipay user i's account passes the real name verification as of April 2021, and 0 otherwise. $Use\ Own\ Account_i$ equals 1 if the Alipay system labels that the Alipay user i uses her own account instead of using others' account as of April 2021, and 0 otherwise. $Complete\ Profile_i$ equals 1 if the Alipay user i fills all the profile information in the Alipay system as of April 2021, and 0 otherwise. $\log\,(1 + In\ Person\ Payment\ Flow)_{i,t}$ is the log transformed amount of in-person payments made by individual i at time t using Alipay; $\log\,(1 + Online\ Payment\ Flow)_{i,t}$ is the log 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 is 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 the regressions with city fixed effects and gender fixed effects. All the standard errors are clustered at the city level. I denote ***, **, and * as the 1%, 5%, and 10% confidence levels, 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) $_{i,t}$	log(1 + Online Payment Flow) $_{i,t}$	In-Person Share in Total Payment $_{i,t}$
	(1)	(2)	(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 the more educated groups, both in the extensive margin and the intensive margin. $Credit\ Access_{i,t}$ is a dummy variable which equals 1 if the Alipay user i has access to Alipay's virtual credit card at time t, and equals 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 the two-stage least-squares 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 the regressions with individual fixed effects and year-month fixed effects. Columns (1) and (3) use the subsample of the less educated people, who do not have a college degree or above; columns (2) and (4) use the subsample of the more educated people, who have a degree of bachelor or above. All the standard errors are clustered at the city and year-month level. I denote ***, **, and * as the 1%, 5%, and 10% confidence levels, 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 that 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 the 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 higher amount of cashless payments. Also, if an individual expects that she would get a higher credit line in the BigTech platform by using cashless payment more frequently, the individual might be encouraged to seek the 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.

There could be many Alipay-bundled bike-sharing companies operating in the same city. In this framework, I model all the Alipay-bundled bike-sharing companies as a representative bike-sharing company. This company decides the bike placement in a city in each period by considering the number of bikes that are already placed in the city in the last period and the average number of times that a local shared bike is ridden 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 is in 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 is ridden 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 of city c at time t.

For simplicity, the 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 the 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:

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

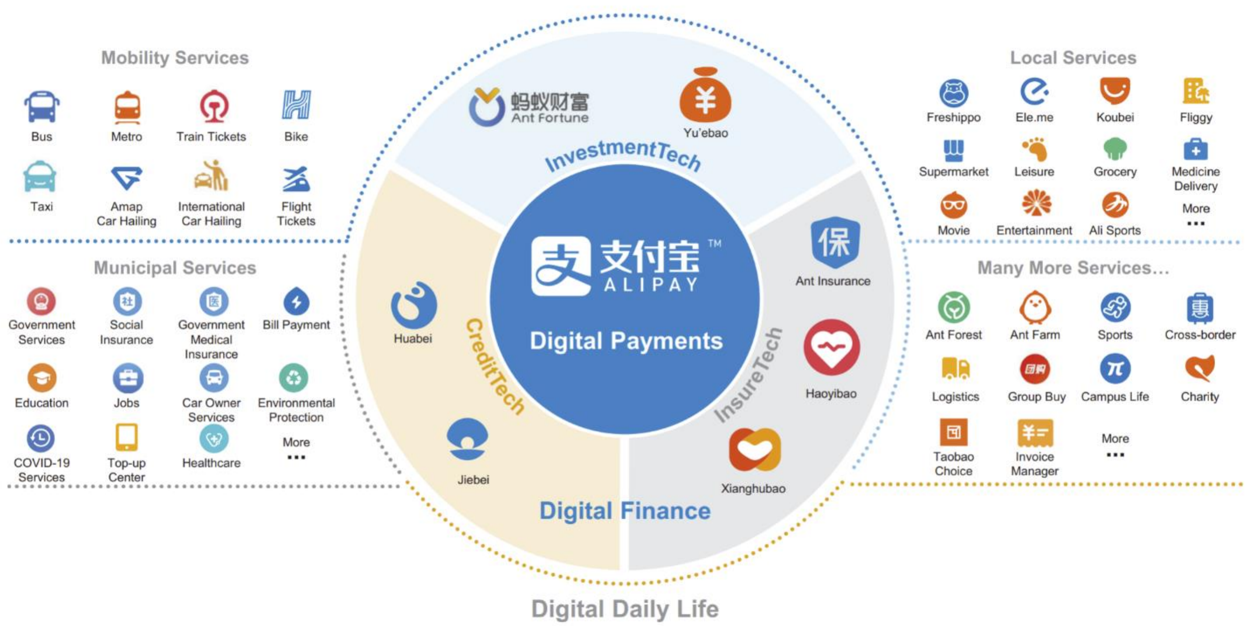
where the bias is captured by $A \cdot (B + C)$, where $A = \frac{1}{1-\alpha_1 \cdot \beta_1}$, $B = \frac{Var(\delta_i+\theta_t+\varepsilon_{i,t}^{OV}+\varepsilon_{i,t}^{EE})}{Var(ipf_{i,t})} \cdot \beta_1$, $C = \frac{Cov(\varepsilon_{i,t}^{OV}, \varphi_{i,t})}{Var(ipf_{i,t})}$.

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 the 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

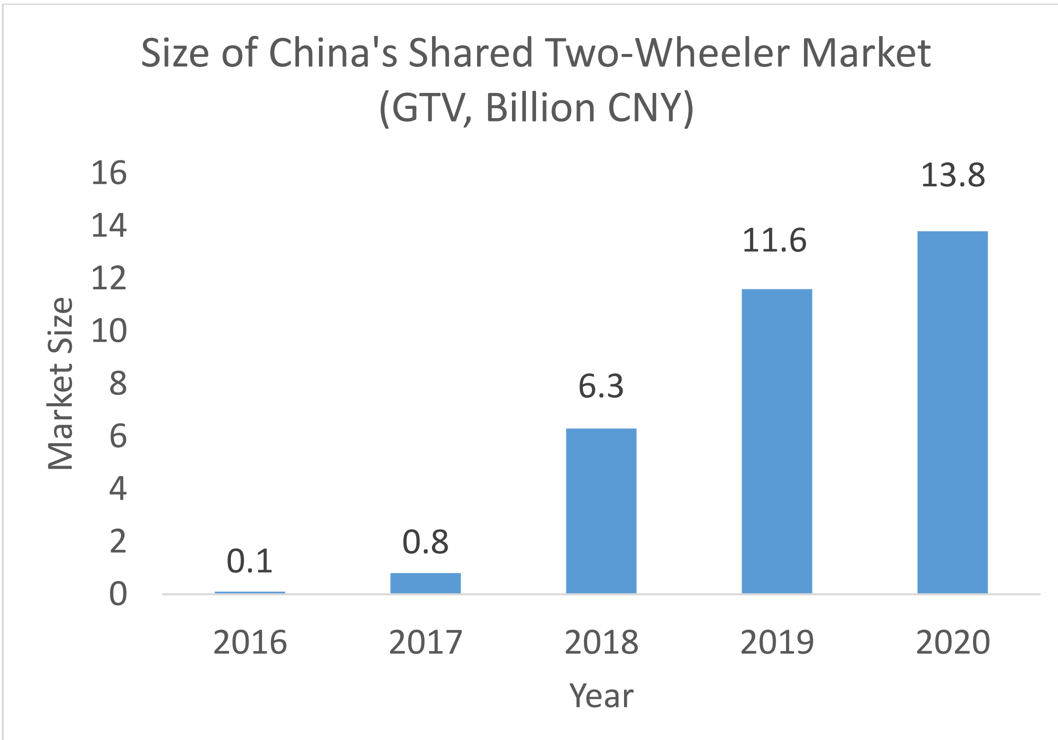
This figure describes the typical use cases that are available via the Alipay app, which cover mobility services, municipal services, local services, and other services. Alipay acts as consumers' one-stop shop for digital payment and digital financial services, including credit, investment, and insurance.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



Source: IPO Prospectus of 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. The 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 of Alipay registration and bike adoption. $Adopt\ Bike\ in\ 1\ Month$ means that the user starts to use Alipay-bundled shared bikes in 1 month right after registering in Alipay; $Adopt\ Bike\ in\ 2\ to\ 12\ Months$ means that the user starts to use Alipay-bundled shared bikes in more than 1 month but less than 1 year after registering in Alipay; $Adopt\ Bike\ Later\ than\ 1\ Year$ means that the user starts to use Alipay-bundled shared bikes in more than 1 year after registering in Alipay; $Never\ Adopt\ Bike$ means that the Alipay user has never used the Alipay-bundled shared bikes in the sample period.

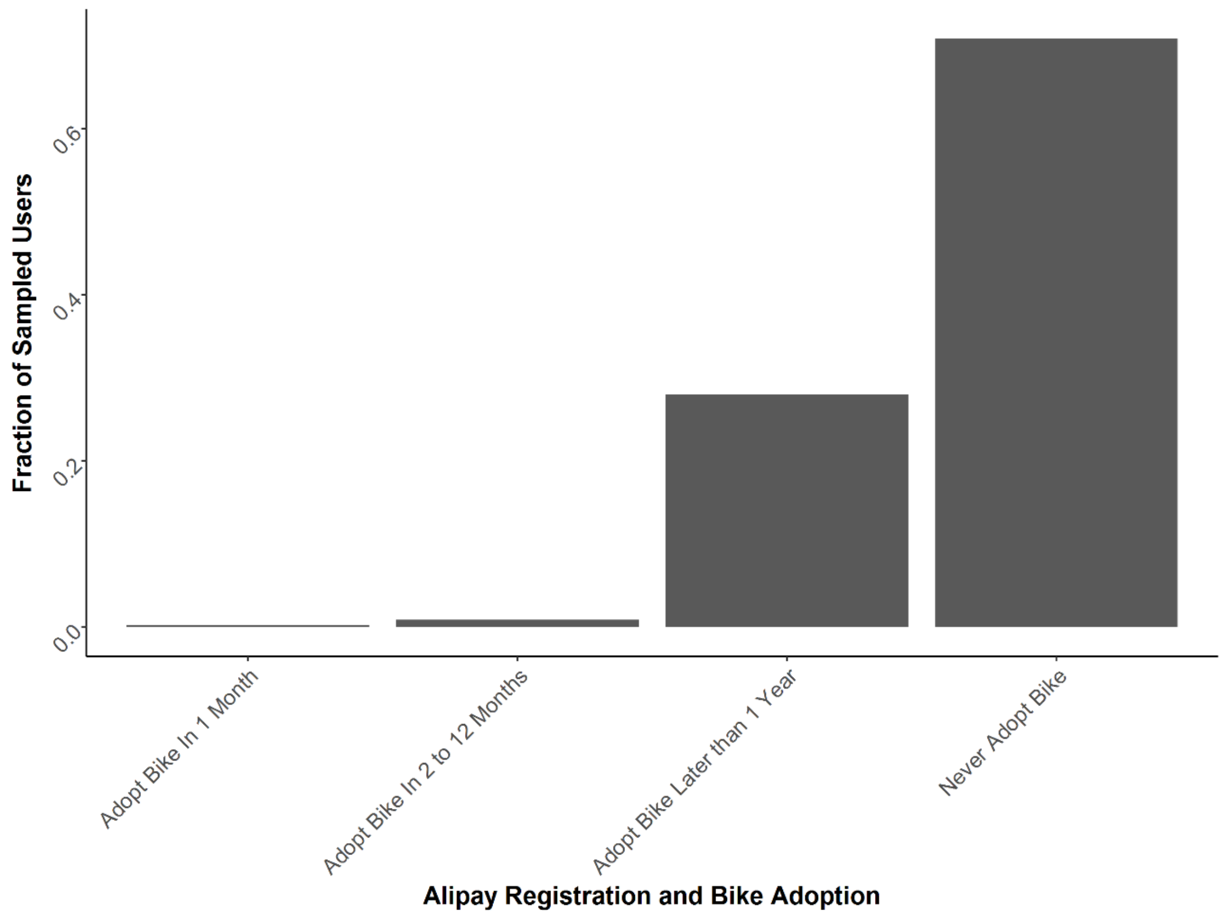


Figure A4. Evidence of the Non-Monotone Payment-Credit Relationship

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

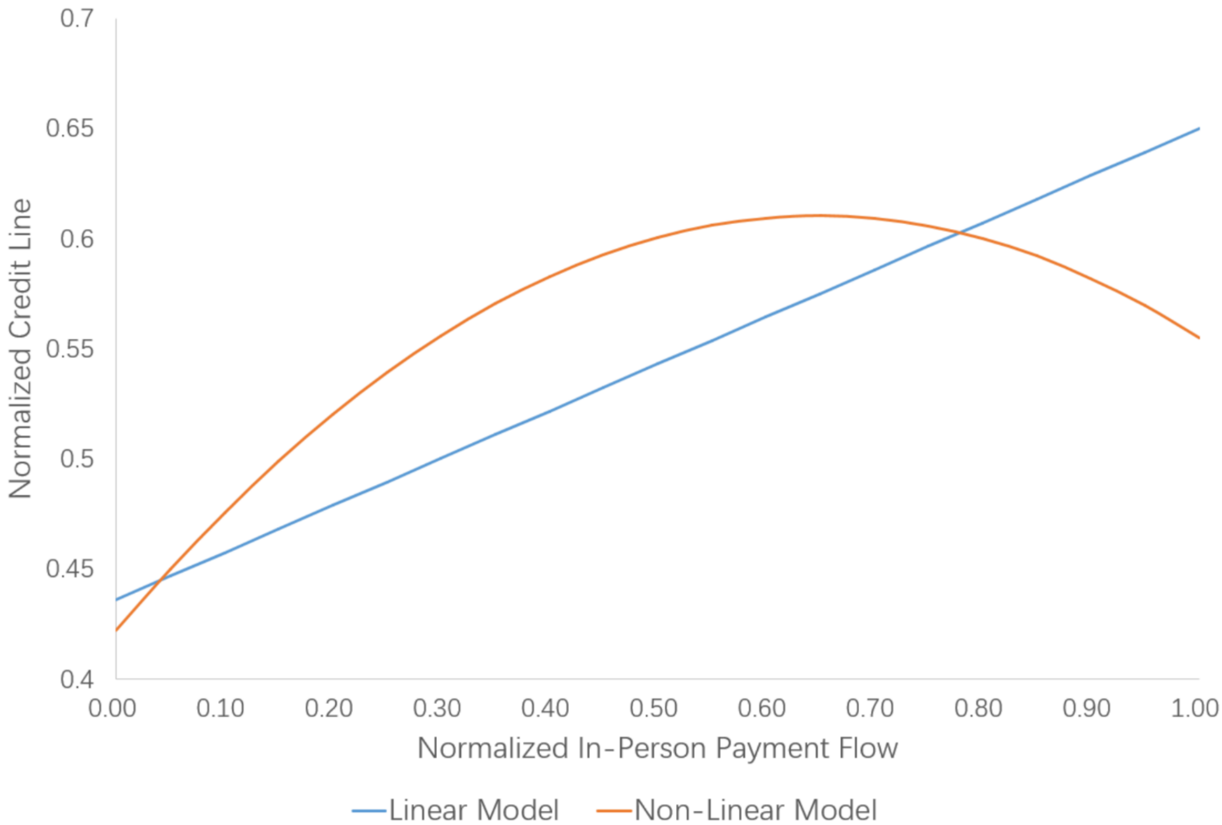


Table A1. Bike Riding Activity and Payment Flow

This table presents empirical evidence showing the relationship between a user's bike riding activity and her cashless payment flow, both with and without the bike-related spending with the cashless payment. $After\ First\ Bike\ Usage_{i,t}$ equals 1 after an Alipay user i uses the 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 transformed number of times that the individual i rides shared bikes at time t. $\log(1 + Riding\ Distance)_{i,t}$ is the log transformed total distance that the individual i rides shared bikes at time t, with the distance measured in kilometers. $\log(1 + In\ Person\ Payment\ Flow)_{i,t}$ is the log 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 transformed total amount of individual i's in-person payment flow through Alipay that are not related with the 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 rode 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 ridden shared bikes at least once, and focus on only the periods after they start using shared bikes. The regressions of all the columns control both individual fixed effects and year-month fixed effects. All the standard errors are clustered at the city and year-month level. I denote ***, **, and * as the 1%, 5%, and 10% confidence levels, 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, indicating whether she has used the 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 that the Alipay user i's account passes the real name verification as of April 2021, and 0 otherwise. $Use\ Own\ Account_i$ equals 1 if the Alipay system labels that the Alipay user i uses her own account instead of using others' account as of April 2021, and 0 otherwise. $Complete\ Profile_i$ equals 1 if the Alipay user i fills all the profile information in the Alipay system as of April 2021, and 0 otherwise. $Bike\ User_i$ equals 1 if the Alipay user i have ridden 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 the Alipay financial activity measures. These measures include $\#\ Linked\ Debit\ Cards_i$, which is the total number of debit cards that are linked to user i's Alipay account on April 2021, $\log(1 + All\ Time\ High\ AUM)_i$, which is the log 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 the standard errors are clustered at the city level. I denote ***, **, and * as the 1%, 5%, and 10% confidence levels, 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 the individual-level in-person payment flow and 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 the Alipay user i has rode 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 of 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 that the Alipay user i's account passes the real name verification as of April 2021, and 0 otherwise. $Use\ Own\ Account_i$ equals 1 if the Alipay system labels that the Alipay user i uses her own account instead of using others' account 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 where the dependent variable is $\log(1 + In\ Person\ Payment\ Flow)_{i,t}$. Panel B reports the results of OLS regressions where the dependent variable is $\log(1 + Credit\ Line)_{i,t}$. The $Characteristic\ Measure_i$ in each column is separately specified. The regressions of all the columns control both individual fixed effects and year-month fixed effects. All the standard errors are clustered at the city and year-month level. I denote ***, **, and * as the 1%, 5%, and 10% confidence levels, respectively. I report standard errors in parentheses.

	Dependent Variable					
	(1)	(2)	(3)	(4)	(5)	(6)
Panel A. Ordinary Least Squares with Dependent Variable: $\log(1 + \text{In-Person Payment Flow})_{i,t}$						
$\log(\text{Bike Placement})_{c,t}$	-0.022	0.008	0.029**	0.021**	-0.013	-0.01
	(0.014)	(0.010)	(0.011)	(0.009)	(0.015)	(0.010)
$\text{Bike User}_i \times \log(\text{Bike Placement})_{c,t}$	0.139***	0.110***	0.092***	0.099***	0.057**	0.112***
	(0.029)	(0.018)	(0.017)	(0.021)	(0.025)	(0.019)
$\text{Characteristic Measure}_i \times \log(\text{Bike Placement})_{c,t}$	0.036**	0.004	-0.038***	-0.023**	0.033*	0.039***
	(0.017)	(0.013)	(0.012)	(0.008)	(0.019)	(0.013)
$\text{Bike User}_i \times \text{Characteristic Measure}_i \times \log(\text{Bike Placement})_{c,t}$	-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: $\log(1 + \text{Credit Line})_{i,t}$						
$\log(\text{Bike Placement})_{c,t}$	0.009	0.014	0.02	0.004	-0.008	0.003
	(0.021)	(0.010)	(0.013)	(0.014)	(0.013)	(0.015)
$\text{Bike User}_i \times \log(\text{Bike Placement})_{c,t}$	0.051*	0.053*	0.057*	0.056**	0.049*	0.042**
	(0.030)	(0.026)	(0.029)	(0.025)	(0.029)	(0.020)
$\text{Characteristic Measure}_i \times \log(\text{Bike Placement})_{c,t}$	0.0001	-0.011	-0.023	0.008	0.024*	0.012
	(0.026)	(0.018)	(0.025)	(0.012)	(0.014)	(0.014)
$\text{Bike User}_i \times \text{Characteristic Measure}_i \times \log(\text{Bike Placement})_{c,t}$	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	$\text{Older than Median}_i$	$\text{Early Alipay User}_i$	Is Male_i	$\text{Pay with Real Name}_i$	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 Local Economy

This table presents empirical evidence illustrating that conditional on the city fixed effects and the year-month fixed effects, the city-level bike placement does not significantly correlate with the key variables describing the 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) in 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. Fiscal $\text{Spending/GDP}_{c,t}$ is the ratio of local fiscal spending over the local GDP in city c at time t. Fiscal $\text{Income/GDP}_{c,t}$ 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 the standard errors are clustered at the city and year-month level. I denote ***, **, and * as the 1%, 5%, and 10% confidence levels, respectively. I report standard errors in parentheses.

	$\log(\text{GDP})_{c,t}$	$\log(\text{GDP per capita})_{c,t}$	Fiscal Spending/GDP $_{c,t}$	Fiscal Income/GDP $_{c,t}$
	(1)	(2)	(3)	(4)
	Ordinary Least Squares			
$\log(\text{Bike Placement})_{c,t}$	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 this person's 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 this person's highest credit line. Regressions specified in columns (1) and (2) are simple regressions without control variables, and regressions specified in columns (3) and (4) control both individual fixed effects and year-month fixed effects. All the standard errors are clustered at the city and year-month level. I denote ***, **, and * as the 1%, 5%, and 10% confidence levels, 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 the city times year-month fixed effects, both in the extensive margin and the intensive margin. $Credit\ Access_{i,t}$ is a dummy variable which equals 1 if the Alipay user i has access to Alipay's virtual credit card at time t, and equals 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 rode shared bikes at least once during the sample period from May 2017 to September 2020. Panel A reports the two-stage least-squares 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 the 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 the standard errors are clustered at the city and year-month level. I denote ***, **, and * as the 1%, 5%, and 10% confidence levels, 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, both in the extensive margin and the intensive margin. $Credit\ Access_{i,T}$ is a dummy variable which equals 1 if the Alipay user i has access to Alipay's virtual credit card at time T and equals 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 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 the two-stage least-squares 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 the columns show results for the regressions with individual fixed effects and year-month fixed effects. All the standard errors are clustered at the city and year-month level. I denote ***, **, and * as the 1%, 5%, and 10% confidence levels, 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 the past in-person payment flows, both in the extensive margin and the intensive margin. $Credit\ Access_{i,t}$ is a dummy variable which equals 1 if the Alipay user i has access to Alipay's virtual credit card at time t, and equals 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 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 the two-stage least-squares 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 the 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 (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. I denote ***, **, and * as the 1%, 5%, and 10% confidence levels, 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 the bike usage, both in the extensive margin and the intensive margin. $Credit\ Access_{i,t}$ is a dummy variable which equals 1 if the Alipay user i has access to Alipay's virtual credit card at time t, and equals 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 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 the two-stage least-squares 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 the 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. I denote ***, **, and * as the 1%, 5%, and 10% confidence levels, 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 the online payment, both in the extensive margin and the intensive margin. $Credit\ Access_{i,t}$ is a dummy variable which equals 1 if the Alipay user i has access to Alipay's virtual credit card at time t, and equals 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 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 the two-stage least-squares 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 the 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 online payment is the online payment flow measured in CNY, while in columns (2) and (4), it is the number of online transactions. I denote ***, **, and * as the 1%, 5%, and 10% confidence levels, 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 the older and the younger groups, both in the extensive margin and the intensive margin. $Credit\ Access_{i,t}$ is a dummy variable which equals 1 if the Alipay user i has access to Alipay's virtual credit card at time t, and equals 0 otherwise. $\log\left(Credit\ Line\right)_{i,t}$ 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. $\log\left(1 + In\ Person\ Payment\ Flow\right)_{i,t}$ 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. $\log\left(Bike\ Placement\right)_{c,t}$ is a log transformation of the number of active shared bikes placed in city c at time t. Panel A reports the two-stage least-squares 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 the regressions with individual fixed effects and year-month fixed effects. Columns (1) and (3) use the subsample of the older people, who are older than more than half of the individuals in the sample; columns (2) and (4) use the subsample of the younger people, who are not older than half of the individuals in the sample. All the standard errors are clustered at the city and year-month level. I denote ***, **, and * as the 1%, 5%, and 10% confidence levels, 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