Cashless Payment and Financial Inclusion

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November 2025

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Abstract

This paper investigates how cashless payment affects credit access for underserved populations using data from Alipay, a leading Chinese BigTech platform with over 1 billion users that offers a wide range of financial services. By exploiting the staggered rollout of Alipay-bundled shared bikes across cities as a natural experiment and analyzing a representative Alipay user sample, I find that cashless payment adoption increases credit access by 56.3% and that a 1% rise in payment flow increases credit lines by 0.41%. These effects are stronger for less educated and older individuals, who have traditionally faced greater barriers to accessing financial services.

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

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

I am grateful to Wei Xiong, Markus K. Brunnermeier, Atif R. Mian, and Ravi Jagannathan for their continuous guidance and support. For useful comments I also thank Mark Aguiar, Torben Andersen, Cynthia Mei Balloch, Paul Beaumont, James Brown, Greg Buchak, Long Chen, Lin William Cong, Natalie Cox, Kim Fe Cramer, Marco Di Maggio, John Driscoll, Elena Falcettoni, Hanming Fang, Andreas Fuster, Leonardo Gambacorta, Sean Higgins, Jing Huang, Sun Yong Kim, Faizaan Kisat, Nobuhiro Kiyotaki, Robert Korajczyk, Kwok Hao Lee, Moritz Lenel, Chen Lin, Ernest Liu, Tong Liu, Xiaomeng Lu, Hong Luo, Xuan Luo, Yufeng Mao, Adrien Matray, Ben Matthies, Simon Mayer, Paolina Medina, Brian Melzer, John Mondragon, Christopher Palmer, Jonathan Payne, Cameron Peng, Lin Peng, Nagpurnanand Prabhala, Amiyatosh Purnanandam, Uday Rajan, Michael Reher, Jonathan Reuter, David Schoenherr, Scott Schuh, André F. Silva, Huan Tang, Lulu Wang, Shang-Jin Wei, Barry Williams, Emily Williams, Mungo Wilson, Carlo Wix, Yuhai Xuan, Liyan Yang, Constantine Yannelis, Motohiro Yogo, Yao Zeng, Shengxing Zhang, Yinuo Zhang, Li Zhao, and Xiang Zheng, as well as participants at Princeton, Luohan Academy, PKU Econ, SUFE, PKU Guanghua, Bank of Canada, JHU Carey, TAMU, MSU, Oxford Saïd, UCI, Michigan Ross, Baruch, McGill, PHBS, UCL, Harvard, IMF, NTU, NUS, TSE, CB&DC JMC Workshop, DC&F Workshop, Inter-Finance PhD Seminar, AFA 2024, CCAF 2023, NBER Chinese Economy Meeting 2022, MIT GCFP 2022, UConn Finance 2022, EFA 2022, NFA 2022, MFA 2022, EasternFA 2022, FIRS 2022, EoP XI 2022, OCC FinTech 2022, EBA PRW 2022, AMES 2022, AEDC 2022, AsianFA 2022, CFRC 2022, BFWG 2022, SEHO 2022, EFT 2022, FMCG 2022, ESDWS 2021, GAIF 2021, NZFM 2021, ICEA Inequality 2021, and SEL Fintech 2021. Thanks to Xiaopeng Wu, Sonny Song, and Li Quan for excellent research assistance. Thanks to Luohan Academy for a dissertation fellowship and access to the data, and to PIIRS for a research grant. I am particularly grateful to Toni Whited and an anonymous referee for their highly constructive feedback in improving this paper. Any errors are my own.

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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.*

Providing financial services, especially extending credit, to the underprivileged has always been challenging. Despite the huge impact of initiatives like the microcredit movement, limitations remain in scaling these solutions cost-effectively and sustainably (Helms et al., 2006). However, recent years have seen a global boom in credit provided by BigTech firms—the dominant players in the information technology industry such as Alibaba, Amazon, Apple, and Tencent. BigTech credit is supplanting FinTech lending (Cornelli et al., 2021) and potentially reaching unbanked and underbanked consumers. At the same time, mobile payments, particularly those enabled by BigTech platforms, are accelerating the transition to a cashless society by integrating key technological advances. These drastic changes raise two central questions in academic and policy circles (Berg et al., 2022): Does payment flow information causally drive the expansion of BigTech credit? And does this expansion benefit consumers historically underserved by traditional financial institutions?

The effects of payment adoption on consumer credit access are theoretically ambiguous. While detailed payment data could help underserved populations build credit profiles by revealing reliable income streams and spending patterns, it could also enable more sophisticated forms of discrimination. Using rich administrative data from Alipay, a leading Chinese BigTech platform with over 1 billion active users offering payment, credit, and other financial services, I empirically investigate this issue. The study focuses on Alipay's *Huabei* credit line, a virtual credit card product, using data through 2020. By that time, *Huabei* had become China's largest consumer finance product. Using a novel instrumental variable (IV) strategy, I show that cashless payment flows significantly influence credit provision on both the extensive and intensive margins, particularly for underserved consumers. These findings go beyond the limits of predictive models, which may be distorted when consumers strategically adapt to known credit rules (Bjorkegren et al., 2020), and offer greater external validity than field experiments with narrow scope. The BigTech lender leverages payment flow information to assess borrower creditworthiness, departing from traditional credit card models relying on repayment histories.

Establishing a causal link between cashless payment and BigTech credit provision presents several challenges. First, identifying an exogenous shock to cashless payment activity is difficult, particularly in mature markets. Second, the analysis requires granular, individual-level data on payments, credit, investments, and sociodemographic characteristics. Third, to isolate the credit supply effect, it is essential to net out credit demand factors from observed credit outcomes.

To address these challenges, I exploit the staggered rollout of Alipay-integrated shared bikes across Chinese cities as a natural experiment. This provides plausibly exogenous variation in in-person Alipay payments, as bike usage encourages more such payments due to the shared QR code mechanism. For individual-level data, I use administrative records from Alipay, which include rich, monthly panel data on users' demographics, consumption, credit, investments, shared-bike usage, and other digital behaviors. The design of Alipay's *Huabei* credit line addresses the supply-side concern: unlike traditional credit cards, it requires no application and instantly reveals eligibility and approximate credit limits, minimizing confounding from endogenous demand.

I perform multiple tests to show the validity of the staggered placement of Alipay-bundled shared bikes in different cities as the IV. The relevance condition requires a strong first-stage relationship between city-level bike placement and the in-person payment flow of Alipay users living in the city. My results confirm this view. The exclusion restriction condition requires that bike placement affect credit provision only through in-person cashless payment. I design tests to rule out potential concerns, including correlated city-level trends, selection into bike usage, direct signaling effects of bike transactions, and non-random or clustered bike deployment timing across cities.

The IV analysis presents three main findings. First, an exogenous increase in consumers' in-person payment flow leads to greater digital credit provision by Alipay and increased credit uptake. On the extensive margin, using in-person payment in a month increases the probability of credit access by 56.3% in that month. On the intensive margin, among those with credit access, a 1% increase in in-person payment flow leads to a 0.41% increase in credit line. Given China's rapidly growing digital payment market, this credit expansion is substantial. Both the learning-by-doing mechanism and the improved credit supply suggest that consumers adapt their borrowing behavior in response. I find that increased in-person payment flow leads to higher credit take-up, both in-person and online. While relaxed credit constraints may benefit rational borrowers, they may also increase overspending among those with behavioral biases such as poor self-control or forecasting errors (Ausubel, 1991; Melzer, 2011; Di Maggio and Yao, 2020). However, based on transaction-level category data and event-study analysis, I find no significant increase in the share of compulsive spending or excessive spending following credit access.

Second, I explore the channels through which in-person payment flow facilitates credit provision. The results indicate that transaction data contain useful information for credit evaluation, aligning with the banking literature on lenders' informational advantages over depositors (Black, 1975). Even when focusing only on noncredit transactions—which exclude repayment history—I still observe a significant positive impact on credit provision. This is consistent with the idea that a consumer's payment behavior reveals their income and financial health. Additionally, payment flow is relevant not only for inferring creditworthiness but also for enforcement capacity, especially when the lender can restrict access to financial services upon default (Brunnermeier and Payne, 2022). To distinguish between these two channels, I control for a proxy of collateral—assets under management (AUM) on Alipay—since these assets can potentially be frozen in the event of non-repayment. The creditworthiness signal from payment flow remains robust even after controlling for AUM.

Third, I analyze the implications of digital payment for financial inclusion. Using an illustrative theoretical example, I show that digital payment adoption, as an information shock to the lender, can potentially lead to opposite credit access outcomes for borrowers with lower creditworthiness. Less creditworthy borrowers can get a higher credit line or lower credit line after the information shock, depending on the parameter values. Empirically, I find that financially underserved consumers—those who are older or less educated—gain more credit access after adopting in-person cashless payments. This is consistent with the idea that such adoption generates a larger marginal improvement in the lender's ability to assess creditworthiness for these groups. In line with survey evidence suggesting these demographics are more likely to be underserved,[1] my data show they engage in fewer financial activities and display lower financial literacy. The exogenous increase in the in-person cashless payment flow results in an increase in credit provision mainly to these segments.

An emerging literature examines the relationship between digital payments and credit access. Berg et al. (2022) and Mo and Ouyang (2025) review the development of FinTech lending, raising key questions about the role of payment data in credit markets. Recent technological advances—especially the widespread adoption of mobile payments—have helped address the longstanding limitations of traditional microcredit programs by enabling access to rich, high-frequency, and manipulation-resistant data. Evidence from India shows that open-banking rails and cashless payments can broaden credit access and stimulate aggregate growth (Alok et al., 2024; Dubey and Purnanandam, 2023). Algorithm-driven FinTech lenders price mortgage risk faster and more precisely, yet often leave underserved borrowers no better off and can widen rate gaps

[1]See Bank of Finland Institute for Emerging Economies (BOFIT), "Chinese Increasingly Likely to Attend University, Nearly All Young Adults are Literate," May 21, 2021.

(Fuster et al., 2019, 2022). Parallel to these, a growing literature explores the advantages of FinTech and BigTech lending models, highlighting their use of alternative data, superior risk assessment tools, and their ability to extend credit to small businesses (Frost et al., 2019; Cornelli et al., 2020; Liu et al., 2022; Beck et al., 2022; Gambacorta et al., 2022; Hau et al., 2019, 2021; Chen et al., 2021c; Huang, 2022; Huang et al., 2025). Traditionally, consumer credit evaluation has relied on credit bureau data, emphasizing usage and repayment history (Chatterjee et al., 2020), but the availability of granular behavioral data has spurred new business models and predictive methods based on digital footprints (Agarwal et al., 2019; Berg et al., 2020) and machine learning (Di Maggio et al., 2021). This paper contributes to the literature by empirically demonstrating the causal effects of payment flow information on consumer credit—evidence that complements but also diverges from prior work focused on business lending. Specifically, I show that payment data from a leading BigTech platform improves credit allocation even in the absence of traditional credit signals, offering new insights into how cashless payments shape consumer behavior. My findings support theories on payment flows in borrower screening Parlour et al. (2022) and relate to work on payment systems and small business lending Ghosh et al. (2025). Unlike their findings of strategic cashless adoption by firms to signal creditworthiness, my analysis indicates less strategic consumer behavior. Consequently, consumer payment flows appear to reflect more organic activity, which may imply that consumer credit outcomes are relatively more responsive to exogenous shifts in payment behavior than those observed for firms.

My paper contributes to the literature on the effects of payment technology adoption on consumers. A growing body of evidence shows that digital payment products—including debit cards, mobile payments, and electronic wallets—can reduce transaction, monitoring, and travel costs, leading to changes in household savings (Bachas et al., 2021), risk-sharing (Jack and Suri, 2014), risk-taking (Hong et al., 2020), and consumption (Suri and Jack, 2016). More recent studies highlight how adoption itself responds to technological or policy shocks (Crouzet et al., 2023), to interest-rate incentives (Ouyang and Peng, 2022), and to network externalities in two-sided payment markets (Higgins, 2024). So far, however, this literature has largely focused on the cost-reduction channel and rarely on the value of the payment data accumulated as a result of digitalization. My paper addresses this gap by quantitatively assessing the real effects of payment-data usage in the consumer credit market. It is also among the first to analyze a BigTech payment app that bundles payments with a wide range of data-driven financial and daily-life services. By doing so, it speaks to recent theoretical work on the interaction between payment data, market power, and household privacy (Agur et al., 2025; Ahnert et al., 2025) and provides suggestive evidence on the potential power of service bundling and interoperability that naturally arises for digital financial platforms (Brunnermeier and Payne, 2022).

This paper contributes to the literature on the real effects of consumer credit. While a growing array of consumer finance products is available, there is less agreement on their welfare implications (Zinman, 2015). For rational borrowers, credit should ease financial constraints and smooth consumption, potentially improving well-being. Indeed, studies find positive effects of consumer credit even when it is expensive (Karlan and Zinman, 2010; Morse, 2011), and the financial inclusion literature broadly supports the benefits of expanding financial access for disadvantaged groups (Erel and Liebersohn, 2022; Stein and Yannelis, 2020; Di Maggio et al., 2021). However, behavioral biases such as time-inconsistent preferences (Laibson et al., 2000), optimal expectations (Brunnermeier and Parker, 2005), and limited attention (Stango and Zinman, 2014) can lead to overspending, overborrowing, and other negative outcomes. Evidence of adverse effects has been found in various credit markets.[2] Despite BigTech consumer credit's rapid growth, research on its impacts remains limited. Using transaction-level data, I find that increased digital payment activities and BigTech credit access do not significantly affect share of compulsive spending. Consumers raise spending after gaining credit access without reversal, consistent with the "flypaper effect" in BNPL (Di Maggio et al., 2022).

The paper is organized as follows. Section 1 provides some institutional background on the Alipay platform and the dockless bike-sharing industry in China. Section 2 describes the data and the identification challenge and provides evidence on the validity of the instrumental variable. IV analysis results are in Section 3, in which I analyze the relationship between cashless payment flow, credit provision, and financial inclusion. I conclude in Section 4.

1 Institutional Background

This study is motivated by two global trends: the rapid growth of cashless payment systems and the rise of consumer lending by FinTech and BigTech firms.

First, mobile payments—especially in-person transactions—have seen remarkable uptake in under a decade. China exemplifies this shift. As Figure 1 shows, China led the world in mobile payment penetration and per-user transaction volume from 2019 to 2023. While countries like India and Nigeria have advanced, China's transition

[2] See Melzer (2011) for payday loans, Ausubel (1991) for credit cards, Begley and Purnanandam (2021) for mortgages, Di Maggio and Yao (2020) for FinTech lending, and deHaan et al. (2022) for Buy Now Pay Later" (BNPL).

from cash to digital payments stands out for its scale and speed. Figure 2 shows mobile payment volume in China rose from 4% to 458% of GDP between 2012 and 2021, compared to under 38% for U.S. card payments. China's experience thus offers a valuable setting for studying the broader implications of going cashless.

Second, BigTech credit has overtaken FinTech credit globally (Cornelli et al., 2020), with China as the largest market. Alipay dominates both segments. In my representative user sample as of September 2020, 72% had access to a *Huabei* credit line, over 95% of whom had used it, with average monthly borrowing of 533 CNY (about 80 USD), roughly 20% of China's median per capita disposable income. Notably, 64% of users without a credit card also accessed *Huabei*, underscoring its financial inclusivity.

China's mobile payment system is distinctive. Unlike SMS-based systems like M-PESA or card-linked apps like Apple Pay, China's "super apps"—notably Alipay and TenPay—offer an integrated platform with in-house and third-party services. This unique model has contributed to China's leap-frogging adoption of mobile payments, a phenomenon explored in recent studies (Han and Wang, 2021). This paper studies mobile payment in China by analyzing Alipay's proprietary data.

1.1 The Alipay Platform

Alipay, launched by Alibaba Group in 2004, is China's largest digital payment provider by total payment volume, reaching RMB 118 trillion between July 2019 and June 2020. By late 2020, the platform had over 1 billion users, 80 million merchants, and more than 2,000 financial partners offering services such as consumer credit. Since its inception, Alipay has been the primary transaction channel on Alibaba's platforms. Its user base and transaction volume have expanded rapidly, especially since 2016. This growth coincides with China's rapid shift from a cash-based to a cashless economy. Today, consumers routinely use Alipay or TenPay to pay for everything, from taxis and utility bills to street food.

Alipay has become a platform that enables merchants and consumers to complete transactions for almost all online and in-person payments. It also offers access to over 1,000 lifestyle services and 2 million mini-programs—covering transportation, local commerce, and public services—without requiring separate app downloads. This extensive ecosystem underscores the importance of user data and data-sharing decisions, as discussed by Chen et al. (2021a,b).

Figure A.1 from Ant Group's prospectus illustrates typical use cases. Digital payments underpin Alipay's broader financial offerings, including credit, wealth management, and insurance. Payment can be made using wallet balances, linked bank cards, Alipay's liquid money market fund, or Alipay's virtual credit line product, *Huabei*.

Huabei is Alipay's flagship digital consumer credit service and, as of late 2020, the largest by outstanding balance in China. Eligibility and approximate credit limits are determined instantly, avoiding the application and waiting process typical of credit cards, which usually require potential borrowers to submit detailed applications. This streamlined process enables us to focus on credit supply effects, without the demand-side selection bias often present in traditional credit products.

Pricing is relatively uniform: most users pay a daily interest rate of 0.05% (or 18.25% annually), reducing price heterogeneity and allowing a clearer focus on credit quantity. As of June 2019, *Huabei*'s delinquency rate was 1.16%, compared to 1.21–2.49% for credit cards issued by publicly listed Chinese banks. This is striking, given that bank-issued credit cards typically target more creditworthy individuals: applicants are generally required to show stable employment, sufficient income, and a favorable credit history.

Lower default rates on *Huabei* credit may reflect Alipay's use of alternative data sources in its credit-assessment models. Additionally, Alipay's powerful enforcement mechanisms, such as the ability to exclude defaulters from certain digital services, likely provide strong incentives for borrowers to prioritize repayment and avoid default. Ant Group's internal KPIs are understood to place considerable weight on risk management, which indicates a strategic preference for keeping default rates low to safeguard long-term profitability.

Huabei has some other features and statistics. Once an Alipay user is granted access to *Huabei*, her credit line is instantly available at the point of sale. The whole process is fully automatic. The minimum credit line is as low as 20 CNY (roughly 3 USD), and Alipay offers consumers an interest-free period of up to 40 days after the corresponding purchase. Consumers have the option to pay in monthly installments over 3 to 12 months after the interest-free period. From July 2019 to June 2020, the average *Huabei* outstanding balance was around 2,000 CNY.

1.2 The Dockless Bike-sharing Market in China

Dockless bike-sharing platforms differ from traditional systems by eliminating the need for docking stations. Users simply scan a QR code on the bike's smart lock via a bike-sharing or mobile wallet app to begin their ride. After parking in an authorized area and paying, they relock the bike, making it available to others.

Two key features define China's bike-sharing sector: affordability and scale. A typical ride costs 0.23 USD for the first 15 minutes and 0.08 USD for each subsequent 15 minutes, with unlimited monthly plans available for around 3 USD. By late 2019, there were 260 million shared bike users. *Hellobike*, a major bike-sharing player integrated with Alipay, reported over 400 million users alone in 2021.

China's first dockless bike-sharing company, *ofo*, launched in 2015 in Beijing. Initially a campus-based peer-to-peer platform, it later transitioned to a one-sided model, offering GPS-enabled bikes via its app (Cao et al., 2018). Following its emergence, the industry saw rapid growth fueled by venture capital and BigTech investment (Figure A.2). By early 2018, 77 firms operated 23 million bikes across hundreds of cities, with *ofo* and *Mobike* capturing 95% of the market. Despite its early dominance, *ofo* failed to sustain operations and ceased rentals by 2020 due to financial troubles. In contrast, *Hellobike*, a minor player in 2017, became the global leader in ride volume by 2020.

1.3 Digital Payment Competition and Dockless Bike-sharing Market

In 2013, China's non-cash retail payments were under RMB 50 trillion, primarily via debit and credit cards. Mobile payments played a minor role. Growth accelerated after 2016; by 2019, non-cash retail payments exceeded RMB 350 trillion, with over RMB 200 trillion in-person mobile transactions.

Ant Group's Alipay and Tencent's TenPay dominate this space. As of June 2020, Alipay had about 55% and TenPay had about 40% of the market share by transaction volume. Both platforms aggressively expanded through strategic partnerships—including with bike-sharing firms. Bike-sharing proved a high-frequency use case for mobile wallets. In turn, wallets enabled seamless integration of payment infrastructure. Ant Group invested over \$0.5 billion in *ofo* and over \$3 billion in *Hellobike*, both of which are tightly integrated with Alipay.

Through Alipay mini-programs, users can unlock *Hellobike* bikes without a separate app or registration. These services are exclusive: TenPay users cannot unlock *Hellobike* bikes. Alipay also waives deposits for users with high credit scores. As stated in Hello Inc.'s IPO filing, this integration fuels both user growth and broader ecosystem development. The competitive landscape intensified when *Meituan-Dianping* acquired *Mobike* for \$2.7 billion in April 2018, rebranding it as *Meituan Bike* and integrating it with their broader service ecosystem. By mid-2024, the bike-sharing industry served over 600 million users nationwide.

Between 2016 and 2020, the rapid expansion of bike-sharing and mobile payments created a natural experiment. The staggered introduction of Alipay-bundled bikes across cities generated exogenous shocks, offering a unique setting to study the causal effects of digital payment adoption.

2 Data and Identification

2.1 Data Description

It has always been challenging to obtain a suitable dataset to study the relationship between payment flow and consumer lending. It requires granular data with linked payment and credit information. It is even harder to study it in a dynamic setting. I overcome these challenges by using proprietary panel data at individual and year-month level from Ant Group, which contain detailed information not only on broad payment and credit activities, but also on rich personal characteristics.

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

Table 1 summarizes the sample across three dimensions. At the individual level, the average user was born in 1983 and engaged in Alipay transactions in 32 of the 41 sampled months. About 54% of users are male; 88% lack a bachelor's degree; and 29% used Alipay-bundled shared bikes at least once during the sample period. At the city-by-month level, the average city in the sample had a log-transformed number of shared bikes of 7.08. At the individual-by-month level, users had a 62% chance of accessing Alipay's virtual credit card, a log-transformed credit line of 7.88, in-person Alipay payments of 5.70, and online payments of 5.76 (in log CNY). On average, 34% of in-person and 33% of online payments were made via virtual credit, while 3% and 1% respectively were linked to compulsive spending categories such as cigarettes, games, lotteries, or live streaming.

Alipay was widely adopted and intensively used by the end of the sample. As of September 2020, the median user had 8 CNY in wallet AUM, and the average was 5,521 CNY. Monthly Alipay transaction amounts at that point had a median of 238 CNY and a mean of 2,628 CNY. For reference, the average monthly disposable income per capita in China in 2020 was 2,682 CNY.

2.2 Identification Challenge

Several endogeneity issues arise in addressing the causal relationship between cashless payment and credit provision. For example, simultaneity can occur when there is synergy between the adoption of cashless payment and credit provision by the payment service provider (Ghosh et al., 2025) or other factors that may simultaneously affect payment and credit. Omitted variables that potentially bias the estimates can also be present. Section A.1 provides an econometric framework to illustrate the economic environment and the endogeneity issues.

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

2.3 Empirical Specification

As illustrated in Figure 3, I use the staggered placement of Alipay-bundled shared bikes across cities as a novel instrumental variable to alleviate endogeneity concerns. As Alipay, the mobile payment leader in China, grew rapidly in recent years, the staggered placements of Alipay-bundled shared bikes across different cities led to exogenous shocks to bike users' adoption of Alipay.

The key idea is that when there are more Alipay-bundled shared bikes placed in the city, the bike-sharing service becomes more valuable for bike users, which in turn motivates them to use Alipay more frequently to unlock bikes by scanning the QR code on the bike. This repeated interaction builds user familiarity and trust in the platform, making it more likely they will use Alipay for other in-person transactions as well. Importantly, the process of scanning a QR code to unlock a bike is technically identical to scanning to pay a merchant, facilitating spillovers in payment behavior beyond bike use.

Building on this identification strategy, I estimate the causal impact of in-person cashless payment flow on BigTech credit provision using a two-stage least squares (2SLS) approach. In the first stage, I instrument the transformed in-person payment flow using the log-transformed city-level placement of Alipay-bundled shared bikes:

$$g(ipf)_{i,t} = \alpha_1 + \beta_1 \cdot log(bp)_{c,t} + \delta_{1i} + \theta_{1t} + \varepsilon_{1i,t}. \tag{1}$$

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

$$Y_{i,t} = \alpha_2 + \beta_2 \cdot g(i\hat{p}f)_{i,t} + \delta_{2i} + \theta_{2t} + \varepsilon_{2i,t}. \tag{2}$$

The corresponding ordinary least squares (OLS) regression is performed using this specification:

$$Y_{i,t} = \alpha_0 + \beta_0 \cdot g(ipf)_{i,t} + \delta_{0i} + \theta_{0t} + \varepsilon_{0i,t}, \tag{3}$$

where $log(bp)_{c,t}$ is log-transformed bike placement in city c at time t; $g(ipf)_{i,t}$ is the transformed measure of the in-person payment flow of individual i at time t; $g(i\hat{p}f)_{i,t}$ is the corresponding instrumented variable; $Y_{i,t}$ is the credit provision variable of individual i at time t; δ_{Ni} ($N = 0, 1, 2$) represents individual fixed effects; and θ_{Nt} ($N = 0, 1, 2$) represents year-month fixed effects.

Note that in some specifications, the outcome variable or a transformed measure of in-person payment flow employs a logarithmic transformation of the form $log(1 + x)$. While this transformation is commonly used to handle skewed data containing zero values, it poses several challenges as highlighted by Cohn et al. (2022), including a lack of clear economic interpretation for the transformed variable, a built-in bias that can potentially invert the sign of estimated effects, and arbitrariness in the added constant. As a superior alternative, Cohn et al. (2022) propose using fixed-effects Poisson (PPML) regression, which is particularly suited to count data and avoids the pitfalls associated with log transformations. However, implementing PPML regression in this study encountered significant computational constraints due to dataset complexity.[3] To address these limitations and ensure robust interpretation, I decompose the effects into extensive and intensive margins. This decomposition approach provides clearer insights into the underlying mechanisms and helps mitigate interpretative challenges associated with variables transformed using $log(1 + x)$.

[3] I attempted to estimate Poisson models using the `glmhdfe` package recommended by Cohn et al. (2022) on the data provider's secure server, which has substantial memory resources. Despite multiple optimization attempts, the complexity of the dataset—comprising over 40,000 individuals with individual fixed effects—resulted in prohibitive memory demands, preventing estimation on the full sample.

2.4 Validity of the Instrumental Variable

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

2.4.1 The Relevance Condition

To assess the strength of city-level bike placement as an instrument for individual-level in-person cashless payment flow, I conduct several analyses that demonstrate the robustness of this relationship, even with granular controls. The results support the view that bike placement acts as an exogenous shock to Alipay users' in-person payment through a behavioral nudge mechanism, rather than via confounding demand-side trends.

Panel A of Table 2 shows the effects of city-level placement of shared bikes on individual-level in-person payment flow. Column (1) shows that when the bike placement of city c in month t increases by 1%, the in-person payment flow of the individuals living in the city increases by 0.041% on average. This effect remains robust when controlling for individual and year-month fixed effects, with standard errors clustered at the city and year-month levels. Individual fixed effects account for time-invariant characteristics such as financial literacy and wealth, while year-month fixed effects capture time-varying shocks like holidays or workdays.

Column (2) provides a placebo test: the positive association exists only among bike users, not among non-users, suggesting that the effect operates through bike usage. For non-users, including those unable to ride bikes, local bike supply should not directly influence payment behavior. This test also helps rule out the possibility that the relationship is driven by unobserved common factors affecting the entire local population, such as local growth potential or infrastructure plans.

Column (3) restricts to bike users and adds city times year-month fixed effects, addressing unobserved time-varying heterogeneity across cities. This specification controls for local business cycles, Alipay penetration, and bike infrastructure trends. The identification relies on comparing in-person payment flow responses to bike placement between bike users who have started using bikes and those who haven't, within the same city, while controlling for individual static characteristics. The intensive margin analysis supports the mechanism whereby bike placement exogenously affects in-person payment flow through bike usage. Among bike users, only after adoption does bike placement significantly influence payment flow: a 1% increase in bike supply leads to a 0.049% rise in in-person payments. Absent bike placement variation, adoption alone has no effect, reducing concerns about endogenous timing or selection into bike use.

Importantly, the relevance of bike placement is driven by a behavioral nudge—users who begin using shared bikes shift their broader payment habits. Figure 4 presents an event study of users' in-person non-bike payment behavior around the time of their first use of Alipay-bundled shared bikes, with panel (a) showing the $log(1 + \text{payment flow})$ measure and panel (b) focusing on the extensive margin. The sharp increase in non-bike-related in-person payment flow—over 80% in the adoption month and more than 30% in subsequent months—suggests a persistent change in payment behavior triggered by bike adoption. Additionally, the extensive margin results in panel (b) reveal a decreasing pattern over time, contrasting with the relatively flat long-run effects observed in the $log(1 + \text{payment flow})$ measure in panel (a), indicating that both participation and volume are critical for sustaining long-term shifts in payment usage. Since this pattern emerges around the idiosyncratic adoption dates of individuals and remains after controlling for both individual and time fixed effects, it is unlikely to be driven by broader consumption changes or reverse causality. Furthermore, Alipay registration patterns (Figure A.3) show that fewer than 1% of users start using Alipay solely for bike access, ruling out mechanical registration effects.

Additional evidence supporting the logic flow is provided in the Appendix. Table A.1 reports OLS estimates based on Alipay users who used a shared bike at least once during the sample period, with Columns (2) and (3) focusing on months when bikes were used. The results indicate a positive relationship between city-level bike placement and individual bike usage on both the extensive and intensive margins. When more bikes are placed in a city, finding an available shared bike becomes easier for bike users, and they are expected to have higher bike-riding activity. In addition, as Cao et al. (2018) demonstrate, since the dockless bike-sharing system is a one-sided network with positive network effects, there might also exist indirect effects, whereby more bike-riding activity by one user also increases others' bike-riding activity. Together, these direct and indirect effects reinforce the positive link between bike placement and user activity. Table A.2 further shows a strong correlation between bike usage and in-person cashless payments.

2.4.2 The Exclusion Restriction Condition

The identifying assumption is that bike placement affects digital credit provision only through in-person cashless payment. Three major concerns arise regarding satisfaction of the exclusion restriction condition when using the bike placement instrument. The first concern is that common factors might influence both bike placement and credit provision. The second concern is that bike usage may have direct effects on credit provision and that selection issues such as differing characteristics of bike users might bias this relationship. The third concern is that bike placement is predictable or clustered within a short time, which renders it not as exogenous as required.

Concern 1: Common Factors A key concern is that common time-varying factors may simultaneously influence both bike placement and Alipay's credit provision. For instance, cities attracting greater economic attention may see both more bike deployments and expanded credit access, confounding the causal interpretation.

Panel B of Table 2 provides reduced-form results on the influence of bike placement on credit provision, and indicates that the positive relationship between bike placement and credit provision is unlikely to be driven by common factors unrelated to the bike-riding channel. Column (1) shows that the higher the bike-placement shock in a city, the higher the credit line the individuals living in the city receive. In this setting, individual fixed effects and year-month fixed effects remove static heterogeneity across individuals and time-varying macroeconomic variations.

To further validate the mechanism that bike placement predominantly affects credit lines through its effect on bike usage, I separate Alipay users into bike users and non-bike users in column (2). The analysis reveals a positive effect of bike placement on credit provision solely for bike users—even though the only difference between the two groups is whether the person used Alipay-bundled shared bikes at least once during the sample period. This supports the channel in which bike placement leads to increased bike usage, triggering more in-person payment flows that, in turn, enhance credit access. It also helps reject the story whereby some factors correlate with both bike placement and credit provision, since the usual common factors are unlikely to affect bike users and non-bike users in different ways—especially when it is extremely inexpensive for an Alipay user to be a bike user as defined herein.

Column (3) focuses on bike users and reports results of the regression with individual fixed effects and city times year-month fixed effects. While the timing of bike adoption is endogenous, the adoption dummy alone does not predict higher credit lines. However, its interaction with bike placement shows a significant positive effect, reinforcing the interpretation that increased bike usage—rather than timing per se—drives improved credit access.

To address methodological concerns around the $log(1 + x)$ transformation, which can be problematic with zero-heavy outcomes (Cohn et al., 2022), Table A.3 decomposes effects into extensive and intensive margins. Both show significant positive responses to bike placement, particularly among bike users. Another potential issue is the impact of bike placement on the local economy. Some might worry that the convenience and widespread use of shared bikes could create new business opportunities, affecting local economic conditions or fiscal policy, and indirectly influencing credit provision. Table A.4 shows the relationships between bike placement and local economic variables. Under city and year-month fixed effects, all coefficients are small and insignificant, suggesting that bike placement is unlikely to have substantial macroeconomic impacts.

Concern 2: Direct Effects and Selection Issues of Bike Usage The second concern incorporates the possibility that bike usage directly affects credit provision as well as that selection issues might be at play. Several institutional details help address this. First, Alipay is only a strategic partner of the bike-sharing companies and likely does not use third-party data directly in its credit models. Bundling appears limited: official bike apps support multiple mobile wallets, and Alipay is not required. Second, the low cost of bike usage makes it easily manipulable. If users could game credit scores through bike activity, a sophisticated platform like Alipay would adjust its models accordingly in equilibrium. Third, the user base is quite large, which limits the scope for selective adoption and, consequently, reduces the signaling value of bike usage. As of late 2019, there were 260 million shared-bike users in China, and *Hellobike* alone had 400 million registered users by 2021.

Table 3 shows that bike usage appears more like a behavioral nudge for payment activity and credit line extension rather than a direct signal of creditworthiness. I distinguish between one-time users—those who used a shared bike via Alipay only once—and repeat users. Among the 41,485 users in the sample, 70.8% never used shared bikes, 4.5% were one-time users, and 24.7% were repeat users. Even if bike usage carries some informational value in the long run, a single ride should reveal little. Still, columns (1) and (3) show that bike placement significantly increases payment activity and credit line for one-time users, but not for non-users. The difference is notable despite only one ride separating the groups. The effects are larger for repeat users, but the marginal gain over one-time users is modest. Columns (2) and (4) indicate that the patterns are very robust, even when city times year-month fixed effects are added to the specification.

To further investigate the plausibility of the effects on one-time bike users, I plot the dynamic effects of the first bike usage on the one-time bike users' non-bike-related in-person payment flow in Figure A.4. Panel (a) shows that non-bike in-person payment flow, measured as $log(1 + \text{In-Person Non-Bike Payment Flow})_{i,t}$, rises immediately after the first bike use and persists for several months. Panel (b) shows similar increases in the probability of non-bike in-person payments. Although the persistence is not uniform, the magnitude is substantial for a single ride. This provides suggestive evidence that the availability of shared bikes and even just a single usage can have a meaningful nudge effect on consumers' adoption of mobile payments. This may occur through a reduction in one-time setup costs, enhanced familiarity with the payment interface, and a boost in perceived convenience. For instance, once a user sets up Alipay for bike payments, they are more likely to use it for other transactions.

Table A.5 separately analyzes the effects of bike placement on the extensive and intensive margins of in-person payment flow and credit provision, confirming the main findings. The monotonicity of the effect size is more pronounced on the extensive margin, suggesting that frequent shared bike usage increases the likelihood of adopting cashless payments and gaining credit access by lowering setup barriers and increasing interface familiarity. On the intensive margin, however, the effect sizes exhibit a non-monotonic pattern, particularly when segmenting users by riding frequency. To explore this, I re-estimated the models with a finer, five-tier ride-count segmentation and visualized the coefficients in Figure A.5, Panels (a)–(d). Two patterns emerge: first, on the extensive margins, the effects rise almost monotonically with riding intensity, aligning with the narrative that bike availability nudges payment and credit adoption. Second, on the intensive margins, there is a pronounced spike for one-time riders, while for users with at least two rides, the coefficients increase monotonically across higher usage brackets. The spike for one-time riders may reflect underlying differences in user characteristics or behavior, though the precise reasons remain unclear. With the current data, it is challenging to fully identify the factors contributing to this non-monotonic pattern on the intensive margin.

Although becoming a bike user is easy, one could argue that bike users and non-bike users have different characteristics that drive the effect of bike placement on credit provision. To address this, I examine personal characteristics associated with being a bike user and their impact on the effects of bike placement. Table A.6 shows several characteristics correlated with being a bike user, including education, age, and gender. Table A.7 reports the heterogeneous effects of bike placement on payment flow and credit provision, interacting bike placement with both the bike user dummy and personal characteristics. Across all specifications, the heterogeneity primarily arises from the bike-user dimension, not personal characteristics. These results suggest that bike-usage-associated behaviors, rather than selection, drive the effects of bike placement on payment flow and credit provision. It's unlikely that bike users benefit from the Alipay credit line shock simply due to different personal characteristics, especially given the ease of becoming a bike user.

Concern 3: Bike Placement The third concern is about the bike placement process. If it is a predictable process or is clustered within a short period for all cities, it is more likely that it will correlate with other factors that are associated with credit provision. From the perspective of bike-sharing companies, it is more beneficial for them to make bike placement a staggered and unpredictable process, and the empirical evidence supports this. There is anecdotal evidence that what bike-sharing companies care most about is local competition and their own operational efficiency, and this could lead to heterogeneous overall strategies. For example, bike-sharing companies such as *Mobike* and *ofo* focused mostly on big cities in the beginning and gradually expanded to smaller cities, while *Hellobike* started bike placement in small cities first to avoid competition and then gradually expanded to larger cities. Regardless of which cities they decide to target first, bike-sharing companies always have an incentive to quickly place their shared bikes in the local market because it helps them build local market power and avoid competitors who may react strategically. Since there are capacity constraints for bike production, it is not feasible to put bikes in all targeted cities within a very short time frame.

Figure 5 plots the β_τ coefficients estimated in the following regression:

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

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

At the same time, the timing of the bike-placement shock is hard for citizens to predict. Figure A.6 shows the monthly time series of the number of cities that are in their month of the largest bike-placement shocks. The critical month for each city's bike placement is distributed broadly over the sample period. This is consistent with the fact that there are capacity constraints on bike production and bike allocation. In that sense, placing shared bikes is like playing chess, in which the players target different cities during different periods. Once they decide on the cities to target, they place many bikes within a very short time frame. Since bike placement is quite staggered and the time of the largest bike-placement shock spreads over time, it is hard for citizens of a specific city to predict shocks from the placement of Alipay-bundled shared bikes using only public information.

3 Instrumental Variable Analysis

This section first presents the results of the main specification, which investigates the causal effect of in-person cashless payment flow on BigTech credit provision and consumer take-up of the credit with the IV strategy. It then demonstrates the importance of the payment information channel in facilitating BigTech credit provision. Finally, it illustrates the implications of in-person cashless payment flow for financial inclusion, whereby the causal effects of in-person payment on credit provision mainly hold for the traditionally financially underserved.

3.1 In-person Cashless Payment Flow and Credit Provision

3.1.1 Causal Effects of In-person Cashless Payment on Credit Provision

Table 4 reports regression results corresponding to equations (1), (2), and (3). Panel A presents second-stage 2SLS estimates, Panel B shows first-stage results, and Panel C displays OLS estimates. Columns (1)-(3) focus on the extensive margin, where Credit Access$_{i,t}$ is a dummy variable that equals 1 if Alipay user i has access to Alipay's virtual credit card at time t and 0 otherwise. Columns (4)-(6) focus on the intensive margin and use only the sample in which users have credit access in the corresponding months, and $log(\text{Credit Line})_{i,t}$ is the log-transformed credit line of Alipay user i's virtual credit card at time t. The outcome variable $g(ipf)_{i,t}$ varies across columns: in

(1) and (4), it is $log(1+x)$ of in-person payment flow; in (2) and (5), a binary indicator for positive payment flow; and in (3) and (6), $log(x)$ conditional on positive flow. All regressions include individual and year-month fixed effects, allowing identification from within-user variation.

Panel A shows that a month with positive in-person payment flow increases the probability of gaining credit access by 56.3% and raises the credit line by 203.3% among users with access. A 1% increase in payment flow leads to a 0.087% rise in credit access likelihood and a 0.409% increase in credit line among eligible users.

Panel B confirms a significant first-stage relationship between bike placement and payment flow, with moderately strong F-statistics. Thus, I employ additional econometric techniques to provide more robust statistical inference. Specifically, I report the Anderson-Rubin (AR) test statistic and corresponding p-values, which are consistently 0.000 across all specifications. The AR test examines whether the structural coefficient equals zero without assuming that the instrument is strong, providing robust inference even in the presence of weak instruments. Panel B also reports the heteroskedastic version of the sample correlation between the main equation and first-stage residuals while imposing the null hypothesis. The correlation is relatively small, and the degree of "endogeneity" is low. The high significance levels obtained under the VtF procedure, in combination with strong first-stage F-statistics and AR test results, suggest that the instrument provides substantial identifying variation. The VtF procedure, like the AR test, tests the null hypothesis that the structural coefficient equals zero while remaining valid under weak identification.[4]

Panel C presents the OLS estimates, which are much smaller than the corresponding IV estimates. There are two potential reasons: (1) omitted variables and (2) the non-monotonic 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. Section A.1 in the Appendix discusses this issue. For example, negative health shocks or unexpected family expenses can reduce credit access while increasing payment activity. Although some factors—like income gains or financial literacy improvements—could bias OLS estimates upward, the data suggest downward-biasing influences dominate. Second, the relationship between credit provision and payment flow may be non-monotonic: at low levels, higher payment activity generates valuable data that facilitates credit access, but at higher levels, it may signal overspending and increased risk. Supporting evidence is shown in Figure A.7 and Table A.8.

[4]Following Lee et al. (2023), I compute the VtF significance by comparing the 2SLS t-statistic against critical values derived from the VtF procedure. While Lee et al. (2023) highlight the advantage of their VtF procedure over the Anderson-Rubin statistic in this context, I report the AR test alongside it, which uniformly rejects the null at the 1% level across all specifications.

Table A.9 supports the view that the IV estimates are quite robust, while the OLS estimates tend to be biased. This table presents the results in which city times year-month fixed effects are added, and the interaction between the bike-user indicator and log-transformed bike placement serves as the instrument. This is the Bartik instrument that takes advantage of the different treatments received by bike users and non-bike users. The instrument is very strong and F-statistics are above 300 in all specifications. This setting allows us to add the city times year-month fixed effects, which remove the unobserved time-varying heterogeneity across cities. Notably, the IV estimates remain consistent with the results in Table 4, while the OLS estimates increase substantially compared to specifications without these additional fixed effects. This convergence of OLS estimates towards IV estimates with more stringent controls suggests that much of the initial discrepancy may be due to omitted variables bias that is mitigated by the additional fixed effects. The stability of IV estimates across specifications, coupled with the movement of OLS estimates, lends credibility to the IV strategy and helps explain the initially large gap between IV and OLS results.

To further address the concern that Alipay might use bike usage data directly in credit assessments—potentially violating the exclusion restriction—I develop a refined empirical strategy using two instrumental variables. Specifically, I interact the city-level log bike placement with a user-level bike-usage indicator to serve as a second instrument, allowing me to simultaneously instrument both in-person payment flow and bike usage. This setup leverages differential responses to local bike availability based on actual user activity. As shown in Table A.10, both instruments are strong, with first-stage F-statistics exceeding conventional thresholds. The two-stage least squares estimates confirm that in-person payment flow remains a robust and positive predictor of credit provision. In contrast, the coefficient on bike usage is negative and statistically significant, suggesting that more frequent bike use is not driving higher credit access. If anything, the results are consistent with the interpretation that bike usage is weakly associated with lower credit provision, possibly because shared bike use is a low-cost activity correlated with lower income. These findings strengthen the case that the primary mechanism through which bike placement affects credit access is via increased payment activity, rather than a direct effect of bike usage. To ensure these findings are not driven by functional form assumptions when both instruments affect both endogenous variables in the same direction, I also implement an extensive margin specification (Table A.11) using dummy variables for whether individuals engage in in-person payments and bike-sharing. This approach captures discrete adoption decisions without imposing log transformations on continuous variables. The results remain robust: the payment flow extensive margin shows positive, statistically significant effects on credit provision, while the bike usage extensive margin remains negative.

As a robustness check, I use an alternative identification strategy by restricting the sample to users with very stable payment flows, assessing whether bike usage affects credit provision for this subsample. This approach allows us to isolate the effect of bike usage on credit provision while minimizing the confounding influence of payment flow variations. The results (Table A.12) across users below the median and 25th percentile of payment fluctuation show that bike usage has negligible and statistically insignificant impacts on both credit access and credit lines, especially when controlling for in-person payment activity. These findings reinforce that bike usage itself does not directly drive credit provision; instead, the main pathway linking bike placement and credit access is increased in-person payment activity, echoing conclusions from both log transformation and extensive margin analyses.

What is more, the patterns illustrated in Table 4 are very robust under various other settings. Table A.13 shows that the in-person payment flow also affects future credit provision. Table A.14 reports results of regressions that control for the in-person payment flow in the past 1, 2, or 3 months. Table A.15 further includes online payment as a control. While these additional controls are not instrumented and their coefficients should be interpreted cautiously, their inclusion serves as a robustness check for our main result. Across these specifications, the effects of the concurrent in-person payment flow on credit provision remain stable and significant, with similar magnitudes. This consistency underscores the robustness of our primary finding regarding the relationship between in-person payment flow and credit provision, even when accounting for various potential confounding factors.

3.1.2 Consumer Take-up of BigTech Credit

As discussed, Alipay users passively receive their virtual credit line—there's no application process, and eligibility is communicated directly in the app. While credit access is supply-driven, actual use depends on demand. It is natural to anticipate that more in-person payment flow leads to a higher fraction of spending paid for with the virtual credit card, both in-person and online, for two reasons. First, a learning-by-doing mechanism: users who transact more are likely to gain familiarity and trust, increasing credit use. Second, a supply-side effect: higher payment activity is associated with higher credit lines, which may further boost usage.

Results in columns (1) and (2) of Table 5 support the above view of consumer credit take-up. With an exogenous increase in the in-person payment flow, the share paid with Alipay's virtual credit card increases for both in-person payment and online payment. The magnitude of the increase is larger for in-person payment.

The welfare implications of increased take-up are ambiguous. On the one hand, rational consumers benefit from relaxed credit constraints and the 40-day interest-free grace period of *Huabei*, which enhances consumption smoothing. On the other hand, if a consumer has behavioral biases, such as self-control or forecasting problems, she might end up suffering a significant debt burden in the future and reduced welfare. There is supporting evidence for both views and there is a lack of consensus in the consumer finance literature (Zinman, 2015).

Using detailed transaction-level data, I assess whether easier credit access disproportionately fuels compulsive spending. If self-control is an issue, easier access could exacerbate impulsive behavior. However, columns (3) and (4) of Table 5 show no increase in the share of compulsive spending, either online or in-person. Though total compulsive spending may rise with overall spending, the stable share suggests proportional growth, not behavioral distortion.

Both self-control and forecasting problems might cause a consumer to overspend after she gets access to a new credit line. I do an event study to evaluate whether consumers have a temporary increase and a sharp reversal in Alipay consumption after they are granted access to a *Huabei* credit line. Figure A.8 illustrates the changes in Alipay payment flow around the consumer's first month of having access to the *Huabei* credit line by plotting the β_τ coefficients estimated in the regression:

$$\begin{aligned} log(1 + \text{Total Payment Flow})_{i,t} &= \alpha_0 \\ &+ \sum_{\tau=-5}^{4} \beta_\tau \cdot \mathbb{1}(t = \tau) \cdot \mathbb{1}(\tau \neq -1) + \beta_5 \cdot \mathbb{1}(t \geq 5) + \delta_i + \mu_t + \varepsilon_{i,t}, \quad (5) \end{aligned}$$

where $log(1 + \text{Total Payment Flow})_{i,t}$ captures the monthly payment volume in Alipay for user i in month t, relative to the time of credit access ($t = 0$). Fixed effects δ_i and μ_t control for individual and time variation. The sample excludes months before $t = -5$.

Consumers' Alipay payment responses to credit access can stem from three forces. First, relaxed credit constraints enable greater spending to smooth consumption. Second, consumers may shift spending from other instruments, such as cash or debit cards, to Alipay. Third, behavioral biases may lead to short-term overspending followed by long-term repayment-driven underspending. I observe a temporary spike and a stable long-term increase in Alipay payments, without a significant reversal (as indicated by β_5), suggesting overspending is likely mild in this context.

Nonetheless, welfare implications are hard to pin down without full consumption data across payment platforms. While the observed patterns in Alipay usage suggest a stable increase in spending without significant reversal, the overall welfare effects remain an open question that would require additional data to assess more definitively.

3.2 The Payment Flow Information Channel

3.2.1 Channels for Credit Provision

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

Information channels include:

- Payment Flow Channel: Use the information on payment flow.
- Credit History Channel: Use the information on credit usage and repayment.
- Application Data Channel: Use the information on the application form.

Enforcement channels include:

- Implicit Collateral Channel: Use AUM in the platform as collateral.
- Explicit Collateral Channel: Explicitly pledge assets as security for loan repayment.

For banks that do not have borrower payment flow information, the Payment Flow Channel is usually not an option. Instead, the Application Data Channel plays an important role before the borrower gains credit access, and the Credit History Channel becomes the most important channel for reducing information asymmetry after the borrower gains credit access. For secured loans such as mortgages, banks usually require borrowers to use the Explicit Collateral Channel and forfeit the collateral in the event of default.

The BigTech company that provides the cashless payment service to borrowers has an advantage in the Payment Flow Channel, whereby the rich information contained in the payment flows reveals valuable information on the borrower's creditworthiness. In the specific setting of Alipay, no application process and explicitly pledged assets are required to access a virtual credit card; thus the Application Data Channel and Explicit Collateral Channel are unlikely to play a role in Alipay's credit provision. Instead, the Credit History Channel can be important, and the enforcement power by the lender can be strong, especially when users use the digital wallets frequently. For example, a borrower's AUM on Alipay's wealth management products (Implicit Collateral Channel) might serve as collateral to facilitate credit provision, since the borrower might worry that the account could be frozen if they do not repay the credit in time.

In this research, I focus on showing the importance of the Payment Flow Channel for credit provision by Alipay and show that the channel holds strongly, whereas the Application Data Channel and Explicit Collateral Channel are unavailable and the Credit History Channel and Implicit Collateral Channel are controlled for.

3.2.2 Control for the Credit History Channel

With the Alipay app, users have several options to make in-person and online payments. On the Alipay platform, they can use the e-wallet account balance, a liquid money market fund called *Yu'ebao*, or *Huabei*, Alipay's virtual credit card. Although Alipay also supports payments using debit card or credit card accounts for some merchants, most transactions on the Alipay platform are paid for with these within-Alipay payment methods since they are cheap, convenient, and widely accepted. I define "in-person credit payment flow" as the amount of in-person Alipay spending paid for by using Alipay's virtual credit card, and this payment flow is directly associated with credit usage and is highly relevant for the credit repayment flow. All other in-person payment flow is defined as the "in-person noncredit payment flow," which does not have a direct relationship with credit usage and repayment.

Table 6 shows the results of the 2SLS and OLS regressions with specifications similar to those of equations (1), (2), and (3), while replacing in-person payment flow with in-person noncredit payment flow, which excludes in-person Alipay payment flow paid for with the virtual credit card. This exclusion helps eliminate the effects of credit use and repayment on BigTech credit provision. Columns (1) and (3) show that the in-person noncredit payment flow has direct effects on BigTech credit provision, and indicates that even after controlling for the Credit History Channel, the Payment Flow Channel still matters. However, there might be concerns that the in-person noncredit payment flow is correlated with the in-person credit payment flow, and the specifications in columns (1) and (3) fail to fully exclude the effects of credit usage and repayment. To alleviate concern about the correlation between payment flows, in the specifications of columns (2) and (4) the in-person credit payment flow is added as a control variable in all regressions. The results are still robust, with very close estimates. Moreover, in the second stage of the 2SLS regressions, the in-person credit payment flow does not seem to have a significant impact on credit provision, on either the extensive margin or 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 4, which indicates that in-person noncredit payment has larger effects than credit payment. This result is reasonable, since the usage of credit directly leads to a heavier repayment burden and riskier consumer profile, while usage of the account balance does not have a direct implication for the risk faced by the BigTech lender.

3.2.3 Control for the Implicit Collateral Channel

Although the Explicit Collateral Channel is unavailable on the Alipay platform, the user's AUM in Alipay's wealth management products can partially play the role of collateral, since the Alipay platform has the right to freeze the user's account if she does not repay the loan on time. This is referred to as the Implicit Collateral Channel. There is a concern that the BigTech credit provision to a user is largely driven by the size of her AUM instead of the information channels. To deal with this concern, the specifications that control for each user's time-varying AUM are analyzed.

Table 7 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) define AUM as all assets in Alipay except for the account balance, while columns (2) and (4) define AUM as all Alipay assets including the account balance. Regardless of which specification is used, the AUM does not have a strong relationship with the credit provision variables, while the in-person payment flow has strong effects on credit provision on both the extensive margin and intensive margin.

While these results suggest that the Payment Flow Channel plays a more significant role in credit provision than the Implicit Collateral Channel, it's important to note that controlling for AUM may not fully capture the complexity of Alipay's enforcement capabilities. The platform's ability to potentially exclude users from its broader ecosystem of services likely serves as an additional deterrent against default, extending beyond just the user's financial assets on the platform.

3.2.4 Heterogeneous Effects of Payment Flows on Credit Access

Having established the significance of the Payment Flow Channel and controlled for other potential channels, it is important to examine how this channel operates in practice. While the previous analysis demonstrates that payment flows generally influence credit access, the relationship is more nuanced than a simple linear correlation. This section explores the heterogeneous nature of how payment information affects credit provision decisions.

Although on average more payment records lead to more credit access, this relationship is neither homogeneous nor monotonic. While BigTech companies might have incentives to extend credit to retain users and gain market share, even if some departments lose money, evidence shown below suggests Alipay prioritizes stringent risk management in its lending operations. A key element of this approach is the continuous assessment of credit risk. This raises the question: Is Alipay learning about credit risk by analyzing users' payment flows? The subsequent analysis suggests that the answer is yes, and this learning process results in heterogeneous impacts on credit access.

First, Alipay appears to strongly prioritize risk management in its lending practices. As of June 2019, the delinquency rate of *Huabei* credit (1.16%) was lower than that of China's publicly listed banks' credit cards (1.21% to 2.49%), despite *Huabei* serving a broader population. Public filings from Ant Group underscore a robust risk-minimization framework, explicitly highlighting their approach to dynamically adjusting credit approval processes and limits based on continuous assessment of users' transactional behavior and credit histories. Specifically, Ant Group's pre-IPO prospectus documents the use of over 100 credit assessment models designed to monitor and dynamically adjust users' risk profiles, allowing for both increases and reductions in credit lines as transactional information is updated.[5] Additionally, Alipay's co-lending model with traditional banks, where external partners bear substantial default risks, further incentivizes prudent risk management and conservative underwriting standards. Though indirect, these findings suggest that Alipay's credit decisions are guided by ongoing evaluations of risk and return.

Second, more payment information does not always translate into increased credit access for all users. The mechanism behind expanded credit provision is that the lender gains insights into borrowers' creditworthiness from payment flows. However, this learning can have disparate effects—creditworthy borrowers may be offered higher limits, while riskier users could face reductions. In my sample, 2.67% of users faced at least one instance of credit reduction. Further analysis using detailed transaction-level data reveals clear patterns in the relationship between specific payment behaviors and credit limits. As shown in Figure A.9, transactions that reflect substantial liquidity reductions, such as real estate brokerage fees, or spending tied to limited financial reserves, such as casual games and tourism attractions or exhibits, are negatively associated with credit lines. Similarly, expenditures typical of older or less digitally active consumers, including cable television subscriptions and payments for government services, also tend to correlate negatively with credit provision. In contrast, stable lifestyle indicators—such as spending on family-related items like bookstores and educational activities, as well as memberships and professional services—are positively associated with credit limits.

[5] Please refer to the section titled "Dynamic Credit Risk Management" in Ant Group's pre-IPO prospectus, available at: https://www1.hkexnews.hk/listedco/listconews/sehk/2020/1026/2020102600165.pdf

Third, a non-parametric binscatter analysis (Figure A.7) demonstrates a concave relationship between normalized in-person payment flows and credit availability. At the upper end of the payment flow distribution, credit provision appears to plateau and even decline slightly. This pattern could indicate increased risk associated with overspending, although the economic significance of this reversal is modest. This pattern is consistent with complementary regressions that use contemporaneous and lagged payment flows (Table A.8).

Finally, credit decisions are informed not only by payment amounts but also by the nature of the transactions. Table A.17 in the Appendix examines how payment flow and compulsive spending share correlate with credit provision on both the extensive and intensive margins. Payment flow amount positively correlates with credit provision, while compulsive spending share exhibits a negative correlation. When including both the direct effect of compulsive spending share and its interaction with payment flows (columns (2) and (4)), the compulsive spending share retains a strong negative association with credit provision. However, the interaction term itself is statistically insignificant on the extensive margin and positive on the intensive margin, contrary to the expected negative relationship where high payment flows coupled with compulsive spending would amplify adverse credit assessments. While these findings are correlational and the interaction results remain somewhat inconclusive, they suggest that the BigTech lender's algorithm may distinguish between payment volume and spending quality, using granular transaction data to assess behavioral signals beyond simple aggregate amounts.

In summary, the relationship between payment flows and credit provision is complex and shaped by Alipay's risk management objective. Increased payment flow information can lead to either expanded or reduced credit access for individual borrowers, depending on the signals it sends about their creditworthiness. The BigTech lender leverages granular payment data, not just payment amounts, to make personalized credit decisions.

3.3 The Financial Inclusion Implications of Cashless Payment

3.3.1 Heterogeneous Outcomes in an Illustrative Example

Before analyzing the heterogeneous effects of cashless payment adoption on credit access empirically, I use an illustrative example to show the potential heterogeneous outcomes predicted by the theory. The detailed setup of the theoretical example is described in Section A.2. Here, I consider the cashless payment adoption as an information shock to the lender and show that it can potentially lead to opposite credit access outcomes for borrowers who are less creditworthy.

There are one lender and a continuum of borrowers in the example. The cashless payment firm, as the only lender, offers a personalized credit line to each borrower. Based on information about the creditworthiness of each borrower, the lender chooses the optimal credit limit to maximize its expected profit. I consider three cases, which represent borrowers' three stages of digital payment adoption. In the first stage—the cash user stage—the borrowers only use cash for transactions, and the lender does not have any creditworthiness information for each borrower. In the second stage—the new digital money adopter stage—borrowers just start to use digital money and submit some personal characteristics information to the lender, and I assume the lender only knows whether the creditworthiness of a borrower is above a threshold or not. In the third stage—the digital money user stage—borrowers start using digital money for daily purchases, which can be observed by the lender, and I assume the lender knows the exact creditworthiness of each borrower.

The relationship between the optimal credit line and the type of borrower in different scenarios is illustrated in Figure 6. Figure (a) shows the financial divide scenario. In this scenario, the threshold value in the new digital money adopter stage is set at 0.25, and some less creditworthy borrowers are worse off in the transition to the digital money user stage. Figure (b) shows the financial inclusion scenario, in which the threshold value in the new digital money adopter stage is instead set at 0.8. As a result, some less creditworthy borrowers are better off in the transition to the digital money user stage. Comparison of the two scenarios shows that better information acquisition by the monopolistic lender does not always lead to more credit access for borrowers with lower creditworthiness.

Without looking into the data, the theory alone does not tell us the impacts of cashless payment adoption on different groups. In the following empirical analysis, I first define traditionally financially underserved segments and then evaluate the heterogeneous effects across segments.

3.3.2 The Traditionally Financially Underserved Segment

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

Columns (1), (2), and (3) in Table 8 show the results of cross-sectional regressions that examine the relationship between users' financial activities with Alipay and their personal characteristics. The less educated and the older groups tend to have fewer Alipay financial activities—fewer Alipay-linked debit cards, smaller all-time-high Alipay AUM, and shorter Alipay investment experience. This is consistent with the argument that these groups are less financially literate and are less served by financial institutions.

Less educated and older groups also tend to have lower financial literacy (Lyons et al., 2019), which can potentially further worsen the problem of inadequate access to financial services. My data confirm that this is also a problem for Alipay users who are less educated and older. Columns (4), (5), and (6) in Table 8 show evidence on how sampled users' education and age relate to measures of financial literacy. Less educated and older users tend to have a smaller likelihood of paying while using their real name, using their own accounts instead of others' accounts, and completing their profile information. These behavioral characteristics are detected automatically by machine learning algorithms. Although it is unclear whether these labels are directly used in making consumer lending decisions for borrowers in the Alipay system, they tend to deliver negative signals about the borrower's creditworthiness, since these behaviors are misaligned with the normal standard.

3.3.3 In-person Cashless Payment and Financial Inclusion

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

Table 9 presents empirical evidence showing the causal relationship between a user's in-person payment flow and the BigTech credit provided to the user, separately for the less and more educated groups and on both the extensive margin and the intensive margin. Panel B shows that, regardless of education group, the first stage is always quite strong. This means that the bike-placement shock consistently increases the in-person cashless payment flow of both the less and more educated. Second-stage results in Panel A reveal that the effects of in-person payment flow on credit provision are quite different for Alipay users with different education levels. The positive relationship only exists for the less educated group and becomes insignificant for the more educated group, on both the extensive margin and the intensive margin. For the less educated group, an increase of in-person payment flow of 1% leads to an increase in the probability of gaining credit access of 0.093% and an increase in the credit line of 0.334%, conditional on credit access. The corresponding numbers for the more educated groups are 0.024% on the extensive margin and 0.038% on the intensive margin, and both estimates are insignificant.

Similarly, Table A.16 presents results for age-based groups. While both older and younger groups show strong first-stage effects, the second stage reveals significant differences. Older users experience notably larger effects from increased payment flow on both the extensive and intensive margins of credit access. This aligns with the previous findings, suggesting that the older, traditionally underserved group benefits more from in-person cashless payment adoption, resulting in greater improvements in their credit access.

4 Conclusion

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

Using deidentified data from Alipay, the world's leading mobile payment platform with 1 billion active users, I document that an exogenous increase in the in-person cashless payment flow leads to more credit provision. This increase in credit provision stems from the useful information for credit evaluation provided by the payment flow, going beyond what is available from credit usage, repayment, and assets under management. To address endogeneity concerns, I employ a novel instrumental variable approach leveraging the staggered placement of Alipay-bundled dockless shared bikes across cities, conducting several tests to confirm the instrument's validity.

A key finding is that previously financially underserved groups, particularly those with lower education levels and older individuals, benefit more from mobile payment adoption in terms of increased credit access. This suggests that digital payment technologies may have the potential to promote financial inclusion. I propose a simple theoretical framework to provide insight into the underlying forces that can generate the corresponding predictions.

These findings have important policy implications, particularly for developing countries that may experience rapid changes in cashless payment markets. The widespread adoption of mobile phones could provide new opportunities for financial inclusion, with mobile payments potentially supporting sustainable business models for lending to underserved populations. As digital payment systems become more prevalent, they may increasingly function as infrastructure for credit evaluation and provision.

However, it is important to note that increased credit provision to relatively underserved groups does not necessarily imply optimal lending practices or improved welfare for all individuals. For instance, it may not be profitable or prudent to lend to extremely disadvantaged individuals. In such cases, government interventions or subsidies might be necessary to address financial inclusion goals.

This paper represents an initial exploration of the implications of digital payments in the consumer credit market. Further research is needed to fully understand the welfare implications of these developments and to inform appropriate public policies. Future studies could benefit from more comprehensive theoretical frameworks and empirical strategies to conduct formal welfare analyses, considering both the benefits of increased credit access and potential risks such as over-indebtedness.

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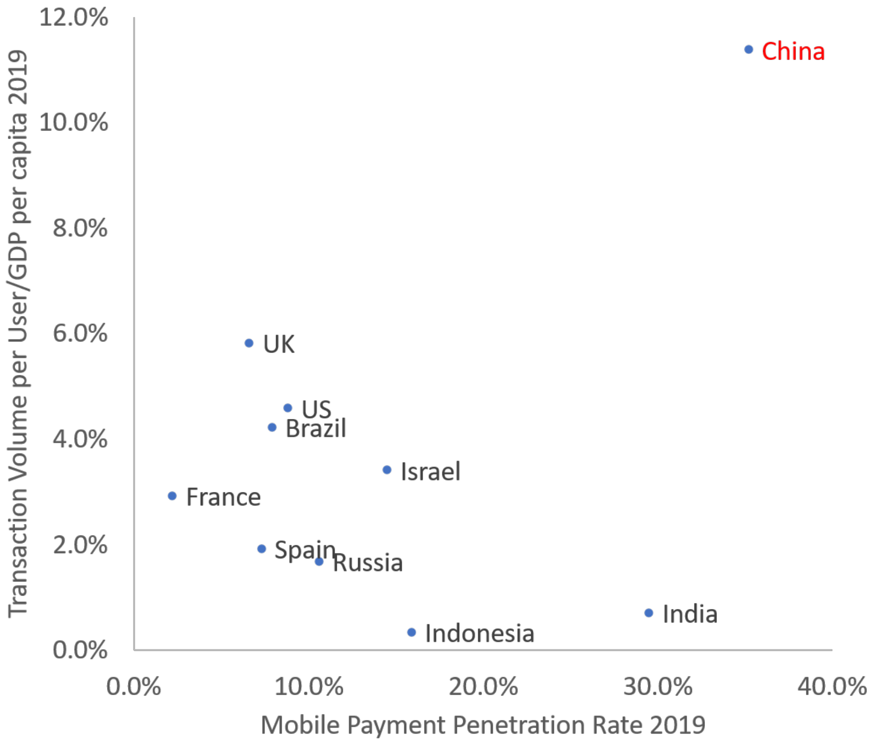
Figure 1: Mobile Payment Penetration across Countries

These figures show the GDP-adjusted mobile payment transaction volume per user and the mobile payment penetration rate for selected countries in 2019 and 2023. Data sources are the Statista Digital Market Outlook and the World Bank.

(a) 2019



(b) 2023

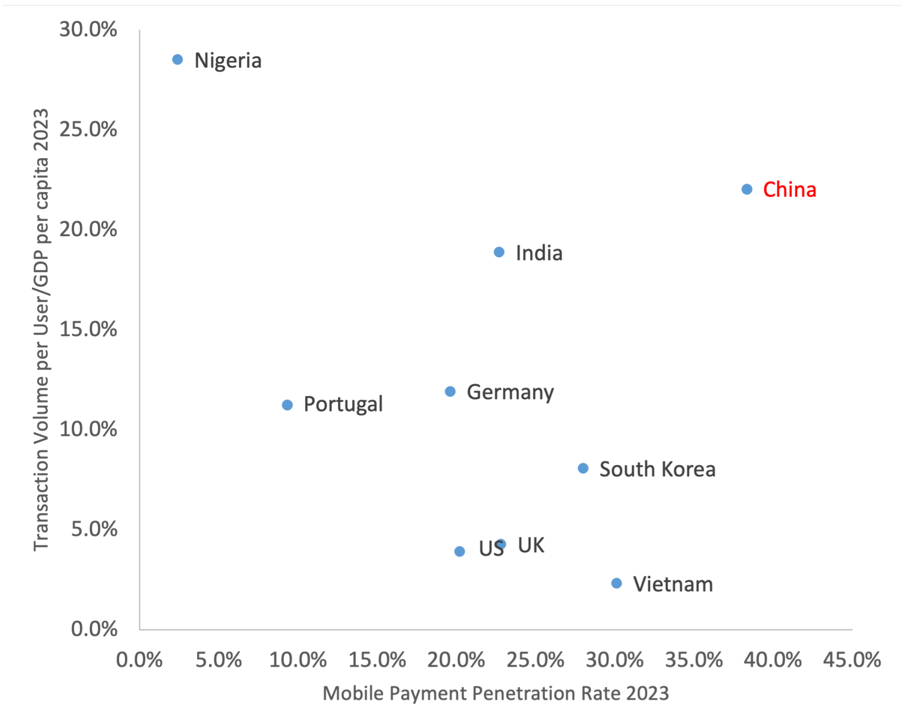


Figure 2: Transaction Volume of Mobile and Card Payment in China and US

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 2021. Data sources are the US Federal Reserve, the People's Bank of China (PBOC), and the World Bank.

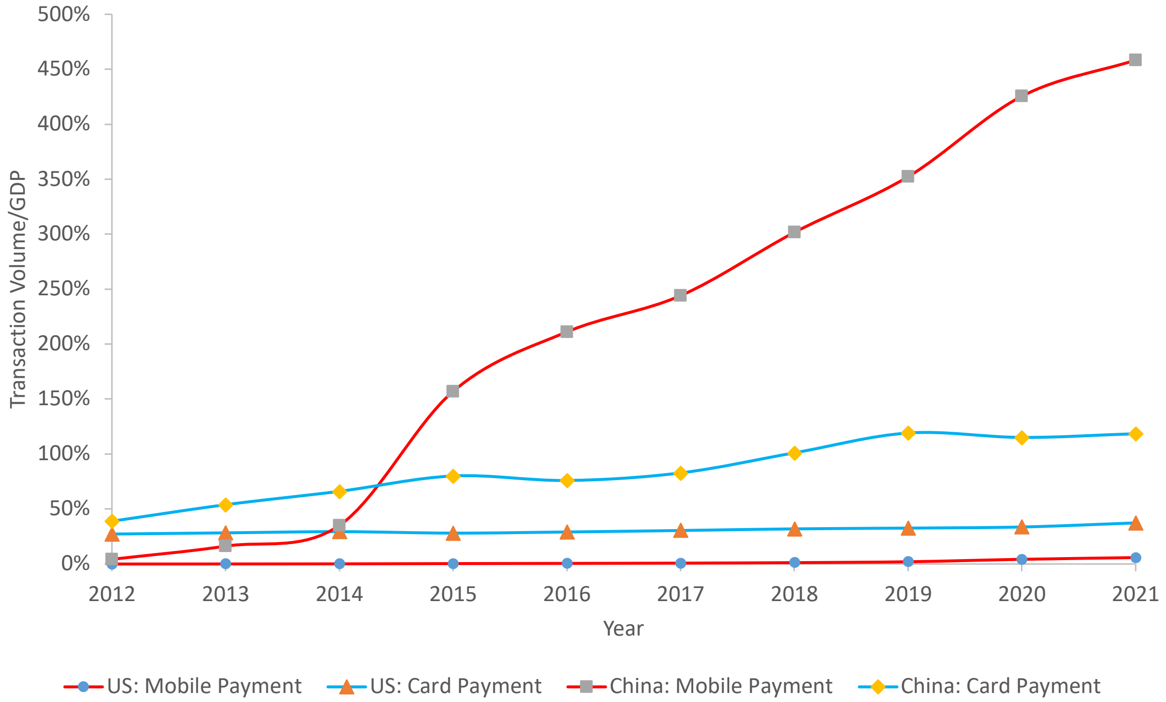


Figure 3: Logic Flow of the Instrumental Variable

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.

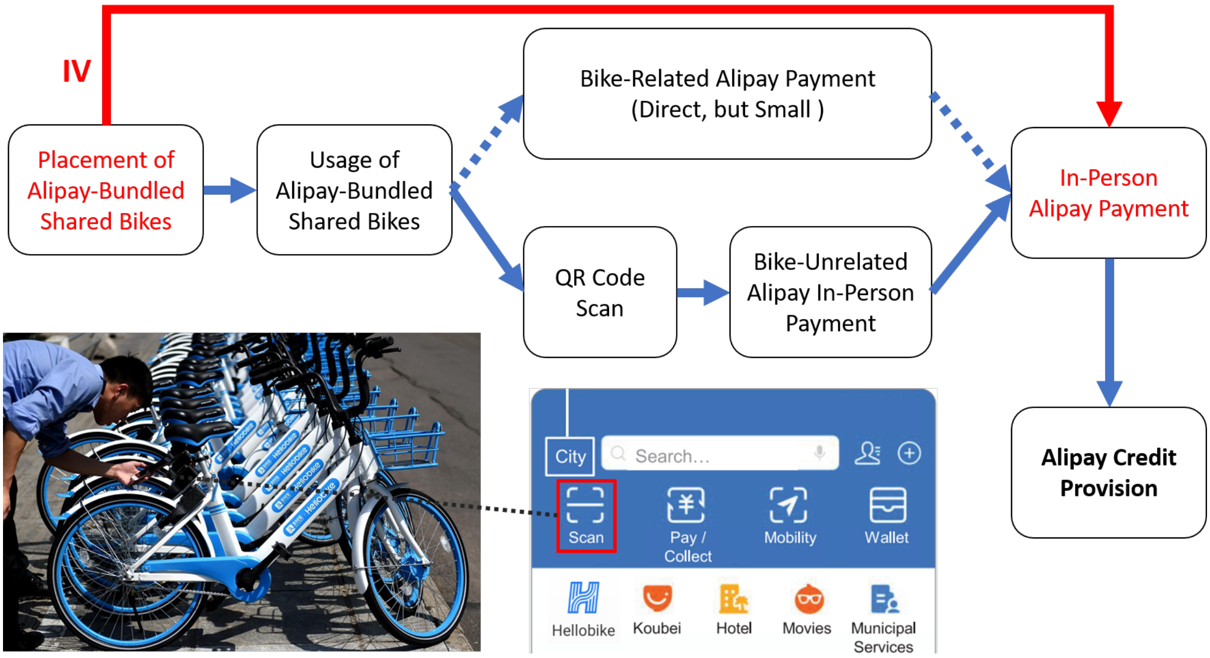


Figure 4: Bike Adoption and Non-bike Payment Flow

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

Panel (a): $log(1 + \text{In-Person Non-Bike Payment Flow})_{i,t} = \alpha_0$

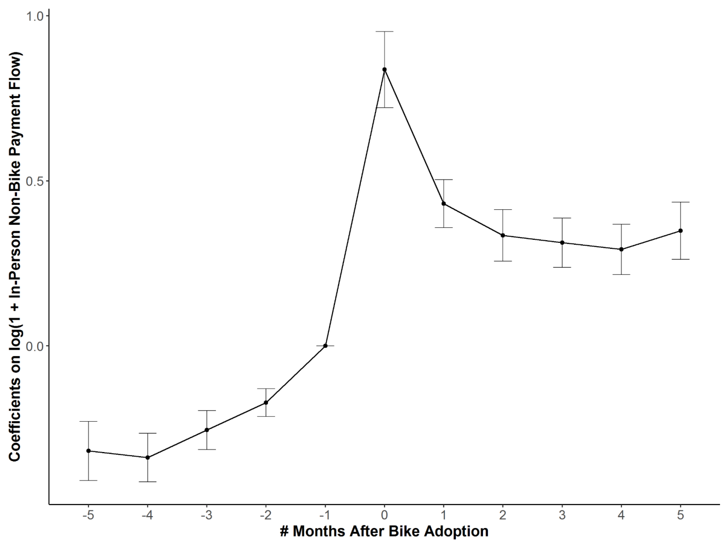
$$+ \sum_{\tau=-5}^{4} \beta_\tau \cdot \mathbb{1}(t = \tau) \cdot \mathbb{1}(\tau \neq -1) + \beta_5 \cdot \mathbb{1}(t \geq 5) + \delta_i + \mu_t + \varepsilon_{i,t},$$

Panel (b): $\mathbb{1}(\text{In-Person Non-Bike Payment Flow} > 0)_{i,t} = \alpha_0$

$$+ \sum_{\tau=-5}^{4} \beta_\tau \cdot \mathbb{1}(t = \tau) \cdot \mathbb{1}(\tau \neq -1) + \beta_5 \cdot \mathbb{1}(t \geq 5) + \delta_i + \mu_t + \varepsilon_{i,t},$$

where $log(1 + \text{In-Person Non-Bike Payment Flow})_{i,t}$ is the $log(1 + x)$ transformed amount of in-person payments on purchases not directly related to the usage of shared bikes by individual i at time t using Alipay, and $\mathbb{1}(\text{In-Person Non-Bike Payment Flow} > 0)_{i,t}$ indicates whether this amount is positive. t corresponds to the number of months after each individual's month of the first usage of Alipay-bundled shared bikes, δ_i is the individual fixed effects, μ_t is the year-month fixed effects, and $\varepsilon_{i,t}$ is the error term that varies across individuals and over time. The sample covers only users who used the Alipay-bundled shared bikes at least once in the sample period, which is from May 2017 to September 2020. For each bike user, the sample only covers periods in which the t is not earlier than -5.

(a) $log(1 + \text{In-Person Non-Bike Payment Flow})_{i,t}$



(b) $\mathbb{1}(\text{In-Person Non-Bike Payment Flow} > 0)_{i,t}$

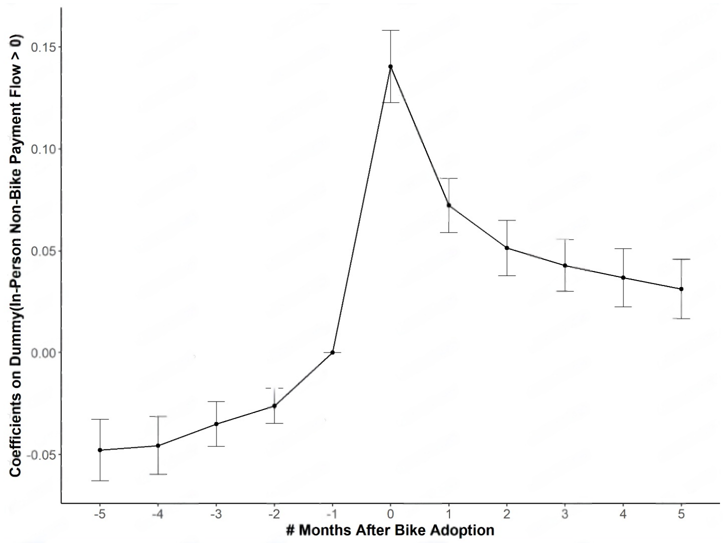


Figure 5: Staggered Placement of Shared Bikes

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

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

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

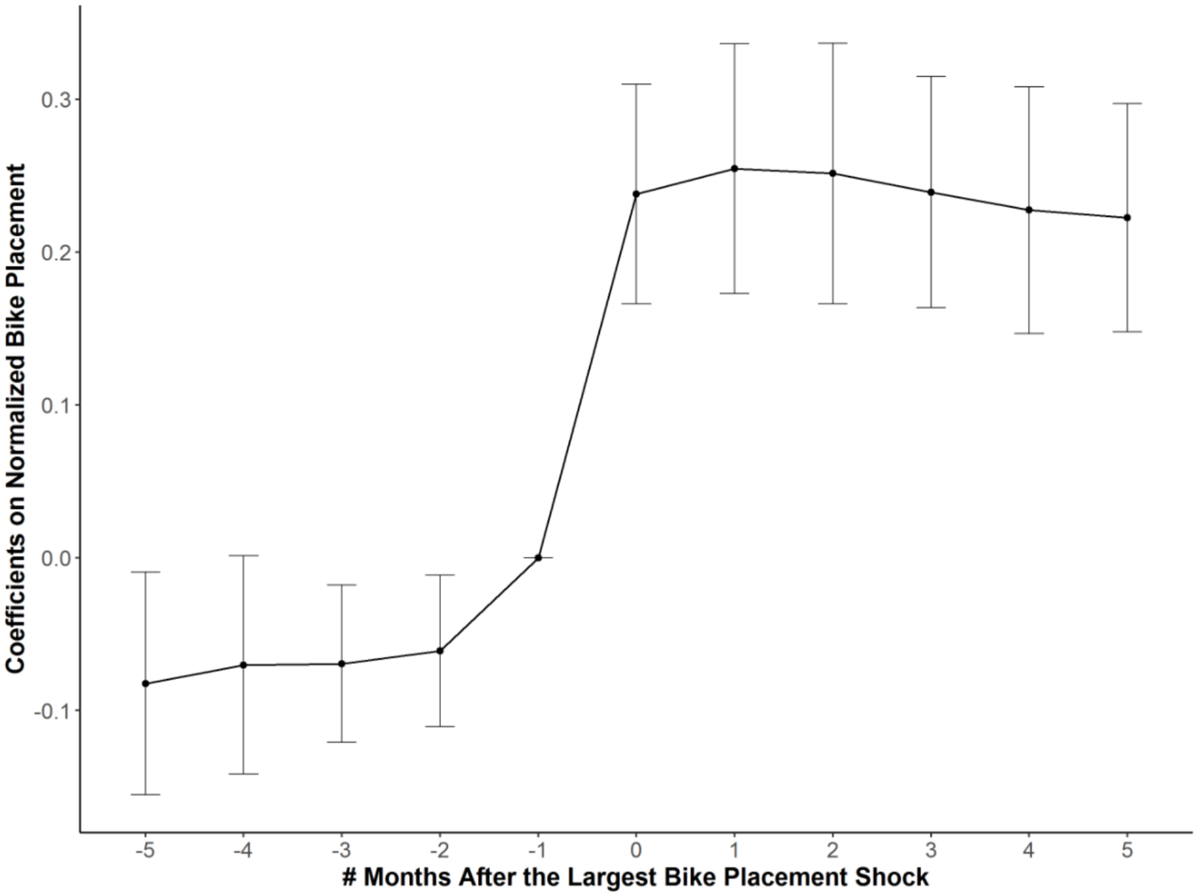
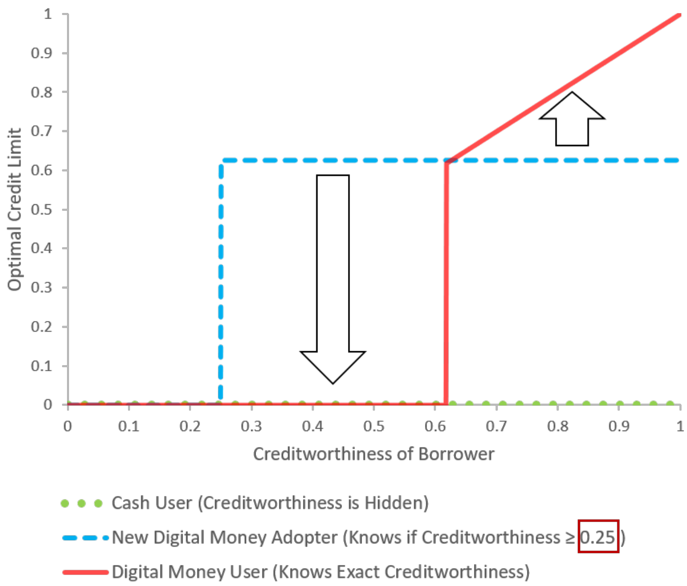


Figure 6: Cashless Payment's Financial Inclusion Implication: An Example

The figures illustrate how a lender sets optimal credit limits for heterogeneous borrowers in an economy with a continuum of borrowers. The illustrative example's setup is in Section A.2. Given knowledge about the borrower's type, the lender chooses the optimal credit limit to maximize the expected profit. There are three cases with different information sets for the lender based on the borrower's digital payment adoption stage. In stage one (green dotted line), borrowers use cash and the lender knows nothing about their creditworthiness. In stage two (blue dash line), borrowers adopt digital money and the lender knows if their creditworthiness is above a threshold. In stage three (red solid line), borrowers use digital money and the lender knows their exact creditworthiness. Figure (a) shows the financial divide scenario, where some less creditworthy borrowers lose in the transition from stage two to three. Figure (b) shows the financial inclusion scenario, where some less creditworthy borrowers gain in the transition to stage three.

(a) Scenario of ***Financial Divide***



(b) Scenario of ***Financial Inclusion***

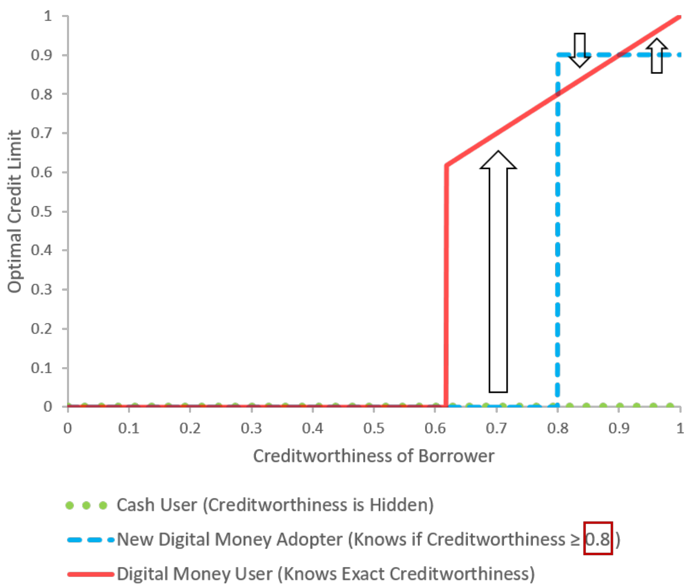


Table 1: Summary Statistics

The table summarizes the key variables for our analysis of 41,485 Alipay users from May 2017 to September 2020. The variables are categorized into three types at different levels. At the individual level, $\#\,\text{Active months}_i$ counts the months with payment activities; Is Male_i is a dummy for male; Low Education_i is a dummy for below bachelor's degree; Birth Year_i records the birth year; Bike User_i is a dummy for using a shared bike at least once. At the city-month level, $log(\text{Bike Placement})_{c,t}$ is the log number of active shared bikes in city c at time t. At the individual-month level, $\text{Credit Access}_{i,t}$ is a dummy for having access to Alipay's virtual credit card at time t; $log(\text{Credit Line})_{i,t}$ is the log credit line conditional on $\text{Credit Access}_{i,t}$; $log(\text{In-Person Payment Flow})_{i,t}$ and $log(\text{Online Payment Flow})_{i,t}$ are the log amounts of in-person and online payments using Alipay; $\text{Virtual Credit Card Share in In-Person Payment}_{i,t}$ and $\text{Virtual Credit Card Share in Online Payment}_{i,t}$ are the shares of in-person and online payments using the virtual credit card; $\text{Compulsive Spending Share in In-Person Payment}_{i,t}$ measures the share of in-person Alipay payments made by individual i at time t for cigarettes, games, and lotteries; $\text{Compulsive Spending Share in Online Payment}_{i,t}$ measures the share of online Alipay payments made by individual i at time t for cigarettes, games, lotteries, or live streaming services.

	N	Mean	Std	Min	p25	Median	p75	Max
Individual Level								
$\#$ Active months$_i$	41,485	31.86	11.38	1.00	24.00	37.00	41.00	41.00
Is Male$_i$	41,214	0.54	0.50	0.00	0.00	1.00	1.00	1.00
Low Education$_i$	41,459	0.88	0.33	0.00	1.00	1.00	1.00	1.00
Birth Year$_i$	41,214	1,983.38	12.75	1,930.00	1,974.00	1,985.00	1,993.00	2,014.00
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 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. $log(\text{Bike Placement})_{c,t}$ is the log number of active shared bikes in city c at time t. Bike User$_i$ is a dummy for using a shared bike at least once from May 2017 to September 2020. After First Bike Usage$_{i,t}$ is a dummy for after the first bike usage. $log(1 + \text{In-Person Payment Flow})_{i,t}$ and $log(1 + \text{Credit Line})_{i,t}$ are the $log(1 + x)$ transformed amounts of in-person payment flow and credit line through Alipay in CNY. Panel A shows the effects on payment flow and Panel B shows the effects on credit line. Columns (1) and (2) use individual and year-month fixed effects with the full sample. Column (3) adds city times year-month fixed effects with the bike user sample. All standard errors are clustered at city and year-month level. ***, **, and * denote the 1%, 5%, and 10% confidence level, respectively. I report standard errors in parentheses.

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

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

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

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

Table 3: 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. $log(\text{Bike Placement})_{c,t}$ is the log number of active shared bikes in city c at time t. One-Time Bike User$_i$ and Repeat Bike User$_i$ are dummies for using a shared bike exactly once and at least twice from May 2017 to September 2020. $log(1 + \text{In-Person Payment Flow})_{i,t}$ and $log(1 + \text{Credit Line})_{i,t}$ are the $log(1 + x)$ transformed amounts of in-person payment flow and credit line through Alipay in CNY. Columns (1) and (3) use individual and year-month fixed effects; columns (2) and (4) add city times year-month fixed effects. All standard errors are clustered at city and year-month level. ***, **, and * denote the 1%, 5%, and 10% confidence level, respectively. I report standard errors in parentheses.

	$log(1 + \text{In-Person Payment Flow})_{i,t}$		$log(1 + \text{Credit Line})_{i,t}$	
	(1)	(2)	(3)	(4)
$log(\text{Bike Placement})_{c,t}$	0.011		0.009	
	(0.009)		(0.010)	
One-Time Bike User$_i$ $\times$ $log(\text{Bike Placement})_{c,t}$	0.088***	0.072***	0.048**	0.035
	(0.020)	(0.019)	(0.023)	(0.025)
Repeat Bike User$_i$ $\times$ $log(\text{Bike Placement})_{c,t}$	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 $\times$ 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 4: In-person Payment Flow and Credit Provision

The table shows the robust relationship between in-person payment flow (IPF) and BigTech credit with different specifications on both margins. Credit Access$_{i,t}$ is a dummy for having access to Alipay's virtual credit card at time t. $log(\text{Credit Line})_{i,t}$ is the log credit line conditional on Credit Access$_{i,t}$. Measure of In-Person Payment Flow$_{i,t}$ is the amount of in-person payment flow through Alipay at time t, defined differently in different columns: $log(1 + \text{In-Person Payment Flow})_{i,t}$ in CNY in columns (1) and (4); a dummy for positive In-Person Payment Flow$_{i,t}$ in columns (2) and (5); $log(\text{In-Person Payment Flow})_{i,t}$ conditional on positive In-Person Payment Flow$_{i,t}$ in columns (3) and (6). $log(\text{Bike Placement})_{c,t}$ is the log number of active shared bikes in city c at time t, conditional on positive $log(\text{Bike Placement})_{c,t}$. The AR Statistic measures instrument strength using the Anderson-Rubin test, while its p-value provides additional evidence on instrument validity. Together, they complement the conventional F-statistic. The $\rho(\beta_0)$-Statistic represents the sample correlation between the main equation and first-stage residuals while imposing the null hypothesis. The VtF significance level is calculated by comparing the t-statistic against t-ratio critical values obtained using the VtF procedure (Lee et al., 2023). Panel A reports 2SLS estimates, instrumenting for payment flow with bike placement; Panel B reports the first stage; Panel C reports OLS estimates. All columns use individual and year-month fixed effects. All standard errors are clustered at city and year-month level. ***, **, and * denote the 1%, 5%, and 10% confidence level, respectively. I report standard errors in parentheses.

	Credit Access$_{i,t}$			$log(\text{Credit Line})_{i,t}$		
	(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$_{i,t}$						
$log(\text{Bike Placement})_{c,t}$	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	15.5	10.8	11.2	13.9	10.6	9.1
AR-Statistic	36.9	36.9	12.4	35.1	35.1	18.4
AR Test P-Value	0.000	0.000	0.000	0.000	0.000	0.000
$\rho(\beta_0)$-Statistic	0.091	0.093	0.049	0.078	0.042	0.079
VtF Significance Level	***	***	**	***	***	***
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	$log(1+x)$	$\mathbb{1}(x>0)$	$log(x)$	$log(1+x)$	$\mathbb{1}(x>0)$	$log(x)$
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	Has Credit	Has Credit
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 5: In-person Payment Flow and Consumer Behavior

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

	Virtual Credit Card $\text{Share}_{i,t}$		Compulsive Spending $\text{Share}_{i,t}$	
	In-Person Payment	Online Payment	In-Person Payment	Online Payment
	(1)	(2)	(3)	(4)
Panel A. Two-Stage Least Squares				
$log(1 + \text{In-Person Payment Flow})_{i,t}$	0.094***	0.030***	0.004	0.002
	(0.034)	(0.011)	(0.010)	(0.002)
Panel B. First Stage for $log(1 + \text{In-Person Payment Flow})_{i,t}$				
$log(\text{Bike Placement})_{c,t}$	0.028***	0.064***	0.028***	0.064***
	(0.009)	(0.014)	(0.009)	(0.014)
F-Statistic	11.0	22.7	11.0	22.7
Adjusted R^2	0.434	0.505	0.434	0.505
Panel C. Ordinary Least Squares				
$log(1 + \text{In-Person Payment Flow})_{i,t}$	-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	662,010	806,938	662,010	806,938
Note:				$^{*}p < 0.1$; $^{**}p < 0.05$; $^{***}p < 0.01$

Table 6: In-person Noncredit Payment Flow and Credit Provision

The table shows the causal relationship between in-person noncredit payment flow and BigTech credit on both margins. Credit $\text{Access}_{i,t}$ is a dummy for having access to Alipay's virtual credit card at time t. $log(\text{Credit Line})_{i,t}$ is the log credit line conditional on Credit $\text{Access}_{i,t}$. $log(1 + \text{In-Person Noncredit Payment Flow})_{i,t}$ and $log(1 + \text{In-Person Credit Payment Flow})_{i,t}$ are the $log(1 + x)$ transformed amounts of in-person Alipay payment flow without and with the virtual credit card in CNY. $log(\text{Bike Placement})_{c,t}$ is the log number of active shared bikes in city c at time t. Panel A reports 2SLS estimates, instrumenting for noncredit payment flow with bike placement; Panel B reports the first stage; Panel C reports OLS estimates. All columns use individual and year-month fixed effects. All standard errors are clustered at city and year-month level. ***, **, and * denote the 1%, 5%, and 10% confidence level, respectively. I report standard errors in parentheses.

	Credit $\text{Access}_{i,t}$		$log(\text{Credit Line})_{i,t}$	
	(1)	(2)	(3)	(4)
Panel A. Two-Stage Least Squares				
$log(1 + \text{In-Person Noncredit Payment Flow})_{i,t}$	0.094***	0.095**	0.329***	0.358***
	(0.024)	(0.026)	(0.103)	(0.124)
$log(1 + \text{In-Person Credit Payment Flow})_{i,t}$		-0.005		-0.044
		(0.006)		(0.029)
Panel B. First Stage for $log(1 + \text{In-Person Noncredit Payment Flow})_{i,t}$				
$log(\text{Bike Placement})_{c,t}$	0.037***	0.035***	0.037***	0.031***
	(0.009)	(0.009)	(0.010)	(0.009)
$log(1 + \text{In-Person Credit Payment Flow})_{i,t}$		0.218***		0.230***
		(0.009)		(0.007)
F-Statistic	16.1	16.1	13.4	12.6
Adjusted R^2	0.475	0.492	0.457	0.480
Panel C. Ordinary Least Squares				
$log(1 + \text{In-Person Noncredit Payment Flow})_{i,t}$	0.006***	0.004***	0.003	-0.004*
	(0.001)	(0.001)	(0.002)	(0.002)
$log(1 + \text{In-Person Credit Payment Flow})_{i,t}$		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	Has Credit
Observations	1,238,309	1,238,309	779,283	779,283
Note:				$^*p < 0.1$; $^{**}p < 0.05$; $^{***}p < 0.01$

Table 7: In-person Payment Flow and Credit Provision, with Enforcement Controls

The table shows the causal relationship between in-person payment flow and BigTech credit after controlling for time-varying assets under management (AUM) on both margins. Credit Access$_{i,t}$ is a dummy for having access to Alipay's virtual credit card at time t. $log(\text{Credit Line})_{i,t}$ is the log credit line conditional on Credit Access$_{i,t}$. $log(1 + \text{In-Person Payment Flow})_{i,t}$ and $log(1 + \text{Assets under Management})_{i,t}$ are the $log(1 + x)$ transformed amounts of in-person payment flow and AUM on Alipay's platform in CNY. $log(\text{Bike Placement})_{c,t}$ is the log number of active shared bikes in city c at time t. Panel A reports 2SLS estimates, instrumenting for payment flow with bike placement; Panel B reports the first stage; Panel C reports OLS estimates. All columns use individual and year-month fixed effects. All standard errors are clustered at city and year-month level. ***, **, and * denote the 1%, 5%, and 10% confidence level, respectively. I report standard errors in parentheses.

	Credit Access$_{i,t}$		$log(\text{Credit Line})_{i,t}$	
	(1)	(2)	(3)	(4)
Panel A. Two-Stage Least Squares				
$log(1 + \text{In-Person Payment Flow})_{i,t}$	0.097***	0.098***	0.280***	0.282***
	(0.025)	(0.026)	(0.085)	(0.086)
$log(1 + \text{Assets under Management})_{i,t}$	-0.005	-0.008	-0.015	-0.026*
	(0.004)	(0.005)	(0.011)	(0.013)
Panel B. First Stage for $log(1 + \text{In-Person Payment Flow})_{i,t}$				
$log(\text{Bike Placement})_{c,t}$	0.038***	0.036***	0.043***	0.043***
	(0.010)	(0.010)	(0.011)	(0.011)
$log(1 + \text{Assets under Management})_{i,t}$	0.147***	0.180***	0.122***	0.152***
	(0.005)	(0.005)	(0.005)	(0.005)
F-Statistic	14.7	14.6	14.4	14.6
Adjusted R^2	0.562	0.566	0.533	0.536
Panel C. Ordinary Least Squares				
$log(1 + \text{In-Person Payment Flow})_{i,t}$	0.009***	0.008***	0.020***	0.020***
	(0.001)	(0.001)	(0.002)	(0.002)
$log(1 + \text{Assets under Management})_{i,t}$	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	Has Credit
Observations	1,220,618	1,220,618	779,283	779,283
Note:		*$p < 0.1$; **$p < 0.05$; ***$p < 0.01$		

Table 8: Financially Underserved Segments

These table provides evidence that the less educated and the older tend to be financially underserved in China. Low Education$_i$ and Older than Median$_i$ are dummies for having no bachelor's degree or above and being older than half of the users. # Debit Cards$_i$ is the number of debit cards linked to Alipay in April 2021. $log(1 + \text{Max. AUM})_i$ is the log highest amount of AUM on Alipay from May 2017 to September 2020. # Investment Months$_i$ is the months since first using Alipay's wealth management service till April 2021. Pay with Real Name$_i$, Use Own Account$_i$, and Complete Profile$_i$ are dummies for passing real name verification, using own account, and completing profile information in Alipay as of April 2021. Regression results show that the less educated and the older have lower financial service usage and literacy. All columns use city and gender fixed effects. All standard errors are clustered at city and year-month level. ***, **, and * denote the 1%, 5%, and 10% confidence level, respectively. I report standard errors in parentheses.

	Financial Service Usage			Financial Literacy		
	# Debit Cards$_i$	$log(1 + \text{Max. AUM})_i$	# Investment Months$_i$	Pay with Real Name$_i$	Use Own Account$_i$	Complete Profile$_i$
	(1)	(2)	(3)	(4)	(5)	(6)
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)
Gender FE	YES	YES	YES	YES	YES	YES
City FE	YES	YES	YES	YES	YES	YES
Year-Month 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: $^{*}p < 0.1$; $^{**}p < 0.05$; $^{***}p < 0.01$

Table 9: Education, In-person Payment Flow, and Credit Provision

The table shows the causal relationship between in-person payment flow and BigTech credit for the less and more educated groups on both margins. Credit Access$_{i,t}$ is a dummy for having access to Alipay's virtual credit card at time t. $log(\text{Credit Line})_{i,t}$ is the log credit line conditional on Credit Access$_{i,t}$. $log(1 + \text{In-Person Payment Flow})_{i,t}$ is the $log(1 + x)$ transformed amount of in-person payment flow through Alipay in CNY at time t. $log(\text{Bike Placement})_{c,t}$ is the log number of active shared bikes in city c at time t. Panel A reports 2SLS estimates, instrumenting for payment flow with bike placement; Panel B reports the first stage; Panel C reports OLS estimates. All columns use individual and year-month fixed effects. Columns (1) and (3) use the less educated subsample with no college degree or above; columns (2) and (4) use the more educated subsample with a bachelor's degree or above. All standard errors are clustered at city and year-month level. ***, **, and * denote the 1%, 5%, and 10% confidence level, respectively. I report standard errors in parentheses.

	Credit Access$_{i,t}$		$log(\text{Credit Line})_{i,t}$	
	(1)	(2)	(3)	(4)
Panel A. Two-Stage Least Squares				
$log(1 + \text{In-Person Payment Flow})_{i,t}$	0.093***	0.024	0.334***	0.038
	(0.027)	(0.044)	(0.109)	(0.073)
Panel B. First Stage for $log(1 + \text{In-Person Payment Flow})_{i,t}$				
$log(\text{Bike Placement})_{c,t}$	0.039***	0.043***	0.039***	0.053***
	(0.010)	(0.013)	(0.011)	(0.014)
F-Statistic	13.7	10.9	11.6	14.2
Adjusted R^2	0.554	0.563	0.528	0.483
Panel C. Ordinary Least Squares				
$log(1 + \text{In-Person Payment Flow})_{i,t}$	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	Full Sample	Full Sample	Has Credit	Has Credit
Subsample	Low Education	High Education	Low Education	High Education
Observations	1,065,769	171,938	657,878	121,194
Note:				*$p < 0.1$; **$p < 0.05$; ***$p < 0.01$

A Online Appendix

A.1 Econometric Framework

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

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

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

$$cl_{i,t} = \alpha_0 + \alpha_1 \cdot ipf_{i,t} + \delta_i + \theta_t + \varepsilon^{OV}_{i,t} + \varepsilon^{EE}_{i,t} \quad (1)$$

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, $\varepsilon^{OV}_{i,t}$ is the omitted variables that affect the credit line of individual i at time t, and $\varepsilon^{EE}_{i,t}$ is an exogenous error term that affects the credit line of individual i at time t.

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

$$ipf_{i,t} = \beta_0 + \beta_1 \cdot cl_{i,t} + \mu_i + \omega_t + \varphi_{i,t} \quad (2)$$

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.

For simplicity, individual-specific and time-specific characteristics are treated as vectors of dimension one. The parameter of interest to estimate is α_1 in the credit provision equation, which captures the direct effect of in-person payment flow on the credit line provided by the BigTech company. Since the BigTech credit provision and in-person cashless payment flow are jointly determined, there are simultaneity issues, and the ordinary least squares (OLS) estimate would be biased. Assuming that

$\varepsilon_{i,t}^{EE} \perp \varphi_{i,t}$, the bias of the OLS estimate is captured in the following equation:

$$\begin{aligned}\hat{\alpha_1^{OLS}} &= \frac{Cov(cl_{i,t}, ipf_{i,t})}{Var(ipf_{i,t})} \\ &= \alpha_1 + \underbrace{\frac{1}{1-\alpha_1\cdot\beta_1}}_{A} \cdot [\underbrace{\frac{Var(\delta_i+\theta_t+\varepsilon_{i,t}^{OV}+\varepsilon_{i,t}^{EE})}{Var(ipf_{i,t})}\cdot\beta_1}_{B} + \underbrace{\frac{Cov(\varepsilon_{i,t}^{OV},\varphi_{i,t})}{Var(ipf_{i,t})}}_{C}]\end{aligned} \tag{3}$$

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

Assume that the bike placement decision $bp_{c,t}$ is exogenous and can be used a valid instrument for $ipf_{i,t}$. That is, $\mathsf{E}[(\varepsilon_{i,t}^{OV}+\varepsilon_{i,t}^{EE})\cdot bp_{c,t}] = 0$ and $\mathsf{E}[\varphi_{i,t}\cdot bp_{c,t}] \neq 0$. The IV estimate is given by:

$$\hat{\alpha}_1^{IV} = \frac{Cov(cl_{i,t}, bp_{c,t})}{Cov(ipf_{i,t}, bp_{c,t})} = \alpha_1 \tag{4}$$

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

A.2 An Illustrative Example on Effects of a Cashless Payment Shock

In the economy, there is a lender and a continuum of borrowers. The type of borrower i follows a uniform distribution between 0 and 1; that is, $\theta_i \sim U[0,1]$. Given the type of borrower θ_i, the lender chooses the optimal lending amount l_i to maximize its expected profit. If the lender decides not to lend, its profit is zero. When the lending amount is positive, there will be some uncertainties, and the expected profit will be creditworthiness-dependent. For example, the interest rate will be different for borrowers of different types, and the probability of repayment will depend on the creditworthiness, the lending amount, and the interest rate. To simplify the specification, I assume that the expected profit function takes the following form:

$$\pi_i(\theta_i, l_i) = \begin{cases} \theta_i + 2 \cdot \theta_i \cdot l_i - l_i^2 - 1 & \text{, if } l_i > 0 \\ 0 & \text{, if } l_i = 0 \end{cases} \tag{5}$$

This functional form has three properties. First, given the lending amount, the expected profit monotonically increases with the borrower creditworthiness. Second, there is an optimal lending amount, below which the expected profit increases with the lending amount and above which the expected profit decreases with the lending amount. Third, given the borrower's creditworthiness, if the optimal lending amount is nonzero, it strictly increases with the borrower's creditworthiness. With this specification in Eq. (5), the nonzero lending amount $l^*(\theta_i) = \theta_i$.

Three cases with different information provided to the lender are used to represent the stages the borrowers are cash users, the borrowers are new digital money adopters, and the borrowers are digital money users. The relationship between the optimal credit line and the creditworthiness of the borrower in different stages is illustrated in Figure 6. Figures (a) and (b) capture different scenarios with different thresholds in the digital money user stage.

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

In the second stage, or the new digital money adopter stage, the lender receives a rough signal about the creditworthiness of borrower, which is specified as $s_i = \mathbb{1}(\theta_i \geq 0.25)$ in the financial divide scenario and as $s_i = \mathbb{1}(\theta_i \geq 0.8)$ in the financial inclusion scenario. This stage captures two facts when the borrowers are new digital money adopters. First, people will submit information about their personal characteristics, such as age, gender, and education when they register as new users of the digital wallet. Second, it is easier for wealthier individuals to prove their creditworthiness with the observed characteristics.

In the third stage, or the digital money user stage, the lender knows the exact creditworthiness of each borrower. This is a stage in which the digital payment system operated by the BigTech company covers almost all the customers and merchants, and the recorded cashless transactions render the information about the creditworthiness of everyone quite precise.

The lender makes very different credit-provision decisions in the stages with distinct information sets.

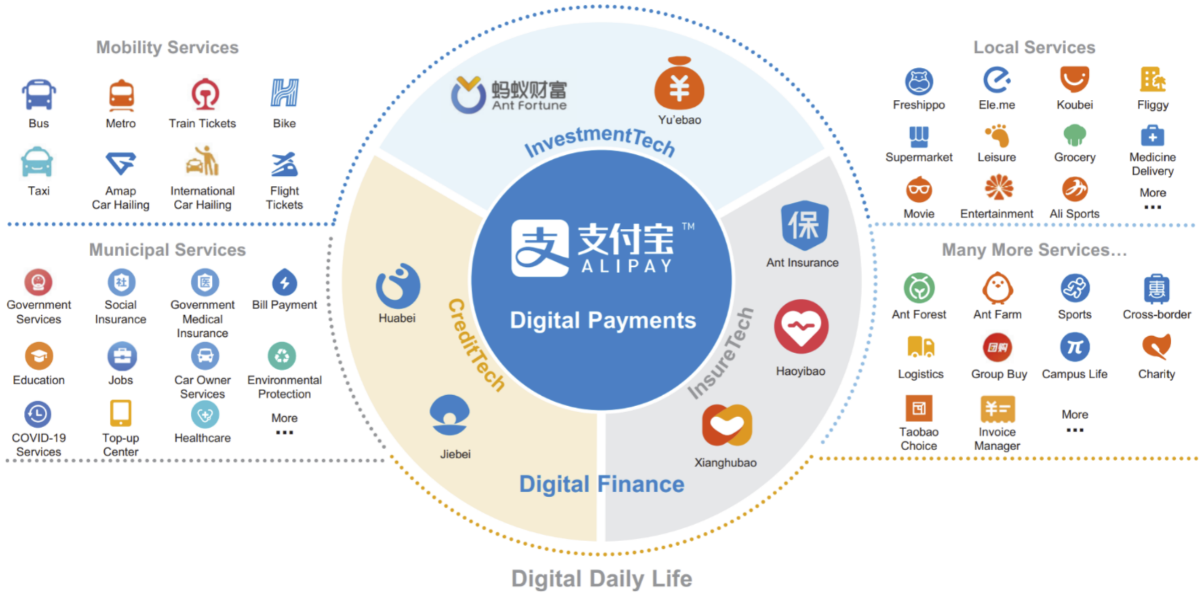
In the first stage, it knows only the distribution of the borrower creditworthiness and will make the same lending decision to every borrower based on the average creditworthiness of borrowers. Under above specification, lending a positive amount is always nonprofitable, and the lender will not lend to any borrower in this stage.

I first consider the financial divide scenario in figure (a), where the threshold in the second stage is 0.25. In the second stage, the lender knows whether each borrower i is the “high creditworthiness” with $\theta_i \geq 0.25$ or the “low creditworthiness” with $\theta_i < 0.25$. Intuitively, the lender will not lend to any low-creditworthiness borrower. For high-creditworthiness borrowers, it is optimal to lend $l^*(s_i = 1) = 0.625$ to everyone in this group, and this will maximize the expected profit from lending. It is not surprising that the rough signal helps the lender extend more credit in the transition from the first stage to the second stage. In the third stage, the lender has precise information on each borrower's creditworthiness, which enables it to make the optimal lending decision for each borrower creditworthiness separately. In this specification, the optimal lending decision is to not lend to borrowers with creditworthiness $\theta_i \leq \frac{\sqrt{5}-1}{2}$, and lend $l^*(\theta_i) = \theta_i$ to borrowers with $\theta_i > \frac{\sqrt{5}-1}{2}$. In the transition from the second stage to the third stage, although the borrowers with creditworthiness larger than 0.625 gain higher credit limit, the less creditworthy borrowers suffer from a large credit limit reduction, especially those with creditworthiness between 0.25 and $\frac{\sqrt{5}-1}{2}$. In this scenario, the gap of credit access between the less creditworthy and the more creditworthy becomes larger after the lender gets more precise information, and that is why I name it as "financial divide".

I then consider the financial inclusion scenario in figure (b), where the threshold in the second stage is 0.8. Now in the second stage, the lender knows whether each borrower i is the “high creditworthiness” with $\theta_i \geq 0.8$ or the “low creditworthiness” with $\theta_i < 0.8$. The lender will still not lend to any low-creditworthiness borrower. For high-creditworthiness borrowers, it is optimal to lend $l^*(s_i = 1) = 0.9$ to everyone in this group, and this will maximize the expected profit from lending. Comparing the second stage with the first stage, the rough signal helps the lender extend more credit. The third stage is the same as the financial divide scenario, while the comparison between the third stage and the second stage is different. In this transition, some of the previously underserved borrowers in the second stage $\frac{\sqrt{5}-1}{2} < \theta_i < 0.8$ now gain access to credit in the third stage. This is what I call "financial inclusion". Fore the high-creditworthiness borrowers, they get a creditworthiness-specific credit limit $l^*(\theta_i) = \theta_i$ instead of the same amount in the third stage, although the average lending amount stays at the level of 0.9.

Figure A.1: Typical Use Cases Available via the Alipay App

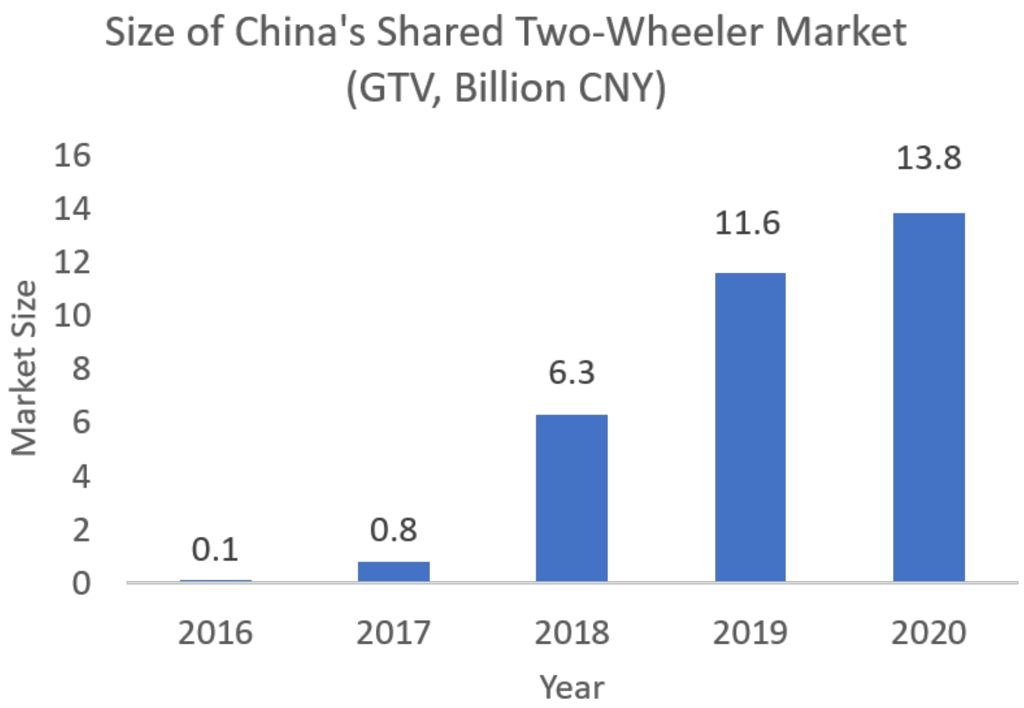
This figure describes the typical use cases that are available via the Alipay app, which cover mobility services, municipal services, local services, and other services. Alipay acts as consumers' one-stop shop for digital payment and digital financial services, including credit, investment, and insurance.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



Source: IPO Prospectus of the Ant Group, 2020

Figure A.2: Development of China's Dockless Bike-sharing Industry

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



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

Figure A.3: Alipay Registration and Shared-bike Adoption

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

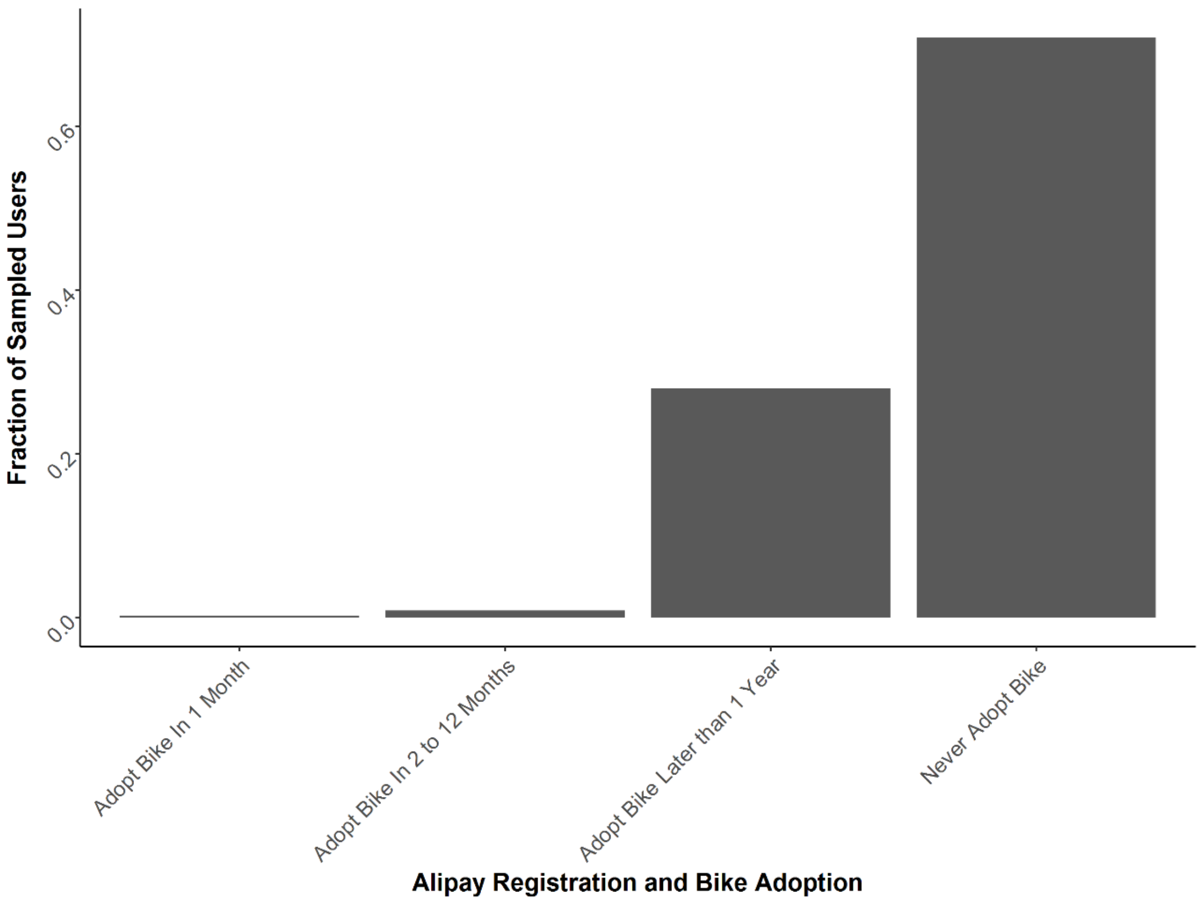


Figure A.4: Bike Adoption and Non-bike Payment Flow: One-Time Bike User

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

Panel (a): $log(1 + \text{In-Person Non-Bike Payment Flow})_{i,t} = \alpha_0$

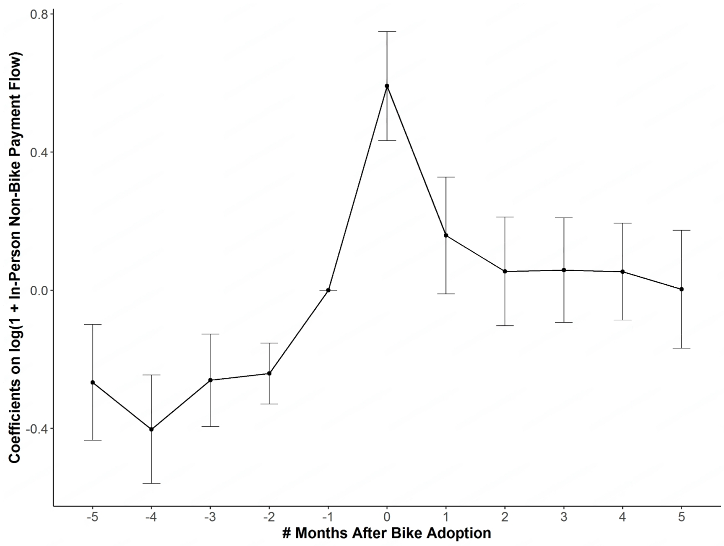
$$+ \sum_{\tau=-5}^{4} \beta_\tau \cdot \mathbb{1}(t = \tau) \cdot \mathbb{1}(\tau \neq -1) + \beta_5 \cdot \mathbb{1}(t \geq 5) + \delta_i + \mu_t + \varepsilon_{i,t},$$

Panel (b): $\mathbb{1}(\text{In-Person Non-Bike Payment Flow} > 0)_{i,t} = \alpha_0$

$$+ \sum_{\tau=-5}^{4} \beta_\tau \cdot \mathbb{1}(t = \tau) \cdot \mathbb{1}(\tau \neq -1) + \beta_5 \cdot \mathbb{1}(t \geq 5) + \delta_i + \mu_t + \varepsilon_{i,t},$$

where $log(1 + \text{In-Person Non-Bike Payment Flow})_{i,t}$ is the $log(1 + x)$ transformed amount of in-person payments on purchases not directly related to the usage of shared bikes by individual i at time t using Alipay, and $\mathbb{1}(\text{In-Person Non-Bike Payment Flow} > 0)_{i,t}$ indicates whether this amount is positive. 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 users who used the Alipay-bundled shared bikes only once in the sample period, which is from May 2017 to September 2020. For each bike user, the sample only covers periods in which the t is not earlier than -5.

(a) $log(1 + \text{In-Person Non-Bike Payment Flow})_{i,t}$



(b) $\mathbb{1}(\text{In-Person Non-Bike Payment Flow} > 0)_{i,t}$

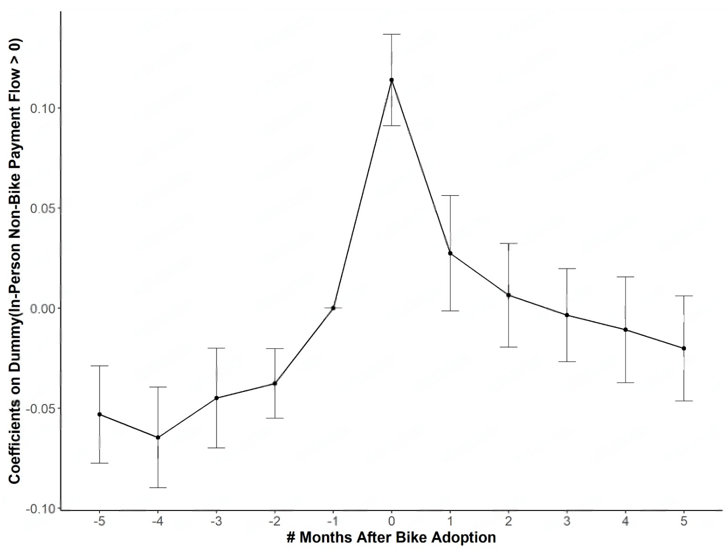
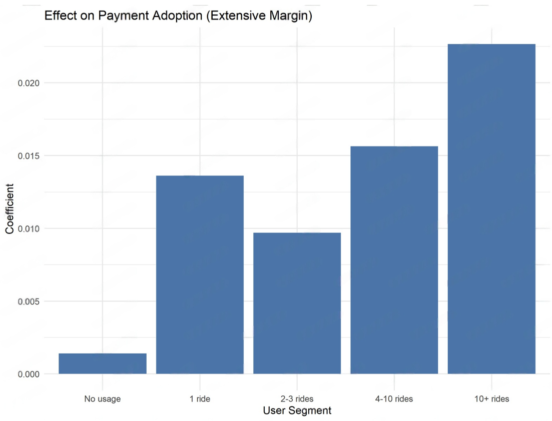


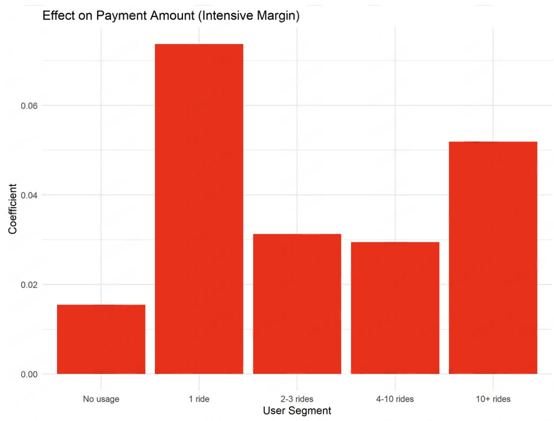
Figure A.5: Granular Bike-usage Intensity and Bike-placement Effects on Both Margins

Each panel plots OLS coefficients from a separate regression estimated on monthly individual panel data from May 2017 to September 2020. The dependent variables are, respectively: (a) an indicator for any in-person payment flow, (b) the log amount of in-person payment flow (conditional on being positive), (c) an indicator for access to Alipay's virtual credit card, and (d) the log credit-line amount (conditional on being positive). Regressors include $log(\text{Bike Placement})_{c,t}$, its interactions with five mutually exclusive dummies that classify users by cumulative ride counts (*No usage*, *1 ride*, *2–3 rides*, *4–10 rides*, *10+ rides*), as well as individual and year–month fixed effects. Standard errors are two-way clustered by city and year-month. Coefficients on $log(\text{Bike Placement})_{c,t}$ measure the effect for non-bike users, while the interaction terms capture differential effects for the other segments; extensive-margin specifications use the full sample, whereas intensive-margin specifications are estimated only on observations with positive outcomes.

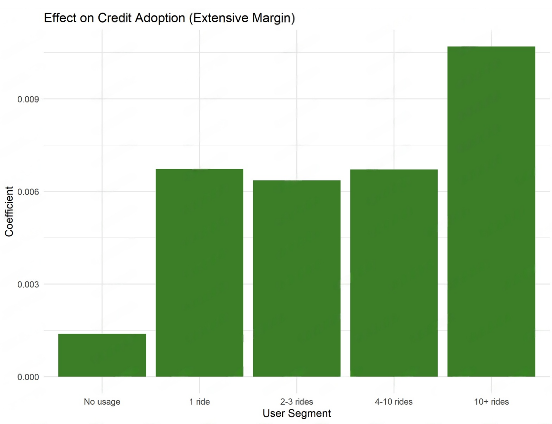
(a) $\mathbb{1}(\text{In-Person Payment Flow}_{i,t} > 0)$



(b) $log(\text{In-Person Payment Flow})_{i,t}$



(c) Credit Access$_{i,t}$



(d) $log(\text{Credit Line})_{i,t}$

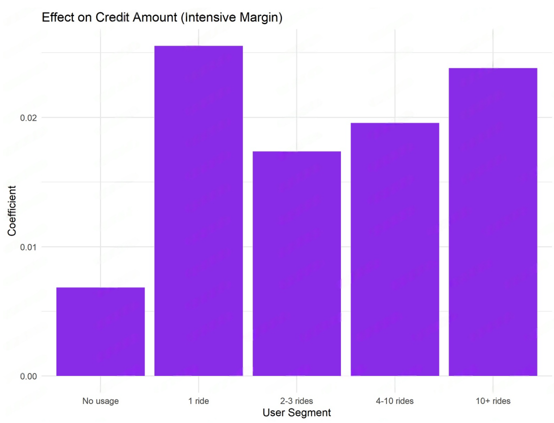


Figure A.6: Broad Distribution of Bike-placement Shock

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

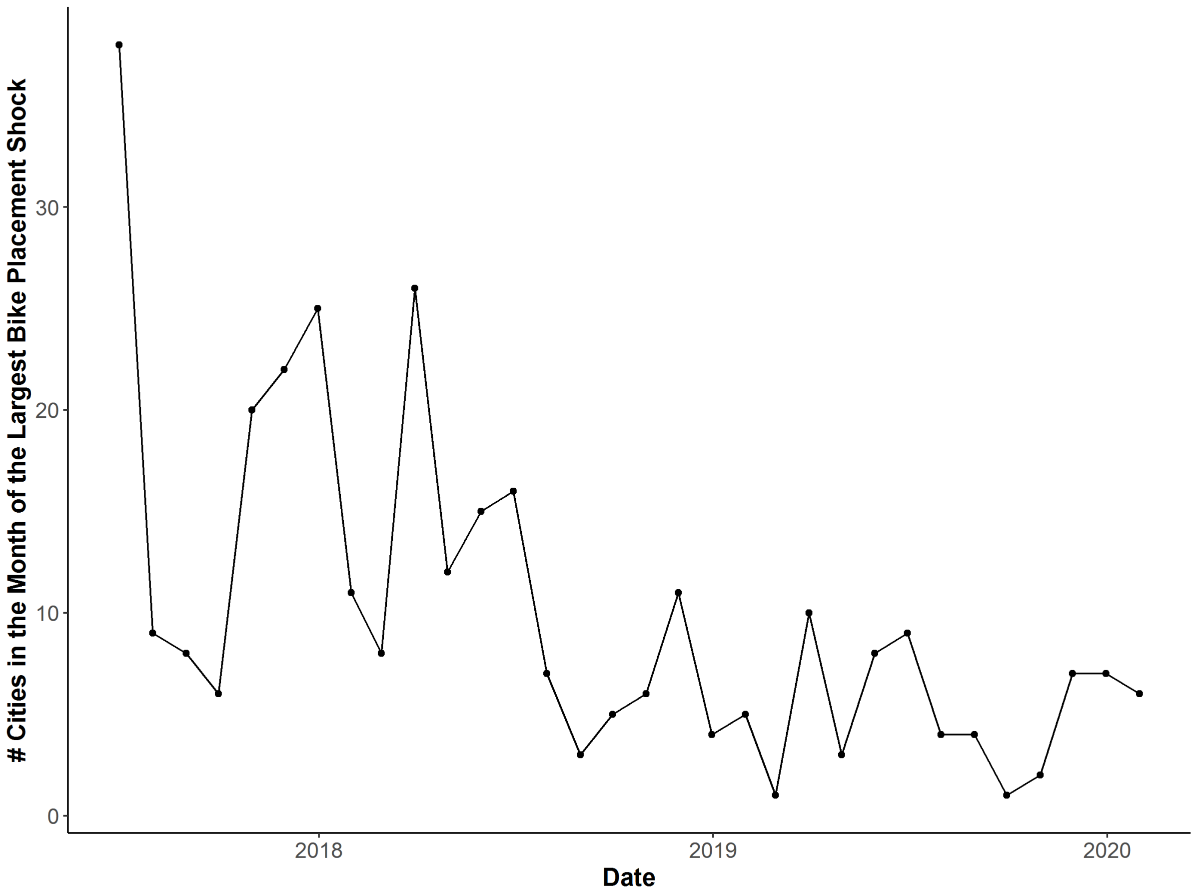


Figure A.7: Binned Relationship Between Payments and Credit

The figure presents a binned scatter plot depicting the relationship between normalized in-person payment flows and normalized credit lines. The x-axis represents the average payment flow within each quantile-based bin, while the y-axis shows the corresponding average credit line. Each point reflects a bin created from one of 25 quantiles of the payment variable, ensuring a roughly equal number of observations per bin. Horizontal line segments indicate the range of payment values within each bin, while vertical error bars represent the standard error of the mean credit amount. The size of each circular marker is proportional to the number of observations in that bin. A smoothed line connects the bin means to highlight underlying trends in the relationship.

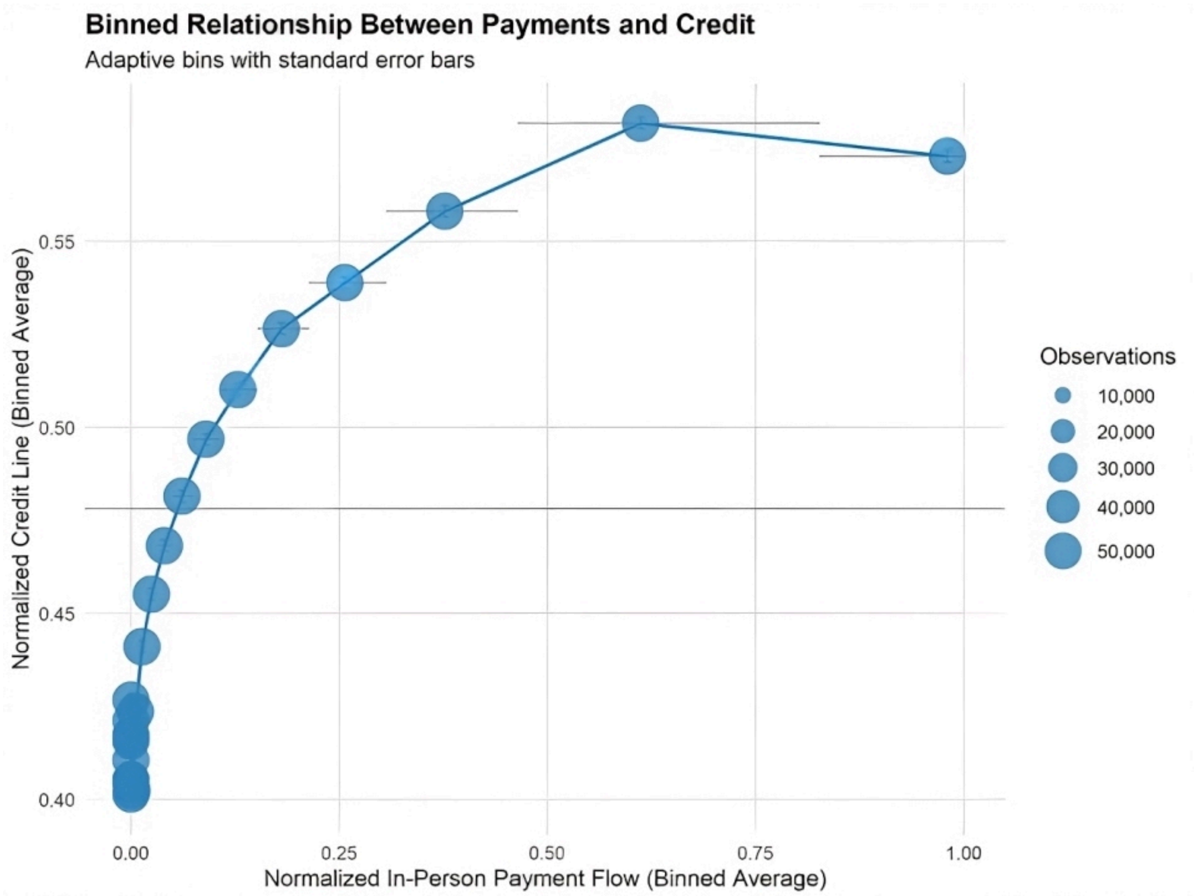


Figure A.8: Credit Access and Total Payment Flow

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

$$
\begin{aligned}
log(1 + \text{Total Payment Flow})_{i,t} &= \alpha_0 \\
&+ \sum_{\tau=-5}^{4} \beta_\tau \cdot \mathbb{1}(t = \tau) \cdot \mathbb{1}(\tau \neq -1) + \beta_5 \cdot \mathbb{1}(t \geq 5) + \delta_i + \mu_t + \varepsilon_{i,t},
\end{aligned}
$$

where $log(1 + \text{Total Payment Flow})_{i,t}$ is the $log(1 + x)$ transformed amount of total payments by individual i at time t using Alipay, t corresponds to the number of months after each individual's first month of having access to *Huabei* credit line, δ_i is the individual fixed effects, μ_t is the year-month fixed effects, and $\varepsilon_{i,t}$ is the error term that varies across individuals and over time. The sample covers only users who have access to *Huabei* credit line in at least one month in the sample period, which is from May 2017 to September 2020. For each user, the sample only covers periods in which the t is not earlier than -5.

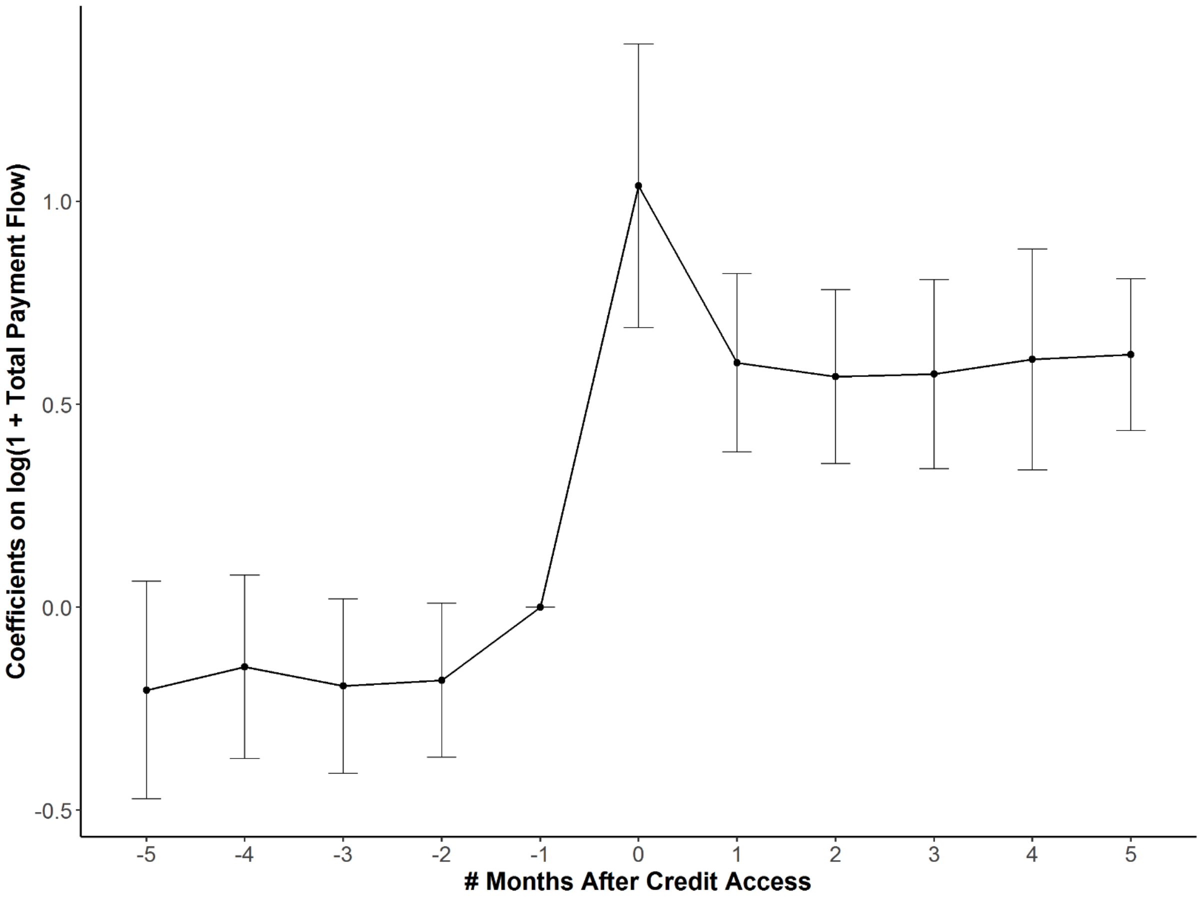


Figure A.9: In-person Spending Categories and Credit Line Correlation

This figure presents the correlation between various in-person spending categories and users' credit lines on Alipay. The horizontal axis shows the correlation coefficient, with positive values indicating spending categories associated with higher credit lines and negative values indicating categories associated with lower credit lines.

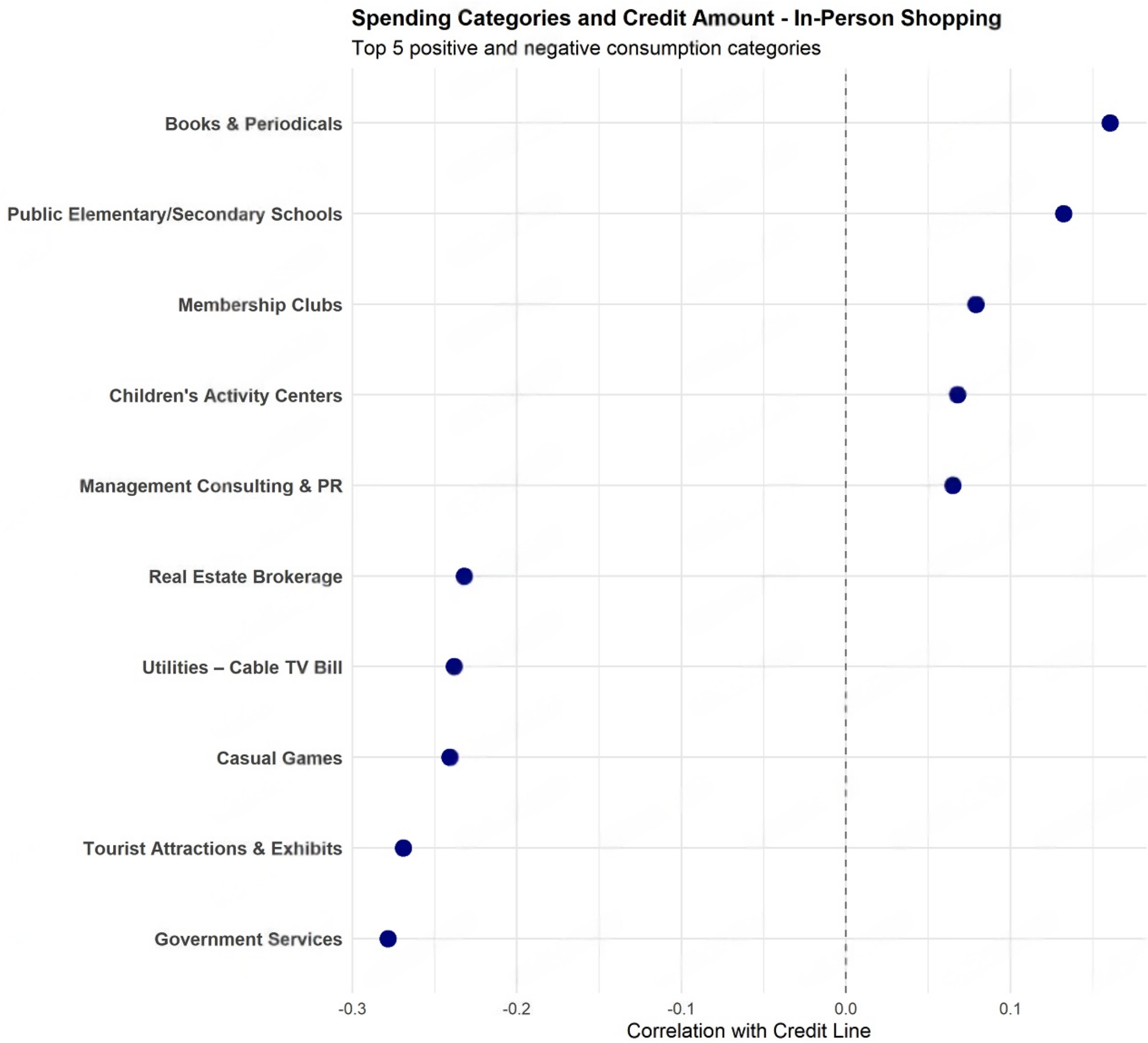


Table A.1: Effects of Bike Placement on Bike Usage

The table shows the effects of city-level bike placement on individual-level bike-riding activities. $log(\text{Bike Placement})_{c,t}$ is the log number of active shared bikes in city c at time t. Use $\text{Bike}_{i,t}$ is a dummy for using a shared bike at time t. $log(\text{\# Bike Rides})_{i,t}$ and $log(\text{Riding Distance})_{i,t}$ are the log number and distance of bike rides at time t. Column (1) uses the sample of bike users who have used a shared bike at least once from May 2017 to September 2020. Columns (2) and (3) use the sample of bike users in the months they used a bike. All columns use individual and year-month fixed effects. All standard errors are clustered at city and year-month level. ***, **, and * denote the 1%, 5%, and 10% confidence level, respectively. I report standard errors in parentheses.

	Use $\text{Bike}_{i,t}$	$log(\text{\# Bike Rides})_{i,t}$	$log(\text{Riding Distance})_{i,t}$
	(1)	(2)	(3)
$log(\text{Bike Placement})_{c,t}$	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 A.2: Bike-riding Activity and Payment Flow

The table shows the relationship between bike-riding activity and cashless payment flow with and without bike-related spending. After First Bike $\text{Usage}_{i,t}$ is a dummy for after using a shared bike for the first time. $log(1 + \text{\# Bike Rides})_{i,t}$ and $log(1 + \text{Riding Distance})_{i,t}$ are the $log(1 + x)$ transformed number and distance of bike rides in kilometers at time t. $log(1 + \text{In-Person Payment Flow})_{i,t}$ and $log(1 + \text{In-Person Non-Bike Payment Flow})_{i,t}$ are the $log(1 + x)$ transformed amount of in-person payment flow in CNY through Alipay at time t, with and without bike-related spending. Columns (1) and (4) use the sample of users who have used shared bikes at least once and cover all their periods. Columns (2), (3), (5), and (6) use the same sample but only after they started using bikes. All columns use individual and year-month fixed effects. All standard errors are clustered at city and year-month level. ***, **, and * denote the 1%, 5%, and 10% confidence level, respectively. I report standard errors in parentheses.

	$log(1 + \text{In-Person Payment Flow})_{i,t}$			$log(1 + \text{In-Person Non-Bike Payment Flow})_{i,t}$		
	(1)	(2)	(3)	(4)	(5)	(6)
After First Bike $\text{Usage}_{i,t}$	0.694***			0.638***		
	(0.055)			(0.053)		
$log(1 + \text{\# Bike Rides})_{i,t}$		0.347***			0.286***	
		(0.015)			(0.012)	
$log(1 + \text{Riding Distance})_{i,t}$			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	After First Ride	After First Ride	Bike Users	After First Ride	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 A.3: Effects of Bike Placement on Payment and Credit on Both Margins

These tables report the effects of city-level placement of shared bikes on the individual-level in-person payment flow and digital credit access on both margins. $log(\text{Bike Placement})_{c,t}$ is the log number of active shared bikes in city c at time t. Bike User$_i$ is a dummy for using a shared bike at least once from May 2017 to September 2020. After First Bike Usage$_{i,t}$ is a dummy for after the first bike usage. $\mathbb{1}(\text{In-Person Payment Flow}_{i,t} > 0)$ is a binary variable indicating whether in-person payment flow is nonzero for user i at time t. $log(\text{In-Person Payment Flow})_{i,t}$ is the log-transformed in-person payment flow in CNY through Alipay for individual i at time t, missing if In-Person Payment Flow$_{i,t}$ is 0. Credit Access$_{i,t}$ is a binary variable indicating access to Alipay's virtual credit card for user i at time t. $log(\text{Credit Line})_{i,t}$ represents the log-transformed credit line of user i's virtual card at time t, missing if Credit Line$_{i,t}$ is 0. Panel A shows the effects on payment flow and Panel B shows the effects on credit line. Columns (1) and (2) use individual and year-month fixed effects with the full sample. Column (3) adds city times year-month fixed effects with the bike user sample. All standard errors are clustered at city and year-month level. ***, **, and * denote the 1%, 5%, and 10% confidence level, respectively. I report standard errors in parentheses.

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

	$\mathbb{1}(\text{In-Person Payment Flow}_{i,t} > 0)$			$log(\text{In-Person Payment Flow})_{i,t}$		
	(1)	(2)	(3)	(4)	(5)	(6)
$log(\text{Bike Placement})_{c,t}$	0.006***	0.001		0.030***	0.015	
	(0.002)	(0.002)		(0.009)	(0.010)	
Bike User$_i$ × $log(\text{Bike Placement})_{c,t}$		0.016***			0.032**	
		(0.002)			(0.015)	
After First Bike Usage$_{i,t}$			0.057**			-0.094
			(0.025)			(0.093)
After First Bike Usage$_{i,t}$ × $log(\text{Bike Placement})_{c,t}$			0.005**			0.026***
			(0.002)			(0.008)
Individual FE	YES	YES	YES	YES	YES	YES
Year-Month FE	YES	YES	-	YES	YES	-
City × Year-Month FE	NO	NO	YES	NO	NO	YES
Clustered by City and Year-Month	YES	YES	YES	YES	YES	YES
Sample	Full Sample	Full Sample	Bike Users	Has In-Person Payment	Has In-Person Payment	Bike Users, Has In-Person Payment
Observations	1,238,309	1,238,309	435,872	662,010	662,010	328,974
Adjusted R^2	0.465	0.466	0.369	0.432	0.432	0.397

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

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

	Credit Access$_{i,t}$			$log(\text{Credit Line})_{i,t}$		
	(1)	(2)	(3)	(1)	(2)	(3)
$log(\text{Bike Placement})_{c,t}$	0.004***	0.001		0.012***	0.007	
	(0.001)	(0.001)		(0.004)	(0.006)	
Bike User$_i$ × $log(\text{Bike Placement})_{c,t}$		0.007**			0.015	
		(0.003)			(0.012)	
After First Bike Usage$_{i,t}$			-0.044**			0.069
			(0.020)			(0.059)
After First Bike Usage$_{i,t}$ × $log(\text{Bike Placement})_{c,t}$			0.010***			0.011**
			(0.002)			(0.005)
Individual FE	YES	YES	YES	YES	YES	YES
Year-Month FE	YES	YES	-	YES	YES	-
City × Year-Month FE	NO	NO	YES	NO	NO	YES
Clustered by City and Year-Month	YES	YES	YES	YES	YES	YES
Sample	Full Sample	Full Sample	Bike Users	Has Credit	Has Credit	Bike Users, Has Credit
Observations	1,238,309	1,238,309	435,872	779,283	779,283	334,475
Adjusted R^2	0.738	0.738	0.686	0.835	0.835	0.840

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

Table A.4: Bike Placement and the Local Economy

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

	$log(\text{GDP})_{c,t}$	$log(\text{GDP per capita})_{c,t}$	Fiscal Spending/GDP$_{c,t}$	Fiscal Income/GDP$_{c,t}$
	(1)	(2)	(3)	(4)
$log(\text{Bike Placement})_{c,t}$	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 A.5: Bike-usage Intensity and Bike-placement Effects on Both Margins

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 on both margins. $log(\text{Bike Placement})_{c,t}$ is the log number of active shared bikes in city c at time t. One-Time Bike User$_i$ and Repeat Bike User$_i$ are dummies for using a shared bike exactly once and at least twice from May 2017 to September 2020. $\mathbb{1}(\text{In-Person Payment Flow}_{i,t} > 0)$ is a binary variable indicating whether in-person payment flow is nonzero for user i at time t. $log(\text{In-Person Payment Flow})_{i,t}$ is the log-transformed in-person payment flow in CNY through Alipay for individual i at time t, missing if In-Person Payment Flow$_{i,t}$ is 0. Credit Access$_{i,t}$ is a binary variable indicating access to Alipay's virtual credit card for user i at time t. $log(\text{Credit Line})_{i,t}$ represents the log-transformed credit line of user i's virtual card at time t, missing if Credit Line$_{i,t}$ is 0. All columns use individual and year-month fixed effects. All standard errors are clustered at city and year-month level. ***, **, and * denote the 1%, 5%, and 10% confidence level, respectively. I report standard errors in parentheses.

	$\mathbb{1}(\text{In-Person Payment Flow}_{i,t} > 0)$	$log(\text{In-Person Payment Flow})_{i,t}$	Credit Access$_{i,t}$	$log(\text{Credit Line})_{i,t}$
	(1)	(2)	(3)	(4)
$log(\text{Bike Placement})_{c,t}$	0.001	0.015	0.001	0.007
	(0.002)	(0.010)	(0.001)	(0.006)
One-Time Bike User$_i$ × $log(\text{Bike Placement})_{c,t}$	0.012***	0.058***	0.005*	0.019*
	(0.003)	(0.016)	(0.003)	(0.011)
Repeat Bike User$_i$ × $log(\text{Bike Placement})_{c,t}$	0.017***	0.028*	0.007**	0.015
	(0.002)	(0.016)	(0.004)	(0.013)
Individual FE	YES	YES	YES	YES
Year-Month FE	YES	YES	YES	YES
City × Year-Month FE	NO	NO	NO	NO
Clustered by City and Year-Month	YES	YES	YES	YES
Sample	Full Sample	Has In-Person Payment	Full Sample	Has Credit
Observations	1,238,309	662,010	1,238,309	779,283
Adjusted R^2	0.466	0.432	0.738	0.835
Note:				*$p < 0.1$; **$p < 0.05$; ***$p < 0.01$

Table A.6: Personal Characteristics of Bike Users

This table presents the relationship between an individual's personal characteristics and the bike user dummy, indicating whether the user has used Alipay-bundled shared bikes at least once. Low Education$_i$, Older than Median$_i$, Early Alipay User$_i$, Male$_i$, Pay with Real Name$_i$, Use Own Account$_i$, and Complete Profile$_i$ are dummy variables defined based on education, age, registration date, gender, real-name verification, account usage, and profile completion, respectively. Bike User$_i$ equals 1 if Alipay user i used shared bikes during May 2017 to September 2020. Columns (1), (2), and (3) show simple regression, regression with city and occupation fixed effects, and regression controlling for financial activity measures, respectively. Financial activity measures include # Debit Cards$_i$, $log(1 + \text{Max. AUM})_i$, and # Investment Months$_i$. All standard errors are clustered at city and year-month level. ***, **, and * denote the 1%, 5%, and 10% confidence level, respectively. I report standard errors in parentheses.

	Bike User$_i$		
	(1)	(2)	(3)
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)
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 A.7: Analysis of the Heterogeneous Effects of Bike Placement

This table reports the heterogeneous effects of city-level placement of shared bikes on individual-level in-person payment flow and the digital credit provided to the user. $log(\text{Bike Placement})_{c,t}$ is the log-transformed count of active shared bikes in city c at time t. Bike User$i$, Low Education$_i$, Older than Median$_i$, Early Alipay User$_i$, Male$_i$, Pay with Real Name$_i$, and Use Own Account$_i$ are dummy variables based on bike usage, education, age, registration date, gender, real-name verification, and account usage, respectively. $log(1 + \text{In-Person Payment Flow})_{i,t}$ and $log(1 + \text{Credit Line})_{i,t}$ are log-transformed measures of individual i's in-person payment flow and virtual credit card credit line in CNY at time t. Panel A shows OLS regressions with $log(1 + \text{In-Person Payment Flow})_{i,t}$ as the dependent variable, while Panel B uses $log(1 + \text{Credit Line})_{i,t}$. The Characteristic Measure$_i$ varies by column. All regressions control for individual and year-month fixed effects. All standard errors are clustered at city and year-month level. ***, **, and * denote the 1%, 5%, and 10% confidence level, respectively. I report standard errors in parentheses.

	Dependent Variable					
	(1)	(2)	(3)	(4)	(5)	(6)
Panel A. Ordinary Least Squares with Dependent Variable: $log(1 + \text{In-Person Payment Flow})_{i,t}$						
$log(\text{Bike Placement})_{c,t}$	-0.022	0.008	0.029**	0.021**	-0.013	-0.010
	(0.014)	(0.010)	(0.011)	(0.009)	(0.015)	(0.010)
Bike User$_i$ × $log(\text{Bike Placement})_{c,t}$	0.139***	0.110***	0.092***	0.099***	0.057**	0.139***
	(0.029)	(0.018)	(0.017)	(0.021)	(0.025)	(0.029)
Characteristic Measure$_i$ × $log(\text{Bike Placement})_{c,t}$	0.036**	0.004	-0.038***	-0.023**	0.033*	0.036**
	(0.017)	(0.013)	(0.012)	(0.008)	(0.019)	(0.017)
Bike User$_i$ × Characteristic Measure$_i$ × $log(\text{Bike Placement})_{c,t}$	-0.040	-0.017	0.009	0.009	0.046**	-0.045
	(0.031)	(0.018)	(0.025)	(0.020)	(0.023)	(0.031)
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	0.020	0.004	-0.008	0.003
	(0.021)	(0.010)	(0.013)	(0.014)	(0.013)	(0.015)
Bike User$_i$ × $log(\text{Bike Placement})_{c,t}$	0.051*	0.053*	0.057*	0.056**	0.049*	0.042**
	(0.030)	(0.026)	(0.029)	(0.025)	(0.029)	(0.020)
Characteristic Measure$_i$ × $log(\text{Bike Placement})_{c,t}$	0.0001	-0.011	-0.023	0.008	0.024*	0.012
	(0.026)	(0.018)	(0.025)	(0.012)	(0.014)	(0.014)
Bike User$_i$ × Characteristic Measure$_i$ × $log(\text{Bike Placement})_{c,t}$	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
Personal Characteristic Measure	Low Education$_i$	Older than Median$_i$	Early Alipay User$_i$	Male$_i$	Pay with Real Name$_i$	Use Own Account$_i$
Individual FE	YES	YES	YES	YES	YES	YES
Year-Month FE	YES	YES	YES	YES	YES	YES
Clustered by City and Year-Month	YES	YES	YES	YES	YES	YES
Observations	1,237,707	1,237,707	1,237,707	1,237,707	1,237,707	1,237,707
Note:						*$p < 0.1$; **$p < 0.05$; ***$p < 0.01$

Table A.8: Non-monotonic Payment-Credit Relationship

This table reports the non-monotonic relationship between normalized in-person payment flows and normalized credit lines, examining both contemporaneous and lagged effects. Normalized In-Person Payment Flow$_{i,t}$ is the total amount of individual i's in-person payment flow through Alipay at time t, normalized by their highest monthly in-person payment flow. Normalized Credit Line$_{i,t}$ is the credit line of Alipay user i's virtual credit card at time t, normalized by their highest credit line. Columns (1) and (2) present the contemporaneous relationship between payment flows and credit lines, while columns (3) and (4) examine the relationship with one-period lagged payment flows (Normalized In-Person Payment Flow$_{i,t-1}$). All columns use individual and year-month fixed effects. All standard errors are clustered at city and year-month level. ***, **, and * denote the 1%, 5%, and 10% confidence level, respectively. I report standard errors in parentheses.

	Normalized Credit Line$_{i,t}$			
	(1)	(2)	(3)	(4)
Normalized In-Person Payment Flow$_{i,t}$	0.040***	0.105***		
	(0.006)	(0.013)		
(Normalized In-Person Payment Flow$_{i,t}$)^2		-0.075***		
		(0.009)		
Normalized In-Person Payment Flow$_{i,t-1}$			0.042***	0.125***
			(0.006)	(0.013)
(Normalized In-Person Payment Flow$_{i,t-1}$)^2				-0.095***
				(0.010)
Individual FE	YES	YES	YES	YES
Year-Month FE	YES	YES	YES	YES
Clustered by City and Year-Month	YES	YES	YES	YES
Observations	1,030,678	1,030,678	1,001,015	1,001,015
Adjusted R^2	0.767	0.767	0.766	0.767
Note:	*$p < 0.1$; **$p < 0.05$; ***$p < 0.01$			

Table A.9: Robustness: In-person Payment Flow and Credit Provision, Controlling for City Times Year-Month Fixed Effects

This table presents empirical evidence of the causal link between a user's in-person payment flow and BigTech credit provided, controlling for city times year-month fixed effects on both extensive and intensive margins. Credit $\text{Access}_{i,t}$ is a binary variable indicating access to Alipay's virtual credit card for user i at time t. $log(\text{Credit Line})_i, t$ represents the log-transformed credit line of user i's virtual card at time t, missing if Credit $\text{Line}_{i,t}$ is 0. $log(1 + \text{In-Person Payment Flow})_{i,t}$ is the $log(1 + x)$ transformed in-person payment flow in CNY through Alipay for individual i at time t. $log(\text{Bike Placement})_{c,t}$ is the log-transformed count of active shared bikes in city c at time t. Bike User_i is 1 if user i used shared bikes at least once during May 2017-September 2020. Panel A reports 2SLS estimates, instrumenting individual-level log in-person payment flow with the interaction 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 OLS regression coefficient for individual-level log in-person payment flow. All columns show results for regressions with individual and year-month fixed effects. Columns (2) and (4) also control for individual characteristics like gender, education, occupation, and year of birth. All standard errors are clustered at city and year-month level. ***, **, and * denote the 1%, 5%, and 10% confidence level, respectively. I report standard errors in parentheses.

	Credit $\text{Access}_{i,t}$		$log(\text{Credit Line})_{i,t}$	
	(1)	(2)	(3)	(4)
Panel A. Two-Stage Least Squares				
$log(1 + \text{In-Person Payment Flow})_{i,t}$	0.115***	0.108***	0.398***	0.418***
	(0.004)	(0.004)	(0.016)	(0.019)
Panel B. First Stage for $log(1 + \text{In-Person Payment Flow})_{i,t}$				
Bike $\text{User}_i \times log(\text{Bike Placement})_{c,t}$	0.209***	0.178***	0.166***	0.134***
	(0.008)	(0.008)	(0.007)	(0.007)
F-Statistic	772.9	476.0	503.2	343.0
Adjusted R^2	0.168	0.190	0.147	0.173
Panel C. Ordinary Least Squares				
$log(1 + \text{In-Person Payment Flow})_{i,t}$	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 × 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	Has Credit
Observations	1,238,309	664,727	779,283	440,418
Note:				*$p < 0.1$; **$p < 0.05$; ***$p < 0.01$

Table A.10: In-Person Payment Flow, Bike Usage, and Credit Provision with Two IVs

This table presents a novel identification strategy that simultaneously addresses the causality of both in-person payment flow and bike usage effects on credit provision. Credit Access$_{i,t}$ is a dummy indicating access to Alipay's virtual credit card for user i at time t. log(Credit Line)$_{i,t}$ represents the log-transformed credit line of user i's virtual card at time t conditional on positive Credit Line$_{i,t}$. $log(1 +$ In-Person Payment Flow$)_{i,t}$ is the $log(1 + x)$ transformed in-person payment flow in CNY through Alipay for individual i at time t. $log(1 +$ # Bike Rides$)_{i,t}$ represents the log-transformed number of bike rides for user i at time t. The identification strategy employs two instruments: (1) the city-level log active shared bikes (log(Bike Placement)$_{c,t}$) and (2) its interaction with a dummy variable indicating whether the user is active in bike-sharing in that month (Bike Using Dummy$_{i,t}$ $\times$ log(Bike Placement)$_{c,t}$). Panel A presents the 2SLS estimates. Panel B reports the first-stage regressions, demonstrating strong instrument relevance with high F-statistics for both endogenous variables. Panel C provides OLS estimates for comparison. Regressions include individual and year-month fixed effects. All the standard errors are clustered at the city and year-month level. ***, **, and * denote the 1%, 5%, and 10% confidence level, respectively. I report standard errors in parentheses.

	Credit Access$_{i,t}$	log(Credit Line)$_{i,t}$	$log(1 +$ In-Person Payment Flow$)_{i,t}$	$log(1 +$ # Bike Rides$)_{i,t}$
	(1)	(2)	(3)	(4)
Panel A. Two-Stage Least Squares				
$log(1 +$ In-Person Payment Flow$)_{i,t}$	0.102***	0.346***		
	(0.032)	(0.123)		
$log(1 +$ # Bike Rides$)_{i,t}$	-0.047**	-0.151**		
	(0.021)	(0.067)		
Panel B. First-Stage Regressions				
log(Bike Placement)$_{c,t}$			0.033***	0.001***
			(0.010)	(0.001)
Bike Using Dummy$_{i,t}$ $\times$ log(Bike Placement)$_{c,t}$			0.086***	0.136***
			(0.004)	(0.003)
F-Statistic			40.9	103.8
Adjusted R^2			0.555	0.762
Panel C. Ordinary Least Squares				
$log(1 +$ In-Person Payment Flow$)_{i,t}$	0.010***	0.021***		
	(0.001)	(0.003)		
$log(1 +$ # Bike Rides$)_{i,t}$	0.010***	0.015***		
	(0.002)	(0.005)		
Adjusted R^2	0.740	0.836		
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	Has Credit	Full Sample	Full Sample
Observations	1,238,309	779,283	1,238,309	1,238,309

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

Table A.11: Extensive Margin of Payment, Bike Usage, and Credit with Two IVs

This table presents a novel identification strategy that simultaneously addresses the causality of both in-person payment flow and bike usage effects on credit provision through extensive margin measures. Credit $\text{Access}_{i,t}$ is a dummy indicating access to Alipay's virtual credit card for user i at time t. $log(\text{Credit Line})_{i,t}$ represents the log-transformed credit line of user i's virtual card at time t conditional on positive Credit $\text{Line}_{i,t}$. $\mathbb{1}(\text{In-Person Payment Flow}_{i,t} > 0)$ is a dummy variable indicating whether user i engaged in any in-person payment through Alipay at time t. $\mathbb{1}(\text{\# Bike Rides}_{i,t} > 0)$ is a dummy variable indicating whether user i used bike-sharing services at time t. The identification strategy employs two instruments: (1) the city-level log active shared bikes ($log(\text{Bike Placement})_{c,t}$) and (2) its interaction with a dummy variable indicating whether the user is active in bike-sharing in that month (Bike Using $\text{Dummy}_{i,t} \times log(\text{Bike Placement})_{c,t}$). Panel A presents the 2SLS estimates. Panel B reports the first-stage regressions, demonstrating strong instrument relevance with high F-statistics for both endogenous variables. Panel C provides OLS estimates for comparison. Regressions include individual and year-month fixed effects. All the standard errors are clustered at the city and year-month level. ***, **, and * denote the 1%, 5%, and 10% confidence level, respectively. I report standard errors in parentheses.

	Credit $\text{Access}_{i,t}$	$log(\text{Credit Line})_{i,t}$	$\mathbb{1}(\text{In-Person Payment Flow}_{i,t} > 0)$	$\mathbb{1}(\text{\# Bike Rides}_{i,t} > 0)$
	(1)	(2)	(3)	(4)
Panel A. Two-Stage Least Squares				
$\mathbb{1}(\text{In-Person Payment Flow}_{i,t} > 0)$	0.688**	2.586**		
	(0.257)	(1.183)		
$\mathbb{1}(\text{\# Bike Rides}_{i,t} > 0)$	-0.097**	-0.314*		
	(0.048)	(0.174)		
Panel B. First-Stage Regressions				
$log(\text{Bike Placement})_{c,t}$			0.005**	0.000
			(0.002)	(0.000)
Bike Using $\text{Dummy}_{i,t} \times log(\text{Bike Placement})_{c,t}$			0.016***	0.088***
			(0.001)	(0.001)
F-Statistic			29.4	1,366.5
Adjusted R^2			0.470	0.977
Panel C. Ordinary Least Squares				
$\mathbb{1}(\text{In-Person Payment Flow}_{i,t} > 0)$	0.062***	0.069***		
	(0.007)	(0.023)		
$\mathbb{1}(\text{\# Bike Rides}_{i,t} > 0)$	0.015***	0.037***		
	(0.004)	(0.009)		
Adjusted R^2	0.741	0.835		
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	Has Credit	Full Sample	Full Sample
Observations	1,238,309	779,283	1,238,309	1,238,309
Note:				*$p < 0.1$; **$p < 0.05$; ***$p < 0.01$

Table A.12: Bike Usage, Payment Flow, and Credit Provision for Users with Low Payment Fluctuation

This table reports the relationship between bike usage and credit provision for Alipay users with low payment fluctuation, with robustness checks across different payment fluctuation thresholds. Credit Access$_{i,t}$ is a binary variable indicating Alipay user i's virtual credit card access at time t. $log(\text{Credit Line})_{i,t}$ denotes the log-transformed credit line for user i at t. $log(1 + \#\text{ Bike Rides})_{i,t}$ represents the $log(1 + x)$ transformed number of bike rides for user i at t. $log(1 + \text{In-Person Payment Flow})_{i,t}$ is the $log(1 + x)$ transformed in-person payment flow through Alipay for user i at t, measured in CNY. Payment Fluctuation is measured as the standard deviation of monthly payment flows normalized by average monthly payment flows. Columns (1)-(4) examine the effect of bike usage on credit access, while columns (5)-(8) examine the effect on credit line. Columns (1), (2), (5), and (6) use users below the median (P50) payment fluctuation, while columns (3), (4), (7), and (8) use users below the 25th percentile (P25) payment fluctuation, representing the most stable payment behavior users. Odd-numbered columns show the effect of bike usage alone, while even-numbered columns control for in-person payment flow. All regressions include individual and year-month fixed effects. All standard errors are clustered at city and year-month level. ***, **, and * denote the 1%, 5%, and 10% confidence level, respectively. I report standard errors in parentheses.

	Credit Access$_{i,t}$				$log(\text{Credit Line})_{i,t}$			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
$log(1 + \#\text{ Bike Rides})_{i,t}$	0.014***	0.004	0.010	-0.006	0.008	0.0003	0.014	0.043
	(0.003)	(0.003)	(0.006)	(0.007)	(0.008)	(0.008)	(0.031)	(0.033)
Individual FE	YES	YES	YES	YES	YES	YES	YES	YES
Year-Month FE	YES	YES	YES	YES	YES	YES	YES	YES
Clustered by City and Year-Month	YES	YES	YES	YES	YES	YES	YES	YES
Control for $log(1 + \text{In-Person Payment Flow})_{i,t}$	NO	YES	NO	YES	NO	YES	NO	YES
Sample: Payment Fluctuation Percentile	$< P50$	$< P50$	$< P25$	$< P25$	$< P50$	$< P50$	$< P25$	$< P25$
Observations	569,912	569,912	249,565	249,565	265,632	265,632	77,395	77,395
Adjusted R^2	0.762	0.765	0.777	0.778	0.829	0.829	0.819	0.819
Note:					*$p < 0.1$; **$p < 0.05$; ***$p < 0.01$			

Table A.13: Robustness: In-person Payment Flow and Future Credit Provision

This table presents empirical evidence of the persistent relationship between a user's in-person payment flow and BigTech credit on both extensive and intensive margins. Credit Access$_{i,T}$ is a binary variable indicating access to Alipay's virtual credit card for user i at time T ($T = t+1, t+2, t+3$). $log(\text{Credit Line})_{i,T}$ represents the log-transformed credit line of user i's virtual card at time T, missing if Credit Line$_{i,T}$ is 0. $log(1 + \text{In-Person Payment Flow})_{i,t}$ is the $log(1+x)$ transformed in-person payment flow in CNY through Alipay for individual i at time t. $log(\text{Bike Placement})_{c,t}$ is the log-transformed count of active shared bikes in city c at time t. Panel A reports 2SLS estimates, instrumenting individual-level log in-person payment flow with city-level log number of active shared bikes; Panel B reports the corresponding first stage. Panel C reports the OLS regression coefficient for individual-level log in-person payment flow. All columns show results for regressions with individual and year-month fixed effects. All standard errors are clustered at city and year-month level. ***, **, and * denote the 1%, 5%, and 10% confidence level, respectively. I report standard errors in parentheses.

	Credit Access$_{i,T}$			$log(\text{Credit Line})_{i,T}$		
	$t+1$	$t+2$	$t+3$	$t+1$	$t+2$	$t+3$
	(1)	(2)	(3)	(4)	(5)	(6)
Panel A. Two-Stage Least Squares						
$log(1 + \text{In-Person Payment Flow})_{i,t}$	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 $log(1 + \text{In-Person Payment Flow})_{i,t}$						
$log(\text{Bike Placement})_{c,t}$	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	15.4	15.1	15.4	15.0	14.6	15.0
Adjusted R^2	0.552	0.553	0.554	0.523	0.522	0.521
Panel C. Ordinary Least Squares						
$log(1 + \text{In-Person Payment Flow})_{i,t}$	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	Has Credit	Has Credit
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 A.14: Robustness: In-person Payment Flow and Credit Provision, Controlling for Past Payment Flows

This table presents empirical evidence of the relationship between a user's in-person payment flow and BigTech credit, controlling for past payment flows on both extensive and intensive margins. Credit Access$_{i,t}$ is a binary variable indicating access to Alipay's virtual credit card for user i at time t. $log(\text{Credit Line})_{i,t}$ represents the log-transformed credit line of user i's virtual card at time t, missing if Credit Line$_{i,t}$ is 0. $log(1 + \text{In-Person Payment Flow})_{i,t}$ is the $log(1 + x)$ transformed in-person payment flow in CNY through Alipay for individual i at time t. $log(\text{Bike Placement})_{c,t}$ is the log-transformed count of active shared bikes in city c at time t. Panel A reports 2SLS estimates, instrumenting individual-level log in-person payment flow with city-level log number of active shared bikes; Panel B reports the corresponding first stage. Panel C reports the OLS regression coefficient for individual-level log in-person payment flow. Columns (1) and (4) control for past payment flow; columns (2) and (5) for past two periods; columns (3) and (6) for past three periods. All columns show results for regressions with individual and year-month fixed effects. All standard errors are clustered at city and year-month level. ***, **, and * denote the 1%, 5%, and 10% confidence level, respectively. I report standard errors in parentheses.

	Credit Access$_{i,t}$			$log(\text{Credit Line})_{i,t}$		
	(1)	(2)	(3)	(4)	(5)	(6)
			Panel A. Two-Stage Least Squares			
$log(1 + \text{In-Person Payment Flow})_{i,t}$	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 $log(1 + \text{In-Person Payment Flow})_{i,t}$			
$log(\text{Bike Placement})_{c,t}$	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	16.7	14.0	11.0	16.4	14.5	12.3
Adjusted R^2	0.636	0.647	0.651	0.596	0.605	0.608
			Panel C. Ordinary Least Squares			
$log(1 + \text{In-Person Payment Flow})_{i,t}$	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 $log(1 + \text{In-Person Payment Flow})_{i,t-1}$	YES	YES	YES	YES	YES	YES
Controls $log(1 + \text{In-Person Payment Flow})_{i,t-2}$	NO	YES	YES	NO	YES	YES
Controls $log(1 + \text{In-Person Payment Flow})_{i,t-3}$	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	Has Credit	Has Credit
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 A.15: Robustness: In-person Payment Flow and Credit Provision, Controlling for Online Payment

This table investigates the relationship between a user's in-person payment flow and BigTech credit on both margins, controlling for online payment. Credit Access$_{i,t}$ is a dummy indicating access to Alipay's virtual credit card for user i at time t. $log(\text{Credit Line})_{i,t}$ represents the log-transformed credit line of user i's virtual card at time t conditional on positive Credit Line$_{i,t}$. $log(1 + \text{In-Person Payment Flow})_{i,t}$ is the $log(1 + x)$ transformed in-person payment flow in CNY through Alipay for individual i at time t. $log(\text{Bike Placement})_{c,t}$ is the log-transformed count of active shared bikes in city c at time t. Panel A displays 2SLS estimates, instrumenting individual-level log payment flow with city-level log active shared bikes. Panel B shows the first stage, and Panel C reports OLS regression coefficients. Regressions include individual 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. ***, **, and * denote the 1%, 5%, and 10% confidence level, respectively. I report standard errors in parentheses.

	Credit Access$_{i,t}$		$log(\text{Credit Line})_{i,t}$	
	(1)	(2)	(3)	(4)
Panel A. Two-Stage Least Squares				
$log(1 + \text{In-Person Payment Flow})_{i,t}$	0.086***	0.085***	0.280***	0.277***
	(0.023)	(0.023)	(0.085)	(0.082)
$log(1 + \text{Measure of Online Payment})_{i,t}$	-0.009	-0.028	-0.037*	-0.107*
	(0.006)	(0.017)	(0.021)	(0.054)
Panel B. First Stage for $log(1 + \text{In-Person Payment Flow})_{i,t}$				
$log(\text{Bike Placement})_{c,t}$	0.041***	0.042***	0.043***	0.044***
	(0.010)	(0.010)	(0.012)	(0.012)
$log(1 + \text{Measure of Online Payment})_{i,t}$	0.260***	0.716***	0.246***	0.649***
	(0.007)	(0.015)	(0.008)	(0.018)
F-Statistic	16.0	16.2	14.0	14.3
Adjusted R^2	0.572	0.574	0.544	0.545
Panel C. Ordinary Least Squares				
$log(1 + \text{In-Person Payment Flow})_{i,t}$	0.008***	0.008***	0.018***	0.018***
	(0.001)	(0.001)	(0.002)	(0.002)
$log(1 + \text{Measure of Online Payment})_{i,t}$	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 Online Payment	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	Has Credit
Observations	1,238,309	1,238,309	779,283	779,283

Note: $^{*}p < 0.1$; $^{**}p < 0.05$; $^{***}p < 0.01$

Table A.16: Age, In-person Payment Flow, and Credit Provision

This table provides empirical evidence of the causal link between a user's in-person payment flow and BigTech credit for older and younger groups on both extensive and intensive margins. Credit Access$_{i,t}$ is a binary variable for Alipay user i's virtual credit card access at time t. $log(\text{Credit Line})_{i,t}$ denotes the log-transformed credit line for user i at t. $log(1 + \text{In-Person Payment Flow})_{i,t}$ represents the $log(1 + x)$ transformed payment flow through Alipay for user i at t, measured in CNY. $log(\text{Bike Placement})_{c,t}$ signifies the log-transformed active shared bikes in city c at t. Panel A displays 2SLS estimates, instrumenting individual-level log payment flow with city-level log active shared bikes; Panel B shows the first stage. Panel C reports OLS regression coefficients against individual-level log payment flow. Regressions include individual and year-month fixed effects. Columns (1) and (3) use the subsample of older people, who are older than sample median age; columns (2) and (4) use the subsample of younger people, who are not older than half of the individuals in the sample. All standard errors are clustered at city and year-month level. ***, **, and * denote the 1%, 5%, and 10% confidence level, respectively. I report standard errors in parentheses.

	Credit Access$_{i,t}$		$log(\text{Credit Line})_{i,t}$	
	(1)	(2)	(3)	(4)
	Panel A. Two-Stage Least Squares			
$log(1 + \text{In-Person Payment Flow})_{i,t}$	0.124***	0.047**	0.440***	0.176**
	(0.041)	(0.020)	(0.177)	(0.065)
	Panel B. First Stage for $log(1 + \text{In-Person Payment Flow})_{i,t}$			
$log(\text{Bike Placement})_{c,t}$	0.032***	0.049***	0.030***	0.054***
	(0.010)	(0.012)	(0.011)	(0.013)
F-Statistic	9.7	17.8	7.0	16.6
Adjusted R^2	0.552	0.539	0.559	0.483
	Panel C. Ordinary Least Squares			
$log(1 + \text{In-Person Payment Flow})_{i,t}$	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	Full Sample	Full Sample	Has Credit	Has Credit
Subsample	Older than Median	Younger than Median	Older than Median	Younger than Median
Observations	577,711	654,823	335,670	443,402
Note:				$^*p < 0.1$; $^{**}p < 0.05$; $^{***}p < 0.01$

Table A.17: Compulsive Spending and Credit Provision

This table provides empirical evidence of the correlation between a user's total payment flow, compulsive spending share, their interaction, and BigTech credit on both extensive and intensive margins. Credit Access$_{i,t}$ is a binary variable for Alipay user i's virtual credit card access at time t. $log(\text{Credit Line})_{i,t}$ denotes the log-transformed credit line for user i at t. $log(1+\text{Total Payment Flow})_{i,t}$ represents the $log(1+x)$ transformed total payment flow (both in-person and online) through Alipay for user i at t, measured in CNY. Total Compulsive Spending Share$_{i,t}$ is the share of total Alipay payments on cigarettes, games, lotteries, or live streaming services by individual i at time t. The interaction term $log(1+\text{Total Payment Flow})_{i,t} \times$ Total Compulsive Spending Share$_{i,t}$ examines how the relationship between payment flow and credit provision changes with different levels of compulsive spending. All standard errors are clustered at city and year-month level. ***, **, and * denote the 1%, 5%, and 10% confidence level, respectively. I report standard errors in parentheses.

	Credit Access$_{i,t}$		$log(\text{Credit Line})_{i,t}$	
	(1)	(2)	(3)	(4)
$log(1+\text{Total Payment Flow})_{i,t}$	0.013***	0.013***	0.050***	0.050***
	(0.001)	(0.001)	(0.004)	(0.004)
Total Compulsive Spending Share$_{i,t}$	-0.015***	-0.022**	-0.061***	-0.140***
	(0.005)	(0.010)	(0.015)	(0.041)
$log(1+\text{Total Payment Flow})_{i,t} \times$ Total Compulsive Spending Share$_{i,t}$		0.001		0.013**
		(0.001)		(0.006)
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	Has Credit
Observations	908,849	908,849	661,861	661,861
Adjusted R^2	0.695	0.695	0.832	0.832
Note:				*$p < 0.1$; **$p < 0.05$; ***$p < 0.01$