



Cashless payment and financial inclusion[☆]

Shumiao Ouyang^{ID}

Saïd Business School and Oxford-Man Institute of Quantitative Finance, University of Oxford, United Kingdom

ARTICLE INFO

Dataset link: [Cashless Payment and Financial Inclusion \(Pseudo-data; original data subject to confidentiality restrictions\)](#)

JEL classification:

G21
G23
G51
G53
O33

Keywords:

Cashless payment
BigTech
Consumer credit
Financial inclusion
Technology adoption

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.

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, 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

[☆] Toni Whited was the editor for this article. I am grateful to her and an anonymous referee for their highly constructive feedback in improving this paper. 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 Ph.D. 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, to PIIRS for a research grant, and to Oxford Saïd Business School for funding support. Any errors are my own.

E-mail address: shumiao.ouyang@sbs.ox.ac.uk.

URL: <https://www.shumiaoouyang.com/>.

<https://doi.org/10.1016/j.jfineco.2026.104277>

Received 16 March 2023; Received in revised form 23 February 2026; Accepted 6 March 2026

Available online 24 March 2026

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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, 2021). 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 (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., 2023; Hau et al., 2019, 2024; Chen et al., 2021b; Huang, 2022; Huang et al., 2025). Traditionally, consumer credit evaluation has relied on credit bureau data, emphasizing usage and repayment history (Chatterjee et al., 2023), but

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.

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 et al., 2026), 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, over-borrowing, 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).

² See Melzer (2011) for payday loans, Ausubel (1991) for credit cards, Be-gley and Purnanandam (2021) for mortgages, Di Maggio and Yao (2021) for FinTech lending, and deHaan et al. (2024) for Buy Now Pay Later” (BNPL).

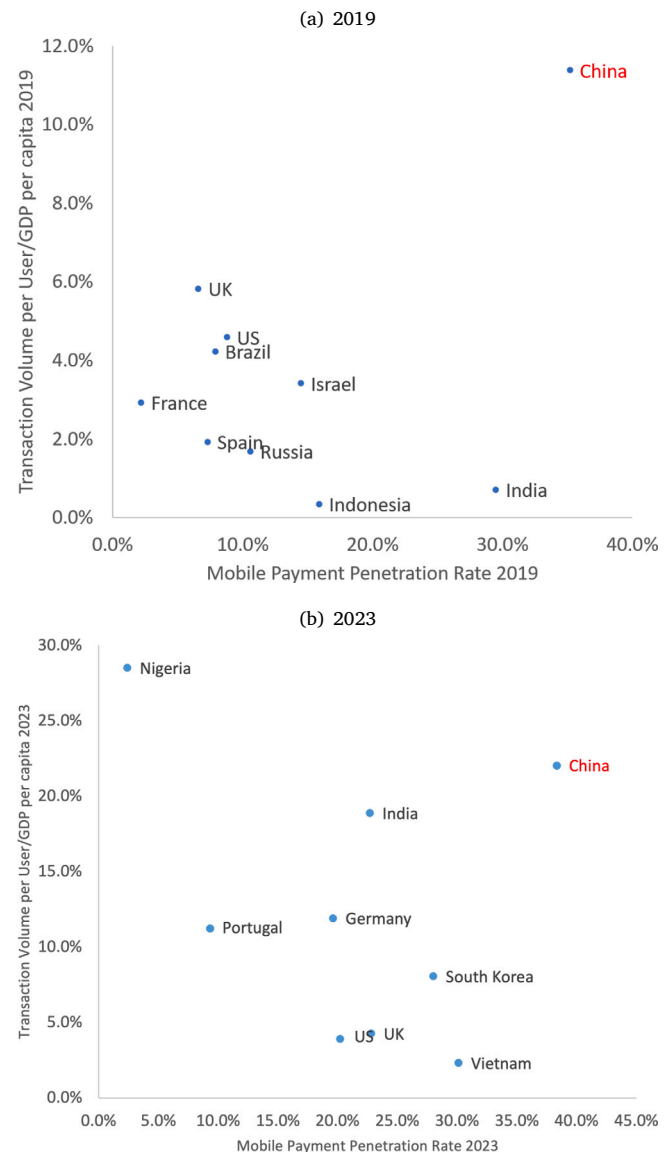


Fig. 1. Mobile Payment Penetration across Countries.

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.

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 Fig. 1 shows, China led the world in mobile payment penetration

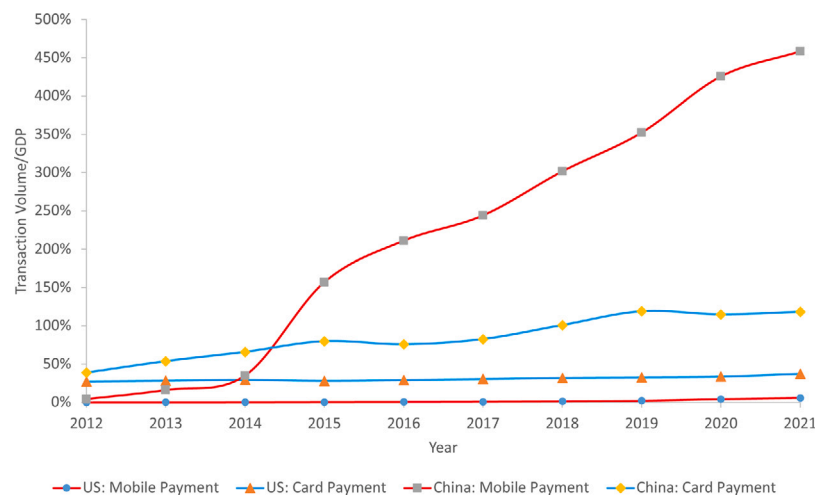


Fig. 2. Transaction Volume of Mobile and Card Payment in China and US.

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.

and per-user transaction volume from 2019 to 2023. While countries like India and Nigeria have advanced, China's transition from cash to digital payments stands out for its scale and speed. Fig. 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 2000 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 1000 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,c).

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 2000 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

Table 1
Summary statistics.

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

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, # 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, 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*}; $\log(\text{In-Person Payment Flow})_{i,t}$ and $\log(\text{Online Payment Flow})_{i,t}$ are the log amounts of in-person and online payments using Alipay; Virtual Credit Card Share in In-Person Payment_{*i,t*} and Virtual Credit Card Share in Online Payment_{*i,t*} are the shares of in-person and online payments using the virtual credit card; Compulsive Spending Share in In-Person Payment_{*i,t*} measures the share of in-person Alipay payments made by individual *i* at time *t* for cigarettes, games, and lotteries; Compulsive Spending Share in Online Payment_{*i,t*} measures the share of online Alipay payments made by individual *i* at time *t* for cigarettes, games, lotteries, or live streaming services.

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 min and 0.08 USD for each subsequent 15 min, 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., 2021). 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

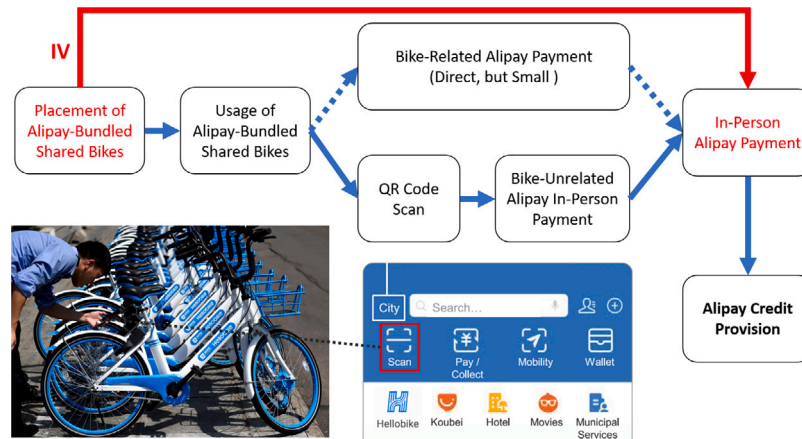


Fig. 3. Logic Flow of the Instrumental Variable.

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.

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 5521 CNY. Monthly Alipay transaction amounts at that point had a median of 238 CNY and a mean of 2628 CNY. For reference, the average monthly disposable income per capita in China in 2020 was 2682 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 Fig. 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:

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

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:

$$Y_{i,t} = \alpha_2 + \beta_2 \cdot g(ipf)_{i,t} + \delta_{2i} + \theta_{2t} + \varepsilon_{2i,t}. \quad (2)$$

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

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

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 ; $g(ipf)_{i,t}$ 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

³ I attempted to estimate Poisson models using the `glmhdfc` package recommended by Cohn et al. (2022) on the data provider's secure server, which has substantial memory resources. Despite multiple optimization attempts, the

Table 2
Effects of bike placement on payment and credit.

| 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*** (0.010) | 0.011 (0.009) | |
| $\text{Bike User}_i \times \log(\text{Bike Placement})_{c,t}$ | | 0.103*** (0.017) | |
| After First Bike Usage $_{i,t}$ | | | −0.123 (0.161) |
| After First Bike Usage $_{i,t} \times \log(\text{Bike Placement})_{c,t}$ | | | 0.049*** (0.014) |
| 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 | 0.551 | 0.552 | 0.490 |

| 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*** (0.008) | 0.009 (0.010) | |
| $\text{Bike User}_i \times \log(\text{Bike Placement})_{c,t}$ | | 0.060** (0.023) | |
| After First Bike Usage $_{i,t}$ | | | −0.231 (0.157) |
| 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 |

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.

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

decomposition approach provides clearer insights into the underlying mechanisms and helps mitigate interpretative challenges associated with variables transformed using $\log(1 + x)$.

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.

complexity of the dataset—comprising over 40,000 individuals with individual fixed effects—resulted in prohibitive memory demands, preventing estimation on the full sample.

2.4.1. 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 have not, 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. Fig. 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. (2021) 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.

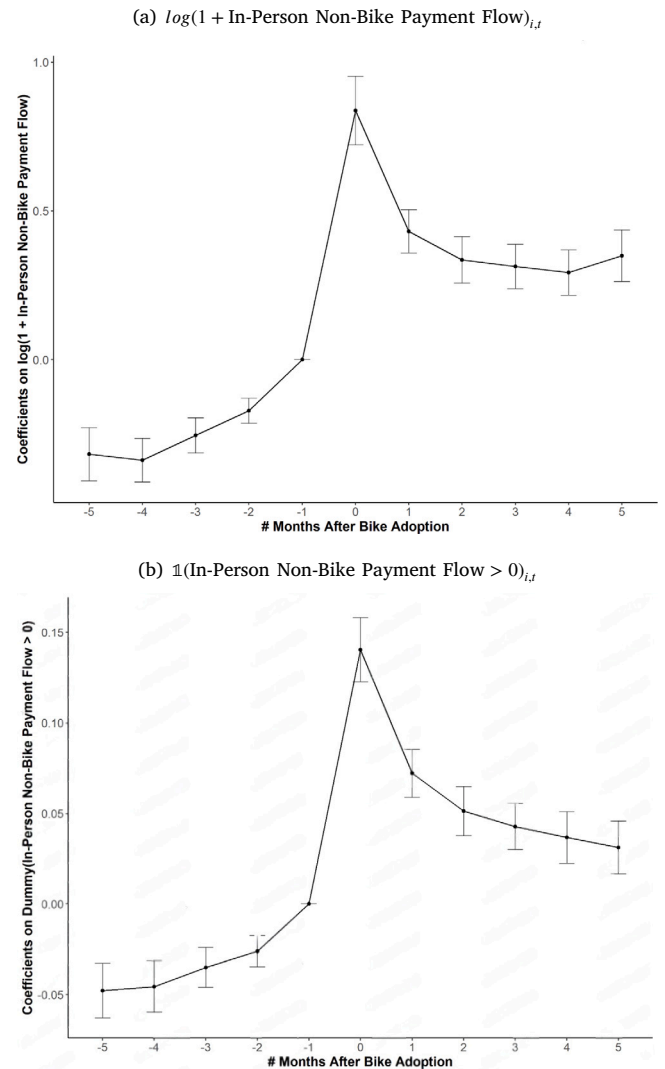


Fig. 4. Bike Adoption and Non-bike Payment Flow.

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

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

$$\text{Panel (b): } \mathbb{1}(\text{In-Person Non-Bike Payment Flow} > 0)_{i,t} = \alpha_0 + \sum_{\tau=-5}^4 \beta_\tau \cdot \mathbb{1}(t = \tau) \cdot \mathbb{1}(\tau \neq -1) + \beta_5 \cdot \mathbb{1}(t \geq 5) + \delta_i + \mu_t + \varepsilon_{i,t},$$

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 .

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

Table 3
Bike-usage intensity and heterogeneous bike-placement effects.

| | $\log(1 + \text{In-Person Payment Flow})_{i,t}$ | | $\log(1 + \text{Credit Line})_{i,t}$ | |
|---|---|---------------------|--------------------------------------|------------------|
| | (1) | (2) | (3) | (4) |
| $\log(\text{Bike Placement})_{c,t}$ | 0.011 (0.009) | | 0.009 (0.010) | |
| One-Time Bike User _{<i>i</i>} $\times \log(\text{Bike Placement})_{c,t}$ | 0.088*** (0.020) | 0.072*** (0.019) | 0.048** (0.023) | 0.035 (0.025) |
| Repeat Bike User _{<i>i</i>} $\times \log(\text{Bike Placement})_{c,t}$ | 0.106*** (0.018) | 0.078*** (0.017) | 0.062** (0.025) | 0.040 (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 |

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.

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

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 is 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.

Fig. 5 plots the β_τ coefficients estimated in the following regression:

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

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

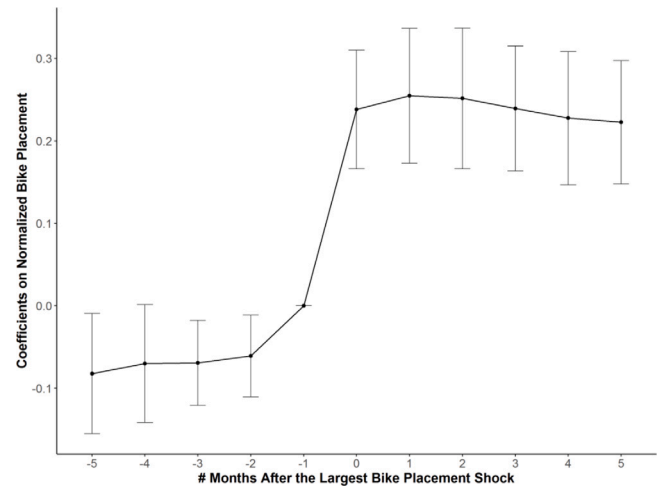


Fig. 5. Staggered Placement of Shared Bikes.

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 .

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

Table 4
In-person payment flow and credit provision.

| | Credit Access _{<i>i,t</i>} | | | log(Credit Line) _{<i>i,t</i>} | | |
|--|-------------------------------------|---------------------|---------------------|--|---------------------|---------------------|
| | (1) | (2) | (3) | (4) | (5) | (6) |
| Panel A. Two-Stage Least Squares | | | | | | |
| Measure of In-Person Payment Flow _{<i>i,t</i>} | 0.086*** (0.024) | 0.563*** (0.175) | 0.087** (0.043) | 0.281*** (0.085) | 2.033** (0.766) | 0.409*** (0.132) |
| Panel B. First Stage for Measure of In-Person Payment Flow _{<i>i,t</i>} | | | | | | |
| log(Bike Placement) _{<i>c,t</i>} | 0.041*** (0.010) | 0.006*** (0.002) | 0.030*** (0.009) | 0.043*** (0.012) | 0.006*** (0.002) | 0.024*** (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>i,t</i>} | 0.010*** (0.001) | 0.062*** (0.007) | 0.007*** (0.001) | 0.022*** (0.003) | 0.072*** (0.023) | 0.029*** (0.002) |
| Adjusted R ² | 0.740 | 0.741 | 0.700 | 0.836 | 0.835 | 0.841 |
| Form of the IPF Measure | log(1 + <i>x</i>) | $\mathbb{I}(x > 0)$ | log(<i>x</i>) | log(1 + <i>x</i>) | $\mathbb{I}(x > 0)$ | log(<i>x</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 |
| 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 |

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(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 + 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(In-Person Payment Flow)_{*i,t*} conditional on positive In-Person Payment Flow_{*i,t*} in columns (3) and (6). log(Bike Placement)_{*c,t*} is the log number of active shared bikes in city *c* at time *t*, conditional on positive log(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.

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

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 Eqs. (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(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

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.

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.

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:

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

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

Table 5
In-person payment flow and consumer behavior.

| | Virtual credit card share _{<i>i,t</i>} | | Compulsive spending share _{<i>i,t</i>} | |
|--|---|-----------------------|---|-----------------------|
| | In-person payment (1) | Online payment (2) | In-person payment (3) | Online payment (4) |
| Panel A. Two-Stage Least Squares | | | | |
| $\log(1 + \text{In-Person Payment Flow})_{i,t}$ | 0.094*** (0.034) | 0.030*** (0.011) | 0.004 (0.010) | 0.002 (0.002) |
| Panel B. First Stage for $\log(1 + \text{In-Person Payment Flow})_{i,t}$ | | | | |
| $\log(\text{Bike Placement})_{c,t}$ | 0.028*** (0.009) | 0.064*** (0.014) | 0.028*** (0.009) | 0.064*** (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*** (0.002) | 0.008*** (0.001) | 0.0002 (0.000) | −0.0003*** (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 |

This table presents empirical evidence showing the causal relationship between a user's in-person payment flow and the structure of the payment flows, in both the in-person payment and the online payment settings. Virtual Credit Card Share_{*i,t*} is the share of Alipay payments using the virtual credit card by individual *i* at time *t*. Compulsive Spending 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.

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

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'e Bao*, 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

Table 6
In-person noncredit payment flow and credit provision.

| | Credit Access _{i,t} | | log(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*** (0.024) | 0.095** (0.026) | 0.329*** (0.103) | 0.358*** (0.124) |
| $\log(1 + \text{In-Person Credit Payment Flow})_{i,t}$ | | −0.005 (0.006) | | −0.044 (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*** (0.009) | 0.035*** (0.009) | 0.037*** (0.010) | 0.031*** (0.009) |
| $\log(1 + \text{In-Person Credit Payment Flow})_{i,t}$ | | 0.218*** (0.009) | | 0.230*** (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*** (0.001) | 0.004*** (0.001) | 0.003 (0.002) | −0.004* (0.002) |
| $\log(1 + \text{In-Person Credit Payment Flow})_{i,t}$ | | 0.015*** (0.001) | | 0.039*** (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 |

The table shows the causal relationship between in-person noncredit payment flow and BigTech credit on both margins. Credit Access_{i,t} is a dummy for having access to Alipay's virtual credit card at time *t*. log(Credit Line)_{i,t} is the log credit line conditional on Credit Access_{i,t}. log(1 + In-Person Noncredit Payment Flow)_{i,t} and log(1 + 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(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.

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

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 Eqs. (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 is 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

Table 7
In-person payment flow and credit provision, with enforcement controls.

| | Credit Access _{<i>i,t</i>} | | log(Credit Line) _{<i>i,t</i>} | |
|--|-------------------------------------|---------------------|--|---------------------|
| | (1) | (2) | (3) | (4) |
| Panel A. Two-Stage Least Squares | | | | |
| $\log(1 + \text{In-Person Payment Flow})_{i,t}$ | 0.097*** (0.025) | 0.098*** (0.026) | 0.280*** (0.085) | 0.282*** (0.086) |
| $\log(1 + \text{Assets under Management})_{i,t}$ | −0.005 (0.004) | −0.008 (0.005) | −0.015 (0.011) | −0.026* (0.013) |
| Panel B. First Stage for $\log(1 + \text{In-Person Payment Flow})_{i,t}$ | | | | |
| $\log(\text{Bike Placement})_{c,t}$ | 0.038*** (0.010) | 0.036*** (0.010) | 0.043*** (0.011) | 0.043*** (0.011) |
| $\log(1 + \text{Assets under Management})_{i,t}$ | 0.147*** (0.005) | 0.180*** (0.005) | 0.122*** (0.005) | 0.152*** (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*** (0.001) | 0.008*** (0.001) | 0.020*** (0.002) | 0.020*** (0.002) |
| $\log(1 + \text{Assets under Management})_{i,t}$ | 0.008*** (0.001) | 0.008*** (0.001) | 0.017*** (0.002) | 0.014*** (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 |

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(Credit Line)_{*i,t*} is the log credit line conditional on Credit Access_{*i,t*}. log(1 + In-Person Payment Flow)_{*i,t*} and log(1 + 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(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.

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

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

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>.

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.

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 Fig. 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.

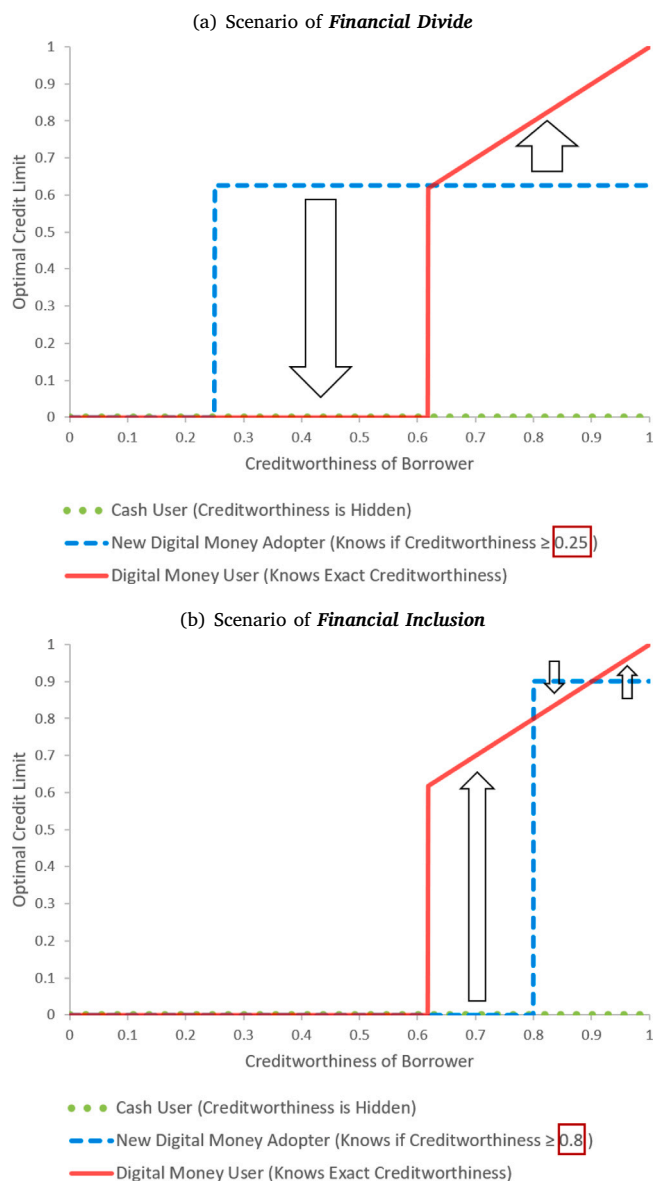


Fig. 6. Cashless Payment's Financial Inclusion Implication: An Example.

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. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

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

Table 8
Financially underserved segments.

| | Financial service usage | | | Financial literacy | | |
|--------------------------------|-----------------------------------|--------------------------------------|---|--|-------------------------------------|--------------------------------------|
| | # Debit cards _i (1) | $\log(1 + \text{Max. AUM})_i$ (2) | # Investment months _i (3) | Pay with real name _i (4) | Use own account _i (5) | Complete profile _i (6) |
| Low Education _i | −0.694*** (0.046) | −1.078*** (0.075) | −3.076*** (0.282) | −0.119*** (0.006) | −0.087*** (0.008) | −0.122*** (0.008) |
| Older than Median _i | −0.863*** (0.025) | −0.671*** (0.045) | −2.512*** (0.141) | −0.191*** (0.006) | −0.223*** (0.009) | −0.089*** (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 |

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

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.

Table 9
Education, in-person payment flow, and credit provision.

| | Credit Access _{<i>i,t</i>} | | log(Credit Line) _{<i>i,t</i>} | |
|--|-------------------------------------|---------------------|--|---------------------|
| | (1) | (2) | (3) | (4) |
| Panel A. Two-Stage Least Squares | | | | |
| $\log(1 + \text{In-Person Payment Flow})_{i,t}$ | 0.093*** (0.027) | 0.024 (0.044) | 0.334*** (0.109) | 0.038 (0.073) |
| Panel B. First Stage for $\log(1 + \text{In-Person Payment Flow})_{i,t}$ | | | | |
| $\log(\text{Bike Placement})_{c,t}$ | 0.039*** (0.010) | 0.043*** (0.013) | 0.039*** (0.011) | 0.053*** (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*** (0.001) | 0.013*** (0.001) | 0.022*** (0.003) | 0.013*** (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 |

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(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.

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

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.

Declaration of Generative AI and AI-assisted technologies in the writing process

During the preparation of this work, the author used ChatGPT for proofreading and language refinement. After using this tool, the author carefully reviewed and edited the content to ensure accuracy, clarity, and integrity, and takes full responsibility for the content of the publication.

Declaration of competing interest

The authors declare the following financial interests/personal relationships which may be considered as potential competing interests: Shumiao Ouyang reports financial support was provided by the Princeton University Institute for International and Regional Studies and the Saïd Business School, University of Oxford. Shumiao Ouyang reports financial support and administrative support were provided by Luohan Academy.

Appendix A. Supplementary data

Supplementary material related to this article can be found online at <https://doi.org/10.1016/j.jfineco.2026.104277>.

Data availability

Cashless Payment and Financial Inclusion (Pseudo-data; original data subject to confidentiality restrictions) (Mendeley Data)

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