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The Use and Disuse of FinTech Credit: When Buy-Now-Pay-Later Meets Credit Reporting

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JEL classification: G21, G41, G51

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Yanfei Dong[†] Jiayin Hu[‡] Yiping Huang[§] Han Qiu[¶]

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1 Introduction

The rise of financial technologies (FinTech) has greatly improved financial inclusion by extending credit to borrowers who are underserved in the traditional banking sector (e.g., Jack et al., 2013; Jack and Suri, 2014; Suri et al., 2021; Goldstein et al., 2019; Stulz, 2019; Erel and Liebersohn, 2022; Berg et al., 2022; Fuster et al., 2019).[1] However, as these FinTech innovations often do not share borrower information with other lenders (particularly banks), their lending practices remain opaque and may accumulate delinquency risks. One prominent example is the fast-growing "Buy Now, Pay Later (BNPL)" industry, which has raised regulatory concerns despite its many benefits. Several problems associated with BNPL, such as overborrowing and overextension risks, relate to its lack of credit reporting.[2]

What is the impact when BNPL meets credit reporting? Although BNPL spurs policy discussions around the world (Cornelli et al., 2023a), few countries have implemented such credit reporting requirements. Even fewer studies examine the impact of information sharing on BNPL borrowers, who constitute a substantial fraction of the consumer credit market. While information sharing through credit registries helps build credit records for unbanked FinTech borrowers, the higher delinquency rates associated with BNPL borrowers may send a negative signal for their bank loan applications. Therefore, how credit reporting changes BNPL users' behavior is an important yet understudied empirical question that has value for both scholars and policymakers.

Our paper is the first to analyze the impact of credit reporting on BNPL borrowers systematically. We exploit a leading regulatory change in China in 2021 that incorporates Ant Huabei, China's largest BNPL lender, into the centralized credit registry managed by the central bank.[3] Launched by the Ant Group in 2014, Huabei has gained mass popularity, with

[1]On the other hand, Fuster et al. (2022) also find that Black and Hispanic borrowers are disproportionately less likely to gain from the introduction of machine learning, which underscores the distributional impact of the adoption of such technologies.

[2]For instance, the Consumer Finance Protection Bureau (CFPB) in the United States noted that few BNPL lenders furnished consumer information to nationwide consumer reporting companies until recently, which could have "downstream effects on consumers and the credit reporting system."

[3]According to China's Regulations of Credit Reporting Administration, institutions engaged in credit

approximately 500 million users as of 2020.[4] In September 2021, Ant Huabei issued a public statement that officially announced its compliance with the credit reporting regulation. Upon the new regulatory framework, the Huabei BNPL product appears as a revolving credit account in users' credit reports at the centralized Credit Reference Center (CRC) under the People's Bank of China. Both positive (e.g., timely repayment) and negative (e.g., defaults) information is reported, together with the basic account information (e.g., the line of credit, account opening date, and utilization.) The regulatory authority indicates that all Huabei users will be incorporated into the centralized credit registry.[5]

To investigate BNPL users' response to the credit reporting policy change, we randomly selected 200,000 BNPL users who have used Huabei at least once before our sample period (i.e., those who have already obtained a Huabei credit line). Since these borrowers already went through the screening process and obtained access to the BNPL product, we are able to isolate the post-lending effect of information sharing (i.e., as a discipline device to reduce moral hazard) from the pre-lending effect (i.e., information provision to alleviate adverse selection). Our sample spans from July 2020 to December 2022, which covers 15 months both before and after the credit reporting regulation in September 2021.

Our purpose-built dataset compiles several sources of information to support our analysis. First, we examine user characteristics using a large cross-section of demographic and Huabei account information, including age, gender, city of residence, Alipay account opening date, and Huabei account opening date. Second, we extract monthly BNPL usage, payment, and consumption records of these users enabled through Alipay's super-app, one of China's two dominant digital platforms with approximately 900 million active users, equivalent to three

business should provide credit information to the credit reporting system. However, FinTech innovations, including the BNPL credit, had circumvented this credit reporting regulation using the micro-loan license instead of a banking license. After the collapse of the peer-to-peer (P2P) lending industry in China in 2019, the regulators started to tighten regulations and close regulatory loopholes.

[4]Ant Group's (suspended) IPO prospectus, http://static.sse.com.cn/disclosure/listedinfo/bulletin/star/c/688688_20201022_1.pdf, August 2020.

[5]There are several institutional differences between China's credit reporting system and that in the United States: the former (1) is operated by the central bank directly rather than by private institutions, (2) is a centralized system rather than separate credit reporting agencies, and (3) provides a full history of borrowing and repayment records in the past seven years but does not provide a summary credit score.

times the population of the United States. Since users often add bank cards to the Alipay platform, we can also observe users' traditional credit usage via the digital platform at the same time.[6] Additionally, we obtain information regarding the push notifications sent by Alipay to obtain users' authorization. Therefore, we can analyze users' immediate reactions to the credit reporting policy.

We guide our analysis by theories on information sharing and contract enforcement (Jappelli and Pagano, 2002; Padilla and Pagano, 1997, 2000; Pagano, Marco and Jappelli, Tullio, 1993). The credit registry serves as an essential financial infrastructure, rewarding those who make timely payments and punishing those who default (e.g., Garmaise and Natividad, 2017). Hence, the credit reporting practice should have heterogeneous impacts on borrowers. BNPL borrowers who view credit reporting more as an increase in the cost of default would reduce their BNPL usage and delinquencies, while those who see it more as an opportunity for credit building are more likely to increase their BNPL usage and make timely repayments.

Given these theoretical possibilities, we let the data speak. Interestingly, we find that the credit reporting regulation has significantly reduced the usage of BNPL credit. On average, consumers reduce the amount of their BNPL payments by 14% relative to the pre-policy period. Furthermore, the decline in BNPL credit is driven by both extensive and intensive margins: consumers are less likely to use Huabei for payment; even when they do, the average payment amount via Huabei also becomes smaller. The share of Huabei BNPL payments in total consumption also decreases by 7 percentage points, demonstrating a structural change in consumer credit usage. Therefore, our results lean more toward the disciplinary effect of information sharing on borrowers, who shift away from BNPL potentially to minimize their default probabilities or avoid the stigma associated with BNPL borrowers.

We then test the disciplinary mechanism of credit reporting in a difference-in-differences (DID) framework, classifying BNPL users based on their default records prior to the enactment of credit reporting practice. We find that BNPL users with previous default records,

[6]Payment via Alipay is ubiquitous even at brick-and-mortar stores and street vendors thanks to the QR code payments (Beck et al., 2022). Hence, we are able to track users' offline consumption as well.

a proxy for borrowers' creditworthiness, reduce their BNPL usage more than BNPL users who previously never defaulted. When using BNPL credit, these users also become more disciplined in terms of repayment when FinTech borrowing status is set to be reported to the national credit bureau and made available for traditional banks and other FinTech lenders. The reduction in FinTech credit usage leads to decreases in online consumption levels, implying that at least a fraction of the FinTech borrowers are financially constrained. Our results are consistent with previous empirical studies on the impact of information sharing in the context of corporate loans, such as Doblas-Madrid and Minetti (2013) and Behr and Sonnekalb (2012), which find that information sharing reduces firms' delinquency rates and improves loan performance mainly by disciplining borrowers.

Notably, we find the default rates on Big Tech platforms persistently low (1-2%), even when many BNPL users do not seem to have access to bank credit. This finding echoes previous studies showing that FinTech lenders use alternative data other than credit scores in screening borrowers and identify "invisible primes" (Brevoort and Kambara, 2017; Di Maggio et al., 2021). Our results also suggest that informal contract enforcement (e.g., platform exclusion costs), to some extent, substitutes for formal enforcement institutions (e.g., credit reporting). Given the advantages of Big Tech platforms in screening and monitoring BNPL borrowers, our results should be interpreted as a lower bound of the impact of credit reporting in disciplining borrowers' behaviors.

Several additional tests corroborate our main findings. First, we do not find statistically significant changes in the line of credit provided by Huabei, implying that this decrease in BNPL usage is not driven by supply-side factors. Second, we extend our analysis to new users to explore the impact on people's adoption of BNPL credit. We find that users who start using BNPL after the credit reporting regulation are older, are more seasoned in using Alipay, and wait longer before they take up BNPL credit than those new users in pre-policy periods. These post-policy new users are also more prudent in using BNPL, with smaller BNPL payments and lower default rates. Third, the disuse effect is more pronounced among younger borrowers and borrowers who have bank credit cards. Given that younger people are more likely to be "credit invisible" (Brevoort et al., 2015, 2016; Cooper et al., 2023), the disuse of BNPL credit implies that they may intentionally choose not to build credit records when their income flows are less stable, hence minimizing the impact of bad records on their future credit access (e.g., Dobbie et al., 2020).

Lastly, to better understand the motives behind these empirical patterns, we conducted surveys on the Big Tech platform to infer BNPL users' attitudes toward credit reporting. Consistent with the stigma effect associated with BNPL borrowing, our survey data show that worries about BNPL's negative impact on credit records rank among the top reasons why consumers do not use Huabei. Survey respondents with previous default experience are also more likely to choose "reducing the usage of Huabei" after the credit reporting regulation. Interestingly, we also find large heterogeneity among consumers regarding the impact of credit reporting, with a large fraction of respondents believing in the credit-building effect of BNPL products, demonstrating the distributional impacts of information sharing. These results echo previous studies on credit builder loans (Burke et al., 2023), which find large credit score drops among borrowers with active baseline installment borrowings and the intended large credit score increase among those less active.

Our work contributes three main insights to the existing literature. First, to the best of our knowledge, our paper is the first to empirically investigate the impact of information sharing on FinTech consumer credit. While there is extensive literature investigating the impact of information sharing via the credit registry on traditional banks,[7] few studies have ever examined the role of credit reporting in the FinTech context. Notably, Liao et al. (2023) conduct field experiments to inform FinTech borrowers that their loan performance will be reported to a public credit registry.[8] Different from Liao et al. (2023), where the focal FinTech

[7]Sharing loan performance among lenders via credit reporting has been shown as an efficient way to address information asymmetry and improve lender screening (Pagano, Marco and Jappelli, Tullio, 1993). Moreover, credit reporting can increase borrowers' repayment efforts by narrowing incumbent lenders' information advantage and reducing their information rates (Padilla and Pagano, 1997) and by restricting defaulted borrowers' access to future credit (Padilla and Pagano, 2000).

[8]Liao et al. (2023) find that FinTech borrowers who have been warned of the credit reporting practice

lender consistently reports borrowers' loan performance to the credit registry, our paper captures the impact of the actual credit reporting policy change on FinTech lending. This feature distinguishes our paper from previous studies focusing on informational intervention.[9] We find that the credit reporting practice reduces rather than increases FinTech credit usage and loan take-up rates, highlighting the potential stigma effect and the benefits of credit reporting in reducing overborrowing and overextension risks. Our paper also provides an interesting mirror image to the open banking literature, which examines the data sharing consented by bank customers to FinTech lenders (e.g., He et al., 2023; Nam, 2023), by investigating mainly the credit information being shared from FinTech lenders with banks.

Second, we document a novel disuse effect on BNPL users when the regulatory gap is closed, highlighting how the regulatory environment shapes the adoption of FinTech among individuals.[10] Our paper builds on the burgeoning BNPL literature focusing mainly on its consumption-stimulating impact (Di Maggio et al., 2022; Bian et al., 2023). Prominently, Di Maggio et al. (2022) provides a first look into the BNPL market in the United States and finds that BNPL access increases both total spending and the retail share in total expenditures, regardless of users' inferred liquidity constraints. Bian et al. (2023) find that BNPL crowds out other e-wallet payment options and expands FinTech credit to underserved consumers, substantially boosting consumer spending. Our paper uses similar payment transactions matched with merchant and consumer information from a world-leading provider based in China as in Bian et al. (2023). Our results demonstrate significant decreases in BNPL usage after the credit reporting policy change, which implies that the regulatory arbitrage previously enjoyed by FinTech consumer credit is one of the reasons behind its popularity.[11]

reduce their default rates and increase their loan take-up rates, implying that credit warnings benefit both lenders and borrowers.

[9] Our context of revolving consumer credit is also different from the fixed-term loan in Liao et al. (2023).

[10] An extensive stream of literature has discussed how FinTech companies compete with banks in providing financial services outside the traditional regulatory framework (e.g., Navaretti et al., 2018; Hau et al., 2019; Goldstein et al., 2019; Thakor, 2020).

[11] We also find that the reduction in BNPL usage leads to a decrease in online consumption, consistent with the borrowing constraint hypothesis that some FinTech borrowers use BNPL credit to finance consumption. This finding relates to Agarwal et al. (forthcoming), which finds that digital payments increase consumer spending.

Our findings echo the broader literature on regulatory arbitrage and the rise of FinTech in other financial markets (e.g., Buchak et al., 2018; Di Maggio and Yao, 2021) and complement the research on the driving forces behind FinTech adoption (Higgins, forthcoming; Chodorow-Reich et al., 2020).

Third, our study speaks to the interplay between formal and informal contract enforcement institutions in FinTech lending. Our data from the leading Big Tech platform demonstrate a minimal default rate, which contrasts the findings concerning default rates in FinTech lending (e.g., Di Maggio and Yao, 2021). The reason for this is that the context of Big Tech platforms is different from that of standalone FinTech lenders, as examined in the growing literature on Big Tech lending (de la Mano and Padilla, 2018; Frost et al., 2019; Stulz, 2019; Boissay et al., 2021; Gambacorta et al., 2022; Beck et al., 2022; Hu, 2022; Huang et al., 2022; Liu et al., 2022; Cornelli et al., 2023a; Chen et al., 2023; Gambacorta et al., 2023). With a vast digital ecosystem and a dominant market share, Big Tech platforms accumulate soft information using big data and machine learning technologies and are able to exert informal contract enforcement, such as the exclusion threat (Gambacorta et al., 2022) similar to the lockout technology of digital collateral (Gertler et al., 2024).[12]

The remainder of the paper proceeds as follows. Section 2 details the institutional background. Section 3 describes the data and empirical methodology. Section 4 provides a descriptive analysis. We present our main regression results in Section 5 and conduct further analysis in Section 6. Section 7 presents survey results. We conclude in Section 8.

[12] Our paper also echoes the broader literature highlighting important synergies between payment and other financial services (e.g., lending, deposit-taking, and investment) including Jack et al. (2013); Jack and Suri (2014); Donaldson et al. (2018); Agarwal et al. (2019, 2020); Buchak et al. (2021); Jiang et al. (2022); Ghosh et al. (2022); Parlour et al. (2022); Chen and Jiang (2022).

2 Institutional Background

2.1 BNPL Industry and the Huabei Product

BNPL schemes, by allowing individuals to divide their consumption expenditures into several interest-free installments, have gained significant popularity in the post-pandemic era. CFPB data show that between 2019 and 2021, BNPL loans issued in the U.S. by the five surveyed lenders skyrocketed by 970%, increasing from 16.8 million USD to 180 million USD. Concurrently, the total value of these loans soared by 1,092%, rising from 2 billion USD to 24.2 billion USD.[13] The global merchandise volume by selected BNPL platforms grew from 51.11 billion USD in 2019 to 368.78 billion USD in 2023 (Cornelli et al., 2023b). According to FIS Global Payments Report 2023, BNPL accounted for 5% of global e-commerce transaction volume in 2022.[14]

BNPL payments in China are expected to grow by 14.3% to reach 136.63 billion USD in 2024.[15] Different from BNPL lenders such as Affirm, Afterpay, and Klarna, which are mainly FinTech companies specializing in BNPL payments, the BNPL products in China are provided mainly by Big Tech platforms, including the Ant Group (formerly Ant Financial, a financial spinoff of the e-commerce giant Alibaba, which owns the payment super-app Alipay) and Tencent (a leading tech company that owns the communications super-app WeChat)). For instance, Ant Group provides two types of consumer credit products through its Alipay app: Huabei (meaning "just spend it" in Chinese) launched in 2014, a BNPL product and the focus of our study, and Jiebei (meaning "just borrow it" in Chinese) launched in 2015, a personal loan product.

Like most BNPL products, Huabei allows consumers to split payments into several interest-free installments and repay over time. Specifically, it offers consumers a 40-day

[13] Consumer Financial Protection Bureau, https://www.consumerfinance.gov/data-research/research-reports/buy-now-pay-later-market-trends-and-consumer-impacts/, September 2022.

[14] https://www.statista.com/chart/31336/popular-buy-now-pay-later-providers-in-the-us/.

[15] https://www.businesswire.com/news/home/20240226273220/en/China-Buy-Now-Pay-Later-Report-2024-75-KPIs-on-BNPL-Market-Size-End-Use-Sectors-Market-Share-Product-Analysis-Business-Model-and-Demographics---Forecasts-to-2029---ResearchAndMarkets.com.

interest-free period, after which consumers can split their bills into installments over 3 to 12 months. The daily interest rate for Huabei can be as low as 0.02% (equivalent to an annual rate of 7.3%), with most loans having a daily interest rate of 0.04% or lower (equivalent to an annual rate of 14.6%).[16] Consumers use Huabei in both online and offline shopping.[17] Huabei has gained massive success in China, facilitating a consumer credit scale exceeding 1 trillion RMB, or 140 billion USD. Approximately 500 million users accessed this consumer credit service between July 2019 and June 2020.[18]

Interestingly, Big Tech platforms in other countries have also moved into the BNPL business recently. For instance, in June 2023, Amazon announced a partnership with Affirm to offer BNPL services on Amazon Pay.[19] Another Big Tech, Apple, introduced Apple Pay Later in March 2023, which allows users to split purchases into four zero-interest, zero-fee payments, with a loan value of 50 USD to 1,000 USD.[20] In December 2023, Google Pay announced a pilot program with Affirm and Zip to add a BNPL option for U.S. online shoppers.[21] Therefore, our research using data from BNPL products provided by Big Tech platforms represents the recent trends of BNPL development and has general implications for other countries.

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[16] The data are as of June 2020. https://static.sse.com.cn/disclosure/listedinfo/bulletin/star/c/688688_20201022_1.pdf

[17] Data from Alipay show that 43.8% of users choose Huabei for offline payments, while 54.2% opt for it when making online payments (Bian et al., 2023).

[18] Ant Group's (suspended) IPO prospectus, http://static.sse.com.cn/disclosure/listedinfo/bulletin/star/c/688688_20201022_1.pdf, August 2020.

[19] Previously in December 2021, Amazon offered the BNPL payment option that allows consumers to split the cost of orders over 100 GBP through a partnership with Barclays. Barclays would carry out a hard credit check on BNPL applicants, hence affecting borrowers' credit records. See https://www.which.co.uk/news/article/amazon-and-barclays-buy-now-pay-later-scheme-explained-aNKhk5g22GjZ.

[20] According to the plans of Apple Financing, users' past, current, and future Apple Pay Later loans may be reported to U.S. credit bureaus starting in Fall 2023 to promote "responsible lending for both the lender and the borrower." See https://www.apple.com/newsroom/2023/03/apple-introduces-apple-pay-later/.

[21] https://www.pymnts.com/buy-now-pay-later/2023/google-pay-pilots-bnpl-consumers-clamor-flexibility-checkout/. Previously in July 2020, Google Pay partnered with Afterpay to provide BNPL services at some U.S. physical retail stores. See https://www.electronicpaymentsinternational.com/news/afterpay-google-pay-buy-now-pay-later-service/.

2.2 Regulatory Framework for BNPL

The BNPL business largely falls outside the purview of existing regulations. Notably, unlike traditional consumer credit, BNPL loans are typically not reported to credit bureaus and, consequently, do not impact consumers' credit scores (Cornelli et al., 2023b). The CFPB has noted that this situation can disadvantage BNPL borrowers who pay on time and are trying to build credit, as they may not reap the benefits of timely payments on their credit reports and scores. This lack of information sharing can also affect both BNPL and traditional lenders attempting to gauge a prospective borrower's total debt load.[22]

Across the Atlantic, the Financial Conduct Agency (FCA) in the United Kingdom raised a question regarding the consumer welfare implications of introducing a mandatory reporting requirement for all lenders, which would "address calls for greater transparency of innovative credit products entering the market (particularly Buy Now Pay Later offers.)" The FCA also indicated that this lack of transparency means that credit providers may not have a comprehensive view of a consumer's financial situation when assessing his or her creditworthiness.[23]

Several regulatory authorities are exploring whether and how to incorporate BNPL data into credit reporting. For instance, the CFPB has been developing strategies for how the industry and consumer reporting companies can establish accurate and appropriate credit reporting practices for BNPL. In 2022, the three largest NCRCs in the United States (i.e., Equifax, Experian, and TransUnion) each released announcements on their plans to accept BNPL payment data.[24] In May 2023, the Australian government announced its intention to implement a customized regulatory framework that requires BNPL providers to obtain a credit license and adhere to specific regulations.[25] Singapore's Monetary Authority has implemented a comprehensive BNPL industry code that addresses various aspects, including credit evaluation, credit information-sharing, and limits on the amount of outstanding

[22] https://www.consumerfinance.gov/about-us/blog/by-now-pay-later-and-credit-reporting/
[23] https://www.fca.org.uk/publication/corporate/woolard-review-report.pdf
[24] https://www.consumerfinance.gov/about-us/blog/by-now-pay-later-and-credit-reporting/
[25] https://treasury.gov.au/consultation/c2024-504798

payments that customers can have with each BNPL provider.[26] The UAE Central Bank (CBUAE) implemented the new Finance Companies Regulation, which officially acknowledges BNPL schemes as a form of consumer short-term credit and establishes requirements for transparency and disclosure.[27]

The potential impact of including BNPL information in credit reporting, however, is not very clear. Several reasons suggest that caution should be taken. First, BNPL usage may result in a stigma effect against borrowers, as lenders noticing frequent BNPL transactions on a potential borrower's bank statements may raise concerns about their spending habits, which can lead to declined credit applications. According to a recent New York Fed research,[28] BNPL users typically tend to be younger, carry higher debt burdens, and have lower credit scores compared to credit card users. More financially fragile households tend to use such a service more frequently than those less financially fragile. Data from the CFPB also shows that BNPL borrowers are generally more likely to be heavily indebted, revolve on their credit cards, have delinquencies in traditional credit products, and use high-interest financial services compared to non-BNPL borrowers.[29]

Second, since BNPL differs from traditional consumer credit in usage patterns, the consequences of incorporating it into credit reporting are unclear and depend on the credit reporting standards. For example, while records of on-time BNPL payments can enhance users' credit profiles, frequent borrowing due to the short-term nature of BNPL can significantly lower the average age of one's credit history, potentially negatively affecting his or her credit score.[30] While major credit bureaus (such as Equifax, Experian, and TransUnion)

[26] https://www.mas.gov.sg/news/parliamentary-replies/2022/reply-to-parliamentary-question-on-bnpl

[27] https://www.centralbank.ae/media/izlhi5rb/cbuae-introduces-framework-for-the-regulation-of-short-term-credit-facilities_en.pdf

[28] Felix Aidala, Daniel Mangrum, and Wilbert van der Klaauw, "How and Why Do Consumers Use "Buy Now, Pay Later"?," Federal Reserve Bank of New York Liberty Street Economics, February 14, 2024, https://libertystreeteconomics.newyorkfed.org/2024/02/how-and-why-do-consumers-use-buy-now-pay-later/.

[29] https://www.consumerfinance.gov/data-research/research-reports/consumer-use-of-buy-now-pay-later-insights-from-the-cfpb-making-ends-meet-survey/

[30] https://www.cnbc.com/select/how-buy-now-pay-later-loans-can-decrease-your-credit-score/

have outlined plans to integrate BNPL credit data, the differing standards among these institutions also raise concerns. For instance, the CFPB is concerned that "this inconsistent treatment will limit the potential benefits of furnished BNPL data to consumers and the credit reporting system."[31] Therefore, the impact of integrating BNPL into credit reporting has become an important empirical topic, which is essential for promoting financial inclusion and preserving financial stability in the FinTech era.

2.3 Credit Reporting Regulation in China

As a pioneering regulatory practice, China's national credit bureau started incorporating Huabei into the credit reporting infrastructure in 2021. On September 22, 2021, Ant Group announced that under the guidance of the People's Bank of China, it was progressively working on integrating its BNPL product with the central bank's credit reporting system. Upon users' authorization, Huabei reports both positive (e.g., timely repayment) and negative (e.g., defaults) information of its users to the centralized credit bureau, together with the basic account information (e.g., the line of credit, account opening date, and utilization.) These credit records are summarized at a monthly frequency starting from the authorization month and do not include transaction-level details. Throughout the paper, we define September 2021 as the starting point of the credit reporting regulation.

Panel A of Figure 1 shows a screenshot of the original social media post of Huabei's official account on September 22, 2021, announcing that its users' borrowing status would be reported to the national credit bureau and become accessible to traditional banks. Immediately after the statement was issued, this topic received widespread attention and became one of the headlines on Weibo social media that day (Panel B). In addition, we use the changes in the Baidu Search Index to illustrate the public's awareness of this policy and show the index on "Huabei's borrowing status is reported to the credit bureau" in Panel C of Figure 1. The Baidu Search Index peaked on September 22, 2021, indicating that the

[31] https://www.consumerfinance.gov/about-us/blog/by-now-pay-later-and-credit-reporting/

majority of the public became aware of the regulatory policies at that time.

We note that the Alipay app started sending push notifications to Huabei users regarding the credit reporting policy change in July 2021. Figure A1 depicts the process of the timing of users receiving the push notification and signing the authorization. After the public announcement in September 2021, the fraction of users who received push notifications and those who signed authorization agreements increased substantially. This pattern supports our argument that September 2021 is critical for the implementation of the credit reporting policy change.[32]

3 Data and Empirical Methodology

3.1 Data and Variables

3.1.1 Data Sources

Our data are from Huabei, China's largest BNPL service provider, as described in Section 2. Our sample is a large cross-section of 200,000 BNPL users randomly selected from the population of active Huabei users, defined as those who have used Huabei credit at least once between January 2020 and June 2020 (i.e., six months before our sample period.) Our sample period spans from July 2020 to December 2022, which covers 15 months both before and after the credit reporting regulation change in September 2021 to allow for comparison.

We extract monthly BNPL usage, payment, and consumption records of these users enabled through Alipay's super app, one of China's two dominant digital platforms with approximately 900 million active users,[33] or nearly three times the population in the United States. Since users can add bank cards to the Alipay platform, we can also observe users'

[32]It is worth mentioning that these push notifications frame the policy change as a service upgrade, placing minimal emphasis on the credit reporting policy change. Therefore, users who do not read the fine print may remain unaware of the policy change even when they have received the push notification and signed the authorization agreement. Hence, the media coverage of Huabei's incorporation into the centralized credit registry is a more accurate gauge of users' awareness of this information-sharing practice.

[33]QuestMobile, https://www.questmobile.com.cn/research/report/1638022399369777153, January 2023.

traditional credit usage via the digital platform. Additionally, payment via Alipay is ubiquitous, even at brick-and-mortar stores and street vendors. Owing to the widespread use of QR code payments in brick-and-mortar stores in China (e.g., Beck et al., 2022; Hong et al., 2020), we can also track users' offline consumption.

Our purpose-built dataset compiles several sources of information to support our analysis: (1) user characteristics, including demographic and Huabei account information such as age, gender, city of residence, Alipay account opening date, and Huabei account opening date; (2) credit reporting regulation information, including the timing of receiving the push notifications sent by Alipay to obtain users' authorization and the timing of signing the user authorization for reporting BNPL borrowing status to the national credit bureau; (3) monthly payment data via different options offered by the Big Tech platform, including the BNPL credit, FinTech money market funds (MMFs), e-cash from the digital wallet, and credit/debit cards that users have linked to the platform; (4) monthly repayment and default status of the BNPL credit; and (5) monthly online and offline consumption data.

3.1.2 Main Variables

Previous default records. To investigate the effects of credit reporting policy on BNPL borrowers with different creditworthiness, we categorize users into two groups: those with and without past default records based on the information before our event window period. Therefore, we define users with (without) past default records as those who ever (never) defaulted as of four months before the credit reporting regulation.

BNPL usage. We use three indicators to measure the BNPL usage in the Big Tech app: (1) whether a user uses BNPL, a binary variable taking the value of 1 if a user has BNPL payment records in a given month; (2) BNPL payment share, the proportion of BNPL payment in total consumption via Alipay; and (3) BNPL payment in natural logarithm value. In addition, we investigate the usage of other FinTech and traditional payment options in the Big Tech app using the share of four primary alternative payment options in total consumption: (1) e-cash payment share, (2) FinTech MMF payment share, (3) credit card payment share, and (4) debit card payment share.

Default indicators. We use four indicators to measure the default behaviors of FinTech credit: (1) default within 3 days after the due date, a binary variable taking the value of 1 if a user does not repay the bill or make an installment repayment within three days after the billing date in a specific month; (2) default within 30 days, a binary variable taking the value of 1 if a user does not repay the bill or make an installment repayment within thirty days; (3) overdue balance ratio, the ratio of the overdue balance (unpaid balance) amount to the total bill amount (the balance on a certain billing date); and (4) average interest-bearing balance ratio, the share of the average interest-bearing balance (the sum of overdue balance and installment balance) in the monthly average balance.

Consumption. Consumption via the Big Tech app comprises two components: online consumption (i.e., the expenditure on online services such as e-commerce purchases) and offline consumption (i.e., the spending in offline scenarios such as payments at local stores). At this moment, we focus on the consumption amount but are able to extend our analysis to more detailed categories such as food and clothing.

3.1.3 Sample Construction

We start with a well-balanced user-month panel that contains 200,000 users and spans from July 2020 to December 2022, comprising a total of 6,000,000 observations. We then impose several restrictions to construct an analysis sample. First, we keep only those observations within our window period spanning four months before and eight months after the credit reporting regulation implementation. Second, we keep observations of users who have at least one BNPL payment record before the window period. Third, we drop observations with missing values for the main variables and impose some logical restrictions on the timing related to receiving push notifications and signing the authorization. Our final sample contains 137,042 users spanning 13 months, constituting 1,693,706 observations.

3.1.4 Summary Statistics

Table 1 reports the summary statistics of the analysis sample. Panel A reports the cross-section statistics for user characteristics. The average user age is approximately 33 years old, consistent with the fact that the BNPL service targets mainly young consumers.[34] The gender distribution is balanced, with male users accounting for 53.3%. Notably, a very small fraction (i.e., 5%) of the users have default incidents, implying the advantages of Big Tech platforms in screening and disciplining borrowers compared to standalone FinTech lenders. Over half of BNPL users have received directed push notifications regarding the credit reporting policy change and signed the authorization.

Panel B of Table 1 reports the user-month panel data summary statistics. The average share of BNPL payment in total expenditure is 47.1%, suggesting the prominence of BNPL as a payment channel within the Alipay platform. In addition to the BNPL option, consumers also use debit cards (payment share equals 20.6%), FinTech MMFs (payment share equals 13.4%), and credit cards (payment share equals 10.0%) for payments. The level of e-cash usage is relatively low (payment share equals 6.6%), potentially attributed to the interest-paying FinTech MMFs, which offer similar payment convenience (Buchak et al., 2021).

The default rate is relatively low, with an average of 0.021 using the 3-day indicator and 0.012 using the 30-day indicator. This pattern of low default rates is consistent with the advantages of Big Tech platforms in controlling credit risks, such as the screening technology using big data and machine learning and the informal contract enforcement within the platform's ecosystem.[35]

Finally, we examine the transactions facilitated by the Alipay app. The average total consumption is 5,154 RMB, comprising 1,643 RMB online and 3,309 RMB offline consump-

[34]For instance, GlobalData's report identifies Millennials and Generation Z as those generations most engaged with BNPL loans. https://www.globaldata.com/media/banking/buy-now-pay-later-global-transaction-value-reached-120-billion-2021-according-globaldata/, May 26, 2022.

[35]For instance, a default record can lead to a reduction in the Sesame Credit Score, a private credit rating mechanism introduced by the Ant Group and widely used by businesses connected to the digital payment platform (e.g., waivers on car rental deposits, expedited airport security checks, FinTech loan applications, and increases in Huabei credit lines).

tion. The logarithmically transformed values of total consumption, online consumption, and offline consumption are 7.439, 6.114, and 5.971, respectively. According to statistics from China's National Bureau of Statistics, the average consumption expenditure reached 26,796 RMB in 2023.[36] Hence, the consumption expenditure on the digital payment platform represents approximately 20% of the average total consumption, which aligns with the fact that Alipay has become a primary payment choice of Chinese consumers.

3.2 Empirical Methodology

3.2.1 Event Study

We start with an event study specification to investigate behavior changes of BNPL users on the platform. The event study approach is based on the sharp changes in the outcomes around the policy shock and allows for a detailed exploration of the dynamic trajectory of effects. Specifically, we conduct the following regression:

$$Y_{it} = \beta_0 + \sum_{r \neq -1} \theta_r \times I_r + \mu_i + \varepsilon_{it}. \tag{1}$$

where Y_{it} is the outcome for user i in month t. I_rs are the relative time indicators. If the current month t equals the policy shock month (S, or September 2021) plus the relative month (r), then $I_r = 1$. μ_i denotes user fixed effects. In our main analysis, we choose the window period from May 2021 to May 2022, with r spanning from -4 to $+8$.

The key coefficients of interest are θ_rs, which measure the effects of the policy shock in event time r relative to base time $r = -1$. The condition of causal identification in the event study framework requires that, conditional on the included controls, the trends in the outcomes follow a smooth path in the absence of the event. As we cannot observe counterfactuals after the event, the parallel pre-trend in the event study results can partly validate this assumption.

[36] National Bureau of Statistics of People's Republic of China, https://www.stats.gov.cn/sj/zxfb/202401/t20240116_1946622.html, January 17, 2024.

3.2.2 DID Analysis

Users with lower creditworthiness tend to have a higher probability of default and thus are more adversely affected by the credit reporting policy compared to users with higher credit quality. Therefore, we consider users with low creditworthiness (proxied by their past default records) to be those users primarily affected by the policy. We use the following DID specification to investigate the effects of the regulatory policy change on users with lower credit quality:

$$Y_{it} = \beta_0 + \beta_1 \times PastDefault_i \times post_t + \mu_i + \delta_{ct} + \varepsilon_{it}. \tag{2}$$

In this specification, $PastDefault_i$ indicates whether a user has a default record before the window period (before May 2021). $post_t$ indicates whether the policy shock has taken place, i.e., whether the time is after September 2021. After September 2021 (excluding September 2021), $post_t = 1$. μ_i and δ_{ct} denote user and city-month fixed effects, respectively. β_1 captures the effects of policy shock on users with previous default records relative to those without such records.

The casual identification assumption of the DID model is that, in the absence of the policy change, the average outcomes for the treatment group and the control group would follow parallel trends over time. We test the identification assumption using the dynamic DID model $Y_{it} = \beta_0 + \sum_{r \neq -1} \theta_r \times PastDefault_i \times I_r + \mu_i + \delta_{ct} + \varepsilon_{it}$, where θ_rs estimate the effects in event time r relative to base period $r = -1$. Validation of identification assumption requires that $\theta_r = 0$ for $r < 0$.

3.2.3 Heterogeneity Analysis

We use a specification similar to the DID approach to investigate how the effects vary by user characteristics of interest, z_i:

$$Y_{it} = \beta_0 + \beta_1 \times z_i \times post_t + \mu_i + \delta_{ct} + \varepsilon_{it}. \tag{3}$$

We adjust the DID design by allowing the group variable to vary in different dimensions. Specifically, by varying z_i, we explore heterogeneity based on user characteristics such as age, consumption level, and access to traditional credit. Our coefficient of interest is β_1, which captures the additional effects between groups with different z_i.

4 Descriptive Analysis

4.1 Reduction in BNPL Usage

Figure 2 presents the changes in BNPL usage following the credit reporting regulation. We characterize BNPL usage by both the extensive (i.e., whether a user uses BNPL in a certain month) and the intensive (i.e., the share of BNPL payment in total consumption) margins. In both panels, the coefficients closely approximate zero before September 2021, indicating that there was no significant change in BNPL usage prior to the policy shock. However, after September 2021, BNPL usage experienced a notable reduction.

Panel A of Figure 2 shows that the fraction of active BNPL users experienced an immediate decrease of 4 percentage points following the policy shock. This decline continued in subsequent months and eventually stabilized at approximately 14 percentage points lower than the pre-policy period. Similarly, Panel B of Figure 2 shows that the BNPL payment share decreases by approximately 5 percentage points immediately after the policy shock and ended at approximately 7 percentage points lower than the pre-policy period, indicating that the reduction in BNPL usage is a structural change. Overall, our results indicate that the regulatory change in BNPL lenders' credit reporting requirement significantly reduces BNPL usage.

4.2 Potential Explanations

Other payment options. We further examine other payment options available on the Alipay app to test the alternative hypothesis that the reduction in BNPL usage is driven by platform-level changes after the regulatory shock. Figure 3 illustrates our results. In contrast, we find slight increases in shares of digital wallet e-cash payments (in Panel A) and FinTech MMF payments (in Panel B) after the credit reporting policy change, although the effects are small in magnitude and diminish after a few months. Furthermore, the payment shares of credit cards (in Panel C) and debit cards (in Panel D) increased significantly after the policy shock by approximately 2 and 5 percentage points, respectively. Hence, the reduction in active users and payment shares is unique to the BNPL product.

Stigma effect? These results show a (partial) switching pattern toward traditional bank credit, corroborating anecdotal evidence on reputation concerns associated with BNPL usage by users who are current or potential bank clients. For instance, there are widespread rumors on major social media platforms in China that using BNPL may have adverse effects on loan applications in the formal credit market (e.g., mortgages from commercial banks). Reports released by financial regulatory authorities in various countries also show that frequent users of BNPL are more likely to engage in overconsumption and end up facing financial difficulties.[37] As a result, there may be a stigma associated with BNPL users, which can potentially contribute to the reduction in BNPL usage after the mandatory credit reporting policy.[38]

Supply-side factors? One may argue that the reduction in BNPL usage may not reflect consumers' lack of willingness to use BNPL credit; rather, it can be driven by supply-side factors (i.e., the BNPL lender cuts its line of credit after the credit reporting regulation, thus leading to a mechanical decrease in BNPL usage). To address this concern, we obtain

[37] For instance, see reports from the New York Fed (`https://libertystreeteconomics.newyorkfed.org/2024/02/how-and-why-do-consumers-use-buy-now-pay-later/`) and the CFPB (`https://www.consumerfinance.gov/data-research/research-reports/consumer-use-of-buy-now-pay-later-insights-from-the-cfpb-making-ends-meet-survey/`).

[38] Additionally, a growing stream of literature (e.g., Cong et al., 2021; Casadesus-Masanell and Hervas-Drane, 2015) emphasizes privacy issues as a primary concern in the digital era. Hence, BNPL users who are unwilling to share personal payment information may also switch to alternative payment methods.

data on the credit line available for use for each consumer. Figure A2 presents the changes in the BNPL credit line around the the credit reporting policy change. We find that the BNPL credit line does not exhibit a reduction around the policy shock; in fact, the BNPL credit line experiences a slight increase after the shock. Therefore, the reduction in BNPL usage is unlikely to be attributed to an adverse shift in BNPL credit supply, ruling out the alternative hypothesis of a tighter borrowing constraint for BNPL credit.

5 Disciplinary Impact of Credit Reporting

Our event-study results are consistent with predictions from a stylized moral hazard model where the credit reporting requirement imposes larger default costs on users, who may reduce their BNPL usage to minimize their default probabilities. In this section, we apply DID analysis to investigate the effects on users with or without previous default records. Our hypothesis is that users with higher default risks, proxied by previous default records, exhibit a larger reduction in their BNPL usage.

5.1 Impacts on BNPL Usage

Panel A of Table 2 presents the impact of credit reporting on the BNPL usage in the Alipay app. Compared with those without past default records, BNPL users with previous default records exhibit a more pronounced reduction in FinTech credit usage. Specifically, the probability of using BNPL among users with a BNPL credit line drops by an additional 4.8 percentage points, BNPL payment share drops by an additional 2.3 percentage points, and the monetary amount of BNPL payments drops by an additional 18%. These negative coefficients support our argument that the credit reporting policy increases the cost of default and has a larger impact on users who previously defaulted and hence tend to have a higher future delinquency probability, compared to those who have not previously defaulted. Consequently, these users became more likely to discontinue their BNPL usage to reduce future probabilities of default (given the same income cash flows), thus minimizing the negative impact on their credit records.

Panel B of Table 2 reports the impacts on other FinTech and traditional payment options. Compared with those without past default records, BNPL users who have previously defaulted tend to exhibit a more pronounced increase in e-cash payment shares and money fund payment shares but exhibit a lower increase in credit card shares, which implies their limited access to alternative credit options. The failure to fully substitute BNPL credit with bank credit may lead to decreased consumption if the BNPL users are financially constrained. We examine this financial constraint hypothesis in Subsection 5.3.

5.2 Impacts on Defaults

Credit reporting policies can reduce default rates for borrowers for several reasons. First, if borrowers repay the loan on time, they will have a positive record in the national credit bureau, which can signal their high credit quality and help them gain access to future credit. Second, if borrowers default on the loan, then the negative record can jeopardize their future access to the credit market. Both effects predict a lower default rate after the credit reporting policy change. In particular, users with default records tend to exhibit higher probabilities of potential default and have more limited access to the formal credit market. Consequently, these effects are more pronounced for such users, ultimately contributing to a reduced default rate.

Table 3 reports the impact of credit report policy on default behaviors, which are consistent with these theoretical predictions. We use the following four indicators to measure default: default by the 3-day standard (column 1), default by the 30-day standard (column 2), overdue balance ratio (column 3), and average interest-earning balance ratio (column 4). Overall, users with past default records exhibit a significantly lower probability of default relative to users without past default records. Specifically, the default rate using the 3-day measure decreases by 5.8 percentage points, while the default rate using the 30-day measure decreases by 1.9 percentage points.

Pretrend analysis. Figure 4 shows the dynamic DID results for the default rate and overdue balance share. The regression specification is $Y_{it} = \beta_0 + \sum_{r\neq-1} \theta_r \times PastDefault_i \times I_r + \mu_i + \delta_{ct} + \varepsilon_{it}$. In these graphs, the relative differences between users with and without a past default record are insignificant before the policy change. However, after the introduction of this regulatory policy, users with past default records exhibit significantly fewer defaults.

Alternative default measures based on BNPL usage. Figure A3 presents the dynamic DID results using an alternative default measure that factors in BNPL users' borrowing activities. This alternative default indicator equals 1 only if a user defaults in a month with active BNPL usage. If there is a previous unpaid balance but the user does not use BNPL in the current month, default indicators would take a value of 0. Hence, this alternative indicator measures the default behaviors conditional on active BNPL usage. We find similar results to our baseline findings. Our estimated coefficients become significantly negative only after the credit reporting policy change, suggesting a disciplinary role played by the information-sharing mechanism.

5.3 Impacts on Consumption

Table 4 reports the impact on consumption. Compared with those without previous BNPL default records, users with past default records exhibit a significant reduction in online consumption by 5%. We do not find such an impact on offline consumption, which may be less prone to impulsive purchase and overextension risks. Overall, total consumption exhibits a slight but not significant decrease.

These findings suggest that the credit reporting policy change has a real impact on consumption, particularly on online expenditures. As shown in Subsection 5.1, we find a substantial decrease in BNPL usage following the credit reporting policy change, particularly among users with previous default records, which can potentially lead to a tightening of consumption liquidity. A primary criticism of BNPL revolves around overconsumption and loan stacking. If the reduction in consumption among users with lower credit quality primarily consists mainly of irrational spending, then the credit reporting policy can aid in mitigating potential risks and enhancing consumer welfare.

6 Further Analyses and Discussions

6.1 Heterogeneity: Age and Consumption Level

A primary concern regarding BNPL is that the convenience of FinTech-based consumer credit may induce consumers, especially unsophisticated ones, to overborrow and overspend (Berg et al., 2022). Overborrowing induced by BNPL may be particularly prevalent among young users and those with high consumption levels. This section focuses on exploring heterogeneity based on age and consumption using specification (3).

FinTech credit providers with lower operation costs can adopt laxer lending standards (Tang, 2019), and consequently, young consumers who have limited access to bank credit can use BNPL conveniently in their daily shopping activities. These users are likely to be financially constrained and engage in overconsumption. Panel A of Table 5 reports the heterogeneous effects along the lines of age. We divide the users into two groups based on the age distribution. The indicator variable $Young_i = 1$ for users whose $age \leq 30$, i.e., below the median age. We find negative coefficients of the triple-interaction term, which are also statistically significant. Our results show that younger BNPL users reduce their usage of BNPL more substantially relative to older users, consistent with our hypothesis that younger borrowers are more responsive to the potential overspending risks associated with BNPL usage.

Panel B reports the heterogeneous effects based on consumption level. Similar to investigating heterogeneous effects by age, we divide users into two groups based on the 50th percentile of monthly consumption before the window period, i.e., approximately 3,000 RMB. Our results show that relative to those with lower previous consumption levels, BNPL users with higher previous consumption levels decrease their probability of using BNPL more significantly after the credit reporting policy shock. The larger reduction in BNPL usage among users with high consumption levels can be partly attributed to the higher probability of irrational and suboptimal borrowing among such users, which may lead to a higher future default probability. Hence, the credit reporting regulation helps to discipline users in terms of their irrational borrowing, particularly for those with higher consumption levels.[39]

6.2 Heterogeneity: Bank Credit Access

Given that BNPL credit complements traditional consumer credit, the investigation into borrowers who have access to both BNPL credit and credit cards helps us explore the impact on users originally having bank credit options. Panel C of Table 5 shows the heterogeneous effects on BNPL usage in the Alipay app based on bank credit access. The coefficients on $BankCredit_i \times post_t$ are negative in all columns, which indicates that the disuse effect is more pronounced among users who have credit cards than those without credit card access. Given that these users already have channels through which to build credit records and access consumer credit, the credit-building benefit of BNPL credit is less valuable. Meanwhile, other concerns over BNPL (e.g., the potential stigma effects) may also contribute to the reduction in BNPL usage among these users.[40]

6.3 New BNPL Adoption

We complement our analysis by investigating BNPL adoption behaviors by new users across this policy change. The time of new BNPL adoption refers to the first time a user uses BNPL for payment. Table 7 compares new users who adopted BNPL before the policy change in

[39] An alternative explanation is that users with higher consumption levels are more likely to be financially unconstrained and have more alternative borrowing options available. Therefore, they may have a lower reliance on BNPL credit and are more inclined to decrease usage after the regulatory policy change due to the stigma effect associated with BNPL borrowing.

[40] As a robustness check, we include all heterogeneous effects (i.e., age, consumption, and bank credit access) in one regression. As shown in Table 6, all heterogeneous effects remain statistically significant, and the estimated coefficients have similar magnitudes to the baseline results.

September 2021 with those who adopted BNPL after.

We find that users who adopt BNPL after the credit reporting policy change (i.e., post-policy adopters) differ from those who adopt BNPL before the policy shock (i.e., pre-policy adopters) in several aspects. First, the average age of post-policy adopters is approximately two years older than that of pre-policy adopters. The relative period between their BNPL adoption and FinTech platform registration is also significantly longer. On average, the relative month of BNPL adoption since the Alipay (Huabei) registration of post-policy adopters is nine (seven) months longer than that of early users. These findings suggest that post-policy adopters wait a longer time before accessing the BNPL credit line, implying more cautiousness in their BNPL adoption decisions.

Second, we find that post-policy adopters exhibit significantly lower BNPL payment amounts and BNPL payment shares relative to pre-policy adopters in the first month of their BNPL adoption. This result echoes our previous finding that users tend to decrease BNPL usage after the implementation of the credit reporting policy, as the policy change elevates the cost of excessive borrowing. Finally, comparing the default behaviors after BNPL adoption between the two groups, we find that the probability of having a default record is 7.5 percentage points lower among post-policy adopters than among pre-policy adopters. This result supports our argument that the credit reporting policy helps discipline borrowers in terms of their repayment behaviors. Given the regulatory policy in place, users with low levels of creditworthiness may become less likely to adopt BNPL. Therefore, our estimates represent the lower bound of the disciplinary effect of credit reporting on new BNPL users.

7 Supplementary Evidence: Online Consumer Survey

7.1 Survey Design and Data Collection

To understand the mechanisms behind our empirical findings, we conducted a supplementary survey on Alipay, the digital payment platform that provides the BNPL product. Our survey respondents contain three types of Alipay users: (1) consumers who have not opened the BNPL service (*non-BNPL consumers*); (2) consumers who have opened the BNPL service but use it infrequently, i.e., less than once a month (*inactive BNPL consumers*); and (3) consumers who use BNPL frequently (*active BNPL consumers*).[41]

Our survey data is collected in March 2024. Users on the Alipay app receive push notifications encouraging them to participate in the survey. We provide monetary rewards to respondents who complete the survey. We obtained 1,497 responses, of which the demographics are comparable with that of our main analysis sample. Approximately 51% of the respondents are male (compared to 53% in the main analysis sample), and the average age is around 34 years old (compared to approximately 33 years old in the main analysis sample).

The survey contains three parts of questions: (1) individual characteristics, including demographics and previous default records on BNPL and any other credit sources; (2) BNPL usage habits, including the reasons for using or not using BNPL; and (3) attitudes toward the credit reporting policy change. We ask whether consumers are aware of this policy change, whether and how the policy affects their behaviors, and their attitudes on BNPL borrowing status being reported to the national credit bureau.

7.2 Reasons for the Use and Disuse of BNPL

We first analyze the primary motivations behind the use and disuse of BNPL. The two related questions are: "For what reasons do you think consumers use BNPL?" and "For what reasons do you think consumers do not use BNPL?". We provide a dozen of options for respondents to choose from.

Figure 5 shows the top ten reasons consumers do not use BNPL. Notably, the second-ranking reason is that consumers worry about "the potential negative impact on credit records," suggesting that the perceived stigma effect associated with BNPL usage has become one of the primary factors affecting people's use of BNPL. That is, a large fraction of

[41] All respondents are above 18 years old, hence all eligible to apply for the BNPL service. Huabei's rejection rate is very low.

consumers believe that using BNPL may have adverse effects on their credit reports, which supports our previous arguments.[42]

We present the top ten reasons for using BNPL in Figure A4. The top-ranking reason is "BNPL offers discounts for purchases," a marketing practice adopted by Alipay to promote BNPL products. Other reasons are primarily related to the convenience provided by BNPL, such as "BNPL applications can be filed online," "BNPL is more convenient than other options," "BNPL applications do not need collateral," and "BNPL applications are approved quickly." Importantly, we also observe the value of the Big Tech ecosystem to consumers. For instance, the second-ranking reason is that "BNPL is introduced by a major FinTech platform," and the seventh-ranking reason is that "using BNPL can increase the Sesame Credit Score (the credit rating mechanism introduced by the Ant Group)."

7.3 Responses to the Credit Reporting Policy

Figure A5 reveals people's attitudes toward BNPL's credit reporting regulation. We find large heterogeneity among consumers. Nearly 700 respondents (close to 50% of total respondents) agree that they only need to worry about the negative effects of BNPL default records. However, over 500 consumers (more than 30% of total respondents) are concerned about the negative impact of reporting BNPL borrowing status to the national bureau even in the absence of delinquencies. The result is consistent with the significant reduction of BNPL usage following the credit reporting regulation, potentially due to the stigma effects associated with BNPL usage. Our findings also echo Burke et al. (2023), which reveals heterogeneous treatment effects after introducing credit builder loans.

Finally, we analyze how respondents' past default experience affect their hypothetical responses to the credit reporting policy change. Table 8 compares the self-reported changes between respondents with and without previous default records. We find that, compared

[42]The top-ranking reason is that consumers have sufficient money and do not need to borrow. Other reasons reflect a lack of trust in BNPL (e.g., "worry about being deceived") and that BNPL products do not meet consumers' borrowing needs (e.g., "the credit line of BNPL is too low" and "the BNPL operation is too complex").

with respondents without default records, those who have previous default records demonstrate a stronger inclination to reduce BNPL usage, increase on-time repayments, and reduce consumption after Huabei's incorporation into the credit reporting system. These survey findings align with our DID results that borrowers with previous default records become more disciplined in repayment and exhibit greater caution in borrowing and spending.

8 Conclusion

Our paper provides novel empirical evidence on the disuse impact of credit reporting on FinTech borrowing. We use a unique, transaction-level dataset from a leading digital payment platform in China, which offers China's largest BNPL product (i.e., Huabei). Our empirical analysis exploits a critical credit reporting policy change in 2021, which incorporates BNPL lenders into the centralized credit registry. Interestingly, borrowers significantly reduce their BNPL usage when the BNPL borrowing status is set to be shared with traditional lenders such as banks. The disuse effect is more pronounced among younger borrowers, borrowers with higher consumption levels, and borrowers with bank credit cards, suggesting that credit reporting practice can help alleviate the overborrowing problem among FinTech borrowers.

Moreover, we find that borrowers with previous default records become more disciplined in repayment, which is consistent with theoretical predictions where an increase in default punishments reduces moral hazard. Our further analysis using new BNPL adoption data and survey responses demonstrates similar patterns. The reduction in BNPL usage has real effects by decreasing online consumption, implying that some FinTech users are financially constrained. Our results also hint at a more market-based solution to overborrowing risks that concern regulators compared to a mandatory credit line limit. Reporting the loan performance of BNPL users to the public credit bureau induces more disciplined BNPL usage, consumption, and borrowing behaviors, potentially benefiting both lenders and borrowers.

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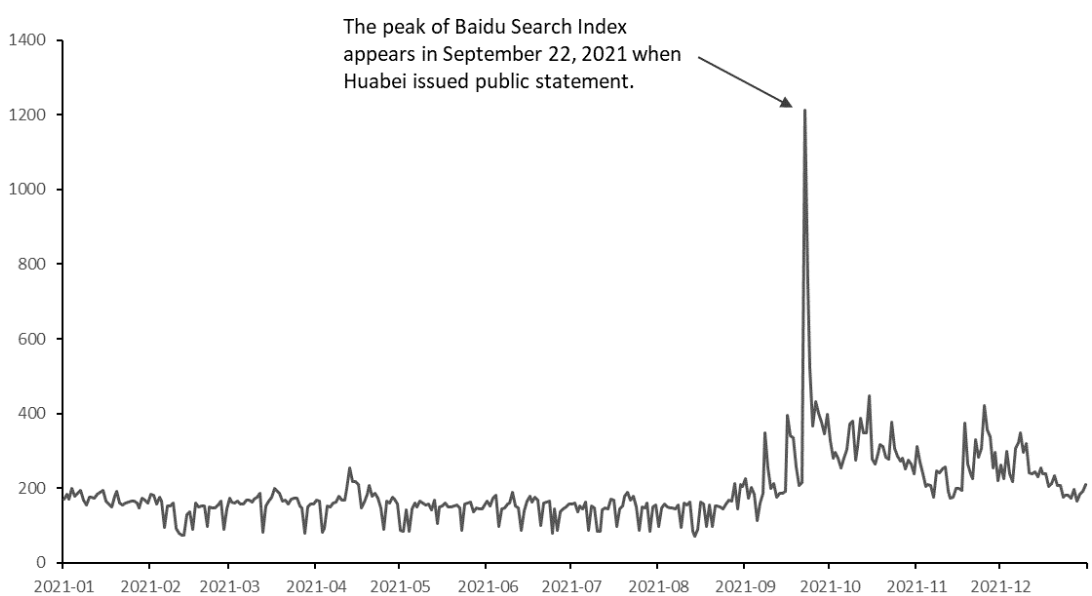
Figure 1: When BNPL Meets Credit Reporting

Note: This figure shows the official announcement regarding the credit reporting regulatory change by Huabei via Weibo, China's largest social media platform similar to Twitter, and the public attention it draws. Panel A is a screenshot of Huabei's original Weibo post and Panel B is a screenshot showing that Huabei's credit reporting practice ranks first in the social media's headlines. Panel C plots the search index for contents related to "Huabei's credit reporting to the credit bureau" between January 1, 2021, and December 31, 2021, calculated by Baidu, China's largest search engine similar to Google.

(a) Weibo announcement by Huabei

(b) Weibo social media headline



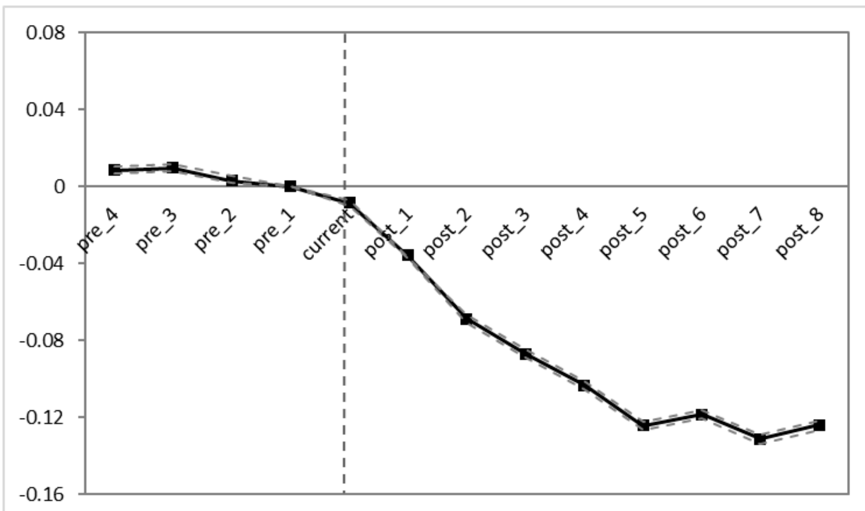
(c) Baidu search index on Huabei's credit reporting

Figure 2: Impacts on BNPL Usage: Event Study

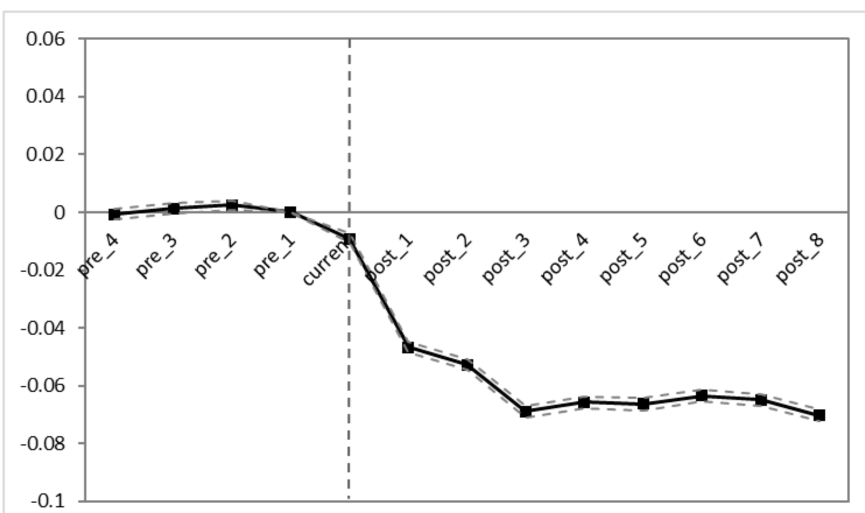
Note: This figure plots the impacts of credit reporting policy on BNPL usage using an event study model. The results are estimated by the following regression using user-month data of Huabei users between May 2021 and May 2022:

$$Y_{it} = \beta_0 + \sum_{r \neq -1} \theta_r \times I_r + \mu_i + \varepsilon_{it}.$$

Y_{it} measures usage of BNPL of user i in month t. We use two indicators to measure the BNPL usage in the Big Tech app: (1) Using BNPL, a binary variable taking the value of 1 if a user has BNPL payment records in a given month; and (2) BNPL payment share, the proportion of BNPL payment in total consumption via Alipay. I_rs are the relative time indicators. μ_i denotes user fixed effects. ε_{it} represents the error term. Standard errors are adjusted for user-level clustering. The solid lines represent the estimated coefficients, and the dashed lines represent the upper and lower bounds of the 95% confidence intervals. The vertical dashed line indicates the month of the credit reporting policy change (i.e., September 2021).



(a) Using BNPL (Yes = 1)



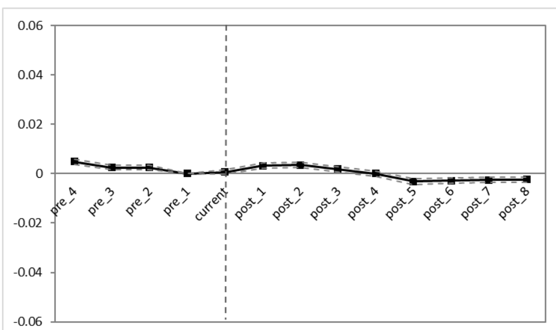
(b) BNPL payment share

Figure 3: Impacts on Non-BNPL Payments: Event Study

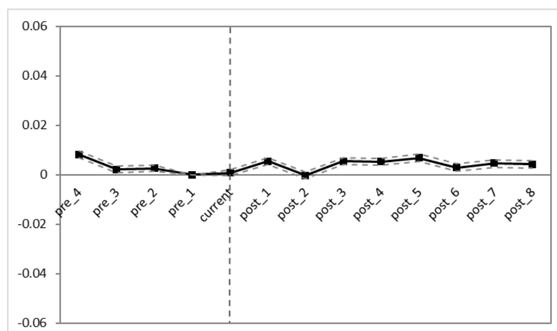
Note: This figure plots the impacts of credit reporting policy on Non-BNPL payments using an event study model. The results are estimated by the following regression using user-month data of Huabei users between May 2021 and May 2022:

$$Y_{it} = \beta_0 + \sum_{r \neq -1} \theta_r \times I_r + \mu_i + \varepsilon_{it}.$$

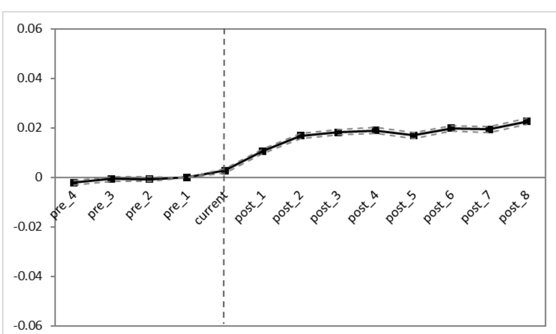
Y_{it} measures usage of other FinTech and traditional payment options of user i in month t. We investigate four primary alternative payment options in total consumption via Alipay: (1) e-cash payment share, (2) FinTech MMF payment share, (3) credit card payment share, and (4) debit card payment share. $PastDefault_i$ indicates whether a user has a default record before the window period (before May 2021). I_rs are the relative time indicators. μ_i denotes user fixed effects. ε_{it} represents the error term. Standard errors are adjusted for user-level clustering. The solid lines represent the estimated coefficients, and the dashed lines represent the upper and lower bounds of the 95% confidence intervals. The vertical dashed line indicates the month of the policy change (i.e., September 2021).



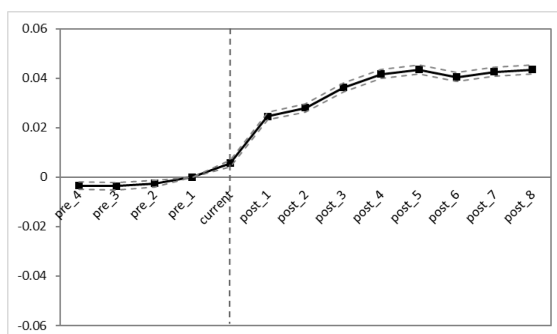
(a) E-cash payment share



(b) FinTech MMF payment share



(c) Credit card payment share



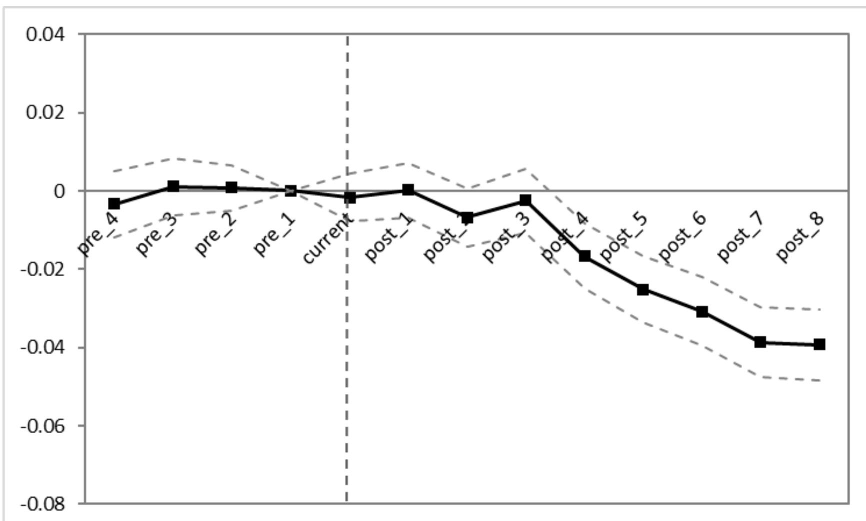
(d) Debit card payment share

Figure 4: Impacts on Default: Dynamic DID

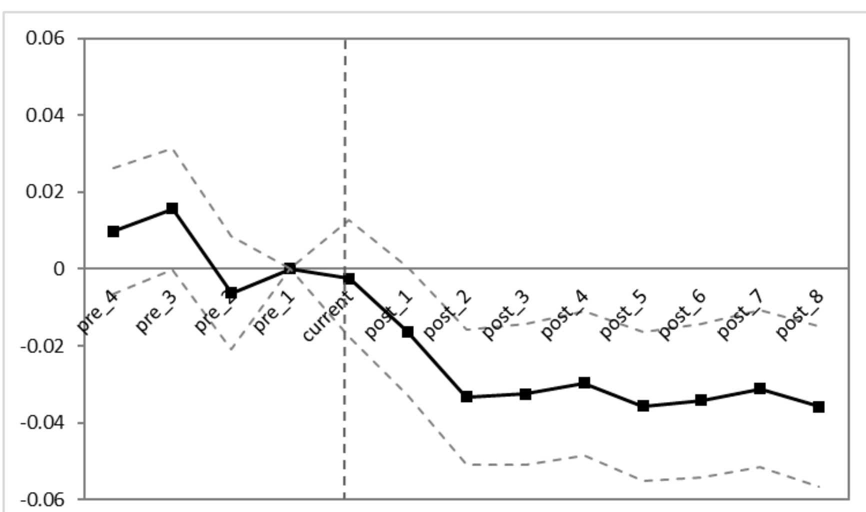
Note: This figure plots the impacts of credit reporting policy on defaults using a dynamic DID model. The results are estimated by the following regression using user-month data of Huabei users between May 2021 and May 2022:

$$Y_{it} = \beta_0 + \sum_{r \neq -1} \theta_r \times PastDefault_i \times I_r + \mu_i + \delta_{ct} + \varepsilon_{it}.$$

Y_{it} measures defaults of user i in month t. We use two indicators to measure the default behaviors: (1) default within 30 days, a binary variable taking the value of 1 if a user does not repay the bill or make an installment repayment within thirty days, and (2) overdue balance ratio, the share of overdue balance (unpaid balance) in bill amount (the balance in a certain billing date). $PastDefault_i$ indicates whether a user has a default record before the window period (before May 2021). μ_i and δ_{ct} denote user fixed effects and city-by-month fixed effects, respectively. ε_{it} represents the error term. Standard errors are adjusted for user-level clustering and reported in parentheses. The solid lines represent the estimated coefficients, and the dashed lines represent the upper and lower bounds of the 95 percent confidence intervals. The vertical dashed line indicates the month of the policy change (i.e., September 2021).



(a) Default-30 days (Yes=1)



(b) Overdue balance share

Figure 5: Reasons for Not Using BNPL

Note: This figure plots responses from the survey question "For what reasons do you think consumers don't use BNPL? Please choose among the following options. Maximum five choices." . We provide thirteen options and present the top ten options selected by consumers. The survey includes 1493 responses from Alipay consumers in March 2024.

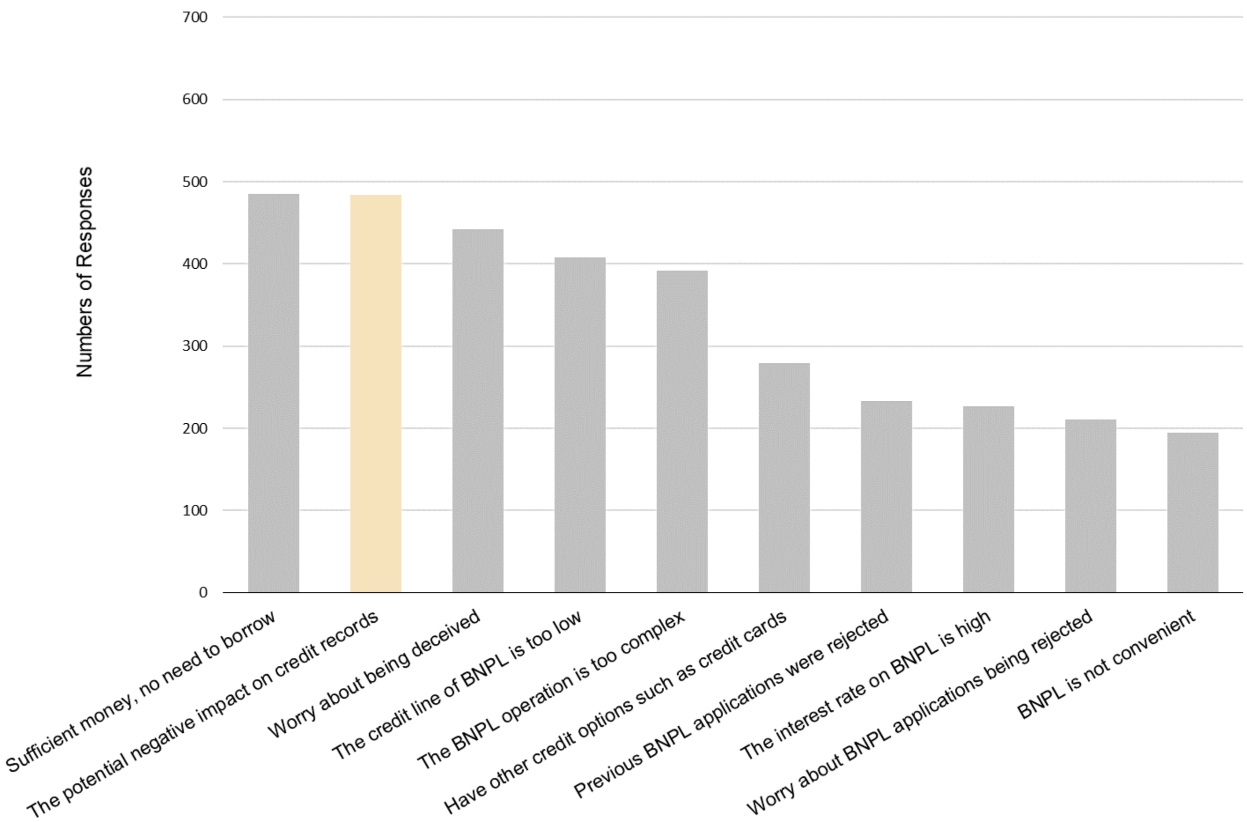


Table 1: Summary Statistics

Note: This table reports the summary statistics of the analysis sample. The sample contains 37,042 users spanning 13 months, constituting a total of 1,693,706 observations. Panel A reports the cross-section statistics for user characteristics. Past default record indicates whether a user has a default record before the window period (before May 2021). $PushNotification$ indicates whether a user received push notifications of the credit reporting policy change during our sample period. $Authorization$ indicates whether a user signed the authorization during our sample period. Panel B reports summary statistics of the user-month panel data. The first part shows three indicators related to BNPL usage. The second part shows the share of four primary alternative payment options on the Alipay platform. The third part shows three indicators related to default behaviors. The fourth part shows consumption through Alipay (in natural logarithm value). All continuous variables are winsorized at the 1% and 99% levels.

	N	Mean	Sd	Min	Max
Panel A. User Cross-Section Data					
User characteristics					
Age	137,042	32.854	9.448	18.000	60.000
Gender (Male = 1)	137,042	0.533	0.499	0.000	1.000
Past default record (Yes = 1)	137,042	0.051	0.220	0.000	1.000
Credit reporting response					
Push notification (Yes = 1)	137,042	0.678	0.467	0.000	1.000
Authorization (Yes = 1)	137,042	0.548	0.498	0.000	1.000
Panel B. User-Month Panel Data					
BNPL usage					
Using BNPL (Yes = 1)	1,693,706	0.778	0.416	0.000	1.000
BNPL payment (ln)	1,693,706	5.191	3.150	0.000	9.960
BNPL payment (share)	1,693,706	0.471	0.403	0.000	1.000
Other payment options					
E-cash payment share	1,693,706	0.066	0.189	0.000	1.000
FinTech MMF payment share	1,693,706	0.134	0.271	0.000	1.000
Credit card payment share	1,693,706	0.100	0.245	0.000	1.000
Debit card payment share	1,693,706	0.206	0.317	0.000	1.000
Default behaviors					
Default-3 days (Yes = 1)	1,693,706	0.021	0.144	0.000	1.000
Default-30 days (Yes = 1)	1,693,706	0.012	0.110	0.000	1.000
Overdue balance ratio	1,299,498	0.180	0.341	0.000	1.000
Interest-bearing balance ratio	1,482,843	0.343	0.416	0.000	1.000
Consumption behaviors					
Total consumption (ln)	1,693,706	7.439	1.623	2.525	11.185
Online consumption (ln)	1,693,706	6.114	2.005	0.000	9.993
Offline consumption (ln)	1,693,706	5.971	2.784	0.000	10.997

Table 2: Impacts of Credit Reporting on BNPL Usage

Note: This table shows the impacts of credit reporting policy on BNPL usage. The results are estimated by the following regression using user-month data of Huabei users between May 2021 and May 2022:

$$Y_{it} = \beta_0 + \beta_1 \times PastDefault_i \times post_t + \mu_i + \delta_{ct} + \varepsilon_{it}.$$

Y_{it} measures usage of BNPL and usage of other FinTech and traditional payment options of user i in month t. In Panel A, we use three indicators to measure the BNPL usage in the Big Tech app: (1) Using BNPL, a binary variable taking the value of 1 if a user has BNPL payment records in a given month; (2) BNPL payment share, the proportion of BNPL payment in total consumption via Alipay; (3) BNPL payment in natural logarithm value. In Panel B, we investigate the share of four primary alternative payment options in total consumption via Alipay: (1) e-cash payment share, (2) FinTech MMF payment share, (3) credit card payment share, and (4) debit card payment share. $PastDefault_i$ indicates whether a user has a default record before the window period (before May 2021). $post_t$ indicates whether the policy shock has taken place, i.e., whether the time is after September 2021. After September 2021 (excluding September 2021), $post_t = 1$. μ_i and δ_{ct} denote user and city-by-month fixed effects, respectively. ε_{it} represents the error term. Standard errors are adjusted for user-level clustering and reported in parentheses. ***, **, * denote statistical significance levels at 1%, 5%, and 10%, respectively.

Panel A. impacts on BNPL usage

	(1) Using BNPL (Yes=1)	(2) BNPL payment (ln)	(3) BNPL payment (share)
$\text{PastDefault}_i \times \text{post}_t$	-0.048***	-0.242***	-0.023***
	(0.0055)	(0.0355)	(0.0037)
Mean of dep.var	0.777	5.191	0.471
Observations	1693706	1693706	1693706
Adjusted R^2	0.602	0.663	0.614
User F.E.	Yes	Yes	Yes
City-month F.E.	Yes	Yes	Yes

Panel B. Share of other payment options in the Big Tech App

	(1) E-cash	(2) FinTech MMF	(3) Credit card	(4) Debit card
$\text{PastDefault}_i \times \text{post}_t$	0.006***	0.016***	-0.008***	0.002
	(0.0020)	(0.0024)	(0.0022)	(0.0037)
Mean of dep.var	0.066	0.134	0.100	0.206
Observations	1693706	1693706	1693706	1693706
Adjusted R^2	0.483	0.531	0.669	0.513
User F.E.	Yes	Yes	Yes	Yes
City-month F.E.	Yes	Yes	Yes	Yes

Table 3: Impacts of Credit Reporting on BNPL Defaults

Note: This table shows the impacts of credit reporting policy on defaults. The results are estimated by the following regression using user-month data of Huabei users between May 2021 and May 2022:

$$Y_{it} = \beta_0 + \beta_1 \times PastDefault_i \times post_t + \mu_i + \delta_{ct} + \varepsilon_{it}.$$

Y_{it} measures defaults of user i in month t. We use four indicators to measure the default behaviors: (1) default within 3 days after the due date, a binary variable taking the value of 1 if a user does not repay the bill or make an installment repayment within three days after the billing date in a specific month; (2) default within 30 days, a binary variable taking the value of 1 if a user does not repay the bill or make an installment repayment within thirty days; (3) overdue balance ratio, the share of overdue balance (unpaid balance) in bill amount (the balance in a certain billing date); and (4) average interest-earning balance ratio, the share of average interest-earning balance (the sum of overdue balance and installment balance) in monthly average balance. $PastDefault_i$ indicates whether a user has a default record before the window period (before May 2021). $post_t$ indicates whether the policy shock has taken place, i.e., whether the time is after September 2021. After September 2021 (excluding September 2021), $post_t = 1$. μ_i and δ_{ct} denote user and city-by-month fixed effects, respectively. ε_{it} represents the error term. Standard errors are adjusted for user-level clustering and reported in parentheses. ***, **, * denote statistical significance levels at 1%, 5%, and 10%, respectively.

	(1) Default-3 days (Yes=1)	(2) Default-30 days (Yes=1)	(3) Overdue balance ratio	(4) Interest-bearing balance ratio
$\text{PastDefault}_i \times \text{post}_t$	-0.058***	-0.019***	-0.034***	-0.010***
	(0.0040)	(0.0031)	(0.0053)	(0.0026)
Mean of dep.var	0.021	0.012	0.180	0.343
Observations	1693706	1693706	1299498	1482843
Adjusted R^2	0.532	0.617	0.601	0.801
User F.E.	Yes	Yes	Yes	Yes
City-month F.E.	Yes	Yes	Yes	Yes

Table 4: Impacts of Credit Reporting on Consumption

Note: This table shows the impacts of credit reporting policy on consumption. The results are estimated by the following regression using user-month data of Huabei users between May 2021 and May 2022:

$$Y_{it} = \beta_0 + \beta_1 \times PastDefault_i \times post_t + \mu_i + \delta_{ct} + \varepsilon_{it}.$$

Y_{it} measures consumption of user i in month t. Total consumption comprises two components: online consumption includes the expenditure on online services such as e-commerce purchases, while offline consumption includes the spending on offline scenarios such as payments at local stores. $PastDefault_i$ indicates whether a user has a default record before the window period (before May 2021). $post_t$ indicates whether the policy shock has taken place, i.e., whether the time is after September 2021. After September 2021 (excluding September 2021), $post_t = 1$. μ_i and δ_{ct} denote user and city-by-month fixed effects, respectively. ε_{it} represents the error term. Standard errors are adjusted for user-level clustering and reported in parentheses. ***, **, * denote statistical significance levels at 1%, 5%, and 10%, respectively.

	Consumption (ln)		
	(1) Total	(2) Online	(3) Offline
PastDefault$_i\times$ post$_t$	-0.009	-0.050***	0.014
	(0.0154)	(0.0176)	(0.0267)
Mean of dep.var	7.439	6.114	5.971
Observations	1693706	1693706	1693706
Adjusted R^2	0.605	0.608	0.543
User F.E.	Yes	Yes	Yes
City-month F.E.	Yes	Yes	Yes

Table 5: Borrowers' Age, Consumption, and Credit Card Access

Note: This table shows the heterogeneous impacts of credit reporting policy on BNPL usage. The results are estimated by the following regression using user-month data of Huabei users between May 2021 and May 2022:

$$Y_{it} = \beta_0 + \beta_1 \times z_i \times post_t + \mu_i + \delta_{ct} + \varepsilon_{it}.$$

Y_{it} measures usage of BNPL of user i in month t. We use three indicators to measure the BNPL usage in the Big Tech app: (1) Using BNPL, a binary variable taking the value of 1 if a user has BNPL payment records in a given month; (2) BNPL payment share, the proportion of BNPL payment in total consumption via Alipay; (3) BNPL payment in natural logarithm value. We explore heterogeneity based on age, consumption level, and access to traditional credit by varying z_i to $Young_i$, $High_i$, and $BankCredit_i$, respectively. $Young_i$ indicates whether a user is younger than the median age (i.e., 30 years old). $High_i$ indicates whether a user's monthly consumption before the window period exceeds the median amount (i.e., 3,000 RMB). $BankCredit_i$ indicates whether a user has bank credit options (i.e., whether a user has used credit cards for payments at least once before the window period). $post_t$ indicates whether the policy shock has taken place, i.e., whether the time is after September 2021. After September 2021 (excluding September 2021), $post_t = 1$. μ_i and δ_{ct} denote user and city-by-month fixed effects, respectively. ε_{it} represents the error term. Standard errors are adjusted for user-level clustering and reported in parentheses. ***, **, * denote statistical significance levels at 1%, 5%, and 10%, respectively.

	(1) Using BNPL (Yes=1)	(2) BNPL payment (ln)	(3) BNPL payment (share)
Panel A. Heterogeneity by age			
Young$_i$× post$_t$	-0.024***	-0.129***	-0.008***
	(0.0016)	(0.0114)	(0.0013)
Observations	1693706	1693706	1693706
Adjusted R^2	0.602	0.663	0.614
Panel B. Heterogeneity by consumption level			
High$_i$× post$_t$	-0.020***	-0.349***	-0.002*
	(0.0016)	(0.0112)	(0.0013)
Observations	1693706	1693706	1693706
Adjusted R^2	0.602	0.663	0.614
Panel C. Heterogeneity by traditional credit access			
BankCredit$_i$× post$_t$	-0.034***	-0.332***	-0.013***
	(0.0017)	(0.0122)	(0.0014)
Observations	1693706	1693706	1693706
Adjusted R^2	0.602	0.663	0.614
All panels			
Mean of dep.var	0.777	5.191	0.471
User F.E.	Yes	Yes	Yes
City-month F.E.	Yes	Yes	Yes

Table 6: Robustness Checks

Note: This table reports results estimated by the following regression using user-month data of Huabei users between May 2021 and May 2022:

$$Y_{it} = \beta_0 + \beta_1 \times PastDefault_i \times post_t + \beta_2 \times Young_i \times post_t + \beta_3 \times High_i \times post_t + \beta_4 \times BankCredit_i \times post_t + \mu_i + \delta_{ct} + \varepsilon_{it}.$$

Y_{it} measures usage of BNPL of user i in month t. We use three indicators to measure the BNPL usage in the Big Tech app: (1) Using BNPL, a binary variable taking the value of 1 if a user has BNPL payment records in a given month; (2) BNPL payment share, the proportion of BNPL payment in total consumption via Alipay; (3) BNPL payment in natural logarithm value. $PastDefault_i$ indicates whether a user has a default record before the window period (before May 2021). $Young_i$ indicates whether a user is younger than the median age (i.e., 30 years old). $High_i$ indicates whether a user's monthly consumption before the window period exceeds the median amount (i.e., 3,000 RMB). $BankCredit_i$ indicates whether a user has bank credit options (i.e., whether a user has used credit cards for payments at least once before the window period). $post_t$ indicates whether the policy shock has taken place, i.e., whether the time is after September 2021. After September 2021 (excluding September 2021), $post_t = 1$. μ_i and δ_{ct} denote user and city-by-month fixed effects, respectively. ε_{it} represents the error term. Standard errors are adjusted for user-level clustering and reported in parentheses. ***, **, * denote statistical significance levels at 1%, 5%, and 10%, respectively.

	(1) Using BNPL (Yes=1)	(2) BNPL payment (ln)	(3) BNPL payment (share)
$\text{PastDefault}_i \times \text{post}_t$	-0.046***	-0.260***	-0.022***
	(0.0055)	(0.0354)	(0.0037)
$\text{Young}_i \times \text{post}_t$	-0.025***	-0.134***	-0.008***
	(0.0016)	(0.0114)	(0.0013)
$\text{High}_i \times \text{post}_t$	-0.013***	-0.291***	0.0004
	(0.0017)	(0.0117)	(0.0014)
$\text{BankCredit}_i \times \text{post}_t$	-0.031***	-0.260***	-0.014***
	(0.0017)	(0.0125)	(0.0014)
Observations	1693706	1693706	1693706
Adjusted R^2	0.603	0.664	0.614
Mean of dep.var	0.777	5.191	0.471
User F.E.	Yes	Yes	Yes
City-month F.E.	Yes	Yes	Yes

Table 7: Impacts on New BNPL Adoption

Note: This table compares user characteristics and user behaviors between users who adopt BNPL after September 2021 (i.e., late adopters) and users who adopt BNPL before September 2021 (i.e., early adopters). The first part compares user characteristics. The second part compares the relative months of BNPL adoption since the Alipay (Huabei) registration. The third part compares first-month behaviors upon adoption. The fourth part compares users' probability of having previous default records as of November 2023. We report the difference between the two groups and *t-test* results in the last column. *** p<0.01, ** p<0.05, * p<0.1.

	New BNPL adoption		**Difference**
	After 2021.9	Before 2021.9	After - Before
User characteristics			
Age	38.998	37.067	1.931***
Gender (Male = 1)	0.591	0.591	0.0002
Time till BNPL adoption			
Months since Alipay registration	43.793	34.592	9.202***
Months since Huabei registration	15.419	8.627	6.792***
First-month behaviors upon adoption			
BNPL payment (ln)	8.853	8.950	-0.097***
BNPL payment (share)	0.526	0.551	-0.025***
Default probability (as of November 2023)			
Having default record	0.125	0.200	-0.075*

Table 8: Differences Between Users Having/Not Having Default Records

Note: This table compares responses from users having BNPL default records and users not having BNPL default records. Row 1 compares the responses to the survey question "After the credit reporting policy change, do you tend to increase or decrease your BNPL usage?". Row 2 compares the responses to the survey question "After the credit reporting policy change, do you tend to increase or decrease your on-time repayments on BNPL?". Row 3 compares the responses to the survey question "After the credit reporting policy change, do you tend to increase or decrease your consumption?". We report the difference between the two groups and the t-test results in the last column. *** p<0.01, ** p<0.05, * p<0.1.

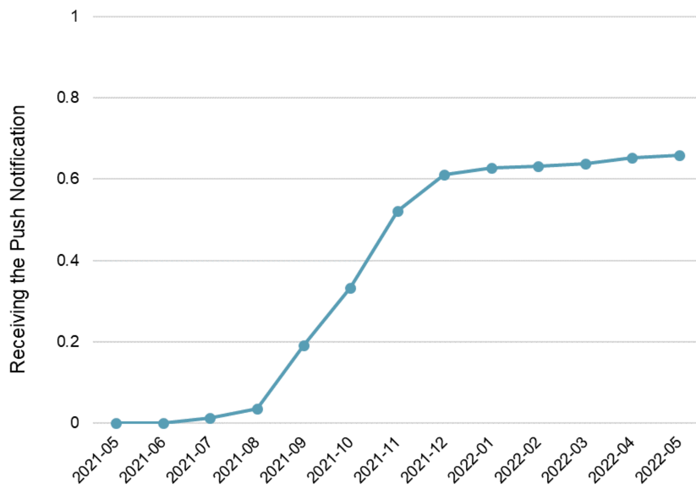
	Users having past default records	Users not having past default records	**Difference**
Reduce BNPL usage (Yes=1)	0.147	0.075	0.071**
Increase on-time repayments (Yes=1)	0.632	0.539	0.093
Reduce consumption (Yes=1)	0.235	0.080	0.155***

Internet Appendix

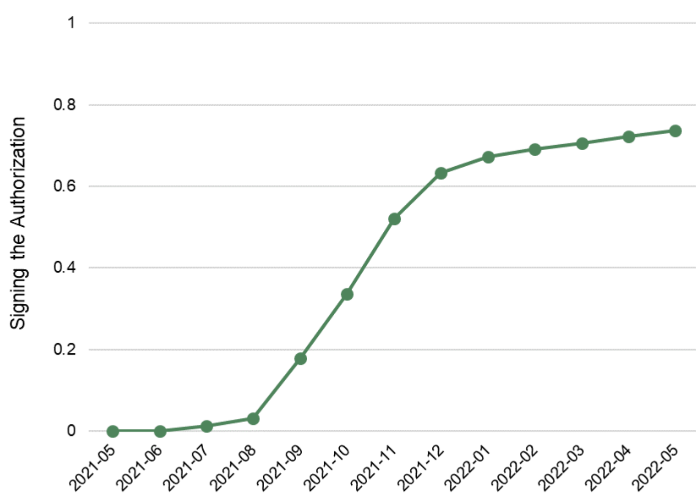
A Supplementary Analyses

Figure A1: User's Response to Push Notifications

Note: This figure presents the cumulative fraction of users who have received the push notification of the credit reporting policy change (Panel A) and who signed the authorization agreement, conditional on receiving the push notification (Panel B).



Panel A: Timeline of receiving the push notification



Panel B: Timeline of signing the authorization

Figure A2: Impacts on BNPL Credit Line

Note: This figure plots changes on BNPL credit lines. The results are estimated by the following regression using user-month data of Huabei users between May 2021 and May 2022:

$$Y_{it} = \beta_0 + \sum_{r \neq -1} \theta_r \times I_r + \mu_i + \varepsilon_{it}.$$

Y_{it} measures BNPL credit line of user i in month t. The BNPL credit line is measured by indexation instead of specific amounts (with a minimum value of 0 and a maximum value of 2.144). $PastDefault_i$ indicates whether a user has a default record before the window period (before May 2021). I_rs are the relative time indicators. μ_i denotes user fixed effects. ε_{it} represents the error term. Standard errors are adjusted for user-level clustering. The solid lines represent the estimated coefficients, and the dashed lines represent the upper and lower bounds of the 95 percent confidence intervals. The vertical dashed line indicates the month of the policy change (i.e., September 2021).

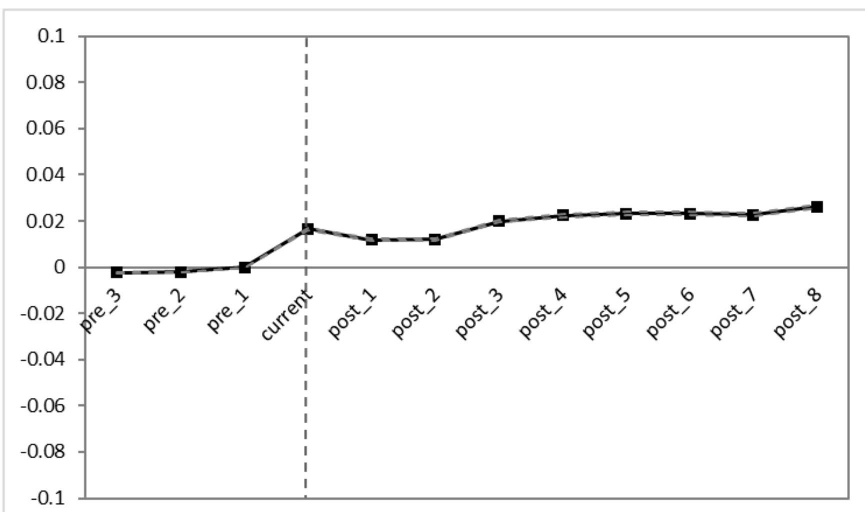
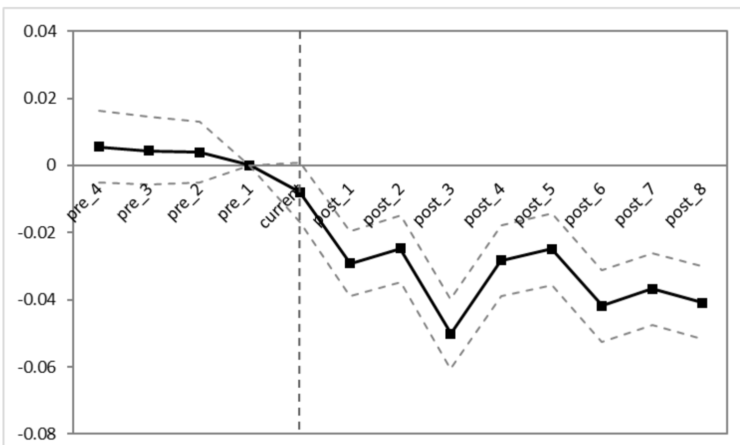


Figure A3: Impacts on Default: Dynamic DID (Alternative Default Measures)

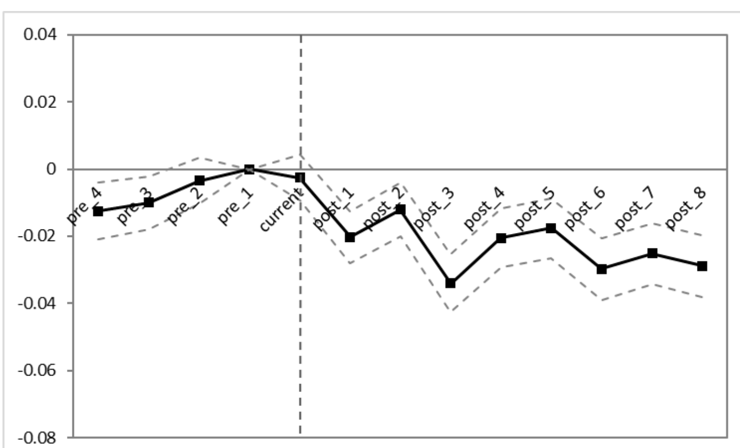
Note: This figure plots the impacts of credit reporting policy on defaults using a dynamic difference-in-difference (dynamic DID) model. The results are estimated by the following regression using user-month data of Huabei users between May 2021 and May 2022:

$$Y_{it} = \beta_0 + \sum_{r \neq -1} \theta_r \times PastDefault_i \times I_r + \mu_i + \delta_{ct} + \varepsilon_{it}.$$

Y_{it} measures defaults of user i in month t. We use two indicators to measure the default behaviors: (1) default within 3 days after the due date, a binary variable taking the value of 1 if a user does not repay the bill or make an installment repayment within three days after the billing date in a specific month; and (2) default within 30 days, a binary variable taking the value of 1 if a user does not repay the bill or make an installment repayment within thirty days. In particular, these alternative default indicators equal 1 only if a user defaults in a month with active BNPL usage. If there is a previous unpaid balance but the user does not use BNPL in the current month, default indicators would take a value of 0. $PastDefault_i$ indicates whether a user has a default record before the window period (before May 2021). μ_i and δ_{ct} denote user and city-by-month fixed effects, respectively. ε_{it} represents the error term. Standard errors are adjusted for user-level clustering and reported in parentheses. The solid lines represent the estimated coefficients, and the dashed lines represent the upper and lower bounds of the 95 percent confidence intervals. The vertical dashed line indicates the month of the policy change (i.e., September 2021).



(a) Default-3 days (Yes=1, alternative measure)



(b) Default-30 days (Yes=1, alternative measure)

Figure A4: Top 10 Reasons for Using BNPL

Note: This figure plots a histogram of responses to the survey question "For what reasons do you think consumers use BNPL? Please choose among the following options (maximum five choices).". We provide fifteen options and present the top ten options selected by consumers. The survey includes 1,493 responses from Alipay consumers in March 2024.

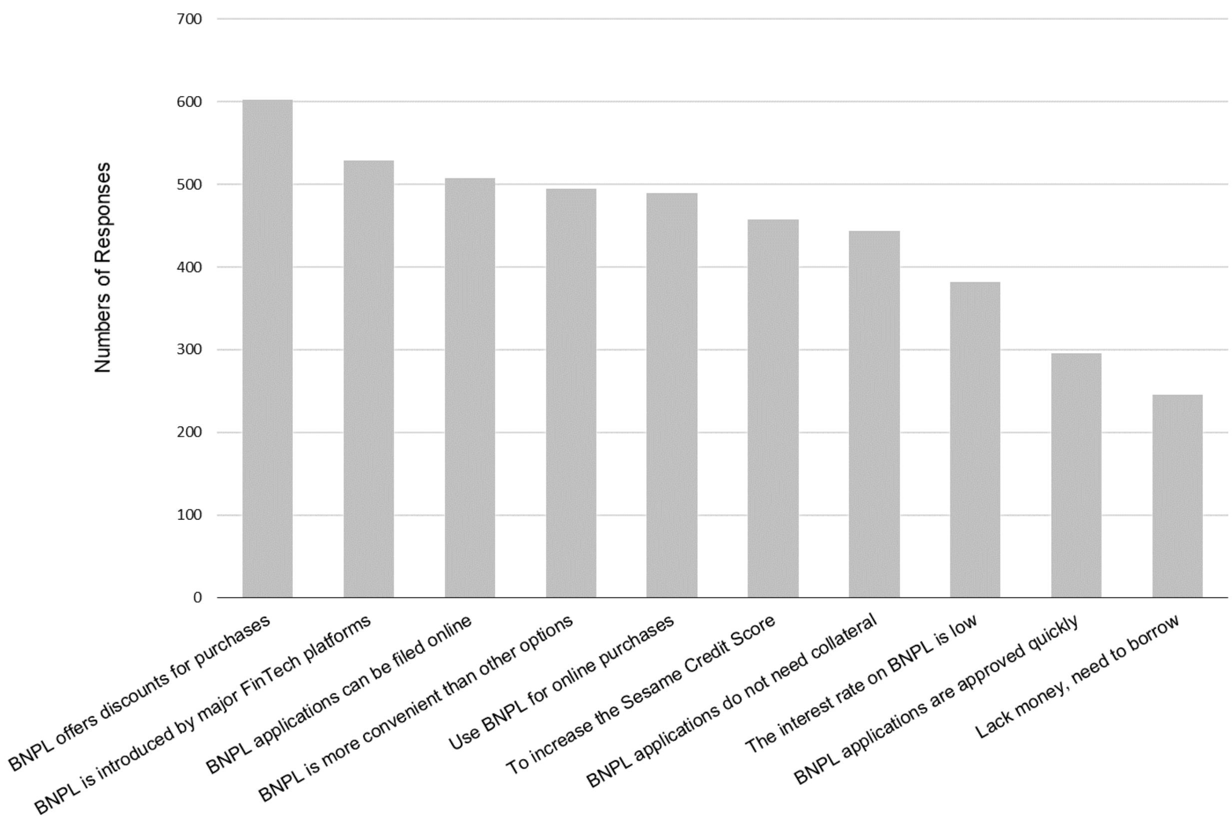


Figure A5: Consumers' Attitudes toward BNPL and Credit Reporting

Note: This figure plots responses to the survey question "Are you worried that using BNPL might have a negative impact on your credit records?". The survey includes 1,493 responses from Alipay consumers in March 2024.