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

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Abstract

How does information sharing affect consumers' usage of FinTech credit? Using a unique dataset of "Buy Now, Pay Later (BNPL)" users from a large digital platform and exploiting a credit reporting policy change, we document that consumers significantly reduce their usage of BNPL credit when the BNPL lender becomes subject to credit reporting regulation. This reduction is particularly pronounced among borrowers with default histories, who also show improved repayment behaviors compared to those without such records. The decrease in BNPL usage also leads to a reduction in online consumption, supporting the financial constraint hypothesis. Our findings indicate that information sharing can help mitigate overborrowing and overspending, with stronger effects seen among younger borrowers, those who previously spent more, or those with credit cards. We also highlight the synergies between BNPL lending and Big Tech platforms' ecosystems, which imperfectly substitute for formal enforcement institutions.

Keywords: FinTech, BNPL, consumer credit, information sharing, credit reporting, overborrowing, Big Tech platforms

JEL classification: G21, G28, G51, G53

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1 Introduction

Financial technologies (FinTech), which enable lenders to extend credit to individuals underserved by banks, have significantly promoted financial inclusion (e.g., Goldstein et al., 2019; Stulz, 2019; Fuster et al., 2019; Suri et al., 2021; Berg et al., 2022). However, the FinTech innovations often do not share borrower information with other lenders, making their lending practices opaque and potentially leading to the accumulation of delinquency riss outside the regulatory framework. A prominent example is the fast-growing "buy now, pay later (BNPL)" industry, which constitutes an increasingly large fraction of the consumer credit market. Several concerns associated with BNPL, such as overborrowing and overextension risks (deHaan et al., 2024; Cornelli et al., 2023b), are often linked to the lack of credit information sharing.[1]

The information sharing via credit registries serves as an essential financial infrastructure, rewarding those who make timely payments and penalizing those who default (e.g., Garmaise and Natividad, 2017). Therefore, consumers who overborrow and overspend may reduce their BNPL usage and delinquency, while those who see credit reporting as an opportunity for credit building are more likely to increase their BNPL usage. However, although BNPL has provoked policy discussions around the world (Cornelli et al., 2023a), few countries have implemented such credit reporting requirements. This raises an important yet understudied empirical question about whether credit reporting help could reduce overborrowing risks associated with BNPL.

Our paper is the first to systematically analyze the impact of information sharing on BNPL credit usage. We assemble a unique dataset of 200,000 randomly selected BNPL users from Huabei, China's largest BNPL lender.[2] Our purpose-built dataset contains user

[1]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."

[2]Launched in 2014 by Alipay, one of the two dominant digital payment platforms in China, Huabei has gained mass popularity, attracting approximately 500 million users as of 2020. See Ant Group's (suspended) initial public offering (IPO) prospectus, http://static.sse.com.cn/disclosure/listedinfo/bulletin/star/c/688688_20201022_1.pdf, August 2020.

characteristics (such as age, gender, and city of residence), account opening date, monthly BNPL usage, and consumption payments via Alipay. Furthermore, we exploit a major regulatory change in China in 2021 that incorporated Huabei into the national credit registry, which serves as a leading example in BNPL regulation.[3] In September 2021, Huabei issued a public statement officially announcing its compliance with credit reporting regulations, before which Huabei's user information remained proprietary data within Alipay's ecosystem.[4]

We guide our analysis following theories on information sharing and contract enforcement (Jappelli and Pagano, 2002; Padilla and Pagano, 1997, 2000; Pagano, Marco and Jappelli, Tullio, 1993). Our main analysis focus on BNPL users who had already obtained a Huabei credit line before our sample period between July 2020 and December 2022. Since these borrowers had already gone through the screening process and obtained access to the BNPL product, we can 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).

Interestingly, we find that the credit reporting regulation has significantly reduced consumers' usage of BNPL credit. On average, consumers reduce their BNPL payments by 14% relative to the pre-policy period. Both extensive and intensive margins drive this decline in BNPL usage: consumers are less likely to use BNPL for payment, and even when they do, the average payment amount via BNPL decreases. Moreover, this shift away from BNPL credit represents a structural change. Specifically, the share of Huabei payments in total consumption decreases by 7 percentage points, while the share of payments through credit

[3]According to China's Regulations of Credit Reporting Administration, institutions engaged in credit business should provide credit information to the credit reporting system. However, FinTech innovations, including BNPL credit, circumvented this credit reporting regulation using microloan licenses instead of banking licenses. After the collapse of the peer-to-peer (P2P) lending industry in China in 2019, regulators started to tighten regulations and close regulatory loopholes.

[4]Specifically, according to 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., line of credit, account opening date, and utilization.) The regulatory authority indicates that all Huabei users will eventually be incorporated into the centralized credit registry.

and debit cards increases by 2 and 4 percentage points, respectively. This finding rules out the possibility that the reduction in BNPL usage is driven by common factors affecting all digital payment options.

We further test the disciplinary mechanism of information sharing in a difference-in-differences (DID) framework. We classify BNPL users based on their default records before the enactment of credit reporting practices, assuming that previous default records are a sufficient indicator of BNPL borrowers' creditworthiness. Compared to users who never defaulted, BNPL users with default records reduce their BNPL usage by a larger magnitude. These borrowers also become more disciplined in repayment, shown by a larger reduction in default rates, supporting our hypothesis that the disciplinary mechanism primarily affects those consumers who are more likely to default.[5]

The reduction in BNPL usage is accompanied by a decrease in online consumption, suggesting that at least some FinTech borrowers are financially constrained. Furthermore, the reduction in BNPL credit usage is more pronounced among younger consumers, who are often seen as more vulnerable to overborrowing risks. We also find stronger effects among borrowers with higher initial consumption levels and borrowers with bank credit cards, who may shift away from BNPL credit to reduce their debt-driven consumption, minimize default probabilities, or avoid the stigma associated with BNPL borrowers. We do not find statistically significant changes in the BNPL credit line, implying that this decrease in BNPL usage is not driven by supply-side factors.

The credit reporting regulation also has an impact on the adoption of BNPL credit. New users who start using BNPL after the regulation's enactment are older, more seasoned in using Alipay, and take longer before adopting BNPL credit compared to those who adopted BNPL in pre-policy periods. These post-policy new users are also more prudent in using BNPL, with smaller BNPL payments and lower default rates. Together, our findings suggest that information sharing helps encourages more prudent behaviors by BNPL users,

[5] We interpret these estimates as a lower bound of the actual impact, considering the potential spillover impact of credit reporting on BNPL borrowers without previous default records.

potentially reducing overborrowing risks.

Finally, to better understand the motives behind these empirical patterns, we conduct a survey on the Big Tech platform to infer BNPL users' attitudes toward credit reporting. Consistent with our regression results, the survey data show that worries about BNPL's negative impact on credit records rank among the top reasons for consumers not using Huabei Survey respondents who previously defaulted more likely to "reduce Huabei usage" after the credit reporting regulation. We also find significant heterogeneity among consumers regarding the impact of credit reporting, with many respondents believing in the credit-building potential of BNPL products, highlighting the distributional impacts of information sharing.

Our work contributes three main insights to the literature on FinTech, information sharing, and consumer credit. To our knowledge, our paper is the first to empirically investigate the impact of information sharing on BNPL borrowers. First, our study highlights a market-based solution for addressing potential overborrowing and overextension risks associated with FinTech lending. A burgeoning literature focuses mainly on the consumption-stimulating impact of BNPL credit (Di Maggio et al., 2022; Berg et al., 2023; Bian et al., 2023).[6] Few studies have examined the implications for the financial health of FinTech borrowers. Notably, using banking data for 10 million U.S. consumers, deHaan et al. (2024) find that BNPL users quickly experience increases in bank overdrafts and credit card balances, which is consistent with the hypothesis that BNPL lending facilitates overborrowing. By showing the benefits of credit reporting in containing BNPL usage and online consumption, we build on the BNPL literature and provide new solutions to the tradeoff in FinTech lending between promoting the inclusiveness of lending and preventing the deterioration of borrowers' financial health.

[6]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 of total expenditures, regardless of users' inferred liquidity constraints. Using a random experiment at an e-commerce company, Berg et al. (2023) document that BNPL increases sales at both the intensive and extensive margin. Bian et al. (2023) use granular data from a world-leading BNPL provider based in China and find that BNPL credit crowds out other e-wallet payment options and expands FinTech credit to underserved consumers, substantially boosting consumer spending. Our dataset is similar to that in Bian et al. (2023). More generally, Agarwal et al. (forthcoming) find that digital payments increase consumer spending.

Second, our paper captures the impact of the actual credit reporting policy change on FinTech lending, which distinguishes our paper from previous studies focusing on informational intervention. While extensive literature has investigated the impact of information sharing on traditional banks,[7] few studies have examined the role of credit reporting in the context of FinTech lending. Notably, Liao et al. (2023) conduct field experiments through a FinTech lender, which provides fixed-term loans and persistently reports borrowers' loan performance to the credit registry, and find that FinTech borrowers who have been warned of credit reporting practices reduce their default rates and increase their loan take-up rates.[8] Complementing previous studies, our paper highlights the disciplinary role of information sharing and the importance of breaking the "credit information segmentation" between traditional and FinTech lenders.[9]

More broadly, we contribute to the accounting literature on how reporting systems affect decision-making. For example, Balakrishnan and Ertan (2021) find that improving banks' information sets and understanding of credit risks improves loan loss recognition. Similarly, Sutherland (2018) report that information sharing can reduce relationship-switching costs. Conversely, if the quality of borrower information is low, then information sharing may introduce potential financial risks (Yang, 2022; Bertomeu and Magee, 2011). By examining the decision-making process of retail borrowers, we focus on information sharing by FinTech lenders and demonstrate its impact on borrower behaviors and credit risks. Our results are also consistent with previous empirical studies on the impact of information-sharing

[7]The sharing of loan performance information among lenders via credit registries has been shown to be 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, reducing their information rates (Padilla and Pagano, 1997), and restricting default borrowers' access to future credit (Padilla and Pagano, 2000). Liberti et al. (2022) use the introduction of a U.S. commercial credit bureau to investigate lenders' adoption of voluntary information sharing technology and the impact on firms' credit access. They find improvements only for high-quality borrowers in markets with greater lender adoption.

[8]Different from Liao et al. (2023), we examine the actual change in the credit reporting practice of FinTech lenders. The borrower pools may also vary between the peer-to-peer lending context in Liao et al. (2023) and the BNPL context in our paper.

[9]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; Alok et al., 2024; Babina et al., 2023).

in the context of corporate loans, such as Behr and Sonnekalb (2012) and Doblas-Madrid and Minetti (2013), who find that information sharing reduces firms' delinquency rates and improves loan performance mainly by disciplining borrowers.

Third, our study speaks to the interplay between formal and informal contract enforcement institutions in Big Tech lending.[10] The BNPL product in our study is provided by a leading Big Tech platform and demonstrates a minimal default rate, which contrasts with those findings concerning default rates in FinTech lending (e.g., Di Maggio and Yao, 2021). Our results are consistent with Berg et al. (2023), who also find moderate costs of payment defaults on BNPL via random experiments on an e-commerce company. With a vast digital ecosystem and a dominant market share, Big Tech platforms can 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). Hence, our paper echoes the broader literature highlighting important synergies between payments and other financial services (e.g., lending, deposit-taking, and investment).[11]

The remainder of the paper proceeds as follows. Section 2 details the institutional background. Section 3 describes the data and empirical methodology. We present the results of BNPL usage and default rates in Section 4 and conduct further analysis on consumption and financial health in Section 5. Section 6 presents the survey results. We conclude the paper in Section 7.

[10] 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).

[11] See, for example, 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, which allow 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 United States 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.[12] The global merchandise volume generated 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 the FIS Global Payments Report 2023, BNPL transactions accounted for 5% of the global e-commerce transaction volume in 2022.[13]

In China, BNPL payments are expected to increase by 14.3%, reaching 136.63 billion USD in 2024.[14] 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).

A leading digital payment platform in China, Ant Group provides the following two types of consumer credit products through its Alipay app: Huabei (meaning "just spend it" in Chinese), the focal BNPL product in our study, launched in 2014, and Jiebei (meaning "just borrow it" in Chinese), a personal loan product, launched in 2015. Like most BNPL products, Huabei allows consumers to split payments into several interest-free installments and repay over time. Specifically, Huabei offers consumers a 40-day interest-free period, after

[12] CFPB, https://www.consumerfinance.gov/data-research/research-reports/buy-now-pay-later-market-trends-and-consumer-impacts/, September 2022.

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

[14] 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.

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%).[15] Consumers use Huabei in both online and offline shopping.[16] Huabei has achieved 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.[17]

2.2 Regulatory Framework for BNPL

The BNPL business falls largely outside the purview of existing regulations. In particular, unlike traditional consumer credit, BNPL loans are typically not reported to credit bureaus and, consequently, do not affect consumer credit scores (Cornelli et al., 2023b). The CFPB 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.[18]

The CFPB has been developing strategies for industry and consumer reporting companies to establish accurate and appropriate credit reporting practices for BNPL. In 2022, the three largest national credit reporting companies (NCRCs) in the United States (i.e., Equifax, Experian, and TransUnion) each released announcements on their plans to accept BNPL payment data. In May 2024, the CFPB issued an interpretive rule concluding that BNPL loans accessed through a digital user account are considered "credit cards" and are therefore subject to Regulation Z dispute and refund requirements. Additionally, there are ongoing

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

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

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

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

state efforts introducing further requirements for BNPL lenders. For instance, the New York state has implemented several requirements as of March 22, 2024, including requiring BNPL lenders to obtain a license and mandating that BNPL lenders make "a reasonable determination that the consumer has the ability to repay" the BNPL loan.[19]

Across the Atlantic, the Financial Conduct Agency (FCA) in the United Kingdom has 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)." For most lenders, "there is currently no regulatory requirement to share information with Credit Reference Agencies (CRAs).[20] This lack of transparency, as indicated by the FCA, means that credit providers may not have a comprehensive view of a consumer's financial situation when assessing his or her creditworthiness.[21]

Several other regulatory authorities are also exploring whether and how to incorporate BNPL data into credit reporting. For instance, 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 payments that customers can have with each BNPL provider.[22] The UAE Central Bank (CBUAE) has implemented its new Finance Companies Regulation, which officially acknowledges BNPL schemes as a form of consumer short-term credit and establishes requirements for transparency and disclosure.[23] 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.[24] Some central banks are also testing BNPL

[19] https://www.skadden.com/insights/publications/2024/06/cfpb-applies-credit-card-rules

[20] See the Woolard Review Report.

[21] https://www.fca.org.uk/publication/corporate/woolard-review-report.pdf

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

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

[24] https://treasury.gov.au/consultation/c2024-504798.

services through sandbox programs.[25]

The potential impact of including BNPL information in credit reporting, however, still lacks empirical investigation. Since BNPL differs from traditional consumer credit in terms of usage patterns, the consequences of incorporating it into credit reporting are unclear and depend on credit reporting standards. While major credit bureaus (such as Equifax, Experian, and TransUnion) have outlined plans to integrate BNPL credit data, the differing standards among these institutions also raise concerns. 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 a consumer's credit history, potentially negatively affecting his or her credit score.[26] The CFPB is also concerned that "this inconsistent treatment will limit the potential benefits of furnished BNPL data to consumers and the credit reporting system."[27] Additionally, BNPL usage may result in a stigma effect against borrowers, as lenders noticing frequent BNPL transactions on loan applicants' bank statements may raise concerns about their spending habits, which can lead to loan applications being declined. Hence, examining the impact of information sharing on BNPL borrowers' behaviors has become an important empirical topic that is of value to both scholars and policymakers.

2.3 Credit Reporting Regulation in China

As a pioneering regulatory practice, China's national credit bureau started incorporating Huabei into its 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

[25] For example, the Qatar Central Bank has approved five companies as the first cohort for the BNPL service. See https://www.qna.org.qa/en/News-Area/News/2024-04/27/0045-qcb-approves-5-companies-as-a-first-cohort-for-bnpl-service. Tamara, a shopping and payments platform, announced that it is a BNPL FinTech that has been granted a permit by the Saudi Central Bank (SAMA) after completing a trial period in their Regulatory Sandbox. See https://www.arabnews.com/node/2333456/business-economy.

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

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

working on integrating its BNPL product with the central bank's credit reporting system. Upon users' authorization, Huabei reports both positive (e.g., timely repayments) and negative (e.g., defaults) information about its users, together with the basic account information (e.g., the line of credit, account opening date, and utilization), to the centralized credit bureau. These credit records are summarized at a monthly frequency starting from the authorization month and do not include transaction-level details.

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, as shown in 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 majority of the public became aware of the regulatory policy at that time. Therefore, throughout the paper, we define September 2021 as the starting point of the credit reporting regulation in China.[28]

[28]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 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 a critical time for the credit reporting policy change.

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. This study was remotely conducted on the Ant Open Research Laboratory[29] in an Ant Group Environment. All data were sampled, desensitized, and analyzed on the Ant Open Research Laboratory. The laboratory is a sandbox environment where the authors can only remotely conduct empirical analysis, and individual observations are invisible. The main regression variables include basic variables, investment variables, and consumption variables.

3.1.2 Sample Construction

Our sample period spans from July 2020 to December 2022, which covers a 30-month time window around the credit reporting regulation in September 2021 to allow for comparison. We start with 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). We extract the monthly BNPL usage, payment, and consumption records of these users through Alipay's super-app, one of China's two dominant digital payment platforms with approximately 900 million active users,[30] or nearly three times the population of the United States.

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 credit reporting regulation implementation. Second, we keep those observations of users with at least one BNPL payment record before the window period. Third, we omit observations with missing values for the main variables and impose some logical restrictions

[29] https://www.deor.org.cn/labstore/laboratory

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

on the timing of receiving push notifications about the credit reporting regulation and signing the information-sharing authorization. Our final sample contains 137,042 users spanning 13 months, constituting 1,693,706 observations.

3.1.3 Main Variables

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 inform users about the credit reporting policy and obtain users' authorization, and the timing of signing the 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. Since users can link bank cards to the Alipay platform, we can also observe users' traditional credit usage via the digital platform. Additionally, because of the widespread quick-response (QR) code payments in China (e.g., Beck et al., 2022; Hong et al., 2020), digital payments are ubiquitous even at brick-and-mortar stores and street vendors. As of June 2020, more than 80 million merchants have access to Alipay payments. Expenditure via Alipay accounts for a significant portion of users' total expenditure.[31] Therefore, we are also able to track users' offline consumption via Alipay.

Previous BNPL defaults. To investigate the effects of credit reporting policy on BNPL borrowers with different levels of creditworthiness, we categorize users into the following two groups: consumers with and without past BNPL default records before our event window period. Therefore, we define users with (without) past default records as those who have

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

ever (never) defaulted as of four months before the credit reporting regulation.

BNPL usage. We use the following three indicators to measure BNPL usage in the Big Tech app: (1) whether a consumer uses BNPL credit, a binary variable taking a 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.

Other payment methods. In addition, we investigate the usage of other FinTech and traditional payment options in the Big Tech app. We use the share of the following 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.[32]

Default indicators. We use the following four indicators to measure the default behaviors of FinTech credit: (1) default within 3 days after the due date, a binary variable taking a 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 a 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 the following two components: online consumption (i.e., expenditures on online services such as e-commerce purchases) and offline consumption (i.e., spending in offline scenarios such as payments at local stores).

[32]Note that we only observe consumers' payments via Alipay and cannot track all transactions from debit and credit cards. However, considering that China has largely become a cashless economy with widespread mobile payments and that Alipay holds over 50% of the mobile payment market share (data from i-Research, https://www.idigital.com.cn/nfs/reports/ea274744e7fbaba835d2/2ca896f9cae51d8e8b98.pdf, June 2020), the Alipay data is fairly representative of consumers' expenditures, especially for those frequent users.

3.1.4 Summary Statistics

Table 1 reports the summary statistics of the analysis sample. Panel A reports the cross-sectional statistics for user characteristics. The average user age is approximately 33 years, consistent with the fact that the BNPL service targets mainly young consumers.[33] The gender distribution is balanced, with male users accounting for 53.3% of the sample. Notably, a very small fraction (i.e., 5%) of the users have had 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 payments in total expenditures 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 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 when the 3-day default indicator is used and 0.012 when the 30-day indicator is used. This pattern of low default rates is consistent with the advantages of Big Tech platforms in controlling credit risks, such as screening technology using big data and machine learning and informal contract enforcement within the platform's ecosystem. For example, default records 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).

[33] For instance, GlobalData's report identifies Millennials and Generation Z as the 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.

We also examine the transactions facilitated by the Alipay app. The average total consumption is 5,154 RMB, comprising 1,643 RMB of online consumption and 3,309 RMB of offline consumption. The logarithmically transformed values of total consumption, online consumption, and offline consumption are 7.439, 6.114, and 5.971, respectively, which aligns with the fact that Alipay has become the primary payment choice of Chinese consumers.

3.2 Empirical Methodology

3.2.1 Event Study

We start with an event study approach to investigate the behavioral 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 period 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.

3.2.2 DID Analysis

Users with lower levels of creditworthiness tend to have a greater probability of default. Since the credit reporting regulation significantly increases the default cost, we expect it to affect users with lower credit quality more than those with higher credit quality. Therefore, we consider users with low creditworthiness (proxied by their past default records) to be 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 BNPL default records before the window period (before May 2021). $post_t$ indicates whether the policy shock has taken place, i.e., $post_t = 1$ for periods after the shock in September 2021 (excluded). μ_i and δ_{ct} denote user and city-month fixed effects, respectively. β_1 captures the effects of the credit reporting policy shock on users with previous default records relative to those without.

The causal identification of the DID regression assumes that in the absence of policy change, the average outcomes for the treatment group and the control group follow parallel trends over time. We test the identification assumption via 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 at event time r relative to the base period $r = -1$. The validation of the identification assumption requires that $\theta_r = 0$ for $r < 0$.

3.2.3 Heterogeneity Analysis

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

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

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 bank credit. Our coefficient of interest is β_1, which captures the additional effects among groups with different z_i values.

4 Credit Reporting and BNPL Usage

4.1 Event Study: The Disuse Pattern

We characterize BNPL usage by both the extensive (i.e., whether a user uses BNPL credit in a certain month) and the intensive (i.e., the share of BNPL payments in total consumption conditional on the usage of BNPL credit) margins. Figure 2 presents the impacts of credit reporting on BNPL usage using the event study approach. Panel A of Figure 2 shows that the percentage of active BNPL users decreases by 4 percentage points immediately after the policy shock. This decline continues in subsequent months and eventually stabilizes 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 stabilizes at approximately 7 percentage points lower than the pre-policy period, indicating a structural change in consumers' payment choices.

To investigate the intensive margin effects on BNPL usage, we present the event study results for users who use BNPL every month in Figure A3. The BNPL payment share decreases by 3 percentage points after the credit reporting regulation, indicating a significant disuse effect on the intensive margin, even for consumers with regular BNPL usage. In all panels, the coefficients closely approximate zero before September 2021, indicating that there are no significant changes in the pre-policy period. After September 2021, BNPL usage experiences notable reductions in both extensive and intensive margins. Overall, our results indicate that the regulatory change in BNPL lenders' credit reporting requirement significantly reduces BNPL usage.

Other payment options. We further examine other payment options on the Alipay app to test the alternative hypothesis that platform-level changes drive the reduction in BNPL usage after the regulatory shock. Figure 3 illustrates the impacts on non-BNPL payment options using the event study approach. We find slight increases in the shares of digital wallet e-cash payments (in Panel A) and FinTech MMF payments (in Panel B) after the credit reporting policy change, but these effects are small in magnitude and diminish after a few months. In contrast, the shares of credit cards (in Panel C) and debit cards (in Panel D) increase significantly after the policy shock. The share of credit cards increases by approximately 2 percentage points, and the share of credit cards increases by approximately 5 percentage points.[34] These results show a partial switch from BNPL to traditional consumer credit (i.e., credit cards). Since the increase in credit card payment share is still smaller than the decrease in BNPL payment share, these results also indicate a decline in borrowing proportion in total spending.

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 data on the credit line available for use by each consumer. Figure A2 presents the changes in BNPL credit line around the credit reporting regulation via an event study. We do not find the credit line decreases around the time of the policy shock; in fact, the BNPL credit line experiences a slight increase. 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.

[34]Note that the dataset only includes expenditures via Alipay, so we are not able to track expenditures made through other methods, such as cash payments, WeChat payments (another payment super-app), bank transfers, and others. Therefore, the changes in credit card payments and debit card payments might be underestimated.

4.2 DID Analysis: Previous Default Records

Our previous 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 different levels of default risks. Our hypothesis is that users with higher-level default risks, proxied by previous default records, exhibit a greater reduction in their BNPL usage than those with lower-level default risks.

Panel A of Table 3 presents the impacts of credit reporting on BNPL usage in the Alipay app estimated by specification (2). Compared with users without past default records, those with previous default records exhibit a more pronounced reduction in FinTech credit usage. Specifically, the probability of using BNPL among users with past default records decreases by an additional 4.8 percentage points, the amount of BNPL payments decreases by an additional 24.2%, and the share of BNPL payments decreases by an additional 2.3 percentage points.[35] These results support our argument that the credit reporting policy change increases the cost of BNPL defaults, with a greater impact on borrowers who have previously defaulted (and hence tend to have a higher probability of future delinquency). Consequently, these users are more likely to discontinue BNPL usage to reduce their future default probabilities (given the same income cash flows), thus minimizing the negative impacts on their credit records.

Panel B of Table 3 reports the impacts on other FinTech and traditional payment options using the DID approach. Compared with those without past default records, BNPL users with past default records exhibit more pronounced increases in e-cash payment share and money fund payment share.The share of e-cash payments increases by an additional 0.6 percentage points and the share of MMF payments increases by an additional 1.6 percentage points. However, these users demonstrate a smaller increase in credit card share. Compared

[35] The average amount of monthly BNPL payment for users with past default records in the pre-policy period is 633 RMB. Therefore, the additional decrease in BNPL payment amount (in natural logarithm value) is approximately equivalent to 633 * 24.2% = 153 RMB.

with users without default records, users with default records exhibit a 0.8 percentage point lower increase in their credit card payment share, which implies their limited access to alternative credit options. If BNPL users are financially constrained, the failure to fully substitute BNPL credit with bank credit may lead to decreased consumption. We examine this financial constraint hypothesis in the next section.

4.3 Real Effects on Consumption

A primary criticism of BNPL revolves around overconsumption and loan stacking. If the reduction in consumption among users with lower credit quality consists primarily of irrational spending, the credit reporting policy can aid in mitigating potential risks and enhancing consumer welfare.

Table 4 reports the impacts on consumption using the DID approach. Compared with users without default records, users with default records exhibit a slight but not statistically significant decrease in total consumption. However, by decomposing consumption into online and offline components, we find a statistically significant and negative coefficient when online consumption is the outcome variable. As shown in Column (2), compared with those without previous BNPL default records, users with past default records exhibit an additional reduction in online consumption by 5%. We do not find such an impact on offline consumption, as shown in Column (3), which may be less prone to impulsive purchase risks than online consumption. These findings suggest that the credit reporting regulation has a real impact on consumption, particularly on online expenditure.

Overall, we find a substantial decrease in BNPL usage following the credit reporting regulation, particularly among users with previous default records, which can potentially lead to a tightening of consumption liquidity. We also document a novel decreasing pattern in online consumption following the credit reporting requirement for BNPL lending. Previous studies have focused mainly on the consumption-smoothing effect of BNPL credit by relaxing borrowing constraints and promoting financial inclusion (e.g., Di Maggio et al., 2022; Bian et al., 2023). Our results provides insights into the regulation of FinTech consumer credit by highlighting the potential benefits of credit reporting in reducing overborrowing and overextension risks.

5 Disciplinary Impact of Credit Reporting

5.1 Heterogeneity Analysis: Age, Consumption, and Bank Credit Access

A primary concern regarding BNPL is that the convenience of FinTech-based consumer credit may induce consumers, especially unsophisticated consumers, to overborrow and overspend (Berg et al., 2022). BNPL helps consumers to overcome short-term liquidity shortfalls but does not improve their income. Therefore, when combined with reward programs, BNPL services may encourage excessive spending (Cornelli et al., 2023b). This overborrowing induced by BNPL lending may be particularly prevalent among young users and those with high consumption levels. This section explores heterogeneity based on borrowers' age, consumption, and access to bank credit.[36]

Panel A of Table 5 reports the heterogeneous effects by age using regression specification (3). The indicator $Young_i$ equals one for users below the median age of 30 and zero otherwise. We find that compared to users above the median age, users below the median age decreases their probability of using BNPL by an additional 2.4 percentage points, the amount of BNPL payments by an additional 12.9%, and the share of BNPL payments by an additional 0.8 percentage points. While some studies show that young people are more likely to be "credit invisible" (Brevoort et al., 2015, 2016; Cooper et al., 2023), our findings suggest that younger consumers are also more likely to reduce BNPL usage after the credit reporting regulation, potentially to minimize the probability of future defaults and therefore the negative impact

[36] 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 as those in the baseline results.

on their future credit access (e.g., Dobbie et al., 2020).

Panel B of Table 5 reports the heterogeneous effects based on consumption level. We divide users into two groups based on the median 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 BNPL usage by a larger magnitude, potentially to reduce their probability of future defaults. Similarly, Panel C shows that the disuse effect is more pronounced among consumers who have credit cards (and hence are more likely to have accumulated debts) than among those without bank credit access. These results echo previous studies on credit builder loans (Burke et al., 2023), which find larger credit score decreases among borrowers with active initial installment loans.

An alternative explanation is that consumers with higher consumption levels or credit cards are more likely to be financially unconstrained, hence having more alternative borrowing options available than those with lower consumption levels or without credit cards. Therefore, for consumers who already have channels to build credit records and obtain consumer credit, the credit-building benefit of the BNPL credit is less valuable. Instead, other concerns over BNPL (e.g., potential stigma effects) may become more salient and contribute to decreased BNPL usage.[37]

According to recent New York Fed research,[38] BNPL users typically tend to be younger, carry greater debt burdens, and have lower credit scores than credit card users. More financially fragile households tend to use such services more frequently than less financially fragile households. Data from the CFPB also show that compared with non-BNPL borrowers, BNPL borrowers are generally more likely to be heavily indebted, revolve on their

[37]For instance, there are widespread rumors on major social media platforms in China indicating that using BNPL may have adverse effects on loan applications in the formal credit market (e.g., mortgages from commercial banks).

[38]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/.

credit cards, have delinquencies in traditional credit products, and use high-interest financial services.[39] 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.[40] These patterns are also consistent with recent studies such as deHaan et al. (2024). Therefore, consumers with lower reliance on BNPL credit are more inclined to decrease BNPL usage after the regulatory regulation due to the stigma associated with BNPL borrowing.[41]

5.2 Reduction in BNPL Defaults

Information sharing via credit registries has the potential to reduce default rates for several reasons. On the one hand, if borrowers repay loans on time, they will have positive credit records, which can signal their high credit quality and help them in future credit applications. On the other hand, if borrowers default on loans, the negative credit records will jeopardize their future access to the credit market. In particular, consumers with previous default records tend to have higher default risks and more limited access to the formal credit market than others, thus the effects of credit reporting can be more pronounced among these consumers.

Table 7 reports the impacts of credit reporting on borrowers' default behaviors using the DID model (2), which is consistent with theoretical predictions above. We use the following four indicators to measure default: delinquency in a 3-day window in Column (1), delinquency in a 30-day window in Column (2), overdue balance ratios in Column (3), and the average interest-bearing balance ratio in Column (4). Overall, users with previous

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

[40]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/).

[41]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 unwilling to share personal payment information may also switch to alternative payment methods.

default records exhibit a significantly larger reduction in default probabilities of default than those without such records, with 5.8 (1.9) percentage points larger decreases under the 3-day (30-day) horizon.[42]

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 past default records are not statistically significant before the policy change. However, after the credit reporting policy change, users with past default records exhibit significantly fewer defaults.

Alternative default measures. Figure A4 presents the dynamic DID results when an alternative default measure is used to factor in consumers' BNPL usage. This alternative default indicator equals one only if a user defaults in a month with positive BNPL payments. If there is a previous unpaid balance but the user does not use BNPL in the current month, this alternative default indicator takes a value of zero. Hence, this alternative indicator measures 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 that the information-sharing mechanism plays a disciplinary role.

Finally, we find that the default rates on Big Tech platforms are relatively low (1-2%) even before the credit reporting regulation. Given that many BNPL users do not appear to have access to bank credit, it is quite amazing that these marginal or unbanked borrowers have not presented significant default risks. We provide three nonexclusive explanations. First, Big Tech platforms have better screening technology than standalone FinTech lenders, echoing the "invisible primes" notion that FinTech lenders use alternative data other than credit scores when screening borrowers (Brevoort and Kambara, 2017; Di Maggio et al., 2021). Second, Big tech platforms have better informal contract enforcement technology

[42]For the full sample, the trends of default indicators do not exhibit significant changes after the credit reporting regulation, as the majority of BNPL borrowers do not have past default records.

(e.g., platform exclusion costs), which 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 on disciplining borrowers' behaviors. A third possibility is that BNPL credit contains delinquency risks by keeping a relatively low credit line (here, several thousand RMB) so that households are able to repay the debt. We find supporting evidence from our borrower survey results.[43]

Interestingly, Big Tech platforms in other countries have also recently moved into the BNPL business. For instance, in June 2023, Amazon announced a partnership with Affirm to offer BNPL services on Amazon Pay.[44] Another Big Tech platform, 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 to 1,000 USD.[45] In December 2023, Google Pay announced a pilot program with Affirm and Zip to add a BNPL option for U.S. online shoppers.[46] Therefore, our research using data from Big Tech platforms represents recent trends in BNPL development and has general implications for other countries.

5.3 New BNPL Adoption

We complement our analysis by investigating the impact of credit reporting on BNPL adoption. We randomly select 1,000 users who use BNPL credit for payments for the first time in

[43]This quantity-based risk control approach, compared to high-tech pricing strategies, is prevalent in FinTech lending in China (e.g., Chen et al., 2022). Recent findings by Johnson et al. (2023) demonstrate FinTech platforms' over-reliance on FICO scores in their pricing decisions. The reliance on capping loan amounts to control default risks could also be the result of a low-tech pricing strategy.

[44]Previously in December 2021, Amazon offered the BNPL payment option, which allowed 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.

[45]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/.

[46]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/.

each month between September 2020 and September 2022. Table 8 compares between new users who adopt BNPL before the credit reporting regulation in September 2021 (12,000 users) and those who adopt BNPL afterward (12,000 users).

We find that users who adopt BNPL after the credit reporting policy (i.e., post-policy adopters) differ from those who do so 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 of the former 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 longer before accessing the BNPL credit line, implying greater caution in their BNPL adoption decisions, than pre-policy adopters.

Second, we find that post-policy adopters exhibit significantly lower BNPL payments than pre-policy adopters in the first month of BNPL adoption. This result echoes our previous finding that consumers tend to decrease BNPL usage after the credit reporting policy change, as it elevates the cost of excessive borrowing. These findings highlight how the regulatory environment shapes the adoption of FinTech credit among individuals.[47] Our paper also echoes the broader literature on regulatory arbitrage and the rise in the popularity of FinTech in other financial markets (e.g., Buchak et al., 2018; Di Maggio and Yao, 2021) and enriches the research on the driving forces behind FinTech adoption (Higgins, forthcoming; Chodorow-Reich et al., 2020).

Finally, the probability of having default records 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

[47] 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).

likely to adopt BNPL. Therefore, our estimates represent the lower bound of the disciplinary effect of credit reporting on new BNPL users.

6 Survey Results

To understand the real-world motivations and mechanisms behind our empirical findings, we conduct a survey on Alipay, i.e., the digital payment platform that provides the focal BNPL product. We obtain 1,506 complete responses, with a response rate (calculated by dividing the number of survey respondents by the number of Alipay users who receive in-app notifications) of approximately 15%, which is comparable to that in previous studies using online platforms to distribute surveys (Epper et al., 2020; Barry et al., 2022; Hvidberg et al., 2023). More details regarding the survey design and data collection process can be found in Appendix A.1.

6.1 Reasons for the Use and Disuse of BNPL

We first analyze the primary motivations behind the use and disuse of BNPL credit. 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 options from which respondents can choose. Figure 5 shows the top ten reasons why consumers do not use BNPL. Notably, the top-ranking reason is that consumers worry about "the potential negative impact on credit records," suggesting that the negative impact of BNPL defaults (and/or perceived stigma associated with BNPL usage) is one of the primary factors affecting individuals' BNPL usage. The tied top-ranking reason is that consumers have sufficient money and do not need to borrow. Other reasons include 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").

Figure A5 presents the top ten reasons for using BNPL credit. The top-ranking reason is that “BNPL offers discounts for purchases,” a marketing practice commonly adopted to promote BNPL products. Importantly, we observe the value of the Big Tech ecosystem for consumers: 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).” Other reasons are related primarily 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.”

6.2 Responses to the Credit Reporting Policy

6.2.1 Attitudes toward Credit Reporting

Figure A6 reveal people’s attitudes toward BNPL’s credit reporting regulation. We find large heterogeneities among consumers. Nearly 700 respondents (close to 50% of total respondents) agree that upon credit reporting, they need to worry only about the negative effects of BNPL default records. However, more than 500 consumers (more than 30% of total respondents) are concerned about the potential negative impacts of credit reporting even in the absence of delinquencies. These results are consistent with the significant reduction in BNPL usage following the credit reporting regulation, potentially due to the stigma effects associated with BNPL usage. Our findings also echo those of Burke et al. (2023), who reveal heterogeneous treatment effects after credit builder loans are introduced.

6.2.2 Previous Default Records

One caveat of the Alipay data is that we cannot observe borrowers’ previous defaults outside the Alipay ecosystem. To obtain a more comprehensive understanding of individuals’ creditworthiness and financial health, we ask them to self-report their current debts and previous default records in the survey.

Table 9 compares their demographics, income, debt, and hypothetical responses to the credit reporting regulation. As shown in Panel A, survey respondents with past default records are less likely to reside in urban areas, attend college, engage in nonfarm employment, or earn annual incomes higher than 100,000 RMB.[48] Panel B shows that survey respondents with past default records are more likely to have unpaid debts, particularly short-term loans such as consumer loans and private borrowings. In contrast, survey respondents without self-reported previous default records are more likely to have long-term loans such as mortgages and auto loans. Regarding people's responses to the credit reporting policy change, respondents with previous default records are more likely to reduce BNPL usage, increase timely repayments, and reduce consumption after Huabei' s incorporation into the credit reporting system than those without, as shown in Panel C. These survey findings align with our DID results, demonstrating the differentiated impacts of information sharing on borrowers with different levels of creditworthiness and financial health.

6.2.3 Role of Financial Literacy

We further explore how financial literacy affects people's attitudes toward BNPL and credit reporting. An established stream of literature has documented the role of financial literacy in financial decision-making. Consumers with higher levels of financial literacy make savvier saving and investment decisions, engage more in retirement planning, show greater participation in the stock market, and enjoy greater wealth accumulation (Lusardi and Mitchell (2007), Lusardi (2008), Lusardi and Mitchell (2014), Van Rooij et al. (2011)). Conversely, individuals with lower levels of debt literacy tend to engage in high-cost borrowing and incur higher fees (Lusardi and Tufano (2015)). In particular, Gerardi et al. (2013) find that numerical ability (assessed through a combination of financial literacy and math knowledge questions) significantly contributed to defaults on subprime mortgages during the recent financial crisis. Therefore, it is important to investigate whether financial literacy shapes

[48] In the survey, respondents select their annual income range from the following options: below 20,000 yuan (250 respondents), 20,000-100,000 yuan (640 respondents), 100,000-300,000 yuan (476 respondents), 300,000-500,000 yuan (82 respondents), 500,000-990,000 yuan (23 respondents), and 1,000,000 yuan and above (22 respondents). Thus, the fraction of high-income respondents is 40.4%.

consumers' debt management and borrowing behaviors in the context of FinTech.

Following the literature (e.g., Van Rooij et al. (2011), Lusardi and Tufano (2015)), we design five questions to evaluate individuals' financial literacy. These questions cover the understanding of interest rates, inflation, compound interest calculations, the time value of money, and knowledge of financial investments. We categorize respondents into three groups based on their answers to these questions. Respondents who correctly answer 0-1, 2-3, and 4-5 questions are categorized into the low, medium, and high financial literacy groups, respectively. By this standard, we have 658, 691, and 144 respondents in each group, respectively.

As shown in Panel A of Figure 6, respondents with higher levels of financial literacy are more likely to disagree with the idea of "consuming immediately and not saving for tomorrow," more likely to agree that "a good credit history is important," and less likely to worry about potential negative effects of BNPL on their credit history unless there are defaults. These results show that individuals with higher levels of financial literacy tend to have a more rational view on consumption and credit reporting.

We also analyze people's hypothetical responses to the credit reporting regulation. Panel B shows that compared with the low-financial-literacy group, respondents with high levels of financial literacy are less likely to reduce BNPL usage, more likely to increase or do not change on-time repayments, and less likely to reduce consumption after the credit reporting regulation. These results imply that more financially literated individuals are more rational in responses to the credit reporting regulation.

6.3 Survey Respondent Behaviors

In this section, we link the survey responses with the respondents' actual behavior on Alipay. We then conduct empirical analyses similar to those in previous sections. Figure A7 shows the event study estimates for survey respondents classified by their attitudes toward BNPL and credit reporting (i.e., responses to the survey question "Are you worried that using

BNPL will have a negative effect on your credit history?"). The red line represents the estimated results for users who are worried about the negative impact of BNPL on credit history regardless of whether they default (3,957 observations), the blue line represents the estimated results for users who are not worried regardless of whether they default (2,543 observations), and the green line represents the estimated results for users who are worried only if they default (5,369 observations). We find that users who are more concerned about the negative effects reduce their BNPL usage more significantly after the credit reporting regulation. Among these respondents, the probability of using BNPL decreases by 8-15 percentage points, and the BNPL payment share decreases by approximately 5 percentage points.

Figure A8 shows heterogeneous impacts based on self-reported previous default records. The red line represents the estimated results for users having past BNPL default records (771 observations), and the blue line represents the estimated results for users not having past BNPL default records (11,098 observations). Compared with users without past default records, users with past default records reduce BNPL usage more significantly after the credit reporting regulation. Among these respondents, the probability of using BNPL decreases by 10-30 percentage points, and the BNPL payment share decreases by approximately 10-25 percentage points.

Figure A9 shows heterogeneous impacts based on financial literacy. The red line represents the estimated results for users with low levels of financial literacy (5,633 observations), the blue line represents the estimated results for users with medium financial literacy (4,966 observations), and the green line represents the estimated results for users with high financial literacy (1,270 observations). While respondents with medium and low levels of financial literacy exhibit similar trends of reducing BNPL usage after the credit reporting regulation, respondents with high levels of financial literacy exhibit much smaller disuse effects. Among these respondents, the probability of using BNPL does not exhibit significant changes, and the BNPL payment share shows a downward but not statistically significant trend.

7 Conclusion

BNPL lending has changed the competitive landscape in the consumer credit industry, promoting financial inclusion while inducing overborrowing and delinquency risks. We provide novel empirical evidence of the impact of information sharing on BNPL users' behaviors using a unique dataset from a leading digital payment platform that offers China's largest BNPL product. Our empirical analysis exploits a critical credit reporting policy change in 2021, which incorporated BNPL lenders into the centralized credit registry. The regulatory change in BNPL lender's credit reporting practice breaks through the credit information segmentation between the traditional banking sector and the burgeoning FinTech sector, which may have heterogeneous impacts on borrowers.

We find that consumers significantly reduce their BNPL usage when their borrowing status is set to be shared with traditional lenders such as banks. This disuse effect is more pronounced among consumers with previous default records, which also become more disciplined in repayment, consistent with theoretical predictions where an increase in default punishments reduces moral hazard. The reduction in BNPL usage has real effects by decreasing online consumption, implying that some FinTech users are financially constrained. We also find larger reductions in BNPL usage among younger borrowers, borrowers with higher consumption levels, and borrowers with credit cards, suggesting that credit reporting practices can help alleviate the overborrowing problem among FinTech borrowers. Our further analysis using new BNPL adoption data and survey responses reveals similar patterns.

Our results therefore hint at a more market-based solution to overborrowing risks that concern regulators than blanket solutions such as 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. Furthermore, an exciting feature of the Big Tech platform lending is an already low default rate, suggesting that the platform possesses screening and monitoring capabilities that, to some extent, substitute for formal enforcement institutions.

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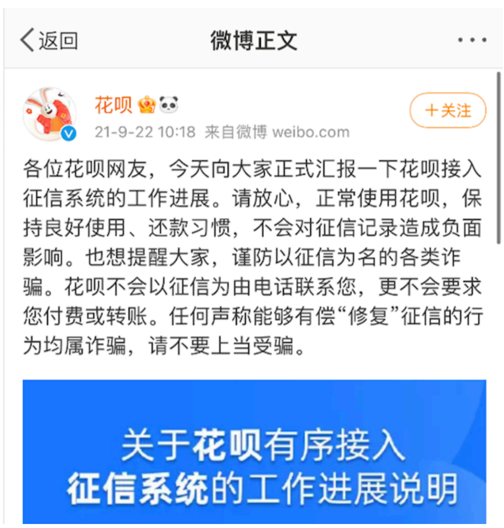
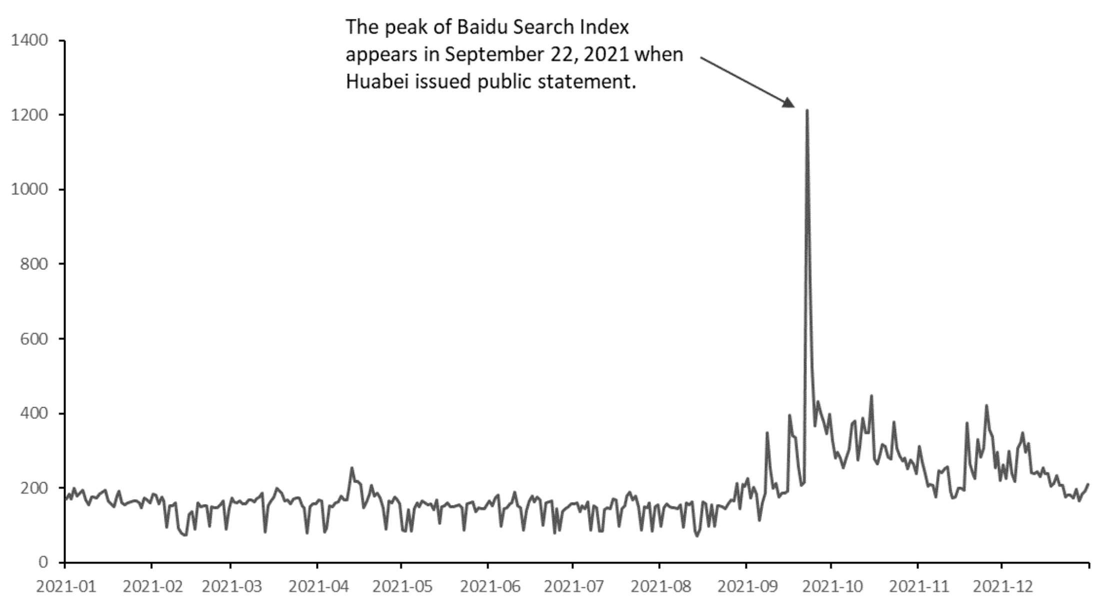
Figure 1: When BNPL Meets Credit Reporting

Note: This figure shows the official announcement regarding the credit reporting regulatory change by Huabei via Weibo, China's largest social media platform, which is similar to Twitter (now X), and the public attention it attracts. Panel A is a screenshot of Huabei's original Weibo post. Panel B is a screenshot showing that Huabei's credit reporting practice ranks first in the social media network's trending news. 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, which is similar to Google.



(a) Weibo Announcement by Huabei

(b) Weibo Social Media Trending News



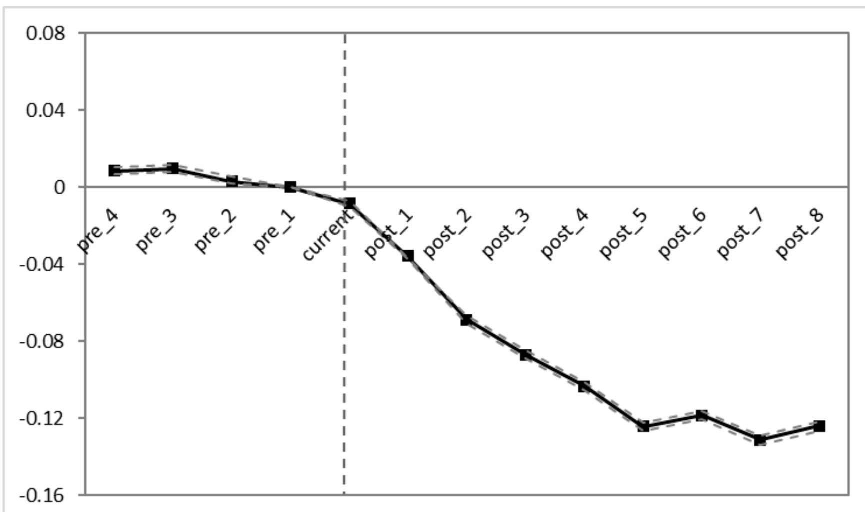
(c) Baidu Search Index

Figure 2: Event Study: Impacts of Credit Reporting on BNPL Usage

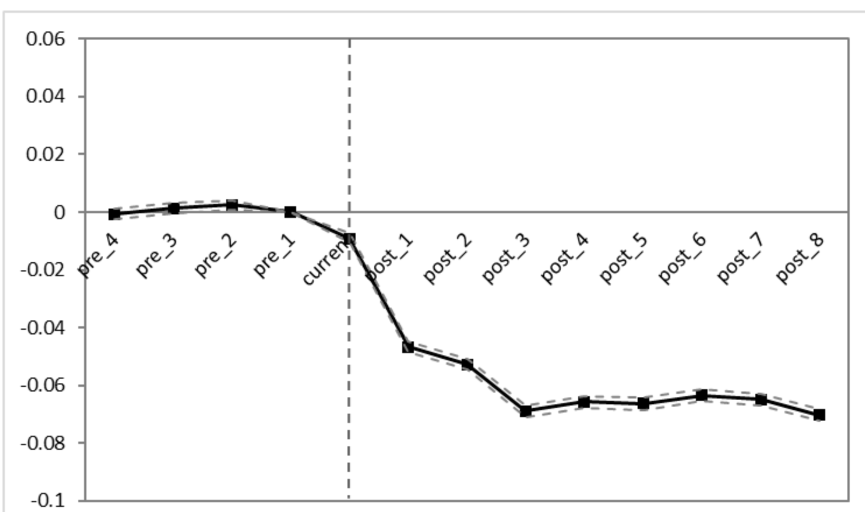
Note: This figure plots the impacts of the credit reporting policy on BNPL usage using an event study model. The results are estimated by the following regression using user-month panel data of 1,693,706 observations between May 2021 and May 2022:

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

Y_{it} measures the BNPL usage of user i in month t. We use two indicators to measure BNPL usage in the Big Tech app: (1) BNPL usage dummy, a binary variable that equals 1 if an individual uses BNPL payments in a given month and 0 otherwise; and (2) BNPL payment share, the fraction of BNPL payments 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) BNPL Usage Dummy (Yes = 1)



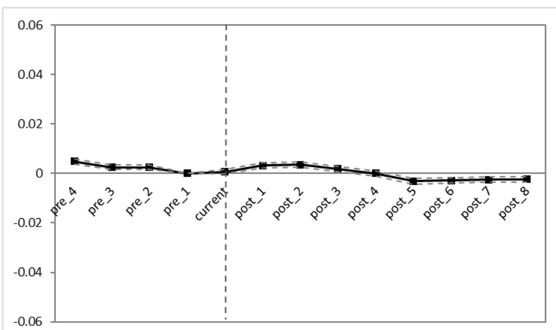
(b) BNPL Payment Share

Figure 3: Event Study: Impacts of Credit Reporting on Non-BNPL Payments

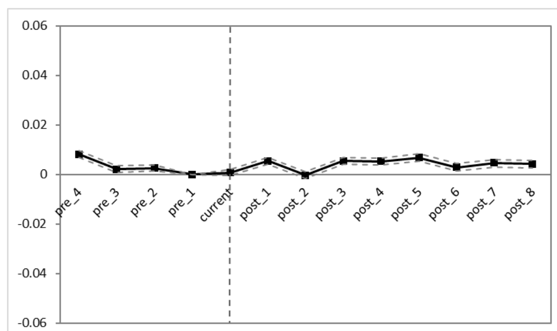
Note: This figure plots the impacts of the credit reporting policy on non-BNPL payments via Alipay using an event study model. The results are estimated by the following regression using user-month data of 1,693,706 observations between May 2021 and May 2022:

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

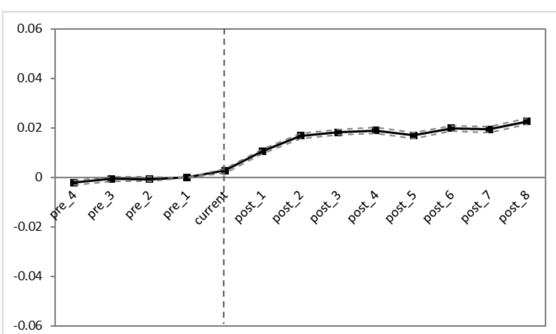
Y_{it} measures the usage of FinTech and traditional payment options of user i in month t. We investigate the following four primary alternative payment options in total consumption via Alipay: (1) e-cash payment share, (2) FinTech MMF (i.e., Yu'ebao) payment share, (3) credit card payment share, and (4) debit card payment share. $PastDefault_i$ indicates whether a user has default records 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).



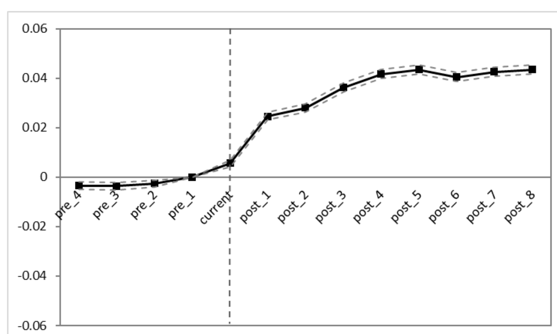
(a) e-Cash Payment Share



(b) FinTech MMF Payment Share



(c) Credit Card Payment Share



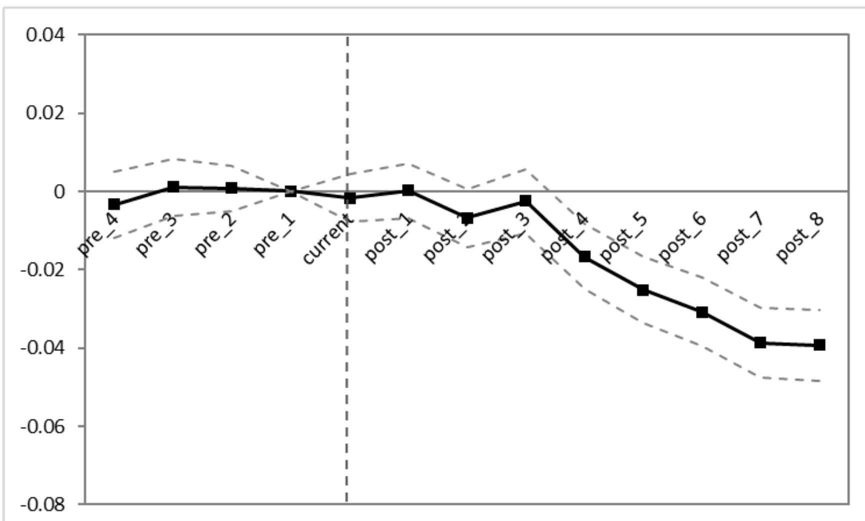
(d) Debit Card Payment Share

Figure 4: Dynamic DID: Impacts of Credit Reporting on Defaults

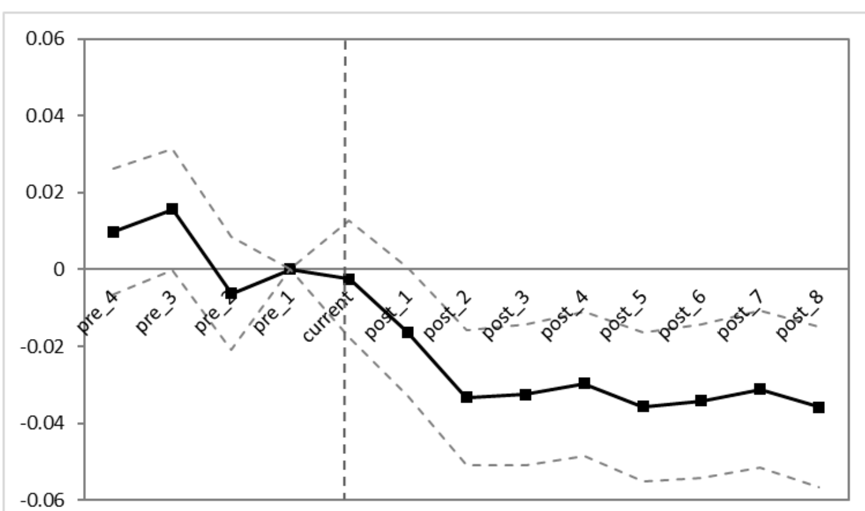
Note: This figure plots the impacts of the credit reporting policy on defaults using a dynamic DID model. The results are estimated by the following regression using user-month panel data of 1,693,706 observations between May 2021 and May 2022:

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

Y_{it} measures defaults of user i in month t. We present the results using the following two indicators to measure individual default behaviors: (1) default within 30 days, a binary variable taking a 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 default records 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% confidence intervals. The vertical dashed line indicates the month of the policy change (i.e., September 2021).



(a) Default under the 30-Day Horizon (Yes=1)



(b) Overdue Balance Share

Figure 5: Reasons for Not Using BNPL

Note: This figure plots the responses from the survey question "For what reasons do you think consumers do not use BNPL? Please choose among the following options. Maximum of five choices." We provide thirteen options and present the top ten options selected by consumers. The survey includes 1,506 responses from Alipay consumers in March 2024. The horizontal axis represents the options, and the vertical axis represents the number of respondents who choose a certain option.

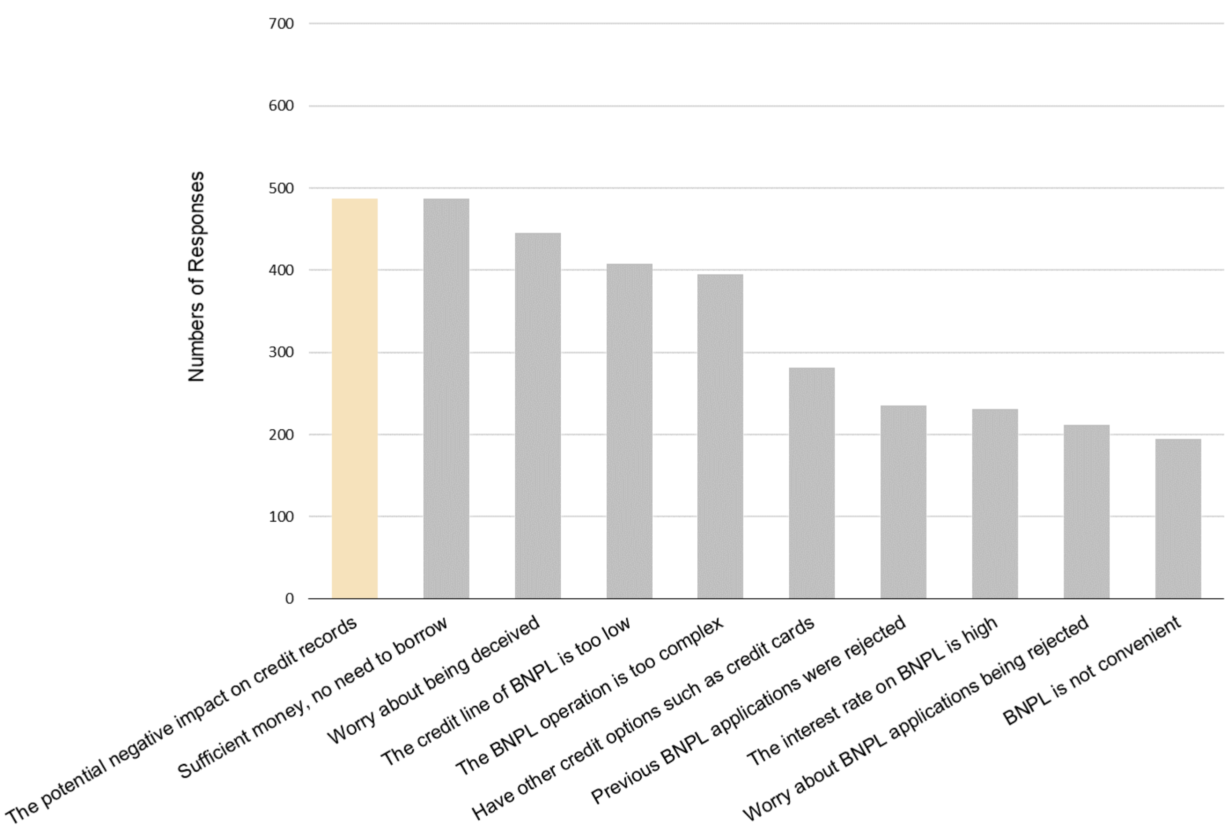
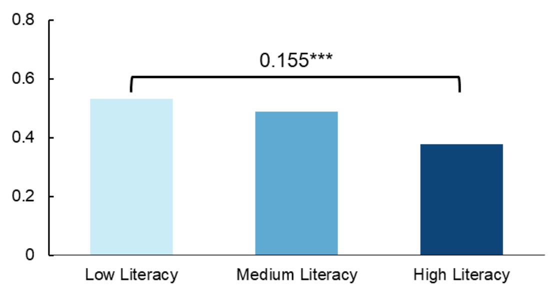


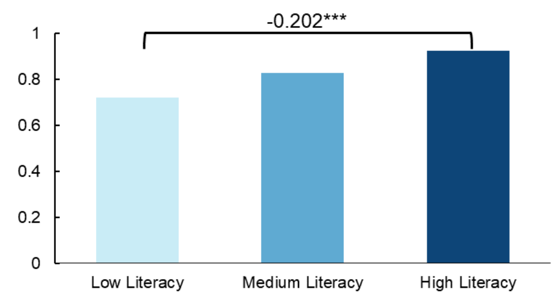
Figure 6: Financial Literacy and Attitudes toward Credit Reporting

Note: This figure plots responses to survey questions by different levels of financial literacy using 1,506 survey responses in March 2024. Panel A plots responses to the survey questions “Do you agree with consuming immediately and not saving for tomorrow,” “Do you agree with that good credit history is important for lifetime,” and “Are you worried that using BNPL might have a negative impact on your credit history.”. Panel B plot responses to the survey questions “After the credit reporting regulation, do you tend to increase or decrease your BNPL usage/do you tend to increase or decrease your on-time repayments on BNPL/do you tend to increase or decrease your consumption?” We categorize respondents into three groups based on their answers to five questions related to financial literacy. These questions cover their understanding of interest rates, inflation, compounding, time value of money, and knowledge of financial investments. Respondents who correctly answer 0-1, 2-3, and 4-5 questions are categorized into the low-, medium-, and high-level financial literacy groups, respectively. By this standard, we have 664, 696, and 146 respondents in each group, respectively.

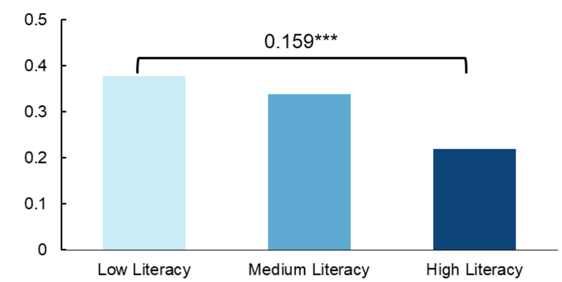
Panel A: Attitudes toward Consumption and Credit Records



(a) Agree with “Consuming Immediately and Not Saving for Tomorrow” (Yes=1)

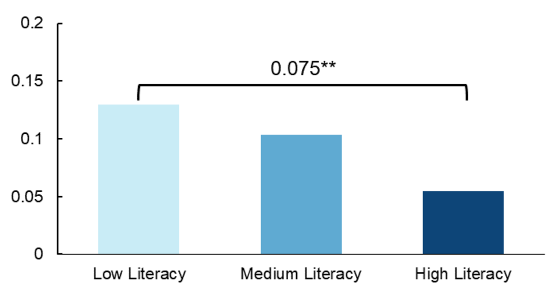


(b) Agree that “A Good Credit History is Important in Life” (Yes=1)

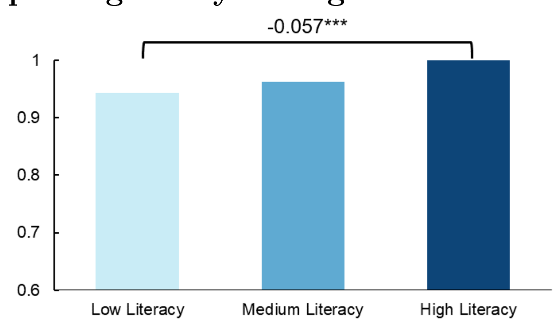


(c) Worried, Regardless of Whether You Default on BNPL (Yes=1)

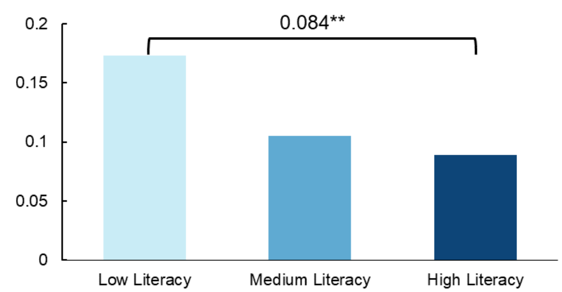
Panel B: Reactions to the Credit Reporting Policy Change



(d) Reduce BNPL usage (Yes=1)



(e) Increase or Do Not Change On-Time Repayments (Yes=1)



(f) Reduce Consumption (Yes=1)

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Table 1: Summary Statistics

Note: This table reports the summary statistics of the analysis sample. The sample contains 137,042 users spanning from May 2021 to May 2022, constituting a total of 1,693,706 observations. Panel A reports the cross-sectional 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 receives notifications regarding the credit reporting policy change during our sample period. $Authorization$ indicates whether a user signs the authorization form 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	Std.	Min	Max
Panel A. User Cross-Sectional 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					
BNPL usage dummy (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 the user-month panel data 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 the BNPL usage of consumer i in month t. We use three indicators to measure the BNPL usage: (1) BNPL usage dummy, a binary variable taking a 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. $post_t = 1$ equals 1 starting from October 2021, i.e., after the credit reporting policy change in September 2021, and 0 before. 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. ***, **, and * denote statistical significance levels of 1%, 5%, and 10%, respectively.

	Y = **BNPL Usage**		
	BNPL usage dummy (Yes=1) (1)	BNPL payment (ln) (2)	BNPL payment (share) (3)
PastDefault$_i$× post$_t$	-0.048*** (0.0055)	-0.242*** (0.0355)	-0.023*** (0.0037)
Mean of dep. var.	0.777	5.191	0.471
Observations	1,693,706	1,693,706	1,693,706
Adjusted R^2	0.602	0.663	0.614
User F.E.	Yes	Yes	Yes
City-month F.E.	Yes	Yes	Yes

Table 3: Impacts of Credit Reporting on Non-BNPL Usage

Note: This table shows the impacts of credit reporting policy on consumers' non-BNPL payments. The results are estimated by the following regression using the user-month panel data 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 the usage of other payment options of user i in month t via Alipay. We investigate the share of four alternative in-app payment options in total consumption: (1) e-Cash, (2) FinTech MMF (i.e., Yu'ebao), (3) credit card, and (4) debit card. $PastDefault_i$ indicates whether a user has a default record before the window period (before May 2021). $post_t = 1$ equals 1 starting from October 2021, i.e., after the credit reporting policy change in September 2021, and 0 before. 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. ***, **, and * denote statistical significance levels of 1%, 5%, and 10%, respectively.

	Y = **Share of Other In-App Payment Options**			
	e-Cash	FinTech MMF	Credit card	Debit card
	(1)	(2)	(3)	(4)
PastDefault$_i$× 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	1,693,706	1,693,706	1,693,706	1,693,706
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 4: Impacts of Credit Reporting on Consumption

Note: This table shows the impacts of credit reporting on BNPL users' consumption. We estimate the following regression using the the user-month panel data 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 (in natural logarithm) 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). $post_t = 1$ equals 1 starting from October 2021, i.e., after the credit reporting policy change in September 2021, and 0 before. 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. ***, **, and * denote statistical significance levels of 1%, 5%, and 10%, respectively.

	Y = **Consumption expenditures (ln)**		
	Total	Online	Offline
	(1)	(2)	(3)
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	1,693,706	1,693,706	1,693,706
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 on BNPL usage. We estimate the following regression using the user-month panel data 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 the usage of BNPL of user i in month t. We use three indicators to measure the BNPL usage in the Big Tech app: (1) BNPL usage dummy, a binary variable taking a 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). $post_t = 1$ equals 1 starting from October 2021, i.e., after the credit reporting policy change in September 2021, and 0 before. 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. ***, **, and * denote statistical significance levels of 1%, 5%, and 10%, respectively.

	(1) BNPL usage dummy (Yes=1)	(2) BNPL payments (ln)	(3) BNPL payments (share)
Panel A. By Age			
Young$_i$× post$_t$	-0.024***	-0.129***	-0.008***
	(0.0016)	(0.0114)	(0.0013)
Adjusted R^2	0.602	0.663	0.614
Panel B. By Consumption Level			
High$_i$× post$_t$	-0.020***	-0.349***	-0.002*
	(0.0016)	(0.0112)	(0.0013)
Adjusted R^2	0.602	0.663	0.614
Panel C. By Bank Credit Access			
BankCredit$_i$× post$_t$	-0.034***	-0.332***	-0.013***
	(0.0017)	(0.0122)	(0.0014)
Adjusted R^2	0.602	0.663	0.614
All Panels			
Mean of dep. var.	0.777	5.191	0.471
Observations	1,693,706	1,693,706	1,693,706
User F.E.	Yes	Yes	Yes
City-month F.E.	Yes	Yes	Yes

Table 6: Robustness Checks

Note: This table reports impacts of credit reporting on BNPL usage estimated by the following regression using the user-month panel data 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 the usage of BNPL of user i in month t. We use three indicators to measure the BNPL usage in the Big Tech app: (1) BNPL usage dummy, a binary variable taking a 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. $PastDefault_i$ 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). $post_t = 1$ equals 1 starting from October 2021, i.e., after the credit reporting policy change in September 2021, and 0 before. 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 of 1%, 5%, and 10%, respectively.

	(1) BNPL usage dummy (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	1,693,706	1,693,706	1,693,706
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 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 the user-month panel data 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 the 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 a 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 a 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) interest-bearing balance ratio, the share of average interest-bearing 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). $post_t = 1$ equals 1 starting from October 2021, i.e., after the credit reporting policy change in September 2021, and 0 before. 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. ***, **, and * denote statistical significance levels of 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
PastDefault$_i \times$ 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	1,693,706	1,693,706	1,299,498	1,482,843
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 8: Impacts of Credit Reporting on New BNPL Adoption

Note: This table reports the t-test results between users who adopt BNPL after September 2021 (i.e., post-policy adopters) and those who adopt BNPL before September 2021 (i.e., pre-policy adopters). For each month from September 2020 to September 2022, we extract 1,000 users who adopt BNPL in the given month, constituting 12,000 post-policy adopters and 12,000 pre-policy adopters. Panel A compares user characteristics. Panel B compares the relative months of BNPL adoption since the Alipay (Huabei) registration. Panel C compares first-month behaviors upon adoption. The fourth part compares users' probability of having previous default records as of November 2023. We report the differences between the two groups and the *t-test* results in the last column. All continuous variables are winsorized at the 1% and 99% levels. We use *** for p<0.01, ** for p<0.05, and * for p<0.1.

	New BNPL Adoption		**Diff.**
	After 2021.9	Before 2021.9	After - Before
Panel A. User Characteristics			
Age	38.998	37.067	1.931***
Gender (Male = 1)	0.591	0.591	0.0002
Panel B. Time until BNPL Adoption			
Months since Alipay registration	43.793	34.592	9.202***
Months since Huabei registration	15.419	8.627	6.792***
Panel C. First-Month Behaviors upon Adoption			
BNPL payment (ln)	8.853	8.950	-0.097***
BNPL payment (share)	0.526	0.551	-0.025***
Panel D. Default Probability (as of November 2023)			
Having a default record	0.125	0.200	-0.075*

Table 9: Responses by Creditworthiness/Financial Health

Note: This table reports the t-test results between respondents with self-reported default records (98 respondents) and respondents without self-reported default records (1,408 respondents) using 1,506 survey responses in March 2024. Panel A compares demographics and annual income, Panel B compares current debt status, and Panel C compares reactions to the credit reporting regulation. *Nonfarm employment* = 1 if a respondent has signed a formal labor contract or operates his or her own business. *High Income* = 1 if a respondent's disposable annual income exceeds 100,000 RMB. *Having debt/long-term debt/short-term debt* = 1 if a respondent has unpaid debt/long-term debt/short-term debt, where long-term debts include mortgages and car loans and short-term debts include consumer loans and private borrowings. We also use responses to the survey questions "After the credit reporting regulation, do you tend to increase or decrease your BNPL usage/do you tend to increase or decrease your on-time repayments on BNPL/do you tend to increase or decrease your consumption?". We report the means of each group in Columns (1)-(2) and the differences and *t-test* statistical significance in Column (3). We use *** for p<0.01, ** for p<0.05, and * for p<0.1.

	(1) Respondents w/ previous defaults	(2) Respondents w/o previous defaults	(3) **Diff.** (1)-(2)
Panel A. Demographics and Income			
Urban (Yes=1)	0.398	0.590	-0.192***
College completion (Yes=1)	0.490	0.698	-0.208***
Nonfarm employment (Yes=1)	0.758	0.859	-0.101***
High income (Yes=1)	0.276	0.413	-0.137***
Panel B. Indebtedness			
Having debt (Yes=1)	0.633	0.455	0.178***
Having long-term debt (Yes=1)	0.082	0.171	-0.090**
Having short-term debt (Yes=1)	0.551	0.283	0.268***
Panel C. Reaction to BNPL's Credit Reporting			
Reduce BNPL usage (Yes=1)	0.225	0.102	0.122**
Increase timely repayments (Yes=1)	0.561	0.479	0.082
Reduce consumption (Yes=1)	0.296	0.122	0.174***

A Internet Appendix

A.1 Survey Design and Data Collection

We conduct a survey on Alipay, i.e., the digital payment platform that provides the focal BNPL product, to complement our main analysis. We design four sections of questions in the survey questionnaire: (1) individual characteristics, including demographics, borrowing history, and previous default records on BNPL and any other credit sources; (2) BNPL usage habits, including the reasons for using or not using BNPL; (3) financial literacy, measured by commonly-used questions on compounding, interest rates, inflation, and investment; and (4) self-reported behavioral changes after the credit reporting regulation. We ask whether consumers are aware of this policy change, whether and how the policy affects their behaviors, and their attitudes toward BNPL and credit reporting.

The survey was conducted in March 2024 by sending notifications in the Alipay app to encourage targeted users to participate in the survey. The targeted users are randomly selected from the following three groups of Alipay users: (1) those who have not opened BNPL accounts (*non-BNPL consumers*); (2) those who have used BNPL infrequently, defined as less than once a month (*inactive BNPL consumers*); and (3) those who use the BNPL service at least once a month (*active BNPL consumers*). All respondents are above 18 years old and eligible to apply for BNPL services. Moreover, the rejection rate of Huabei is very low and BNPL applicants can obtain approval quickly, although the line of credit may be small. We provide small monetary rewards to those respondents who complete the survey.

We obtain 1,506 responses, with a response rate of approximately 15%, which is calculated by dividing the number of survey respondents by the number of Alipay users who receive in-app notifications. This response rate is comparable to that in previous studies using online platforms to distribute surveys (Epper et al., 2020; Barry et al., 2022; Hvidberg et al., 2023). As shown in Table A1, the demographics of survey respondents are comparable to those of our main analysis sample. Approximately 49.8% of the respondents are male (compared with 53.3% in the main analysis sample); the average age is approximately 31.6 years old, very close to the mean value of 32.9 years in the empirical analysis sample; the fractions of consumers living in Tier 1 and Tier 2 cities are also comparable between the two samples.

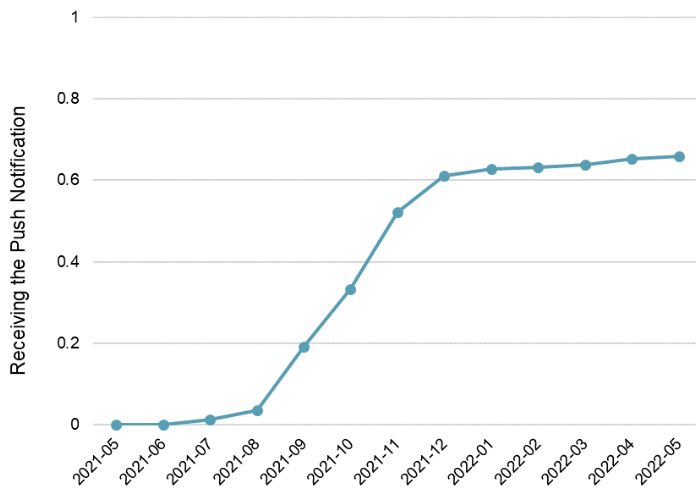
Table A1: Comparison between the Randomly Selected Sample and the Survey Respondent Sample

Note: This table reports the cross-sectional summary statistics of the randomly selected sample used in our main empirical analysis and the survey respondent sample. The empirical analysis sample contains 137,042 users. The survey sample contains 1,506 users. The standards for Tier 1 and Tier 2 cities are consistent with the National Bureau of Statistics of China. Tier 1 cities include Beijing, Shanghai, Guangzhou, and Shenzhen. Tier 2 cities include Tianjin, Shijiazhuang, Taiyuan, Hohhot, Shenyang, Dalian, Changchun, Harbin, Nanjing, Hangzhou, Ningbo, Hefei, Fuzhou, Xiamen, Nanchang, Jinan, Qingdao, Zhengzhou, Wuhan, Changsha, Nanning, Haikou, Chongqing, Chengdu, Guiyang, Kunming, Xi'an, Lanzhou, Xining, Yinchuan, and Urumqi.

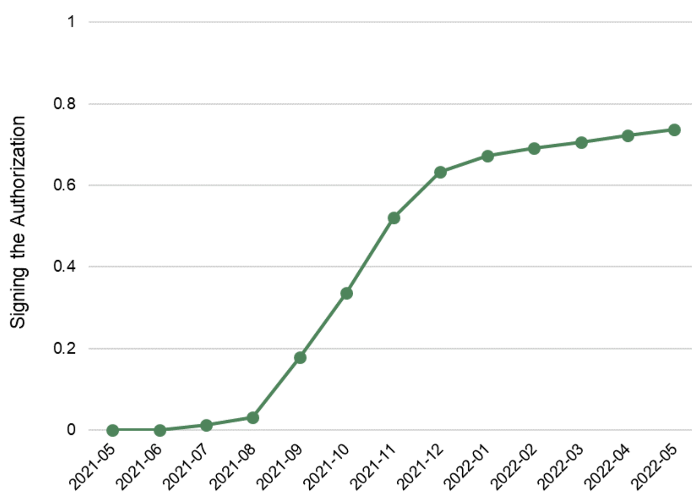
	Randomly selected sample	Survey respondent sample
Age	32.854	31.575
Gender (Male = 1)	0.533	0.498
Residing in Tier 1 cities	0.068	0.057
Residing in Tier 2 cities	0.229	0.181

Figure A1: Users' 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 and who have signed the authorization agreement using the user-month panel data of 1,693,706 observations between May 2021 and May 2022. Panel A presents the cumulative fraction of users who have received the push notification of the credit reporting policy change. Panel B presents those users who have signed the authorization agreement, conditional on receiving the push notification.



Panel A: Timeline of Receiving the Push Notification



Panel B: Timeline of Signing the Authorization Form

Figure A2: Impacts on the BNPL Credit Line

Note: This figure plots the changes in BNPL credit lines. The results are estimated by the following regression using the user-month panel 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% confidence intervals. The vertical dashed line indicates the month of the policy change (i.e., September 2021).

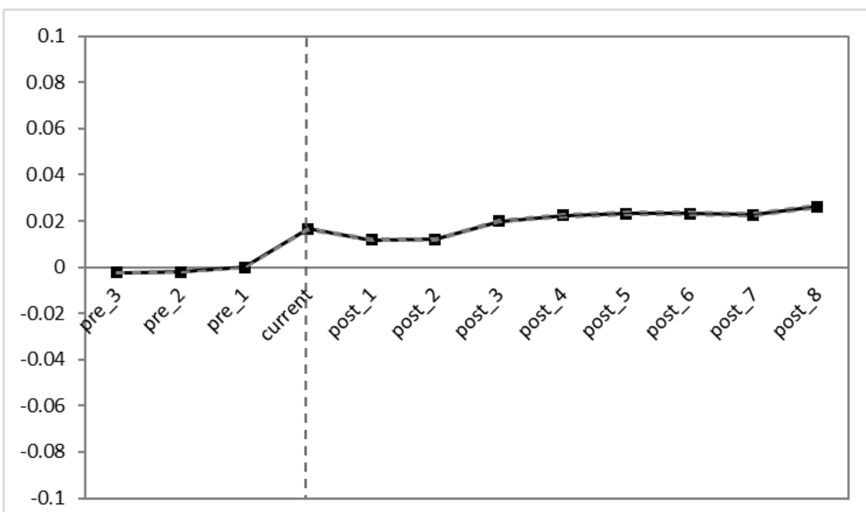


Figure A3: Subsample Analysis: Borrowers Who Use BNPL Credit Every Month

Note: This figure plots the impacts of credit reporting policy on the BNPL payment share using a user-month panel subsample of users who use BNPL every month. The subsample contains 699,897 observations between May 2021 and May 2022. The results are estimated by the following regression:

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

Y_{it} measures the BNPL payment share of user i in month t. The BNPL payment share is the proportion of BNPL payment in total consumption via Alipay. 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).

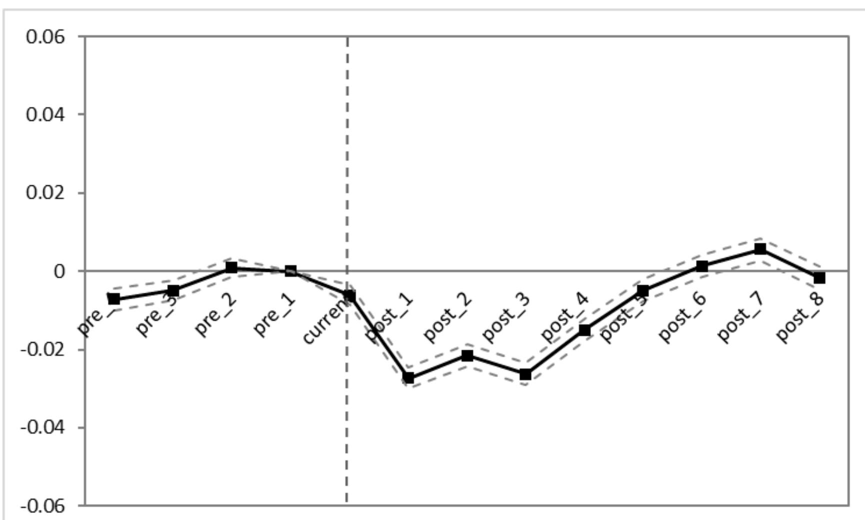
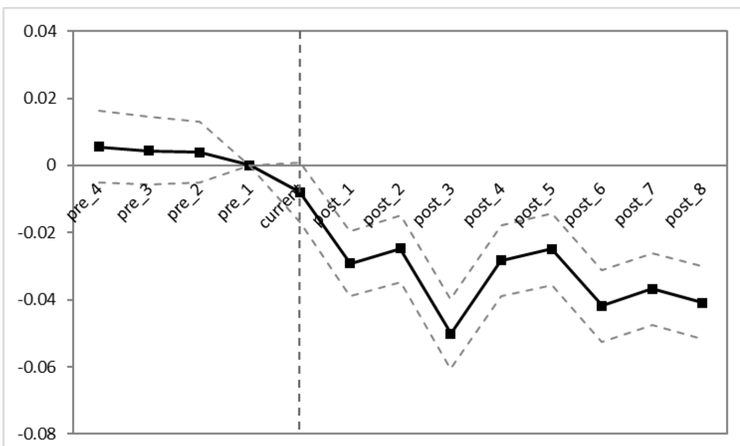


Figure A4: Impacts on Default: Dynamic DID (Alternative Default Measures)

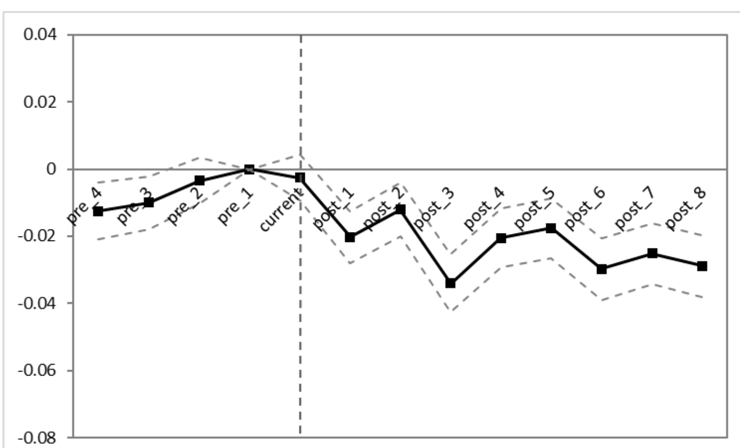
Note: This figure plots the impacts of the credit reporting policy on defaults using a dynamic difference-in-difference (dynamic DID) model. The results are estimated by the following regression using the user-month panel data of Huabei users between May 2021 and May 2022:

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

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, then the default indicators 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% 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 A5: 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 of five choices).". We provide fifteen options and present the top ten options selected by consumers. The survey includes 1,506 responses from Alipay consumers in March 2024. The horizontal axis represents the options, and the vertical axis represents the number of respondents who chose each option.

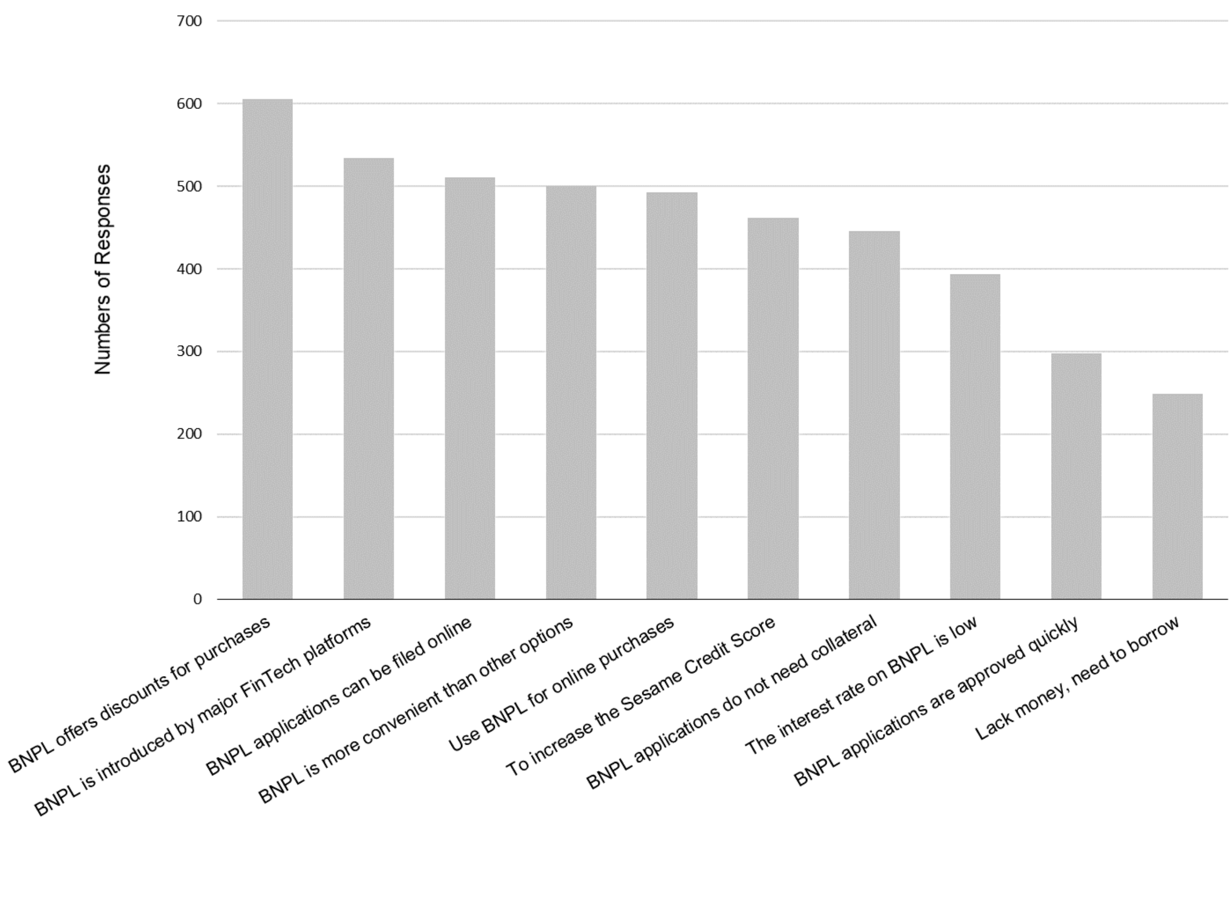


Figure A6: Consumers' Attitude toward BNPL and Credit Reporting

Note: This figure plots responses to the survey question "Are you worried that using BNPL would have a negative impact on your credit records?". We provide three options: 1) worried, regardless of whether you default on BNPL; 2) not worried, regardless of whether you default on BNPL; and 3) worried only if you default on BNPL. The survey includes 1,506 responses from Alipay consumers in March 2024. The horizontal axis represents the options, and the vertical axis represents the number of respondents who choose a certain option.

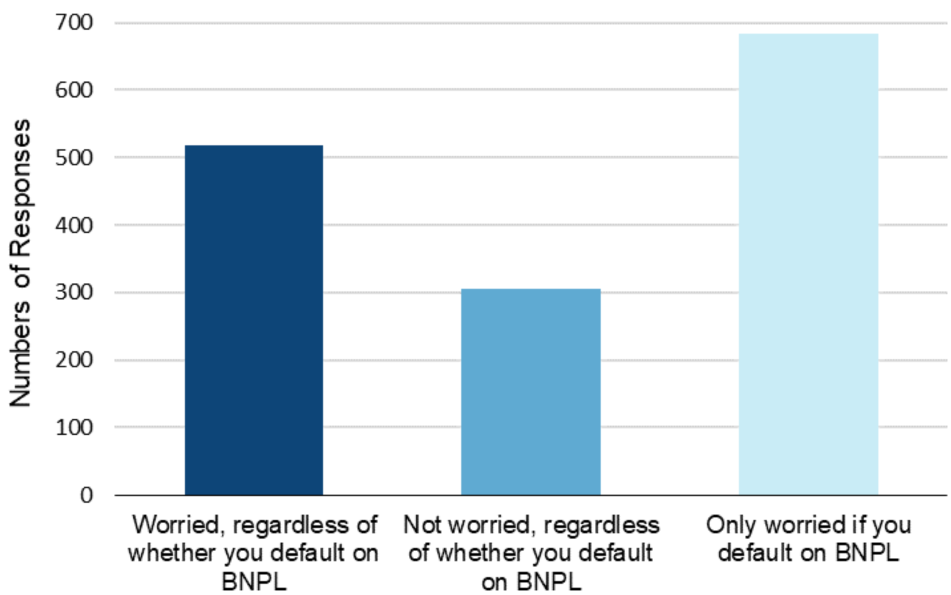
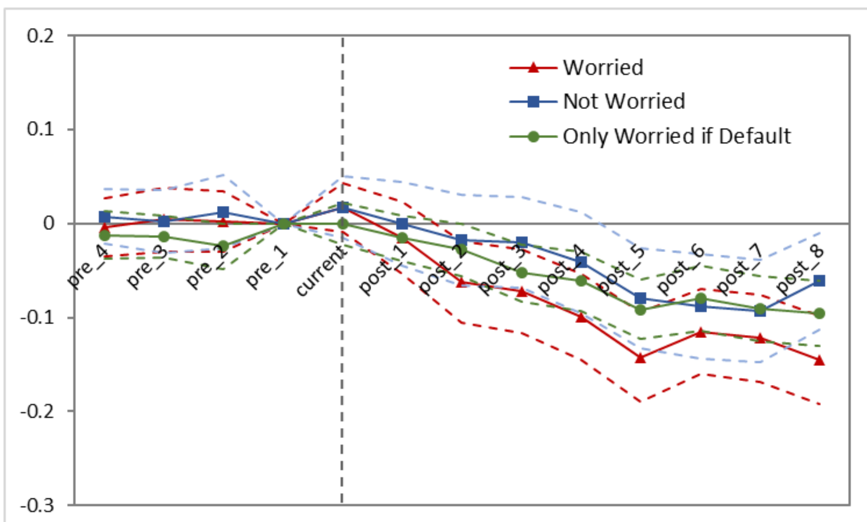


Figure A7: Survey Respondent Behaviors: Heterogeneity by Attitude toward BNPL and Credit Reporting

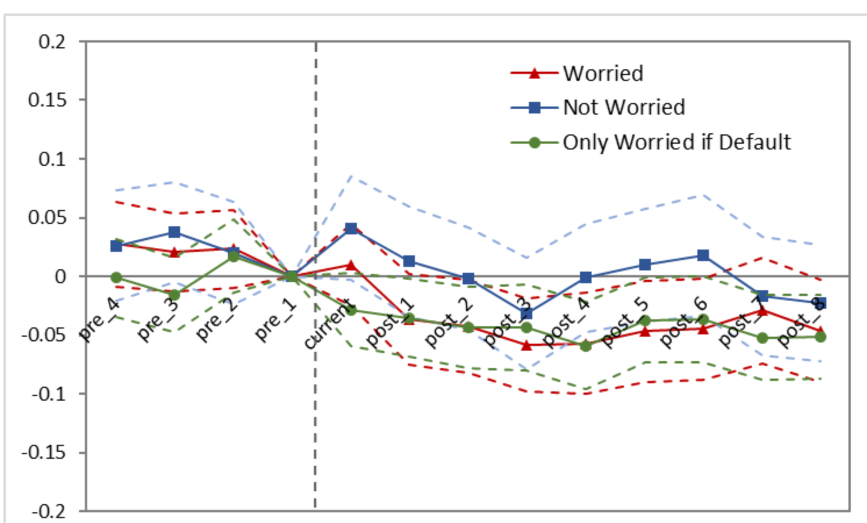
Note: This figure plots the heterogeneous impacts of the credit reporting policy on BNPL usage using the respondent sample. We divide the sample into three subsamples based on their attitude toward credit reporting (responses to the survey question "Are you worried that using BNPL credit will have a negative impact on your credit records?"). The results are estimated by the following regression:

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

Y_{it} measures the BNPL usage of consumer i in month t. The red line represents the estimated results for the subsample of users who are worried about the negative impact of BNPL on credit records regardless whether they default (3,957 observations between May 2021 and May 2022). The blue line represents the estimated results for the subsample of users who are not worried regardless whether they default (2,543 observations between May 2021 and May 2022). The green line represents the estimated results for the subsample of users who are worried only if they default (5,369 observations between May 2021 and May 2022). The dashed lines represent the upper and lower bounds of the 95% confidence intervals.



(a) BNPL Usage Dummy (Yes = 1)



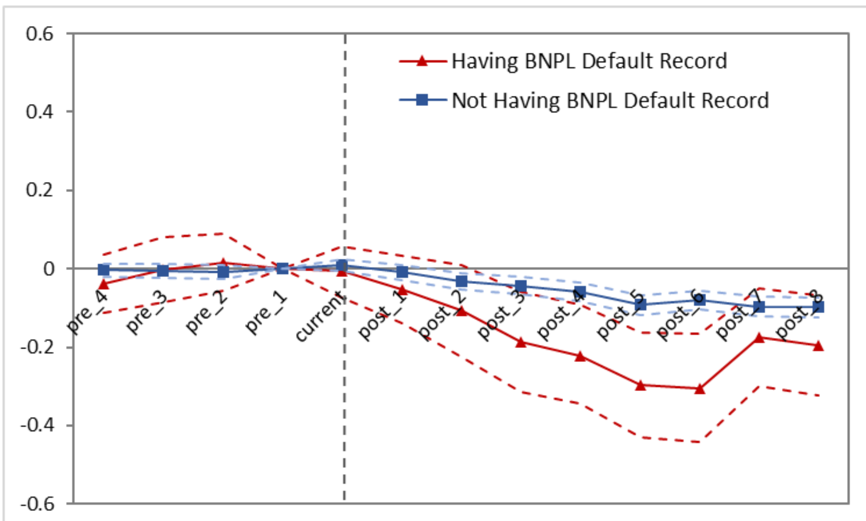
(b) BNPL Payment Share

Figure A8: Survey Respondent Behaviors: Heterogeneity by Previous Default Records

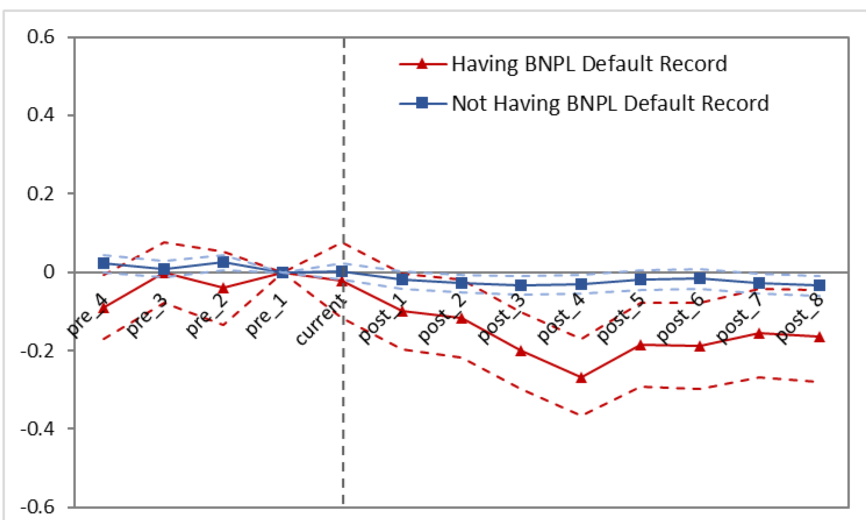
Note: This figure plots the heterogeneous impacts of the credit reporting policy on BNPL usage using the respondent sample. We divide the sample into two subsamples based on the self-reported default records. The subsample of users with BNPL default records contains 771 observations between May 2021 and May 2022, and the subsample of users without BNPL default records contains 11,098 observations between May 2021 and May 2022. The results are estimated by the following regression:

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

Y_{it} measures the BNPL usage of consumer i in month t. 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 red line represents the estimated results for the subsample of users with BNPL default records. The blue line represents the estimated results for the subsample of users without BNPL default records. The dashed lines represent the upper and lower bounds of the 95% confidence intervals.



(a) BNPL Usage Dummy (Yes = 1)



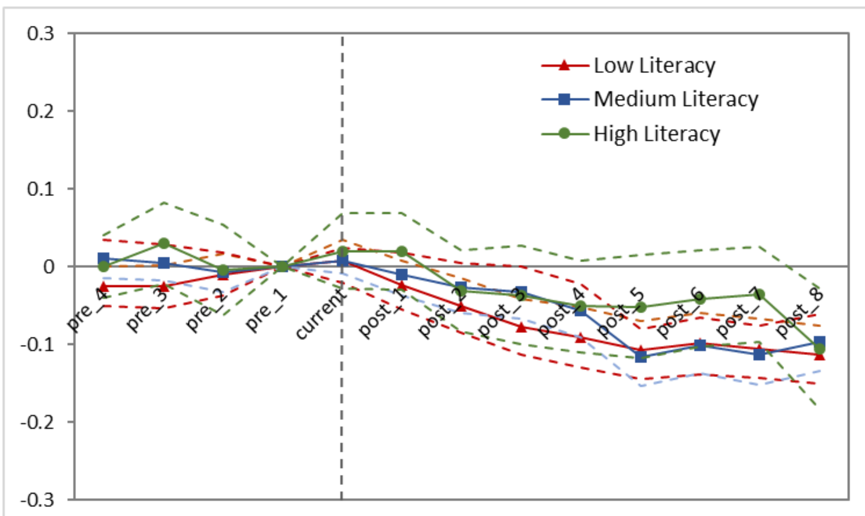
(b) BNPL Payment Share

Figure A9: Survey Respondent Behaviors: Heterogeneity by Financial Literacy

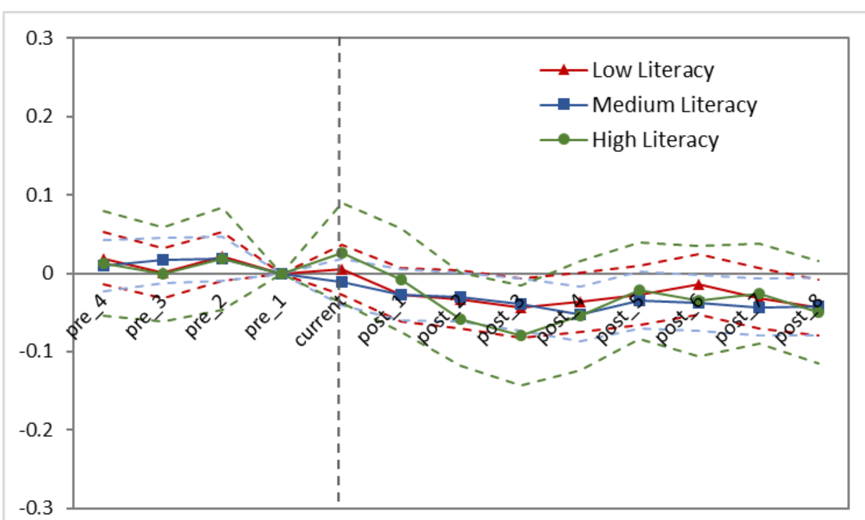
Note: This figure plots the heterogeneous impacts of the credit reporting policy on BNPL usage using the respondent sample. We divide the sample into three subsamples based on financial literacy. The results are estimated by the following regression:

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

Y_{it} measures the BNPL usage of consumer i in month t. 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 red line represents the estimated results for the subsample of users with low levels of financial literacy (5,633 observations between May 2021 and May 2022). The blue line represents the estimated results for the subsample of users with medium levels of financial literacy (4,966 observations between May 2021 and May 2022). The green line represents the estimated results for the subsample of users with high levels of financial literacy (1,270 observations between May 2021 and May 2022). The dashed lines represent the upper and lower bounds of the 95% confidence intervals.



(a) BNPL Usage Dummy (Yes = 1)



(b) BNPL Payment Share