Journal of Empirical Finance 81 (2025) 101592

Contents lists available at ScienceDirect

Journal of Empirical Finance

journal homepage: www.elsevier.com/locate/jempfin

# Unveiling the villain: Credit supply and the debt trap

Shun Fu [a], Emma Li [b], Li Liao [c], Zhengwei Wang [c], Hongyu Xiang [d,*]

[a] School of Finance, Nanjing Audit University, Nanjing, Jiangsu, China
[b] Business School, Deakin University, Melbourne, Australia
[c] PBC School of Finance, Tsinghua University, Beijing, China
[d] Business School, Beijing Normal University, Beijing, China

ARTICLE INFO

*JEL Classification:*
**D12**
**G21**
**I3**

*Keywords:*
Credit supply
Debt trap
Cash loan
Consumer finance
FinTech

ABSTRACT

Based on unique data containing the loan history and online consumption information of cash loan borrowers, we apply an exogenous credit supply shock to these borrowers and show that increased credit increases individuals' delinquency rates and reliance on cash loans. Higher credit supply increases the likelihood of a loan being overdue over 60 days by 5.7% and decreases platform exit by 33%. This effect on delinquency is significantly less prominent among individuals with greater financial literacy. Second, we demonstrate that credit expansion is positively associated with an increase in subsequent borrower consumption, particularly addictive consumption.

## 1. Introduction

With technologically advancements, unsecured consumer debt has grown significantly worldwide over the last five years. In the U. S., outstanding consumer credit rose by 23.1% from 2015 to reach USD 4.18 trillion at the end of 2020, and was 28% of total debt issued to consumers (14.56 trillion).[1] The consumer credit market has expanded even more dramatically with the boom in the FinTech industry in emerging markets. For example, China's outstanding short-term consumer loans issued by commercial banks increased by 115% from 2015 to 2020.[2] In India, the growth rate of consumer loans between 2017–2021 fiscal years was 91%. However, with the rapid consumer credit expansion, there are also many delinquent consumer loans. At the end of 2020, the U.S. had USD 349 billion in seriously delinquent consumer loans (90 days late or severely derogatory).[3] China's outstanding credit loans that were at least six months overdue totaled CNY 83.9 billion in 2020, an increase of over 100% since 2015. 6.5% of India's outstanding personal loans are at least 30 days late. Considering the rapidly growing market and delinquencies, understanding the impact of access to consumer credit, especially on financial distress and loan delinquency, can significantly shape the decision-making of economists and policy-makers, especially in emerging economies.

The effects of access to consumer credit on individual default decisions and welfare have been controversial topics in the literature.

* Corresponding author at: Beijing Normal University, Haidian, Beijing, China 100875.
*E-mail address:* xianghy@bnu.edu.cn (H. Xiang).

[1] The outstanding loan data are collected from the U.S. Federer Reserve's Consumer Credit Historical Data. The total debt of consumers is extracted from the Household Debt and Credit Report 2020Q4, Federal Reserve Bank of New York.

[2] The data on China's outstanding loans and delinquencies are collected from the People's Bank of China.

[3] The data on loan delinquencies in the U.S. are collected from the Household Debt and Credit Report 2020Q4, Federal Reserve Bank of New York.

https://doi.org/10.1016/j.jempfin.2025.101592
Received 24 November 2023; Received in revised form 4 September 2024; Accepted 28 January 2025
Available online 31 January 2025
0927-5398/

Some researchers find that access to more credit provides liquidity to credit-constrained consumers, thereby improving their ability to smooth consumption (Dobridge, 2018). However, other researchers argue that consumer credit is usually costly for credit-constrained households. Rather, expanding consumer credit supply may exert a high debt burden on these borrowers, resulting in negative welfare effects (Melzer, 2011; Campbell et al., 2012; Gathergood et al., 2019).

In this paper, we examine the effect of consumer credit on individual's repayment behavior and consumption pattern in China in a quasi-natural experiment that provides an exogenous shock to borrowers' credit limits, by using a novel dataset combining individuals' borrowing activities with their consumption records from Alibaba's e-commerce platforms Taobao and Tmall.

This research is especially important in emerging markets, where the consumer credit market has expanded dramatically with the booming FinTech industry. With technological advancements, a new form of high-interest consumer credit, "cash loan," has aroused increasing concern in recent years in China. These loans are small, short-term, unsecured consumer loans for individuals. A cash loan's typical annual percentage rate (APR) is above 100%. The funding and repayment procedures for cash loans are typically conducted online. Underdeveloped financial systems and FinTech development in emerging markets have contributed to the growth of the cash loan industry. In 2017, when China's cash loan market peaked, over 2,600 cash loan platforms facilitated cash loans to approximately 10 million borrowers. Most cash loan borrowers are unserved or underserved by commercial banks, which, as Karlan and Morduch (2010) argue, find it difficult to provide credit access profitably to credit-constrained borrowers. The entire market size was estimated to be larger than CNY 1 trillion. Though it has grown rapidly, cash loan lending has been criticized because of its high borrowing cost, invasion of privacy, and abusive debt collection.

Despite the current headwinds in cash loan lending, the cash loan industry's growth has provided a unique setting and data-rich environment for conducting a targeted experiment. Most cash loan platforms collect borrowers' information, such as phone numbers, online shopping records, gender, age, and borrowing and repayment behaviors. Thus, using these readily available borrower attributes, we extract a unique comprehensive dataset from a large Chinese cash loan platform where borrowers can borrow and repay cash loans online. Our data include borrower characteristics, as described above, as well as borrowing and repayment records, and online shopping information. To explore the causal effect of consumer credit supply, we use an experiment conducted by the cash loan platform on existing and new cash loan borrowers in late April 2016. Specifically, the provider selected borrowers and increased their credit limits permanently by over CNY 2,000 on average in the experiment, providing us with a rare opportunity to identify the causal effect of consumer credit supply.

In our analysis and breakdown of the experiment's results, we employ stratification in the field experiment and randomly drop observations from the sample to remove the differences between the treatment and control groups. Based on this methodology, we focus on the effect of the consumer credit supply resulting in loan delinquency. As argued by Bhutta (2014) and Gathergood et al. (2019), this is considered evidence of declining financial health.

Our findings are summarized as follows: First, we confirm that this credit limit expansion significantly increases treated customers' borrowing. Our empirical analysis provides evidence that treated borrowers increase their borrowing right after the additional consumer credit supply compared to the control group borrowers. In the first two fortnights after the experiment, access to more consumer credit increases the borrowing amount by approximately CNY 641 per fortnight (or CNY 1,282 in total). The effect on the borrowing amount lasts as long as 16 weeks after the experiment.

Second, we find supporting evidence that higher consumer credit supply increases loan delinquency. Compared to the control group, the treated borrowers have a 5.7 percentage points higher probability of loans that are due 60 days or longer. We argue that obtaining more high-interest credit lines may impose an extra financial burden on borrowers and significantly increase their likelihood of descending into a "debt trap." We find some relevant supporting evidence for this. First, higher credit supply increases the likelihood of staying longer on the cash loan platform; second, the treated borrowers increase the number of new loan applications after obtaining access to higher consumer credit supply.

Next, we show that higher consumer credit supply increases online consumption, especially addictive consumption. By employing the difference-in-differences (DiD) approach, we find that the treated borrowers with increased credit limits significantly increased their online shopping by CNY 375 in the first month after the experiment compared with controlled borrowers. This result is consistent with Kaboski and Townsend (2011), who predict a positive consumption response to credit supply for credit-constrained borrowers. The marginal propensity of consumption out of liquidity (MPC-L) in our study is approximately 17.5% in the first pre-experiment month, consistent with the positive MPC-L documented by Gross and Souleles (2002). Our estimate provides a lower bound estimate on MPC-L as borrowers might also purchase products on other online platforms or offline. The relative magnitude of the consumption effect is particularly prominent for addictive consumption: spending on addictive goods increased by CNY 27 in the first month after the experiment, approximately 66% of the sample mean. Considering that addictive consumption is likely to be related to weaker self-control, and thus, leads to a negative welfare effect, we document further supporting evidence that access to high-interest credit may have negative welfare implications.

Moreover, we explore whether this loan delinquency effect varies with one particular aspect of borrowers' characteristics: financial literacy. Many argue that it plays an important role in default decisions when a borrower is facing credit expansion. We leverage the detailed consumption data from each borrower and construct a new variable as a proxy for borrowers' financial literacy, which is otherwise difficult to measure. We provide supporting evidence that the loan delinquency effect is more prominent among consumers with lower financial literacy, as measured by expenditures on financial education and knowledge products one year before the experiment. For borrowers with no consumption of financial education or knowledge products, the marginal effect of credit supply on the probability of being overdue on a loan 60 days or longer is 8.1 percentage points, compared to the marginal effect of -2.7 percentage points for borrowers with financial education expenditure.

To the best of our knowledge, this study is among the first to use random expansion of credit supply as an exogenous shock to examine the causal effect of high-interest consumer credit supply on loan delinquencies. Studies have exploited indirect exogenous shocks to the consumer credit supply, such as regulatory differences across states (Melzer, 2011; Melzer, 2018), field experiments (Karlan and Zinman, 2010), and discontinuities in the likelihood of obtaining consumer credit (Gathergood et al., 2019). In the microcredit literature, Banerjee et al. (2015) and Karlan and Zinman (2010) use randomized control trials to study the impact of access to microcredit on borrowing, spending, and business creation. Aydin (2022) uses a large-scale field experiment with randomized credit limits for credit card holders in Turkey to explore the effects of consumer credit access on spending, contract choice, and balance sheets. Our research is set in an environment where borrowers typically face credit constraints and high interest rates. Therefore, it is plausible that our conclusions could be applicable in similar contexts, such as payday lending in the US and the UK (Cuffe and Gibbs, 2017; Gathergood et al., 2018; Melzer, 2011; Morgan et al., 2012; Morse, 2011), and cash loans in South Africa (Karlan and Zinman, 2010). We contribute to this literature by demonstrating how directly increasing the consumer credit supply affects loan delinquency. By examining how high-interest credit access affects loan performance, our study broadly relates to the literature on characteristics associated with loan performance, including education (Brown et al., 2016), relationship banking (Agarwal et al., 2018), borrower misreporting (Garmaise, 2015), appearance (Duarte et al., 2012), and social interaction (Lin et al., 2013). This paper also connects broadly to researches on the impact of fintech adoption on Chinese households. Recent studies have found evidence that fintech adoption boosts household consumption (Yang and Zhang, 2022), stabilizes consumption patterns (Huang et al., 2023), increases earnings among rural households (Cai et al., 2024), encourages risk-taking (Hong et al., 2020), and enhances women's intra-family bargaining power (Han et al., 2023). Our findings on the positive effects of credit supply on online shopping align with those of Yang and Zhang (2022). Furthermore, we contribute to this field by exploring how credit supply impacts loan delinquencies and addictive consumption, potentially affecting family welfare in China.

Secondly, this study adds to the debate on the welfare effect of the consumer credit supply on financially constrained borrowers, especially in emerging markets. Studies document both the positive and negative welfare effects of access to consumer loans, especially high-interest loans like payday loans. On the one hand, access to consumer credit, may have a negative welfare effect for several behavioral reasons, such as cognitive biases (Bertrand and Morse, 2011) and exponential growth bias (Stango and Zinman, 2009). Researchers show that access to more credit increases hardship in paying mortgages, rent, and utility bills (Melzer, 2011), and impairs military readiness (Carrell and Zinman, 2014). Access to consumer credit can also increase the likelihood of involuntary bank account closures (Campbell et al., 2012), bankruptcy rates (Morgan et al., 2012), delayed repayments (Gathergood et al., 2019), suicides (Lee, 2019), and increased liquor sales (Cuffe and Gibbs, 2017). On the other hand, increasing the consumer credit supply may positively affect borrower welfare by increasing borrowers' choice sets (Melzer, 2011), reducing foreclosures and crimes after natural disasters (Morse, 2011), decreasing bank overdrafts (Zinman, 2010), and improving food consumption, economic self-sufficiency, mental health (Karlan and Zinman, 2010), self-employment (Augsburg et al., 2015; Herkenhoff et al., 2019), consumption smoothing (Dobridge, 2018), labor market activities, and income levels (Bruhn and Love, 2014). Our study complements this literature by showing that the consumer credit supply may negatively affect individual welfare by increasing the loan delinquency rate.

Finally, this study contributes to the financial distress literature by documenting the effect of the consumer credit supply on financial distress and how this effect varies with borrowers' financial literacy. This literature can be separated into two streams. One stream emphasizes the impact of local institutional and economic factors on financial distress, such as state-level bankruptcy laws (Fay et al., 2002) and local economic shocks (Agarwal and Liu, 2003). The second stream investigates the relationship between individual characteristics and financial distress, such as risk preference (Gathergood et al., 2019), social capital (Agarwal et al., 2011), and other behavioral characteristics (e.g., financial literacy and self-control; Gathergood, 2012).

The remainder of this article is organized as follows: Section 2 presents the institutional background. Section 3 introduces our dataset and empirical strategy. The empirical results are presented in Section 4. Section 5 presents the conclusion of this study.

## 2. Institutional Background

### *2.1. Cash loan lending industry*

In this article, "cash loans " refer to small, short-term, unsecured consumer loans offered by non-banking institutions. Given the underdeveloped banking and credit systems in emerging markets, many individuals do not have access to loans from commercial banks.[4] Cash loans are an important funding channel for these credit-constrained consumers in several emerging countries. For instance, in India, small ticket personal loans (STPL), referring to loans whose size is less than 100,000 rupees (approximately USD 1,300) increased by 200% from 2017 to 2021.[5] STPLs have high borrowing costs (approximately 15% monthly) and high delinquency rates (8.8% of the outstanding loan amount is overdue for 30–180 days). Non-bank finance companies are the dominant lenders of STPL, accounting for 80% of the STPL loans. In China, between 2015 and 2017, the cash loan industry was unregulated, and the monthly cash loan lending volume increased from USD 130 million in January 2016 to approximately USD 2 billion at its peak in

[4] For example, the number of credit cards per capita was 0.29 in 2015, suggesting that over 71% of individuals do not have credit cards. Based on data from the China Household Finance Survey (Gan et al., 2013), 58.9% of families in need of bank liquidity cannot obtain loans from commercial banks.

[5] The data of the STPL industry are collected from "How India Lends 2021 Report: Credit Landscape in India FY 2021," released by CRIF, https://www.crifhighmark.com/media/2362/how-india-lends-fy2021.pdf.

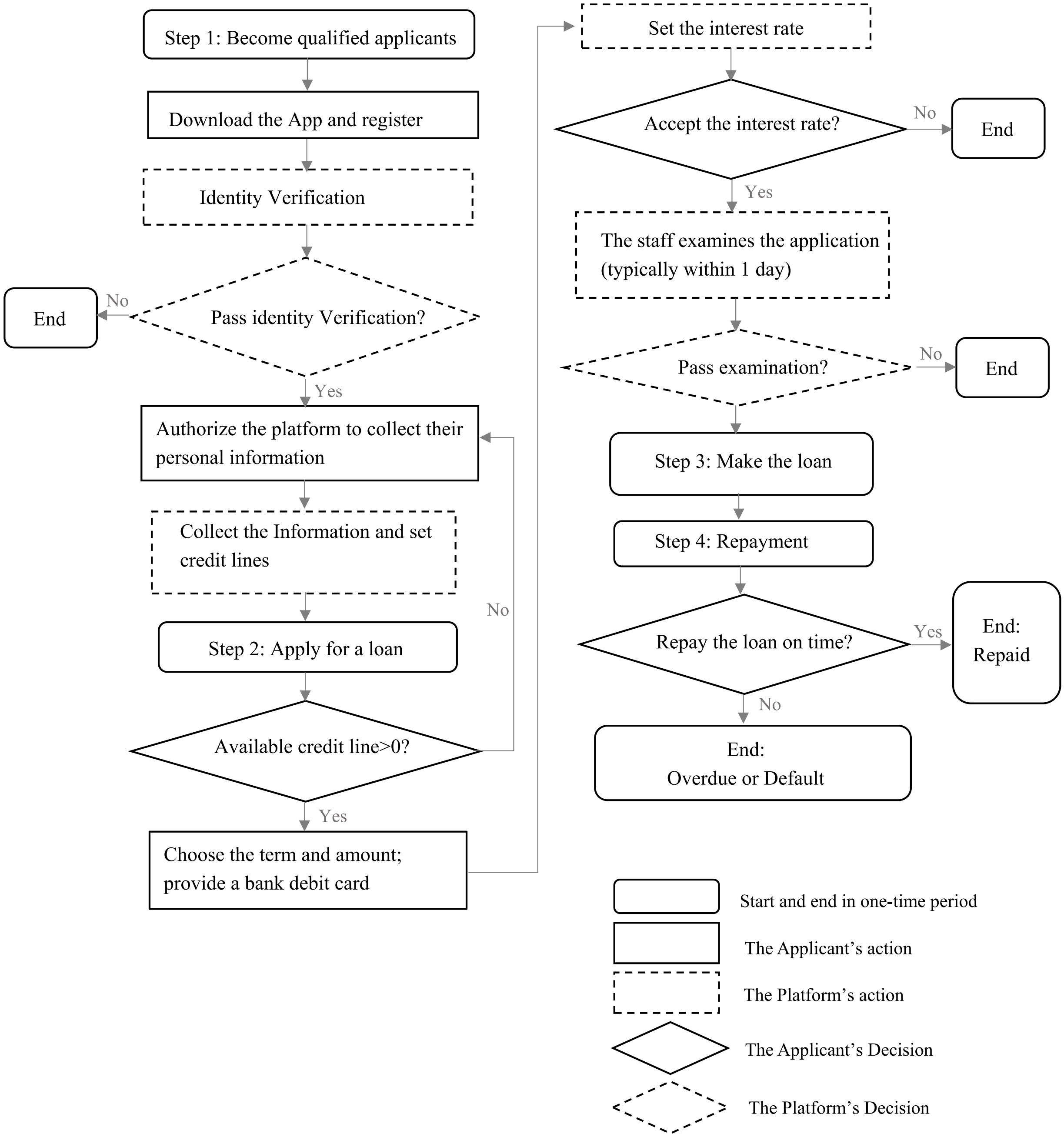


**Fig. 1.** Flow Chart of the Lending Procedure on the Platform.

October 2017.[6] Approximately 10 million Chinese individuals take cash loans. [7] Cash loans are usually made for a maturity of 7–180 days at less than CNY 1,400 (USD 300), with an extremely high APR of over 100%. Young males under 40 account for approximately 70% of cash loan borrowers. South Africa also has a cash loan industry offering consumer credit to credit-constrained individual borrowers (Karlan and Zinman, 2008; Karlan and Zinman, 2010).

Notably, cash loan lending has aroused controversy and criticism due to its negative consequences. For instance, cash loans impose a high financial burden on low-income borrowers who cannot repay this high-cost debt, and consequently, more likely to slip into a debt trap. In addition, some cash loan platforms collect borrowers' private information for risk management, leading to widespread

[6] Please see https://www.wdzj.com/news/yc/1458892.html for details.
[7] The report is available at https://www.ifcert.org.cn/industry/187/IndustryDetail.

concern that this information can be misused. Some cash loan providers engage in abusive debt collection such as repetitious phone calls to defaulted borrowers and their relatives and friends.

Given these controversial practices, Chinese regulators have issued rules to limit the rampant growth of the industry. Since late 2017, regulatory authorities intensified their scrutiny of the cash loan lending sector. This included bans on practices such as encouraging excessive borrowing, employing aggressive debt collection tactics, and misappropriating customers' private data. Following these regulatory measures, the cash loan lending industry in China has seen a significant downturn, with numerous providers reducing their lending activities to nearly non-existent levels. Nevertheless, the cash loan industry remains robust in other emerging markets. Therefore, it is crucial to assess whether cash loan lending has positive or negative impacts in these regions.

### 2.2. The cash loan platform and data provider

We cooperated with a leading Chinese cash loan platform. Founded in 2014, this platform grew into a market leader in 2016. The platform offers cash loans with an average size of CNY 1,000 and an average maturity period of six months.[8] We cannot access the exact interest rates of these cash loans since the platform refuses to disclose this information.

The funding procedure for cash loans proceeds as follows (See Fig. 1): Loan applicants download the cash loan platform's app on their mobile device and sign up with their phone number. They are then requested to upload photocopies of their ID cards for identity verification. Subsequently, the applicant is asked to sign a consent form that allows the platform to collect their gender, age, and complete transaction records on Alibaba's e-commerce platforms, mobile phone call records, and other information related to credit quality. Next, the platform uses its internal credit evaluation system to assess the applicants' credit quality, calculate their credit scores, and determine credit lines for each applicant. The applicants choose the loan amount and maturity level. Then, the system automatically computes the interest rate based on the applicant's internal credit score. If the resulting interest rate is acceptable to the applicants, they can choose to access the loan. Funds are then deposited in the applicant's bank accounts. In general, the entire funding process takes less than one day.

When borrowers do not repay on time, the debt collection procedure starts: platform staff make a phone call to the borrowers and to individuals who are listed as contacts (usually the borrower's family members or friends). This information is automatically collected from the borrowers' phone contacts with the borrowers' permission in the application procedure. The platform downgrades the internal rating of any defaulting borrowers. Defaults on the platform are not reported to the credit bureau. However, there are other significant consequences for serious loan delinquencies. First, borrowers who default will be downgraded by the platform, resulting in higher borrowing costs or even the inability to borrow from the platform in the future. Second, the platform staff will contact both the borrowers and their listed contacts (whose information is automatically collected from the borrowers' phone contacts with their permission during the application process). This could lead to a loss of reputation within their social network. Given these negative repercussions, we believe that the likelihood of strategic default is limited.

### 2.3. The experiment

To examine the effect of credit supply, we exploit an experiment conducted by the cash loan platform in late April 2016. Per discussion with the management team, the platform obtained VC funding in 2015 and used it to conduct experiments to explore profit-maximizing strategies. This experiment was part of a trial-and-error initiative to promote the business and evaluate the platform's risk-control strategy.

Between April 20th and 30th, 2016, the platform announced that all registered users could apply for an online credit line increase through the platform's app. This announcement was displayed prominently as a flashing advertisement. Users who logged into the app during this period could view the advertisement and click on it to apply for a credit line increase. The platform classified all applicants into four strata based on an internal score and randomly assigned applicants within each stratum to either the treatment (i.e., those with an increase in credit lines) or control groups (i.e., those without an increase in credit lines). The total number of applicants was approximately 23,000, of whom 10% were provided as a sample to us.

The platform divided these participants into four strata according to an internal score computed by the platform. The probabilities of selection in the treatment group were 1/6, 3/10, 2/5, and 3/5 for borrowers in these four strata, respectively. The platform permanently raised credit lines for treated borrowers. As Athey and Imbens (2017) argue, this stratification can reduce the likelihood of uninformative assignments regarding the treatment effect of interest. The experiment involved a substantially large credit supply shock to affected borrowers. Specifically, the credit lines of treated borrowers were raised by CNY 2,163.71 on average, which was approximately 10% of the annual income per capita in China in 2016. Our regression results in Section 4 provide a formal analysis, showing that this credit line raise substantially increases the borrowing amount of the selected individuals after the experiment.

While the experiment was randomized within the applicant pool, the pool was self-selected. Although this self-selection process may not be ideal, it is appropriate for our experimental goals. Loan providers and policymakers are primarily concerned with individuals requiring or applying for additional credit. Therefore, this self-selection process is acceptable in our experimental setting. Our study focuses on identifying the causal effects of credit access on loan delinquency and online consumption. The possibility of receiving a credit increase remains random in our setting and we are confident that our identification strategy can provide causal

[8] After the Chinese regulators released the rules on cash loan lending, the platform stopped its lending business in China and started cash lending in another emerging market in South-east Asia.

evidence of the credit supply effect.

### 2.4. Alibaba E-commerce platforms

We measure cash loan borrowers' consumption using their transaction records with timestamps on Taobao and Tmall, two leading retail e-commerce platforms owned by Alibaba Group. Alibaba Group is the world's largest retail e-commerce company in terms of gross merchandise volume (GMV), as of its 20-F form filed in the 2019 fiscal year (ending March 31, 2019). Like Amazon and e-Bay, Alibaba's e-commerce platforms match buyers and sellers, and facilitate online sales of numerous types of goods or services.

Online shopping in China has grown significantly in recent years. Between 2014 and 2018, online shopping volume had a 34.0% compound annual growth rate in China.[9] In the 2019 fiscal year, Alibaba facilitated a GMV of CNY 5,727 billion, or 16.4% of the total household consumption in China, and served 654 million active buyers, approximately 46.9% of the population in China. The Taobao and Tmall platforms accounted for over 90% of Alibaba's total GMV (during 2020–2022) and over 50% of online shopping transaction volumes in China since 2016.

Alibaba's online shopping platforms provide a wide coverage of most consumption goods and services in China, including food, apparels, housing items, transportation, vehicle maintenance, healthcare products, over-the-counter medicines, video games, entertainment services, books, and other common goods and services. Therefore, our consumption measurements based on data from Alibaba are generally representative and in line with the China Family Panel Studies (CFPS) survey.[10] However, we highlight three differences between online shopping via Alibaba and household consumption in general. First, in-hospital treatment cannot be sold on e-commerce platforms. Second, vehicles are usually purchased offline through a dealer, and rarely on e-commerce platforms. Finally, Alibaba does not facilitate cash contributions to religious, educational, or charitable organizations. Considering the above differences, e-commerce consumption on Alibaba provides us with a comprehensive overview of individuals' consumption in China based on the comparison between the data from Alibaba online shopping and the CFPS survey (see Section 3.2 for details).

The cash loan platform and the e-commerce platforms are separate entities, and have no partnerships or ownership relationships. The platform can access borrowers' online shopping records with the authorization of borrowers. This information, along with other information collected during the application procedure (as mentioned in Section 2.2), is used to evaluate the borrowers' creditworthiness.

## 3. Data

### 3.1. The dataset and sample construction

The cash loan platform provided us with a random sample of 2,322 borrowers, or approximately 10% of participants in the experiment. For each applicant, we can identify the stratum to which they belong and whether they were selected for the treatment group, and thus, enjoyed a higher credit line.

The dataset contains borrowers' personal information, including participants' gender and age. Our dataset also includes information on borrowers' borrowing and repayment behaviors, specifically for loans taken between the experiment date and the end of 2016. This includes details such as the loan amount, maturity, loan origination date, expected repayment date, and actual repayment time. However, we do not have data on loans taken before the experiment date. Our proxies for loan delinquency are based on borrowers' repayments for loans issued after the experiment. We compute *Overdue7days, Overdue30days,* and *Overdue60days* as indicator variables for borrowers who have loans which are 7-, 30-, and 60-days past-due, respectively, and were granted from the start of the experiment till the end of 2016 (the last day of the sample). These measures are computed at the borrower level. Our dataset contains detailed information on 1,286,806 consumption transaction records on Alibaba. This information includes the CNY amount of the products/services, transaction time, and item description. Leveraging this extensive and distinctive data, we can create consumption metrics at an individual-fortnight level. Due to data constraints, our sample period comprises only four fortnights pre-experiment and eight fortnights post-experiment.

### 3.2. Consumption measures

To construct our consumption measures, we perform textual analyses on the item descriptions of 1,286,806 e-commerce transactions to classify them into different consumption categories.

We perform four classification tasks. First, to test the representativeness of our consumption measure, we compare the e-commerce consumption data with household survey consumption data. We classify each transaction into seven categories based on the Consumption Expenditure Survey (CEX)[11]: food, apparel, housing, transportation, healthcare, entertainment, and others. Second, we define financial literacy consumption as spending on financial education and knowledge products, including books or educational programs related to finance, accounting, wealth management, and investment. Third, we identify addictive and non-addictive

[9] The data are collected from the National Bureau of Statistics of the People's Republic of China.

[10] China Family Panel Studies (CFPS) are a series of household surveys on China's households. The CFPS is funded by Peking University and the National Natural Science Foundation of China, and maintained by the Institute of Social Science Survey of Peking University

[11] https://www.bls.gov/cex/

**Table 1**
**Performance of Textual Analysis.**
**This table presents the performance measures of the four consumption-classification algorithms in the test sample of 4,000 item descriptions of goods on Alibaba platforms.** *Accuracy* is the number of correct predictions in the test sample divided by the test sample size. *Precision* is the number of true positives divided by the sum of the true positives and true negatives. *Recall* is the number of the true positives divided by the sum of the true positives and false positives. *F1-score* is the harmonic mean of *Precision* and *Recall. Precision, Recall*, and *F1-score* are first calculated for each category, and then averaged across categories.

| | Accuracy | Precision | Recall | F1-score |
|---|---|---|---|---|
| Seven CEX Categories | 86.2% | 85.2% | 82.0% | 83.4% |
| Addictive, Non-addictive | 97.0% | 94.5% | 91.4% | 92.9% |
| Financial Literacy, Non-financial Literacy | 99.9% | 70.0% | 83.3% | 75.0% |
| Discretionary, Non-discretionary | 96.7% | 96.3% | 95.8% | 96.0% |

**Table 2**
**Representativeness of E-commerce Consumption.**
**This table presents the proportions of the seven consumption categories in the Consumption Expenditure Survey (CEX), our consumption measures, and household consumption.** To measure household consumption, we use the consumption data of 3,449 households from the 2014 wave of the CFPS survey, excluding hospital treatment, vehicle purchases, and cash contributions.

| | E-commerce consumption in our sample | Household consumption in the nationwide survey |
|---|---|---|
| Food | 4.1% | 8.2% |
| Housing | 41.4% | 36.5% |
| Apparel | 17.9% | 13.5% |
| Entertainment | 11.6% | 9.6% |
| Transportation | 5.1% | 1.0% |
| Healthcare | 0.5% | 2.4% |
| Others | 19.3% | 28.8% |

consumption. Following Gul and Pesendorfer (2007), we define addictive consumption as spending on goods or services that tend to increase consumers' compulsivity. We conduct a literature review to identify goods or services likely to be addictive according to this definition and available for purchase on Tabao or Tmall. The previous literatures suggest that video games (Fisher, 1994), caffeine products (Olekalns and Bardsley, 1996), alcohol (Baltagi et al., 2002), and tobacco (Becker et al., 1991) are examples of such addictive products. These four categories comprise our measure of addictive consumption. The remaining transactions are classified as non-addictive consumption. We also define non-discretionary consumption as food (excluding alcohol, following Olafsson and Pagel (2018)) and medical care (Fornell et al., 2010), and discretionary consumption as the remaining consumption.

Following previous literature (e.g., Tetlock, 2007; Loughran and Madonald, 2011; You et al., 2018), we build a word list for each consumption category. We manually review the item description and select all frequent words for each category. We also collect keywords from Alibaba e-commerce platforms' websites. After combining the collected words, we manually check the words and decide on preliminary word lists.

We conduct a trial test on the preliminary word lists and test our classification algorithms. The detailed procedure starts with classifying all e-commerce transaction records based on preliminary word lists. For each task, we classify each transaction into a consumption category if its item description contains words from the corresponding word list. By manually reviewing transactions that are classified into two or more categories, or in none of these categories, we update the word lists and classification algorithms. We make a final classification based on the updated word lists and classification rules.

We randomly select 4,000 out of the 1,286,806 e-commerce transaction records to construct a test sample. We read the item description of each record in the test sample and manually determine the categories to which it belongs. We then tested the validity of our classification methods by comparing the results of the textual analysis and the manually classified categories. We use four commonly used measures in machine learning to evaluate the performance of textual analyses. *Accuracy* is measured as the fraction of correct predictions in the test sample. For each consumption category, *Precision* is measured as the number of true positives divided by the sum of the true positives and true negatives. *Recall* is the number of true positives divided by the sum of the true and false positives. *F1-score* is the harmonic mean of *Precision* and *Recall*. For each classification task, *Precision, Recall*, and *F1-score* are first calculated for each consumption category and then averaged across categories. The performance measure for our classification algorithm is reported in Table 1. All performance measures range from 70% to 90%, which are comparable to those documented in Chen et al. (2019).

Although online shopping and overall household consumption may have different compositions, our analysis reveals the similarities and differences between them. For this analysis, we collect data on 3,449 Chinese families who participated in the 2014 wave of the CFPS and provided valid answers to questions on household spending. The data contain the families' annual expenditures for different consumption categories. We exclude expenditure on hospital treatment, vehicle purchases, and cash contributions from CFPS survey respondents' consumption, because it is unlikely that a consumer buys these goods and services on e-commerce platforms. We find that household consumption and online shopping have similar compositions in terms of CEX categories, as shown in Table 2. Consequently, some conclusions drawn from the online shopping data may also apply to overall household consumption[12].

### 3.3. Summary statistics

The different treatment probabilities across the four strata raises concern about selection bias: borrowers in some strata are more likely to be "selected" into the treatment group than others. Selection bias may affect the estimation of treatment effects (Angrist and Pischke, 2008). To address this, we randomly drop some observations from each stratum to ensure that the treatment probabilities are the same across all four strata. Specifically, for any stratum in which the treatment probability is lower than 60%, we randomly drop observations from the control group to make the proportion of treated borrowers 60% of the remaining sample. For any stratum in which the treatment probability is higher than 60%, we randomly drop observations from the treatment group. After this randomization procedure, we obtain a sample of 1,279 borrowers. Our results are robust when we include all users in the sample and run weighted least squares regressions.

To reduce the concern that the individual applicants in our sample differ significantly from general users on other cash loan platforms, we provide a broader comparison of age, gender, loan amount, and borrowing behavior using relevant data from an industry report (https://www.weiyangx.com/251360.html). In Panel A of Table 3, we find no significant differences in terms of age, gender, location, or borrowing behavior between our sample borrowers and the broader industry estimates.

Panel B reports the summary statistics of the 1,279 individuals in the sample. The average borrower age is 27 years.[13] 75.7% of the borrowers are males. The average outstanding loan amount prior to the experiment date is CNY 815 (approximately USD 140). The average total consumption within one year prior to the experiment is CNY 13,053. The 7-day delinquency rate is 32.1%, and the default rate (60-day delinquency rate) is 14.4%.

Panel C reports the results of a balance test examining whether the treatment and control borrowers significantly differ in various covariates, including gender, age, online shopping consumption, and outstanding loans, and whether the user purchases financial knowledgeable goods/services in the past year. All these differences are insignificant. Therefore, the concern that the difference in these covariates drives the difference of dependent variables is mitigated.

Panel D presents descriptive statistics of the consumption, borrowing, and repayment measures at the individual-fortnight level. The mean fortnightly e-commerce consumption by a cash loan user is CNY 531 (Approximately USD 65). Spending on addictive and non-addictive consumption is CNY 20 and 483, respectively.[14] The average fortnightly borrowing amount and principal repayment are CNY 238 and 84, respectively.

In the next section, we conduct DiD studies on borrowing and consumption behaviors. We present and validate the parallel trends of these variables before the experiment in Panels A–E of Fig. 2.

These figures indicate a declining consumption trend for the control group borrowers. Given that all individuals in our sample are cash loan borrowers who typically face credit constraints and require liquidity, it's probable that without an increase in their credit line or other income source, these borrowers would in general reduce their consumption to live daily life.

Our results are robust when we use *Treat* as the instrumental variable for the credit line increase and run a two-stage least squares (2SLS) regression.

## 4. Results

### 4.1. Expanding credit supply and borrowing behavior

First, we investigate whether expanding consumer credit supply increases borrowing. We use borrowing and repayment amounts as dependent variables, and estimate the following regression model

$$\begin{aligned} Y_{it} = {} & \gamma_{-1} \times Treat_i \times Month(-1)_t + \gamma_1 \times Treat_i \times Month(1)_t + \gamma_2 \times Treat_i \times Month(2)_t + \gamma_{3-4} \times Treat_i \times Month(3-4)_t + \beta_{-1} \\ & \times Month(-1)_t + \beta_1 \times Month(1)_t + \beta_2 \times Month(2)_t + \beta_{3-4} \times Month(3-4)_t + IndividualFEs + \varepsilon_{it} \end{aligned} \quad (1)$$

where $Y$ denotes the amount of borrowing or repayment of a given borrower in a given fortnight, *Treat* is an indicator variable if the individual $i$ is in the treatment group, *Month(-1)* is a dummy variable for the first and second fortnights before the experiment, *Month (1)* is a dummy variable for the first and second fortnights after the experiment, *Month(2)* is a dummy variable for the third and fourth

[12] Unfortunately, we lack access to data on borrowers' offline consumption, however, we find it unlikely that borrowers switch from offline to online consumption solely due to increased cash loan credit lines or receiving cash loans. Firstly, while the cash platform can extract borrowers' online shopping records, its app doesn't directly link to E-commerce platforms. Secondly, upon loan approval, funds are deposited into borrowers' bank accounts, not E-commerce accounts.

[13] All continuous variables are winsorized at 1% and 99% before performing descriptive analysis.

[14] Because of winsorization, the sum of addictive and non-addictive consumption may not equal total consumption.

**Table 3**
**Summary Statistics.**
Panel A compares the borrower characteristics of our sample with a cash loan industry report[a] . Panel B reports the summary statistics for the borrower characteristics. Panel C presents balance tests on covariates between the treatment and the control groups. Panel D reports the summary statistics for borrowers' fortnightly consumption, borrowing, and repayment behavior during the period between the fourth fortnight before and eighth fortnight after the experiment. *Male* is a dummy variable for males. *Age* is the age of individuals in 2016. *OutstandingLoan* is the outstanding loans immediately before the start date of the experiment. *PastConsum* is the total online shopping spending within one year before the start date of the experiment. *HighFLConsum* is a dummy variable which equals one if the total online shopping spending on financial education and knowledge products is positive within one year before the experiment. *Overdue7days, Overdue30days*, and *Overdue60days* are indicator variables which equal one for individuals with 7-, 30, and 60 days past-due loans issued between the start date of the experiment and end of 2016 (the last date of the sample). *Consumption, AddictConsum, NoAddictConsum, DiscretConsum,* and *NoDiscretConsum* are the total online shopping amount, addictive consumption, and non-addictive consumption, respectively, for each borrower each fortnight, respectively. *BorrowAmount* represents the total amount borrowed each fortnight. *RepayAmount* is the total principal repaid each fortnight. All continuous variables are winsorized at the 1% and 99% levels.

Panel A. Comparison of Our Sample and a Cash Loan Industry Report

| | Our Sample | Cash Loan Industry Report |
|---|---|---|
| Male | 75.7% | 78.0% |
| Age | | |
| 18–24 | 37.3% | 32.0% |
| 25–30 | 40.3% | 35.2% |
| 31–40 | 20.2% | 24.5% |
| 41–50 | 2.3% | 7.2% |
| >50 | 0.2% | 1.1% |
| Location | | |
| Eastern China | 41.5% | 38.4% |
| Western China | 26.2% | 27.4% |
| Middle China | 25.2% | 20.5% |
| North East | 7.1% | 5.8% |
| Average Loans Borrowed Annually | 3.84 (control group only) | 2–3 |
| Average Loan amount (CNY) | 1672 (control group only) | 2000–3000 |

Panel B. Borrower Characteristics

| | N | Mean | SD | Min | Q1 | Median | Q3 | Max |
|---|---|---|---|---|---|---|---|---|
| Male | 1,279 | 0.757 | 0.429 | 0 | 1 | 1 | 1 | 1 |
| Age | 1,279 | 26.986 | 5.496 | 19.000 | 23.000 | 26.000 | 30.000 | 46.000 |
| OutstandingLoan | 1,279 | 815.002 | 1,606.706 | 0 | 0 | 0 | 1,000.000 | 8,310.590 |
| PastConsum | 1,279 | 13,053.070 | 197,10.500 | 0 | 2,508.320 | 6,678.110 | 15,041.680 | 112,230.000 |
| HighFLConsum | 1,279 | 0.036 | 0.186 | 0 | 0 | 0 | 0 | 1 |
| Overdue7days | 1,279 | 0.321 | 0.467 | 0 | 0 | 0 | 1 | 1 |
| Overdue30days | 1,279 | 0.185 | 0.389 | 0 | 0 | 0 | 0 | 1 |
| Overdue60days | 1,279 | 0.144 | 0.351 | 0 | 0 | 0 | 0 | 1 |

Panel C. Balance Test

| | Treat | | Control | | Treat-Control | |
|---|---|---|---|---|---|---|
| | N | Mean | N | Mean | Diff | T-stats |
| Male | 768 | 0.763 | 511 | 0.748 | 0.015 | 0.628 |
| Age | 768 | 26.923 | 511 | 27.080 | -0.157 | -0.506 |
| OutstandingLoan | 768 | 801.662 | 511 | 835.051 | -33.388 | -0.362 |
| PastConsum | 768 | 12,853.690 | 511 | 13,352.720 | -499.030 | -0.427 |
| HighFLConsum | 768 | 0.033 | 511 | 0.041 | -0.009 | -0.785 |

Panel D. Consumption, Borrowing, and Repayment

| | N | Mean | SD | Min | Q1 | Median | Q3 | Max |
|---|---|---|---|---|---|---|---|---|
| Consumption | 15,348 | 530.864 | 1135.751 | 0 | 19.960 | 149.700 | 490.725 | 7807.640 |
| AddictConsum | 15,348 | 20.492 | 102.844 | 0 | 0 | 0 | 0 | 825.571 |
| NoAddictConsum | 15,348 | 483.099 | 1015.371 | 0 | 14.350 | 136.000 | 443.925 | 6786.640 |
| DiscretConsum | 15,348 | 438.282 | 1045.968 | 0 | 0 | 65 | 360.96 | 7110.581 |
| NoDisCretConsum | 15,348 | 78.406 | 134.291 | 0 | 0 | 19.96 | 99.8 | 800 |
| BorrowAmount | 15,348 | 238.545 | 800.979 | 0 | 0 | 0 | 0 | 4955.560 |
| RepayAmount | 15,348 | 83.880 | 223.732 | 0 | 0 | 0 | 0 | 1331.930 |

[a] https://www.weiyangx.com/251360.html

fortnights after the experiment, *Month(3-4)* is a dummy variable for the fifth to eighth fortnights after the experiment.

The results are presented in Table 4. The insignificant coefficients of *Treat* × *Month(-1)* suggest parallel trends in borrowing and repayment amounts before the experiment. In Column (1), the coefficient of *Treat* × *Month(1)* is 641.291, which is significantly different from zero at the 1% level. This suggests that the average treatment effect on borrowing is CNY 641 per fortnight

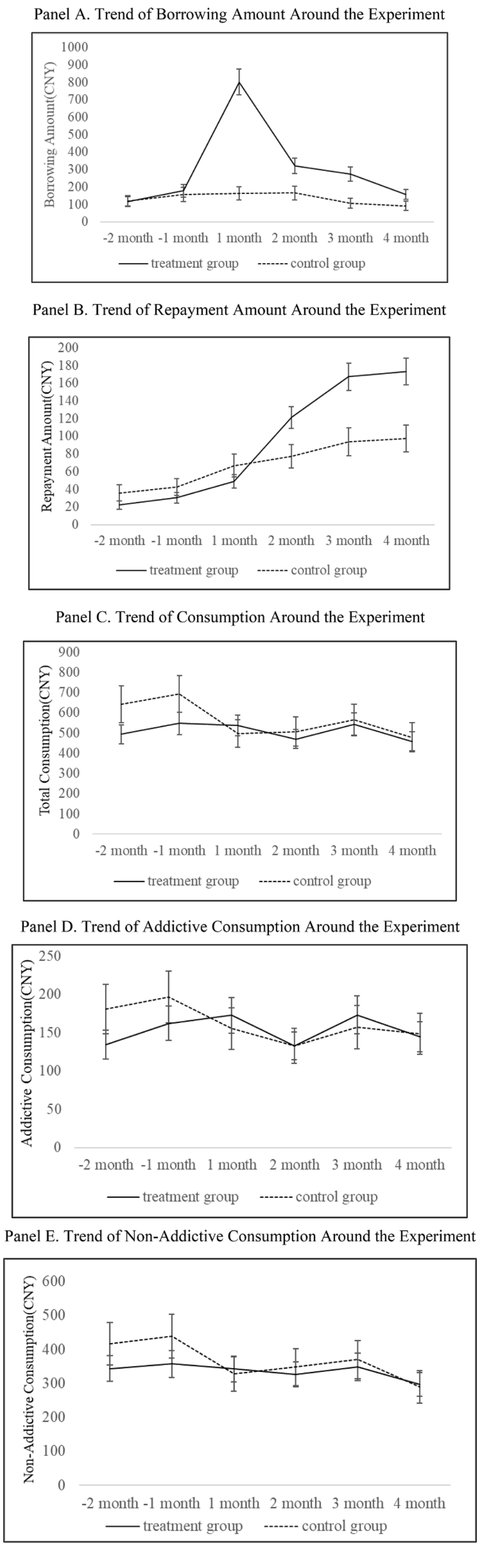


**Fig. 2. Parallel Trends**.
This figure presents the borrowing and consumption behaviors of the treatment and control groups around the time of the experiment.

**Table 4**
**Credit Supply and Borrowing/Repayment Behaviors.**
**This table reports the results of OLS regressions that investigate the effect of credit supply on borrowing and repayment behaviors. The sample includes 15,348 individual-fortnight observations of 1,279 individuals during the period between the fourth fortnight before and the eighth fortnight after the experiment. *BorrowAmount* represents the total amount borrowed each fortnight.** *RepayAmount* is the total principal repaid each fortnight. *Treat* is a dummy variable which equals one for the treatment group individuals. *Month(-1)* is an indicator variable for the first two fortnights before the experiment. *Month(1)* is an indicator variable for the first two fortnights after the experiment. *Month(2)* is an indicator variable for the third and fourth fortnights after the experiment. *Month(3-4)* is an indicator variable for the fifth to the eighth fortnights after the experiment. ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively. The t-statistics are reported in parentheses. Standard errors are two-way clustered at the individual and fortnight levels.

| | (1)<br>BorrowAmount | (2)<br>RepayAmount |
|---|---|---|
| Treat × Month (-1) | 22.589 | 1.731 |
| | (1.610) | (1.522) |
| Treat × Month (1) | 641.291*** | -3.947** |
| | (4.002) | (-2.341) |
| Treat × Month (2) | 157.667** | 57.613*** |
| | (2.684) | (9.016) |
| Treat × Month (3-4) | 117.477*** | 88.201*** |
| | (3.861) | (8.460) |
| Month (-1) | 32.477* | 6.500*** |
| | (2.026) | (4.415) |
| Month (1) | 42.744*** | 30.923*** |
| | (5.158) | (18.151) |
| Month (2) | 45.714*** | 41.369*** |
| | (3.584) | (19.465) |
| Month (3-4) | -19.614 | 59.782*** |
| | (-1.485) | (9.867) |
| Individual FE | YES | YES |
| Observations | 15,348 | 15,348 |
| R-squared | 0.167 | 0.371 |

**Table 5**
**Credit Supply and Loan Delinquency.**
**This table reports the results of the logit regressions investigating the effect of credit supply on loan delinquency.** The sample includes 1,279 individuals. *Treat* is a dummy variable which equals one for the treatment group individuals. *Overdue7days, Overdue30days*, and *Overdue60days* are indicator variables that equal one for individuals with 7-, 30-, and 60-days past-due loans issued between the start date of the experiment and end of 2016 (the last date of the sample). ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively. The t-statistics are reported in parentheses.

| | (1)<br>Overdue7days | (2)<br>Overdue30days | (3)<br>Overdue60days |
|---|---|---|---|
| Treat | 0.703*** | 0.708*** | 0.486*** |
| | (5.480) | (4.452) | (2.830) |
| Constant | -1.192*** | -1.944*** | -2.095*** |
| | (-11.390) | (-14.543) | (-14.793) |
| Observations | 1,279 | 1,279 | 1,279 |
| Pseudo R-squared | 0.020 | 0.017 | 0.008 |

(approximately CNY 1,282 per month). The coefficients of *Treat* × *Month(2)* and *Treat* × *Month (3-4)* are 157.667 and 117.477, respectively, and also significant at the 1% level. This suggests treatment effects of approximately CNY 158 per fortnight (CNY 316 per month) in the second month, and CNY 117.5 per fortnight (CNY 235 per month) in the third and fourth months. These results are consistent with our conjecture that borrowers are more likely to borrow if they have access to additional credit.

Column (2) presents the regression results with repayment amount as the dependent variable. The repayment amount starts increasing in the second month after the experiment. It is not surprising because the platform requires an equal monthly repayment schedule, and borrowers start repaying one month after obtaining new loans. Overall, these results suggest that expanding credit supply increases borrowing and repayment amounts.

### *4.2. Expanding credit supply and loan delinquencies*

Next, we estimate the effect of expanding credit supply on loan delinquency. Due to limited pre-experiment loan data, conducting a Difference in Differences (DiD) analysis on delinquency rates isn't feasible. We discussed those concerns with the experiment designer,

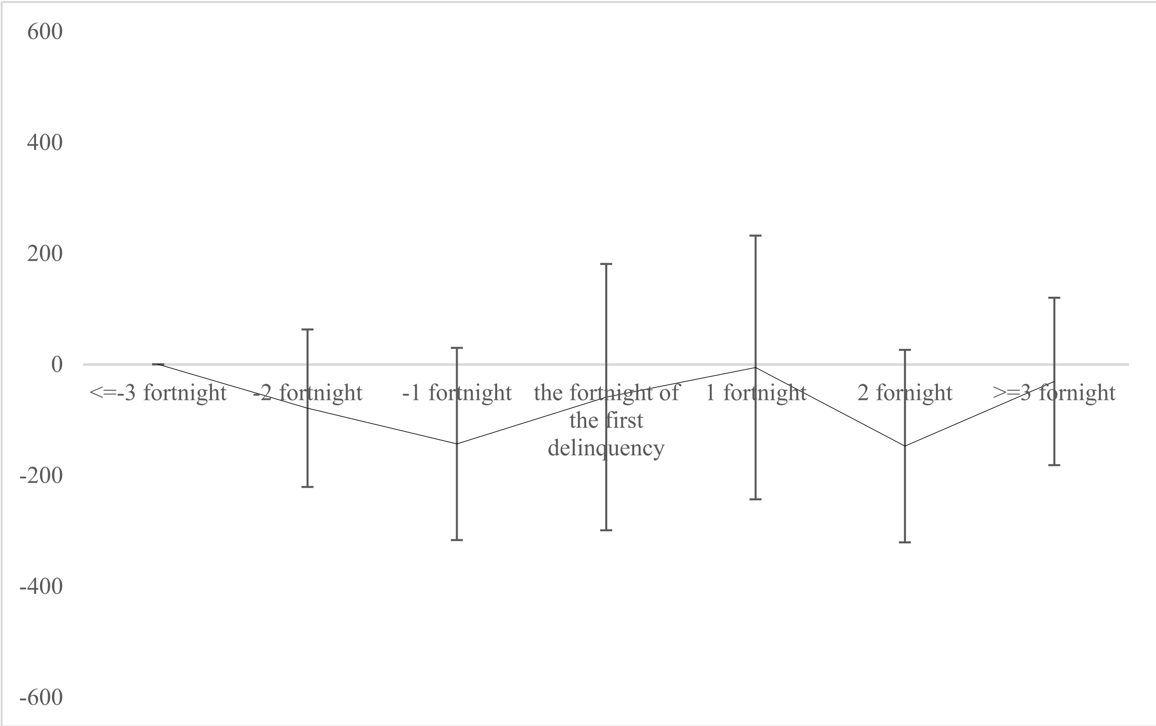


**Fig. 3. Consumption around First Loan Delinquencies**.
This figure plots the consumption trend (the estimated coefficients of the following model) around the first loan delinquencies in the post-experiment period and the corresponding 95% confidence interval.

$$\begin{aligned} Consum \ = \ & \alpha + \gamma_{-2}\text{Fortnight}(-2) + \gamma_{-1}\text{Fortnight}(-1) + \gamma_0\text{Fortnight}(0) \\ & + \gamma_1\text{Fortnight}(1) + \gamma_2\text{Fortnigth}(2) + \gamma_{3+}\text{Fortnight}(3+) + \text{IndividualFEs} \\ & + \text{WeekFEs} \end{aligned}$$

*Fortnight(-2)* and *Fortnight(-1)* are indicator variables for the second and first fortnight before the first delinquency (the first 7-day overdue event in the post-experiment period), respectively. *Fortnight(0)* is an indicator variable for the fortnight of the first delinquency. *Fortnight(1), Fortnight(2)*, and *Fortnight(3+)* are indicator variables for the corresponding fortnights after the first delinquency.

who informed us that nearly all participants (98.4%) had no loan delinquencies at the time of the experiment. Unfortunately, they declined to provide individual loan level data before the experiment day. Nonetheless, we believe this high rate of non-delinquency can serve as indirect evidence that any differences in loan delinquencies during the pre-experiment period may be minimal. If the pre-experiment differences are indeed limited, the potential bias from analyzing only the post-experiment data would likely be small. Additionally, the experimental design inherently introduces exogenous variations in credit supply, enabling inference of causality through cross-sectional logit regression analyses.

We run logit regressions with indicators for loan delinquency as the dependent variables and whether a borrower is treated as the independent variable. As shown in Table 5, the likelihood of loan delinquency is significantly higher for the treated borrowers than for the control group. The marginal effects of treatment on *Overdue7days, Overdue30days,* and *Overdue60days* are 14.5%, 10.4%, and 5.7%, respectively, or equivalently, 45%, 56%, and 40% of the sample mean. This suggests that borrowers who have access to extra credit are, on average, more likely to default than those without access to increased credit.

These findings suggest that more consumer credit supply increases the financial burden on individual borrowers, and are consistent with the broad literature that identifies the negative welfare effect of access to consumer credit. (Melzer, 2011; Campbell et al., 2012; Morgan et al., 2012; Carrell and Zinman, 2014; Cuffe and Gibbs, 2017; Gathergood et al., 2019; Lee, 2019).

Even when borrowers can afford loan repayments, they may strategically default if it enhances their welfare. If strategic defaults are the primary cause of loan delinquencies in our sample, then these delinquencies might not accurately reflect financial stress.

However, we contend that strategic default is not the primary driver of loan delinquencies. While defaults on this platform are not reported to credit bureaus, there are several negative consequences for serious loan delinquencies. First, borrowers who default are downgraded by the platform, leading to higher borrowing costs or even loss of access to future loans. Second, the platform staff contacts both the borrowers and their listed contacts (whose information is automatically collected from the borrowers' phone contacts with their permission during the application process). This could result in a loss of reputation within their social network. Given these negative repercussions, we believe that the likelihood of strategic default is limited.

**Table 6**
**Credit Supply and Cash Loan Lending Reliance.**
**Panel A reports the results of the COX hazard model, which tests whether credit supply affects the hazard ratio of leaving the cash loan platform.** The sample includes 1,279 individuals in the full sample. *Treat* is a dummy variable which equals one for individuals in the treatment group. We consider a borrower to have left the platform if they have not submitted loan applications to the platform for at least two, four, or six fortnights. We define the "time of leaving" as the time of the last loan application. Panel B presents the results of OLS regressions that test whether credit supply affects the number of loans that individuals take. *NumLoan* is the number of loans taken by an individual after the experiment. *LnNumLoan* is equal to the logarithm of one plus *NumLoan.* ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively. The t-statistics are reported in parentheses.

Panel A. Credit Supply and Leaving Hazard Ratio

| Definition of Leaving | (1) No new applications for two fortnights | (2) No new applications for four fortnights | (3) No new applications for six fortnights |
|---|---|---|---|
| Treat | -0.400*** | -0.457*** | -0.509*** |
| | (-6.016) | (-6.169) | (-6.530) |
| Observations | 1,279 | 1,279 | 1,279 |
| Pseudo R-squared | 0.003 | 0.004 | 0.005 |

Panel B. Credit Supply and Number of Loans

| | (1) NumLoan | (2) LnNumLoan |
|---|---|---|
| Treat | 2.236*** | 0.581*** |
| | (8.262) | (10.790) |
| Observations | 1,279 | 1,279 |
| R-squared | 0.051 | 0.084 |

Additionally, we analyzed consumption patterns around the time of loan delinquencies. If loan delinquencies are primarily driven by financial stress, we would expect to see a decline in consumption around the time of default. Conversely, if strategic default is the main reason, consumption would likely remain stable. To investigate this, we conducted the following regression analysis to examine consumption patterns around loan delinquencies.

$$\begin{aligned} Consum \; = \; & \alpha + \gamma_{-2}\text{Fortnight}(-2) + \gamma_{-1}\text{Fortnight}(-1) + \gamma_0\text{Fortnight}(0) \\ & + \gamma_1\text{Fortnight}(1) + \gamma_2\text{Fortnigth}(2) + \gamma_{3+}\text{Fortnight}(3+) \\ & + \text{IndividualFEs} + \text{WeekFEs} \end{aligned}$$

where *Fortnight(-2)* and *Fortnight(-1)* are indicator variables for the second and first fortnight before the first delinquency (the first 7-day overdue event in the post-experiment period), respectively. *Fortnight(0)* is an indicator variable for the fortnight of the first delinquency. *Fortnight(1), Fortnight(2)*, and *Fortnight(3+)* are indicator variables for the corresponding fortnights after the first delinquency.

Fig. 3 presents the coefficients and the 95% confidence level. All the coefficients around the first delinquency are negative. Though none of the coefficients are statistically significant, the joint test of that all the coefficients are zero are rejected at conventional level (p=0.0000), providing suggestive evidence that strategical default is not the primary reason.

### 4.3. Expanding credit supply and reliance on cash loan lending

Access to high-interest credit and obtaining high-interest loans can result in high borrowing costs that borrowers may not be able to repay. These borrowers may have to rely on new loans to repay old ones. That is, borrowers with access to more credit lines are less likely to leave the high-interest cash loan platform, and rather, fall into a debt trap.

To test this hypothesis, we use the COX proportional hazard ratio model to explore whether the treated borrowers leave the platform later than the control group.

$$h_i(t) = h_0(t) \times exp(\beta \times Treat_i + Controls) \tag{2}$$

where $h_i(t)$ is the hazard ratio of leaving the platform permanently for individual i, and $h_0(t)$ is the baseline hazard function.

We assume that a borrower leaves the platform permanently if the borrower has not borrowed from the platform for a predefined period. Specifically, we define "leaving" when any individual has not borrowed from the platform for two fortnights, and "time of leaving" as the date of the last application. The results are presented in Panel A of Table 6. In Column (1), the coefficient of *Treat* is -0.400 and significant at the 1% level. This magnitude is economically significant. Specifically, borrowers with access to additional credit are 33% (= 1 – (exp (-0.400))) less likely to leave the platform compared to those without access to increased credit lines. Thus, access to more credit is positively associated with the likelihood of remaining on the platform. To validate the robustness of this finding, we redefine "leaving" as when an individual has not borrowed from the platform for at least four or six fortnights, respectively, and report the results in Columns (2) and (3), respectively; again, our findings are qualitatively similar.

To demonstrate the robustness of our findings on cash loan lending reliance, we also use the number of loans that an individual

**Table 7**
**Credit Supply and Consumption.**
**This table reports the results of regressions that examine the effect of credit supply on consumption.** The sample includes 15,348 individual-fortnight observations of 1,279 individuals during the period between the fourth fortnight before and eighth fortnight after the experiment. *Consumption, AddictConsum, NoAddictConsum, DiscretConsum*, and *NoDiscretConsum* represent the total online shopping amount, addictive consumption, nonaddictive consumption, discretionary consumption, and nondiscretionary consumption, respectively. *Treat* is a dummy variable which equals one for the treatment group individuals. *Month(-1)* is an indicator variable for the first two fortnights before the experiment. *Month(1)* is an indicator variable for the first two fortnights after the experiment. *Month(2)* is an indicator variable for the third and fourth fortnights after the experiment. *Month(3-4)* is an indicator variable for the fifth to the eighth fortnights after the experiment. ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively. The t-statistics are reported in parentheses. Standard errors are two-way clustered at the individual and fortnight levels.

| | (1)<br>Consumption | (2)<br>AddictConsum | (3)<br>NoAddictConsum | (4)<br>DiscretConsum | (5)<br>NoDiscretConsum |
|---|---|---|---|---|---|
| Treat × Month (-1) | 3.532 | 4.484 | -8.335 | -17.034 | 3.952* |
| | (0.054) | (0.866) | (-0.191) | (-0.307) | (1.917) |
| Treat × Month (1) | 187.486** | 13.457*** | 133.844** | 134.658** | 16.913*** |
| | (2.956) | (4.034) | (2.547) | (2.519) | (4.518) |
| Treat × Month (2) | 112.097 | 8.584* | 87.209 | 50.653 | 22.601*** |
| | (1.447) | (2.062) | (1.416) | (0.822) | (5.983) |
| Treat × Month (3-4) | 128.382** | 8.791* | 96.393* | 75.181 | 18.031*** |
| | (2.238) | (2.097) | (2.167) | (1.567) | (4.766) |
| Month (-1) | 50.472 | -6.396 | 60.563 | 73.703 | -5.069 |
| | (0.589) | (-1.385) | (0.951) | (1.065) | (-0.293) |
| Month (1) | -143.583* | -11.337*** | -90.281 | -100.784* | -12.747 |
| | (-1.889) | (-4.055) | (-1.429) | (-2.020) | (-0.844) |
| Month (2) | -135.075 | -8.432** | -98.569 | -89.633 | -18.905 |
| | (-1.366) | (-2.985) | (-1.185) | (-1.281) | (-1.174) |
| Month (3-4) | -120.281 | -11.474*** | -84.697 | -71.880 | -16.383 |
| | (-1.542) | (-3.994) | (-1.273) | (-1.322) | (-1.092) |
| Individual FEs | YES | YES | YES | YES | YES |
| Observations | 15,348 | 15,348 | 15,348 | 15,348 | 15,348 |
| R-squared | 0.398 | 0.360 | 0.399 | 0.384 | 0.311 |

takes after the experiment to measure cash loan lending reliance. The results presented in Panel B of Table 6 suggest that the treatment group borrowers borrow significantly more loans, which is consistent with the finding that credit supply increases borrowers' reliance on platform cash loans.

### 4.4. Expanding credit supply and consumption

To test whether expanding credit supply increases consumption, addictive consumption, and non-addictive consumption, we estimate the following model:

$$Y_{it} = \gamma_{-1} \times Treat_i \times Month(-1)_t + \gamma_1 \times Treat_i \times Month(1)_t + \gamma_2 \times Treat_i \times Month(2)_t + \gamma_{3-4} \times Treat_i \times Month(3-4)_t + \beta_{-1} \times Month(-1)_t + \beta_1 \times Month(1)_t + \beta_2 \times Month(2)_t + \beta_{3-4} \times Month(3-4)_t + IndividualFEs + \varepsilon_{it} \quad (3)$$

where *Y* denotes the consumption variables, including total online shopping expenditure, addictive consumption, and non-addictive consumption.

The results are presented in Table 7. Column (1) shows that the total consumption of the treated borrowers increases after the experiment. The coefficient of *Treat* × *Month(1)* is 187.486, with a t-statistic of 2.956. That is, the total online shopping increases by approximately CNY 375 (=187.486 × 2) in the first month after the experiment. The magnitude is approximately 35% (187/530) of the sample mean. This suggests MPC-Ls of 17.5% in the first post-experiment month and 51.4% in the first four post-experiment months[15]. This finding is consistent with Gross and Souleles (2002), who demonstrate that releasing liquidity constraints by increasing credit lines increases consumption. The coefficients of *Treat* × *Month(2)* and *Treat* × *Month(3-4)* are also significantly positive at least at the 10% level, implying that the effect on consumption lasts for at least four months. Since our sample period concludes after the eighth fortnight post-experiment, unfortunately we are unable to observe whether or when this effect diminishes in the longer term.

Column (2) estimates the effect of credit supply on addictive consumption. Our addictive consumption measure incorporates spending on video games, tea, alcohol, and caffeine products. Researchers demonstrate that addictive consumption weakens self-control (Gul and Pesendorfer, 2007). We argue that access to more credit increases expenditure on addictive goods, possibly weakening self-control and reducing borrowers' ability to repay debt. Our findings support this hypothesis. The addictive consumption of treated borrowers increases by CNY 13.457 per fortnight (CNY 27 per month) in the first month after the experiment, suggesting another potential negative welfare implication of consumer credit supply. This finding is economically significant at approximately

[15] 17.5%= (187.486*2/2163.71); 51.4%= (187.486*2+112.097*2+128.382*4)/2,163.71

**Table 8**
**Heterogeneous Effects of Financial Literacy on Loan Delinquency.**
**This table reports the results of the logit regressions examining the heterogeneous effect of credit supply on loan delinquency across borrowers with different levels of financial literacy.** *Treat* is a dummy variable which equals one for individuals in the treatment group. *Overdue7days, Overdue30days*, and *Overdue60days* are indicator variables that equal one for individuals who have 7, 30, and 60 days past-due loans issued between the start date of the experiment and end of 2016 (the last date of the sample). *HighFLConsum* is an indicator variable that equals one if an individual has positive spending on financial literacy consumption. *Male* is a dummy variable for males. *Age* is the age of individuals in 2016. ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively. The t-statistics are reported in parentheses.

| | (1) Overdue7days | (2) Overdue30days | (3) Overdue60days | (4) Overdue7days | (5) Overdue30days | (6) Overdue60days |
|---|---|---|---|---|---|---|
| Treat | 0.789*** | 0.840*** | 0.618*** | 1.824*** | 0.898 | 0.297 |
| | (5.952) | (5.043) | (3.446) | (2.619) | (1.033) | (0.319) |
| HighFLConsum | 1.359*** | 1.562*** | 1.504*** | 1.356*** | 1.557*** | 1.500*** |
| | (3.017) | (3.315) | (3.090) | (3.007) | (3.299) | (3.075) |
| HighFLConsum × Treat | -1.829*** | -2.797*** | -3.103*** | -1.841*** | -2.810*** | -3.108*** |
| | (-2.867) | (-3.181) | (-2.734) | (-2.878) | (-3.192) | (-2.737) |
| Age | | | | -0.002 | -0.010 | -0.012 |
| | | | | (-0.122) | (-0.378) | (-0.450) |
| Age × Treat | | | | -0.036 | -0.011 | 0.003 |
| | | | | (-1.500) | (-0.373) | (0.079) |
| Male | | | | 0.179 | -0.088 | -0.203 |
| | | | | (0.718) | (-0.288) | (-0.637) |
| Male × Treat | | | | -0.099 | 0.315 | 0.337 |
| | | | | (-0.322) | (0.846) | (0.853) |
| Observations | 1,279 | 1,279 | 1,279 | 1,279 | 1,279 | 1,279 |
| Pseudo R-squared | 0.026 | 0.028 | 0.019 | 0.026 | 0.028 | 0.019 |

66% of the sample mean. Our findings reveal a disproportionately larger effect of the exogenous credit supply shock on addictive consumption. Specifically, the credit supply's impact on addictive consumption is 7.1% of that on total consumption (CNY 27 vs. CNY 375 in the first month), approximately 87% larger than the ratio of mean addictive consumption to mean total consumption (3.9% =20.5/530.9). Thus, with an increase in cash loan credit lines, borrowers experience a disproportionate increase in their addictive consumption. In Column (3), non-addictive consumption similarly increases but is only approximately 27.8% of the sample mean.

We also examine the effects on discretionary and non-discretionary consumption, and present our findings in Columns (4) and (5), respectively. Non-discretionary goods—as defined by Olafsson and Pagel (2018) and Fornell et al. (2010)—include food (excluding alcohol) and medical care. Discretionary spending is calculated as total consumption minus nondiscretionary spending. Our results suggest that both discretionary and non-discretionary consumption increase significantly after credit supply. The effect on discretionary (non-discretionary) consumption is 31% (27%) of its sample mean. This is consistent with our observations of differences between addictive and non-addictive consumption.

### 4.5. Heterogeneous borrower types

This section examines how the effect of consumer credit supply varies across different types of borrowers. Gathergood et al. (2019) find that the effect of access to consumer credit on loan delinquency is more prominent among riskier borrowers, but indistinguishable among different age or income groups. Importantly, financial literacy can positively impact individual financial decisions (Lusardi and Mitchell, 2014), influence planning behavior that increases wealth (Lusardi and Mitchell, 2007), decrease reliance on student loans, and increase repayment behaviors (Brown et al., 2016). Therefore, we argue that more financially literate borrowers understand borrowing costs better and are less likely to be delinquent after borrowing.

We use prior spending on financial education and knowledge products to measure financial literacy, and analyze the heterogeneous effects of credit supply on loan delinquency. Contrary to previous studies that usually construct proxies for financial literacy from surveys (Lusardi and Mitchell, 2007; Van Rooij et al., 2011), we measure financial literacy using real online shopping behaviors; we hope that this provides a more accurate proxy for financial literacy. Measuring financial literacy through online shopping can potentially avoid intended or unintended response bias in surveys.

To test this hypothesis, we run the following logit regressions.

$$\Pr(LoanDelinquency_i = 1) \ = Logit(\alpha + \beta \times Treat_i + \gamma \times Treat_i \times HighFLConsum_i + \theta \times HighFL_i + \varepsilon_i) \tag{4}$$

where *LoanDelinquency* is a dummy variable if an individual has ever had a loan issued after the experiment that is due over 7, 30, or 60 days, and *HighFLConsum* equals one if the individual has spent on financial education and knowledge products within one year before the experiment.

The results are shown in Table 8. In Panel A, the coefficient of *Treat* is significantly positive, while the interaction terms of *HighFLConsum* and *Treat* are significantly negative in all specifications. This suggests that the loan delinquency effect is significant lower among borrowers with a higher consumption of financial literacy products. That is, higher financial literacy is associated with lower loan delinquency effects of credit supply. This result is consistent with Gathergood (2012), who documents a negative

**Table 9**
**Heterogeneous Effects of Financial Literacy on Consumption.**
**This table presents the results of the regressions examining the heterogeneous effect of credit supply on consumption across borrowers with different levels of financial literacy.** The regression model is specification (5). The sample includes 15,348 individual-fortnight observations of 1,279 individuals during the period between the fourth fortnight before and eighth fortnight after the experiment. The dependent variables include *Consumption, AddictConsum,* and *NoAddictConsum,* which are the total online shopping amount, addictive consumption, and non-addictive consumption for each borrower each fortnight, respectively. *HighFLConsum* is an indicator variable that equals one if an individual has positive spending on financial education and knowledge products. *Treat* is a dummy variable which equals one for the treatment group individuals. *Month(-1)* is an indicator variable for the first two fortnights before the experiment. *Month(1)* is an indicator variable for the first two fortnights after the experiment. *Month(2)* is an indicator variable for the third and fourth fortnights after the experiment. *Month(3-4)* is an indicator variable for the fifth to eighth fortnights after the experiment. *Other Variables* include all other variables on the right-hand side that are not presented in the table. For conciseness, we only present the coefficients of all three-way interaction terms. ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively. The t-statistics are reported in parentheses. Standard errors are two-way clustered at the individual and fortnight levels.

| | (1) Consumption | (2) AddictConsum | (3) NoAddictConsum |
|---|---|---|---|
| HighFLConsum × Treat × Month(-1) | -140.201 | 11.191 | -146.113 |
| | (-0.414) | (0.404) | (-0.445) |
| HighFLConsum × Treat × Month(1) | 190.494 | -8.575 | 194.643 |
| | (0.561) | (-0.254) | (0.618) |
| HighFLConsum × Treat × Month(2) | 393.673 | 1.831 | 468.431* |
| | (1.525) | (0.045) | (1.880) |
| HighFLConsum × Treat × Month(3-4) | 517.461 | 19.551 | 426.258 |
| | (1.587) | (0.641) | (1.480) |
| Other Variables | YES | YES | YES |
| Individual FEs | YES | YES | YES |
| Observations | 15,348 | 15,348 | 15,348 |
| R-squared | 0.012 | 0.001 | 0.013 |

relationship between financial literacy and over-indebtedness. As Columns (4) to (6) indicate, the coefficients of *HighFLConsum* × *Treat* are robust when we include the interaction terms of *Treat* and gender or age[16].

This heterogeneous effect is economically significant: among borrowers who do not consume financial education and knowledge products, the marginal effect on the probability of being more than 60 days late on repayment is 8.1 percentage points. This shows a more prominent loan delinquency effect on less financially literate borrowers. However, among borrowers with financial literacy consumption, the marginal effect is -2.7 percentage points, suggesting a negative loan delinquency effect among more financially literate borrowers.

Next, we examine whether financial literacy can also mitigate the effect of credit supply on addictive consumption. We estimate the following model:

$$\begin{aligned} Y_{it} = & \sum_{k\in\{-1,1,2,3-4\}} \beta_k \times HighFLConsum_i \times Treat_i \times Month(k) + \sum_{k\in\{-1,1,2,3-4\}} \gamma_k \times Treat_i \times Month(k) + \sum_{k\in\{-1,1,2,3-4\}} \theta_k \times HighFLConsum_i \\ & \times Month(k) + \sum_{k\in\{-1,1,2,3-4\}} \rho_k \times Month(k) + IndividualFEs + \varepsilon_i \end{aligned} \tag{5}$$

The coefficients of the triple interaction terms denote the heterogeneous credit supply effects across borrowers with different levels of financial literacy.

The results are presented in Table 9. Due to potential influences from various unaccounted factors, particularly those beyond our control, it is unsurprising to observe high standard errors in online shopping analysis. Despite notable point estimates, the coefficients remain statistically insignificant. Therefore, our empirical analysis provides no support for the existence of heterogeneous credit supply effects on total, addictive, or non-addictive consumption.

## 5. Conclusion

Understanding the effect of expanding high-interest credit supply is essential for policymakers and researchers, especially in emerging markets. It may have direct policy implications for addressing the rapidly growing online cash loan market in emerging markets.

[16] Our financial literacy measure, based on online shopping behavior, may interact non-linearly with consumption and individual characteristics. To account for this, we apply Baker and Wurgler's (2006) method to create a refined measure that controls for borrower characteristics like gender, age, outstanding loans, and past consumption. Using a random forest model, we generate residuals as a more accurate proxy for financial literacy. Re-running the regressions with this refined measure, the interaction term remains negatively significant, indicating a stronger effect among the financially illiterate. The refined proxy is insignificant, suggesting no significant link between financial literacy and loan delinquencies after controlling for other factors.

This study investigates the loan delinquency effect of expanding consumer credit supply using a comprehensive dataset combined with a unique experiment. By analyzing an experiment in which a collaborating cash loan platform increased the credit lines of selected clients, we obtain a few interesting findings. First, expanding credit supply significantly increases the probability of loan delinquency, implying a potentially negative effect on the financial health of consumers' credit. This effect is more prominent for consumers with lower financial literacy. This supports the importance of financial literacy in the use of financial services (Lusardi and Mitchell., 2014; Van Rooij et al., 2011; Hsiao and Tsai, 2018). Second, a higher credit supply significantly increases reliance on cash loan lending, suggesting that credit supply may drive consumers into a debt-trap. Third, the additional credit supply positively affects online shopping consumption, especially addictive consumption, suggesting another form of negative welfare effect resulting from consumer credit supply.

As policymakers around the world try to keep up with the fast-growing online, unsecured lending industry, this study may provide valuable for regulators who want to consider the response of individuals with different levels of financial literacy after they get access to more consumer credit. Our findings highlight the critical role of financial education in improving individuals' financial literacy, thereby improving the welfare of participants in financial transactions.

## CRediT authorship contribution statement

**Shun Fu:** Writing – review & editing. **Emma Li:** Writing – review & editing, Methodology, Conceptualization. **Li Liao:** Supervision, Conceptualization. **Zhengwei Wang:** Supervision, Methodology, Conceptualization. **Hongyu Xiang:** Methodology, Formal analysis.

## Declaration of competing interest

The authors declare no interests to disclose.

## Acknowledgements

Hongyu Xiang acknowledges the financial support provided by National Natural Science Foundation of China (72203024;72103110) and Fundamental Research Funds for the Central Universities (2021NTSS09). We thank the editor, the associate editor, and the anonymous referee for very helpful comments to our draft. We also thank our discussants Ronghong Huang, Xing Li, and other conference participants at the FIRN annual meeting and CFRC. We also thank Bing Han, Christian Lundblad, William Megginson, Lyndon Moore, Jingjian Xiao, Jun Yang, and brownbag participants at Tsinghua University for helpful comments and suggestions. We are grateful to the FIRN Annual Conference Committee for awarding us the best paper prize. Any errors are our own.

## Supplementary materials

Supplementary material associated with this article can be found, in the online version, at doi:10.1016/j.jempfin.2025.101592.

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