Individual Consumption Response to Expanding Credit Access: Evidence from online cash loan platform

Emma Li, Li Liao, Zhengwei Wang, and Hongyu Xiang*

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Abstract

This paper exploits a detailed new dataset with comprehensive financial and consumption information to investigate the relationship between a cash-loan borrower's access to credit and their respective consumption response. In particular, we test whether consumption among borrowers with a high level of addiction is more sensitive to a given change in credit. We use an exogenous credit supply shock to cash-loan borrowers and show that expanding credit access is positively associated with increased individual borrowers' consumption, especially on gaming related consumption.

Key words: Consumption, Cash loan, Debt, Credit access, Consumer finance, Fintech

JEL Classification: D12, G21, I31

* Li is from Finance department, Deakin University, Melbourne, Australia; Email: emma.li@deakin.edu.au. Liao is from PBC School of Finance, Tsinghua University, Beijing, China; Email: liaol@pbcsf.tsinghua.edu.cn; Wang is from PBC School of Finance, Tsinghua University, Beijing, China; Email: wangzhw@pbcsf.tsinghua.edu.cn; Xiang is from PBC School of Finance, Tsinghua University, Beijing, China. Email: xianghy.11@pbcsf.tsinghua.edu.cn;

I. Introduction

Understanding the determinants of consumption decisions bears significant implications for economists and policy-makers as consumption is the largest component of GDP in many countries. Researchers have made substantial progress in investigating the effect of liquidity constraints on consumption (e.g. Johnson et al. 2006; Agarwal et al., 2007; Agarwal and Qian, 2014). One particular stream of research is dedicated to investigating how relaxing liquidity constraints by expanding credit access impacts consumption of credit-constrained individuals (Gross and Souleles, 2002; Karlan and Zinman, 2010; Cuffe and Gibbs, 2017).

The effect of access to consumer credit on consumption is controversial in the literature. Some researchers argue that access to credit may also increases consumption by reducing precautionary saving motives since it reduces the likelihood that liquidity constraint will bind in the future (Gross and Souleles, 2002). However, expensive consumer credit may exert high debt burden on borrowers (Cambell et al, 2012), which may in turn reduce consumption in the long term.

Researchers generally two major challenges in identifying the effect of credit access on consumption. The first is how to accurately measure individual consumption. Existing literature has heavily relied on indirect measures, such as survey data or data that are not at the individual consumption level. These data may bring concerns on the accuracy and frequency of the consumption measures. Second, with the possibility of reversal causality, such as individuals planning to consume more in the future may intend to get access to more credit, it is difficult to identify the causal effect of credit access on consumption.

To measure individual borrowers' consumption, we use borrowers' full spending transaction level records from Alibaba ("Taobao" and "Tmall"), which accounts for a market share of approximately 70% in China's e-commerce industry[1]. Similar to the Amazon in the US, online shopping has becoming an important medium of disposable consumption in China, and approximately 18% of personal consumption in the country is purchased online. Our consumption measures have the following key advantages: first, these measures are calculated from real individual consumption transactions with timestamp, which may provide more accurate and frequent data points as compared with survey data; second, the data is on the individual level, which allows us to track down the borrowing history of the same individuals in our proprietary dataset[2], so that we can capture individual information such as age, sex, borrowing and repayment history; finally, for each transaction, we have the detail for each purchased item. By employing textual analysis on item description for each transaction, we can categorize each transaction record into different consumption categories to better differentiate consumption behavior.

To further investigate the effect of expanding credit access, we use an experiment from the online cash loan platform on their existing and new cash loan borrowers between Apr, 20 2016 and Apr, 30 2016. As part of the platform's trial and error initiatives, the cash loan provider randomly selected a set of borrowers from its user

[1] Alibaba is the world's largest retail e-commerce company in terms of gross merchandise volume (GMV) according to its 20-F Form in the 2017 fiscal year (ended March, 31 2017).
[2] The data provider is a leading cash loan platform in China. Until Apr 2017, 2.2 billion loans had been facilitated to its borrowers.

base during the above time period and permanently increased the borrowers' credit limits. This credit supply shock substantially increased the credit access of the borrowers. On average, it raised the treated individuals' credit lines by over CNY 2,000, which is even 70% higher than the average loan size in that period. Combined with detailed consumption information from each individual, this experiment provides us a rare opportunity to investigate the direct association between expanding credit access and individual consumption.

We use propensity score matching to remove the observation difference between treatment group and control group and employ the difference-in-difference approach to estimate the effect of credit access on consumption. Within a month after obtaining cash loans, the treated borrowers with increased credit limits have significantly increased their consumption online by RMB 105 compared to the consumption from controlled borrowers without credit limit increase, suggesting a 10% of marginal propensity to consume out of borrowing amount. It is a considerably large magnitude, given that Alibaba e-commerce consumption accounts for 12.9% of the total personal consumption in China. By contrast, expanding credit access has little effect on consumption after the first month of obtaining the loan.

This paper also shows that expanding credit access has significantly increased the spending on gaming related products. If gaming is addictive (Fisher, 1994; Kim et al 2008) and addictive products attract individuals to engage in utility-destroying consumption (Gul and Pesendorfer, 2007), expanding credit access could make constrained borrowers worse off. We show that the effect of expanding credit access on both total consumption and gaming consumption is most prominent for the borrowers with addictive consumption history in the highest quartile from our sample.

Researchers have examined the effect of income shocks (e.g. Johnson et al. 2006; Agarwal et al., 2007; Parker et al., 2013; Agarwal and Qian, 2014), wealth (e.g. Ando and Modigliani, 1963; Poterba, 2000; Lettau and Ludvigson, 2004), and interest rates (e.g. Weber, 1970; Boskin,1978; Gross and Souleles, 2002) on consumption. We contribute to the vast literature by documenting the effect of increased credit access on individual consumption behavior.

This paper also contributes to the long debate of the welfare effects from increased credit to credit-constrained borrowers. We showed that increased credit to borrowers with addiction may tempt them to engage in utility-destroying consumption and may put on an extra financial burden. Little consensus exists on whether access to consumer credit necessarily provides a benefit to the individual. Previous studies find that an increase of consumer credit access may have both positive and negative welfare effects on borrowers. On one hand, access to consumer credit may have a negative effect for a number of behavioral reasons, such as cognitive biases (Bertrand and Morse, 2011) and exponential growth bias (Stango and Zinman, 2009). Researcher documented that accessing more credit increases hardship in paying mortgage, rent, and utility bills (Melzer, 2011), impairs military readiness (Carrell and Zinman, 2010), and increases involuntary bank account closures (Campbell et al., 2012) and bankruptcy rates (Morgan et al., 2012). On the other hand, consumer credit access may have a positive effect on borrower welfare as it enlarges borrowers' choice set (Melzer, 2011), reduces foreclosures and crimes after natural disaster (Morse, 2011), decreases bank overdrafts and late bill payments (Zinman, 2010), and improves food consumption, economic self-sufficiency, mental health, and outlook (Karlan and Zinman, 2010), increases self-employment (Herkenhoff et al., 2016).

The rest of the paper proceeds as follows. Section II presents the institutional background including the online cash loan industry, the cash loan platform and Alibaba e-commerce platforms. Section III introduces our dataset and empirical strategy. Our empirical results are presented in Section IV. Section V concludes.

II. Institutional Background

A. Cash loan industry

In this article, "cash loan" refers to the small, short-term, unsecured consumer loans offered by non-banking institutions. The cash loan market is an important funding channel for credit constrained consumers in many countries. In the U.S., the payday lending transaction volume of the payday loan market, one type of cash loan market, was on average USD 50 billion in each year (Morse, 2011). In 2010, 12 million individuals took payday loans from around 20,000 payday loan lenders (Cuffe and Gibbs, 2017). In the U.K, the payday loan lending volume rose tenfold from €0.33 billion in 2006 to EUR 3.7 billion (around USD 4.7 billion) in 2012 (ACCA, 2014). In China, the monthly cash loan lending volume increased from 130 million USD in Jan 2016 to approximately 2 billion USD in Oct 2017. Approximately 10 million Chinese individuals are involved in cash loan borrowing[3].

Academics argue that two possible reasons may explain the fast growing cash loan market. First, transaction cost and default risk makes it infeasible for banks to offer small short-term loans (Morse, 2011). Second, banks are reluctant to offer credit to individuals with poor credit history (Morse, 2011; Karlan and Zinman, 2010). In China, the problem can be even more serious with the underdeveloped banking system. A recent household survey finds that 58.9% of households in need of credit are unable to obtain loans from commercial banks (China Household Finance Survey, 2014).

In the US, payday loans are usually made for a maturity of 7 to 30 days at less than USD 300 and with extremely high APRs over 400%. Previously, payday loan applications and funding used to happen in a payday loan shop but now and increasing number of payday loan providers are moving to online platforms[4]. A typical funding procedure for a payday loan is as follows: a borrower visits a payday loan lender's store, writes a postdated check, and obtains cash from the lender if he is qualified. Then, the lender holds the check and deposits it to its own account after the due date (Stegman, 2007). Through online payday lending, a borrower provides his personal information, including social security number, and signs e-documents on the lender's website before he can receive funds. Chinese cash loan providers operate in a very similar way as the US payday loan providers: the payday loan

[3] https://www.ifcert.org.cn/industry/187/IndustryDetail
[4] Typical examples of online cash loan lenders are Lendup, Opportun, Elevate, and Insikt.

provider offers small and short-term credit to credit constrained individuals. One major difference is that the maturity of a cash loan in China is approximately 3-6 months while typical US payday loans have less than two weeks maturity. According to an official industry report, a payday loan is a small-size loan with a maturity of less than half a year; the average size of cash loans in China is CNY 1400 (around USD 250); most of the borrowers are credit constrained individuals with low income[5].

B. The cash loan platform and our data provider

Our cooperating cash loan platform and data provider was founded in 2014 and has grown substantially to a market leader over recent years. The platform offers cash loans with average size of CNY 1000 and average maturity of 3-4 months. Until Apr 2017, 2.2 billion loans had been facilitated to its borrowers.

[Insert Figure 1 About Here]

The funding procedure for cash loans proceeds as follows (See Figure 1): First, a loan applicant downloads the cash loan platform's app on his mobile device and sign up with his phone number. Then the system asks the loan applicant to upload photocopies of his ID card and verifies his identity. In the identity verification process, the system can automatically identify the age and sex of the applicant. Second, the applicant signs consent forms that allow the platform to collect his personal information, such as full transaction records on Alibaba e-commerce platforms (see Section II.C for details of these e-commerce platforms), mobile phone

[5] https://www.ifcert.org.cn/industry/187/IndustryDetail

call records, and other personal information. After that, the platform uses its internal credit assessment model to evaluate the applicants' information, calculates their credit scores, and decides their credit lines. Third, the applicant chooses the amount and maturity of the loan and then the computer system determines the interest rate based on the applicant's credit score. If the applicant accepts the interest rate, the loan will be approved and the cash will be sent to the applicant's bank account. Generally, the whole funding process takes less than 1 day from downloading the app.

C. The Experiment

To test the effect of expanding credit access on consumption, we use an experiment that was conducted by the cash loan platform between Apr 20, 2016 and Apr 30, 2016. The experiment intended to permanently increase credit lines for selected users. Per discussion with the platform's management team and learning from other news sources, the platform obtained VC funding in 2015 and used the funds in conducting a series of experiments to explore how to make profit. As one of those experiments, this experiment can be deployed as part of a trial and error initiative to both promote the business and test their risk control strategy. In the experiment, the platform announced that all the registered users could apply to the platform and had chance to obtain higher credit lines. The probability with which one could obtain a higher credit line depends on his credit score calculated by the platform's private internal model. The experiment prominently expanded the credit access on the treated individuals. As is estimated using the dataset we obtain from the cash loan platform, the average credit line increase for selected individuals is CNY 2163.71, 70% higher than the average loan size around the experiment. As is shown in Figure 2, the outstanding loans of treated individuals increased dramatically after the experiment.

D. Alibaba E-commerce Platforms

In this paper, we measure cash loan borrowers' consumption by using their full transaction records with timestamp on Taobao Marketplace and Tmall, two leading retail e-commerce platforms owned by Alibaba. Alibaba Group is the world's largest retail e-commerce company in terms of gross merchandise volume (GMV) according to its 20-F Form in the 2017 fiscal year (ended March, 31 2017). Similar to Amazon and e-Bay, the Alibaba e-commerce platforms match buyers and sellers and facilitate online sales.

Online shopping has been growing tremendously in China in recent years compared to the rest of the world. Between 2014 and 2016, the online shopping volume had a 35.9% annual growth rate in China[6], compared to around 25% annual growth rate in the world[7]. Alibaba has been one of the biggest winners. In 2017, Alibaba facilitated GMV of CNY 3,767 billion, or 12.9% of Chinese household consumption, and served 454 million active buyers, accounting for 32.8% of the Chinese population[8]. Alibaba online shopping platforms have a wide coverage of most of the consumption goods and services in China, including food, apparel,

6 The data is collected from the National Bureau of Statistics of the People's Republic of China.
7 https://www.statista.com/statistics/288487/forecast-of-global-b2c-e-commerce-growt/
8 The data of Taobao and Tmall mentioned in this paragraph are collected from the 20-F form of Alibaba Group in 2017 fiscal year. (See https://www.sec.gov/Archives/edgar/data/1577552/000104746917004019/a2231121z20-f.htm.) We collect the data of household consumption and population from National Bureau of Statistics.

housing items, transportation, vehicles maintenance, healthcare products, over-the-counter medicines, video games, entertainment services, books, and other common goods and services. Therefore, our measurements of consumption using data from Alibaba are generally representative and are in line with the CFPS survey (China Family Panel Studies[9]). But we want to point out three differences between online shopping via Alibaba and household consumption in general. First, in-hospital treatment is prohibited from being sold on e-commerce platforms. Second, vehicles are usually purchased offline through a dealer and rarely on e-commerce platforms. Last, Alibaba doesn’t facilitate cash contributions to religious, educational and charitable organizations. Even considering the above differences, the e-commerce consumption on Alibaba still provides us a comprehensive overview on individuals’ consumption in China according to the comparison between our data and the CFPS survey data.

III. Data and Empirical Strategy

A. The Dataset

We obtain a proprietary dataset from our cooperating company, a leading cash loan platform in China. Our dataset contains the information of a randomly selected sample of 10,000 individuals who had participated in the experiment by applying for higher credit lines during the period of the experiment (04/20/2016~04/30/2016). The randomly selected sample is approximately 50% of all the applicants

[9] http://opendata.pku.edu.cn/dataverse/CFPS

participated in the experiment. We can identify the individuals who were selected to obtain higher credit lines ("treatment group" hereafter) and those who were not ("control group" hereafter).

Approximately 70% of individuals in our sample have disclosed the full transaction records on Alibaba e-commerce platforms. For each individual, our dataset contains all the transactions that happened from his registration on Alibaba to the latest data collect date. Our datasets contains detailed information of 1,286,806 consumption transaction records. The information includes transaction volume (dollar amount and number of the products/services), transaction time, item description (including description on both goods and sellers). Rather than observing consumption behavior indirectly (Gross and Souleles, 2002; Karlan and Zinman, 2010) or using store-level consumption data (Cuffe and Gibbs, 2017), our unique data of e-commerce transaction records allows us to construct individual-level consumption measures based on real time transactions. Since item descriptions may reflect the detailed information of the goods/services, our unique data also allows us to construct measures for expenditures on different consumption categories.

This datasets also contain information related to all the loans offered to these 2,322 individuals and these individuals' personal information. The loan information includes the amount, term, interest rate category, repayment records, and the current loan status (repaid, overdue, or default, which is defined as 60-day plus past due). The personal information includes sex and age.

B. Consumption Measures

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

Our analysis includes the following three classification tasks. First, according to the definition of Consumer Expenditure Survey (CEX), we classify each transaction into one of the following seven CEX categories: food, apparels, housing, transportation, healthcare, entertainment, and others. This classification is motivated by a large strand of studies (e.g. Souleles, 1999; Storesletten et al, 2004; Aguiar and Hurst, 2013) that use CEX as the primary data source. We use it later to illustrate the representativeness of our consumption data.

Next, we identify addictive consumption and non-addictive consumption. Following Gul and Pesendorfer (2007), we define addictive consumption as the spending on the goods or services which make consumers more compulsive. As is suggested by previous literature, the addictive consumption primarily includes purchases on video games (Fisher, 1994), caffeine products (Olekalns and Bardsley, 1996), alcohol (Gul and Pesendorfer, 2007), tobaccos (Becker, Grossman, and Murphy, 1991), and the other products that may lead to compulsive actions. The rest of transactions are classified as non-addictive consumption.

Finally, we distinguish gaming consumption and non-gaming consumption as video game may provide negative welfare impact on its consumers. Investigating the effect on gaming consumption may help us understand the welfare implication of expanding credit access. Gaming consumption includes expenditures on video games, as well as spending on computers and mobiles phones, which are closely connected with video games. The rest of the transactions are identified as non-gaming consumption.

Following the methodologies in the previous literature (e.g. Tetlock, 2007; Loughran and Madonald, 2011; You, Zhang and Zhang, 2017), our textual analysis methodology relies on word lists, one for each consumption category. In building the word lists, we manually review the item description and select all the frequent and representative words for each category; we also collect the key words from the websites of Alibaba e-commerce platforms. Combining the words collected, we manually check the words one-by-one and decide the preliminary word lists.

To improve the accuracy of the classification, we do a trial test on the word lists and update our classification methods according to the test results. The detailed procedures start with classifying all the e-commerce transaction records based on the preliminary word lists. Each transaction is then classified into one particular consumption category if its item description contains one or more words in the corresponding category's word lists. By manually reviewing the transactions which are classified into zero category or two or more categories, we update our word lists and design more detailed classification rules to further improve the effectiveness of the classification method. Then we make a final classification based on the updated word lists and classification rules.

In order to examine the validity of our textual analysis, we construct a test sample by randomly selecting 4,000 transaction records from all the 1,286,806 e-commerce transaction records and make manual classification for the test sample. We use the four following commonly-used measures to show the performance of our classification algorithm on the test sample. Accuracy is the number of correct predictions in the test sample divided by 4000, the total number of observations in the test sample. For each consumption category, Precision is the number of true positives divided by the sum of true positives and true negatives; Recall is the number of true positives divided by the sum of true positives 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.

[Insert Table I About Here]

The performance measure for our classification algorithm is reported in Table I. When identify the seven CEX categories, all the performance measures of our algorithm are 80%~90%, indicating that in over 80% cases our algorithm gives the correct prediction on each CEX category. The performance measures are even higher when identifying addictive consumption and non-addictive consumption. The performance measure of our classification is higher than the out-of-sample performance measure (most of which are below 80%) of machine learning methods documented in Chen et al (2018).

C. Summary Statistics

We construct the sample in our study from the information related to the 10,000 individuals who participated in the experiment. We drop all the individuals that failed to disclose to the cash loan platform all the Alibaba e-commerce transactions happened before Aug 9, 2016 (16 weeks after the first day of the experiment), so that we can look at the effect of expanding credit access up to 16 weeks. The resulting sample contains 2,322 individuals and is called "full sample" hereafter. We limit the sample period of the full sample between Dec 30, 2015 and Aug 9, 2016, or the 8 fortnights before the experiment[10] and the 8 fortnights after the experiment.

[Insert Table II About Here]

Table II Panel A reports the summary statistics of the 2,322 individuals and their 5,810 loans in the full sample. 33.2% or 771 individuals are in the treatment group. The average borrower was around 27 years old. Males constitute 79.2% of the borrowers in the full sample. This suggests that most of the individuals in our full sample are young males. For all the 5,810 loans in the full sample, the average size is 1264.4 CNY (around 200 USD) and the average maturity is 6.719 months. The average interest rate category of the loans in the full sample is 2.259. As to loan performance, 21.3% of the loans have experienced seven or more days overdue payments. Defaulted loans, defined as over 60-day past due loans, accounts 6.3% of all the loans.

Table III Panel B presents the descriptive statistics of consumption variables and borrowing behavior across the 37,152 (=2,322*16) individual-fortnight observations. The average fortnight e-commerce consumption from a cash loan user is CNY 424.528 (Approximately USD 65), approximately 52% of the fortnightly

[10] When mentioning "before the experiment" or "after the experiment", we refer to "the experiment" as the first day of the experiment (Apr 20, 2016).

household consumption per capita in China in 2016[11].

In order to validate whether our consumption measures are representative, we compare the composition of the experiment participants' e-commerce consumption in our sample with the survey data from Chinese household consumption. To analyze the composition of Chinese household consumption, we collect the data of 3,449 Chinese families which participated in 2014 CFPS survey and offered a valid response of household spending. The data contains the families' spending on various uses in the latest year. In our analysis, we exclude expenditure on hospital treatment, vehicle purchase, and cash contribution since it is unlikely that a consumer buys these types of goods/service on e-commerce platforms.

In Table II Panel C, we present the share of each consumption category for e-commerce consumption in the first column and for household consumption in the second column. We find that most of the consumption categories account for similar percentages in E-commerce consumption and household consumption. Hence, our online consumption measures are in general reasonable proxies to represent the daily individual consumption in China.

D. Empirical Strategy

We use the DiD approach in an attempt to identify the effect of expanding credit access on credit-constrained individuals' consumption. Based on the experiment, the DiD methodology compares the consumption of the treatment group individuals to the consumption of the control group individuals, before and after the experiment.

[11] The household consumption per capita in China is calculated using the data from National Bureau of Statistics of China

The DiD approach helps identify causality as tests are conducted surrounding the experiment that causes variation in credit access and is unlikely correlated with individuals' planning of future consumption.

[Insert Table III Here]

Table III Panel A compares the means of the key characteristics of both treatment group individuals and control group individuals. We find that these two groups are statistically different in terms of sex ratio, age, times of past borrowing, the proportion of individuals with unpaid due payment, outstanding loans, and past consumption, though there is no statistically significant difference in past addictive consumption. The findings suggest that the probability of being assigned to treatment group depends on one's characteristics.

In order to address the concern that difference in observable covariates may bias our empirical results, our DiD analysis starts with employing propensity score matching on the treatment group and the control group. We first estimate a pre-match Probit model based on all 2,322 indivudlas in the full sample. The dependent variable, *Treat*, is equal to one if the individual is in the treatment group. The independent variables include sex, age, the natural logarithm of one plus the times of past borrowing, whether the individual has unpaid due payment, outstanding loans, past consumption, and past addictive consumption.

Table III Panel B Column (1) reports the estimate of the pre-match Probit. The result suggests that the Probit specification captures some variation in the dependent variable, as is indicated by a pseudo-R2 of 3.8% and a p-value from the chi2 test of

0.000. We then predict the propensity scores from the estimation result of Column (1) and perform the nearest-neighbor propensity score matching algorithm with replacement allowed. The propensity matching process generates the matched sample that contains 771 pairs of matched individuals.

We conduct two diagnostic tests to verify that the treatment group and the control group in the matched sample are similar in the observable covariates. First, we re-run the same Probit model in the matched sample. The estimate now is reported in Table III Panel B Column (2) and none of the coefficients of independent variables are statistically significant. The p-value of the chi2 test is 0.277, implying that we cannot reject the null hypothesis that all coefficients of independent variables are significantly different from 0. Second, we test the difference of covariates between treatment group individuals and control group individuals. The results are reported in Table III Panel C, which shows that the observable characteristics are not significantly different between the treatment group and the control group after matching. The above results imply that the propensity score matching algorithm is able to remove the effect of difference in observable covariates.

Then we perform the DiD analysis by estimating the coefficients of the following model.

$$\mathrm{Y_{it}} = \alpha + \gamma_1 * \mathrm{Treat_i} * \mathrm{After}(1-2)_{\mathrm{it}} + \gamma_2 * \mathrm{Treat_i} * \mathrm{After}(3-4)_{\mathrm{it}} + \gamma_3 * \mathrm{Treat_i} * \mathrm{After}(5+)_{\mathrm{it}} + \mu * \mathrm{Treat_i} + \beta_1 * \mathrm{After}(1-2)_{\mathrm{it}} + \beta_2 * \mathrm{After}(3-4)_{\mathrm{it}} + \beta_3 * \mathrm{After}(5+)_{\mathrm{it}} + \varepsilon_{\mathrm{it}} \tag{1}$$

where Y_{it} denotes the interested dependent variables, $Treat_i$ is a dummy variable which takes the value of 1 if the borrower i is in the treatment group and takes the value of 0 if the borrower i is in control group, $After(1-2)_{it}$ is the dummy variable with the value of 1 for the first two fortnights after the experiment. $After(3-4)_{it}$ is a dummy variable for the third and fourth fortnights after the experiment, $After(5+)_{it}$ is a dummy variable for the fifth fortnight after the experiment or later. γ_1 denotes the average fortnightly DiD effect on the consumption variable in the first two fortnights after experiment. γ_2 denotes the effect in the third and the fourth fortnights after the experiment. γ_3 denotes the effect in the fifth fortnight after the experiment or later.

IV. Results

A. Expanding Credit Access and Total Consumption

First, we estimate the effect of increasing credit access on total consumption by estimating specification (1) with the total consumption as the dependent variable.

[Insert Table IV About Here]

As is indicated in Table IV Column (1), the coefficient of Treat*After(1-2) is 105.737, with a t-statistics of 2.506, indicating that the average fortnightly treatment effect on total consumption in the first two fortnights after the experiment is CNY 105.737. Considering the average increase of credit line for the treatment group individuals is CNY 2163.71, the result suggests a 9.8% (=105.737*2/2163.71) marginal propensity to consume out of credit in the first month after the experiment.

In other words, obtaining one more dollar credit lines increases individual's expenditure on Alibaba e-commerce platforms by 9.8 cents in the first month. It is a considerable magnitude given that Alibaba e-commerce consumption accounts for only 12.6% of the total household consumption.

In contrast, both the coefficients of Treat*After(3-4) and Treat*After (5+) are not significantly different from zero, indicating that expanding credit access may not have long term treatment effects on total consumption.

[Insert Figure 3 About Here]

To demonstrate the parallel trend assumption that is key to the validity of DiD methodology, we include Before(3-4) (a dummy variable for the third and fourth fortnight before the experiment), Before(1-2) (a dummy variable for the first and second fortnight before the experiment), Treat*Before(3-4), Treat*Before(1-2), in the previous regression. As is shown in Column (2), both the coefficients of Treat*Before(3-4) and Treat*Before(1-2) are not significantly different from zero, suggesting that it is unlikely the parallel trend assumption is violated. The estimated treatment effect in Column (2) is consistent with that in Column (1). Figure 3 plots the time dynamics of the treatment effects graphically.

Our finding that expanding credit access has a short-term positive effect on total consumption is consistent with the economic intuition that credit-constrained individuals may consume more after relaxing credit constraints. It is also similar to the findings of Gross and Souleles (2002) that exogenous credit line increase raises consumption.

B. Expanding Credit Access and Gaming Consumption

"There is ample evidence to suggest that people are spending more time playing games….also spending more on them[12]." As is documented by psychologists (e.g. Fisher, 1994), video games are addictive. Researchers argue that addictive consumption weakens self-control ability and may in turn reduce consumers' welfare (Gul and Pesendorfer, 2007). Therefore, looking into the effect of expanding credit access on gaming related consumption may contribute to the debate on whether the access to consumer credit has positive or negative welfare effects.

To test the effects of expanded credit access on gaming related spending. Gaming related consumption includes expenditure. It also contains expenditures on mobile phones and personal computers, which are likely to be used to play video games. We use the CNY value of gaming related consumption as the dependent variable and re-estimate the coefficients of specification (1).

[Insert Table V About Here]

The estimate of coefficients and the corresponding t-statistics are reported in the first column of Table V. We find that the coefficient of *Treat*After (1-2)* is 31.289 with a t-statistic of 2.130, implying that the average fortnightly treatment effect of on gaming related consumption in the first four weeks is CNY 31.289, approximately 30% of the treatment effect on total consumption. That is to say, a considerable proportion of consumption induced by credit access expansion is gaming related consumption.

[12] https://www.economist.com/blogs/babbage/2014/02/electronic-entertainment

In terms of the longer term effect, we find that both the coefficients of *Treat*After(3-4)* and *Treat*After (5+)* are not significant different from zero, suggesting that expanding cash loan credit access has little treatment effect on gaming related consumption after one month.

Our findings suggest that expanding credit access may have a negative welfare effect as it raises addictive gaming related consumption. This is consistent with some previous studies (e.g. Bertrand and Morse, 2011; Carrell and Zinman, 2010; Campbell et al 2012) that document the negative welfare effect of increased credit access to payday loan borrowers.

Table X Column (2) shows that the average fortnightly treatment effect on non-gaming consumption in the first four weeks after the treatment is CNY 51.985 with significance at 10% level, while the coefficients of Treat*After(3-4) and Treat*After(5+) are not significantly distinguishable from zero. It indicates that credit access may also have positive effect on non-gaming consumption in the first month, but have little effect in the longer term. Given that the sample average non-gaming consumption is over four times as higher as gaming consumption, the treatment effect on non-gaming consumption looks less prominent than that on gaming consumption.

C. Expanding Credit Access and addicted borrowers

Next, we test whether the treatment effects varies with individuals' addictive consumption. As is documented in Gul and Pesendorfer (2007), addictive consumption leads to weaker self-control. When being offered more credit, individuals with weaker self-control are likely to over consume (Morse, 2011). Hence, we hypothesize that the effect of increasing credit lines on consumption is more prominent for the more addicted consumers, or consumers with higher addictive consumption.

To test this hypothesis, we test whether the treatment effect on the consumption is significantly different between the more addicted individuals and the less addicted individuals. Considering that average treatment effect on total consumption only concentrates in the first two fortnights. We restrict our sample to the first eight fortnights before the experiment and the first two fortnights after the experiment and estimate the coefficients of the following specification.

$$\mathrm{C_{it}} = \alpha + \gamma_1 * \mathrm{Addicted_i} * \mathrm{Treat_i} * \mathrm{After}(1-2)_{\mathrm{it}} + \beta_1 * \mathrm{Addicted_i} * \mathrm{Treat_i} + \beta_2 * \mathrm{Treat_i} * \mathrm{After}(1-2)_{\mathrm{it}} + \beta_3 * \mathrm{Addicted_i} * \mathrm{After}(1-2)_{\mathrm{it}} + \beta_4 * \mathrm{Addicted_i} + \beta_5 * \mathrm{Treat_i} + \beta_6 * \mathrm{After}(1-2)_{\mathrm{it}} + +\varepsilon_{\mathrm{it}} \quad (2)$$

where $C_{it}, Treat_i, After(1-2)_{it}$ are defined in Section III.D. $\mathrm{Addicted_i}$ is a dummy variable with the value of 1 if the borrower i spent over CNY 63.8, which is the 75th percentile of the addictive consumption within the eight fortnights before the experiment for individuals in the matched sample. ε_{it} is the error term. γ_1 represents the average difference between the treatment effect on the more addicted individuals and that on the less addicted individuals.

[Insert Table VI About Here]

Table VI reports the estimate of coefficients of the specification (2). Column (1) reports the estimated coefficients with total consumption as the dependent variable. We find that the coefficient of Addicted*Treat*After(1-2) is 288.801, with a t-statistic of 2.994. It indicates that the treatment effect of increasing credit lines on total consumption is significantly larger for more addicted individuals, which is consistent with our hypothesis that more addicted borrowers may over consume after obtaining more credit. Considering the average fortnightly treatment effect on total consumption is CNY 105.737 in the first month, the CNY 288.801 difference between the treatment effects also has economic significance.

In Column (2), we replace the dependent variable with the total gaming related consumption. The coefficient of Addicted*Treat*After(1-2) suggests that increasing credit lines has larger treatment effect on gaming consumptions for the more addicted individuals versus the less addicted individuals. In Column (3), we re-estimate specification (2) using non-gaming consumption as the dependent variable. The estimated coefficient shows that there is no significant difference in the treatment effect between the more addicted individuals and the less addicted individuals.

D. Expanding Credit Access and Loan Delinquency

In the literature, researchers (e.g. Melzer, 2011; Campbell et al., 2012) argue that increased credit access to cash loan borrowers is associated with default on other payments because of the extra financial burden from high interest payments. We intend to examine whether expanding credit access connects with increased loan delinquency.

To test this, we use two proxies for loan delinquency at each individual-fortnight observation. The first proxy, *Overdue%*, is defined as the proportion of seven or more days overdue repayments among all the repayments that are due in the given fortnight for the given individual. The second proxy, *Default%*, is defined as the proportion of 60 or more days overdue repayments among all the repayments that are due in the given fortnight for the given individual. We then construct a sub-sample from the post-matched full sample by dropping any individual-fortnight when there are no due repayments in the given fortnight for the given individual. The sub-sample contains 5,166 individual-fortnight observations.

[Insert Table VII About Here]

Table VII reports the results of the DiD approach using the two delinquency proxies as the dependent variables and controlling for individual fixed effects and fortnight fixed effects. The results show that there is significantly negative treatment effect of increasing credit lines on *Overdue%* and *Default%* within the first eight fortnights. It indicates that increasing credit access may generally improve individuals' credit quality.

V. Conclusion

Understanding the effect of expanding credit access on individual consumption is important since it provides insights into how underserved borrowers spend their loans. It may also have direct policy applications in addressing the fast growing online cash loan market. However, it has been challenging for researchers to measure consumption accurately at an individual-level.

In this paper, we investigate the effect of expanding credit access on consumption by using a unique and comprehensive dataset combined with a rare experiment that expanded credit access for a selected set of its users. Our dataset contains a cash loan platform's clients and their full transaction records on the Alibaba e-commerce platform. Using textual analysis on item description for each spending transaction, we measures consumption in different categories at the borrower level based on real transactions. Leveraging the experiment in which the cash loan platform increased the credit lines of selected clients, we are able to provide a few interesting findings: First, expanding credit access has positive treatment effect on the total expenditure on e-commerce platforms within the first month, with the marginal propensity to consume out of credit lines around 10%. Second, expanding credit access has positive treatment effect on gaming related consumption in the first month after the experiment. However, expanding credit access does not have longer term effect on both total consumption and gaming related consumption. Third, the treatment effect of expanding credit access on both total consumption and gaming related consumption is more prominent for individuals with higher past addictive consumption. Finally, we find that increasing credit lines may help reduce the likelihood of loan deliquency.

As policy makers around the world try to keep up with the fast growing online unsecured lending industry, this paper may provide insights for regulators when considering the response of different types of individuals who face an increase in credit access.

Reference

ACCA. Payday lending: fixing a broken market. 2014

Aguiar M, Hurst E. 2013. Deconstructing Life-cycle Expenditure [J]. Journal of Political Economy, 2013,121(6): 437-492

Agarwal S, Liu C, Souleles N S. The reaction of consumer spending and debt to tax rebates—evidence from consumer credit data[J]. Journal of Political Economy, 2007, 115(6): 986-1019.

Agarwal S, Qian W. Consumption and Debt Response to Unanticipated Income shocks: Evidence from a Natural Experiment in Singapore[J]. American Economic Review, 2014, 104(12): 4205-4230

Ando A, Modigliani F. The "life cycle" hypothesis of saving: Aggregate implications and tests[J]. American Economic Review, 1963, 53(1): 55-84.

Becker G S, Grossman M, Murphy K M. Rational Addiction and the Effect of Price on Consumption[J]. American Economic Review, 1991, 81(2): 237-241.

Bertrand M, Morse A. Information disclosure, cognitive biases, and payday borrowing[J]. Journal of Finance, 2011, 66(6): 1865-1893.

Boskin M J. Taxation, saving, and the rate of interest[J]. Journal of Political Economy, 1978, 86(2, Part 2): S3-S27.

Campbell D, Martínez-Jerez F A, Tufano P. Bouncing out of the banking system: An empirical analysis of involuntary bank account closures[J]. Journal of Banking and Finance, 2012, 36(4): 1224-1235.

Carrell S, Zinman J. In harm's way? Payday loan access and military personnel performance[J]. Review of Financial Studies, 2014, 27(9): 2805-2840.

Chen M A, Wu Q, Yang B. How Valuable is FinTech Innovation?[J]. 2018. Available at SSRN: https://papers.ssrn.com/sol3/papers.cfm?abstract_id=3106892

China Household Finance Survey. 2014. The report on development of small businesses in China.

Cuffe H E, Gibbs C G. The effect of payday lending restrictions on liquor sales[J]. Journal of Banking and Finance, 2017, 132-145

Fisher S. Identifying video game addiction in children and adolescents[J]. Addictive Behaviors, 1994, 19(5): 545-553.

Gul F, Pesendorfer W. Harmful Addiction [J]. Review of Economic Studies, 2007, 74: 147-172

Gross D B, Souleles N S. Do liquidity constraints and interest rates matter for consumer behavior? Evidence from credit card data[J]. Quarterly Journal of Economics, 2002, 117(1): 149-185.

Herkenhoff K, Phillips G, Cohen-Cole E. The impact of consumer credit access on employment, earnings and entrepreneurship[J]. NBER working paper, 2016.

Johnson D S, Parker J A, Souleles N S. Household expenditure and the income tax rebates of 2001[J]. American Economic Review, 2006, 96(5): 1589-1610.

Karlan D, Zinman J. Expanding credit access: Using randomized supply decisions to estimate the impacts[J]. Review of Financial Studies, 2010, 23(1): 433-464.

Kim E J, Namkoong K, Ku T, et al. The relationship between online game addiction

and aggression, self-control and narcissistic personality traits[J]. European psychiatry, 2008, 23(3): 212-218.
Melzer B T. The real costs of credit access: Evidence from the payday lending market[J]. Quarterly Journal of Economics, 2011, 126(1): 517-555.
Morgan D P, Strain M R, Seblani I. How payday credit access affects overdrafts and other outcomes[J]. Journal of Money, Credit and Banking, 2012, 44(2‐3): 519-531.
Morse A. Payday lenders: Heroes or villains?[J]. Journal of Financial Economics, 2011, 102(1): 28-44.
Lettau M, Ludvigson S C. Understanding trend and cycle in asset values: Reevaluating the wealth effect on consumption[J]. American Economic Review, 2004, 94(1): 276-299.
Loughran T, McDonald B. When is a liability not a liability? Textual analysis, dictionaries, and 10‐Ks[J]. Journal of Finance, 2011, 66(1): 35-65.
Olekalns N, Bardsley P. Rational Addiction to Caffeine: An Analysis of Coffee Consumption[J], Journal of Political Economics, 1996,104(5): 1100-1114
Parker J A, Souleles N S, Johnson D S, et al. Consumer spending and the economic stimulus payments of 2008[J]. American Economic Review, 2013, 103(6): 2530-2553.
Poterba J M. Stock market wealth and consumption[J]. Journal of Economic Perspectives, 2000, 14(2): 99-118.
Souleles N S. The Response of Household Consumption to Income Tax Refunds[J]. American Economic Review, 1999,89(4): 947-958.
Stango V, Zinman J. Exponential growth bias and household finance[J]. Journal of Finance, 2009, 64(6): 2807-2849.
Stegman M A. Payday lending[J]. Journal of Economic Perspectives, 2007, 21(1): 169-190.
Storesletten K, Telmer C I, Yaron A. Consumption and risk-sharing over the life cycle[J]. Journal of Monetary Economics, 2004, 51:609-633.
Tetlock P C. Giving content to investor sentiment: The role of media in the stock market[J]. Journal of Finance, 2007, 62(3): 1139-1168.
Weber W E. The effect of interest rates on aggregate consumption[J]. American Economic Review, 1970, 60(4): 591-600.
You J, Zhang B, Zhang L. Who captures the power of the pen?[J]. Review of Financial Studies, 2017, 31(1): 43-96.
Zinman J. Restricting consumer credit access: Household survey evidence on effects around the Oregon rate cap[J]. Journal of Banking and Finance, 2010, 34(3): 546-556.

Figures and Tables

Figure 1

Flow Chart of the Lending Procedure on the Platform

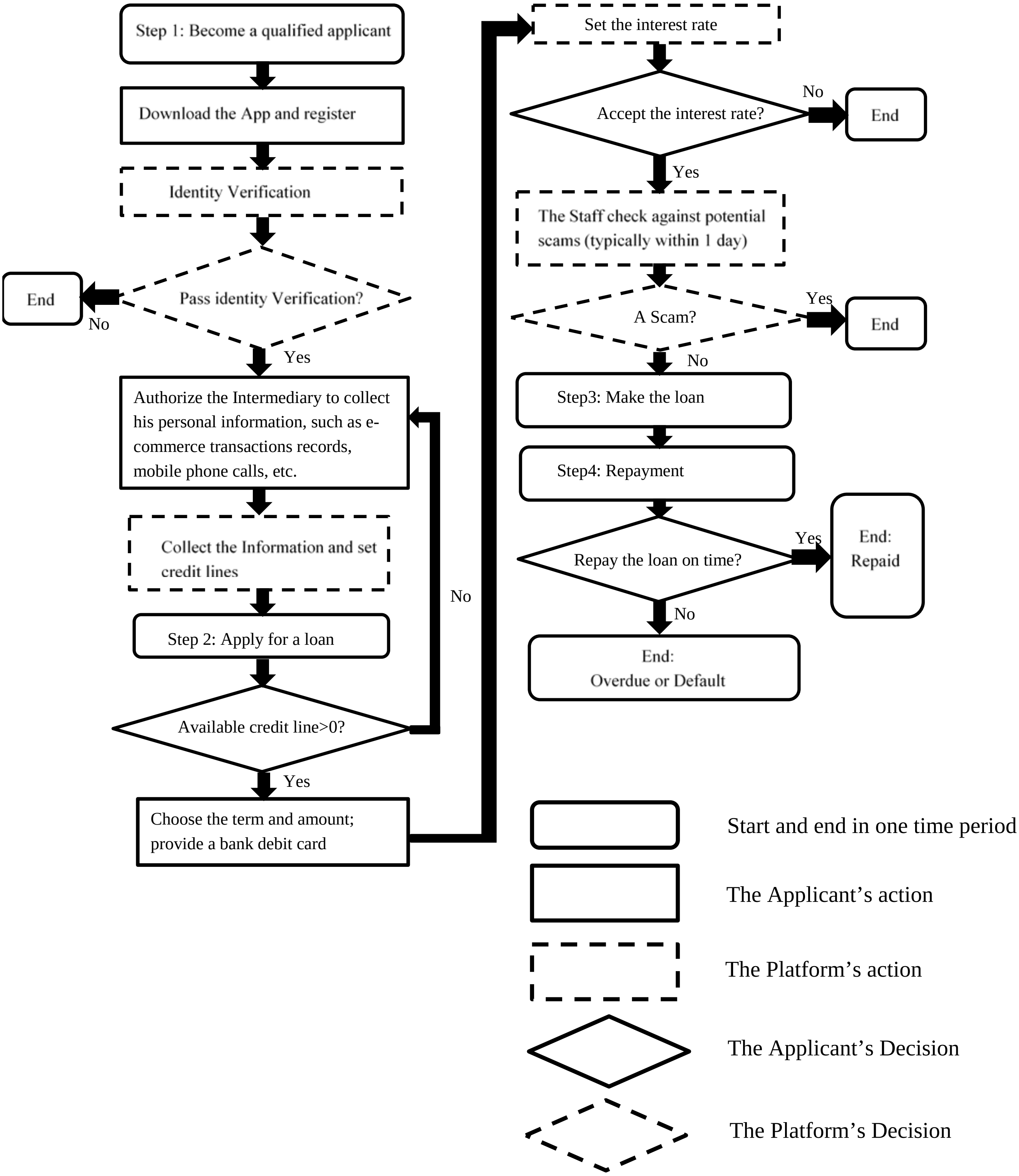
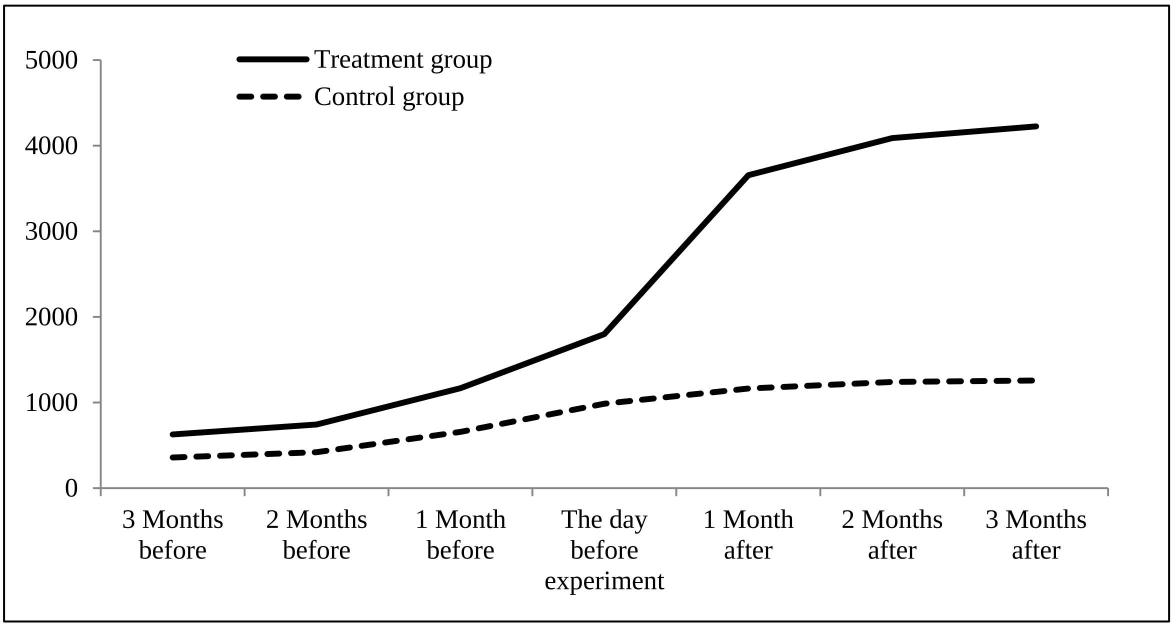


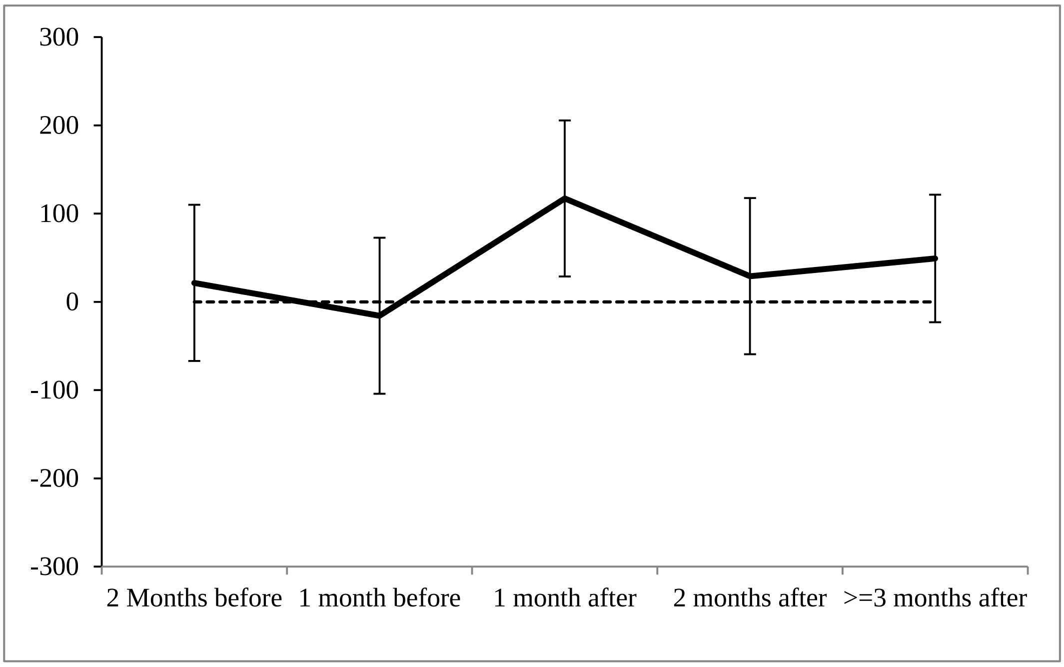
Figure 2
The Dynamics of Outstanding Loans Around the Experiment



This figure plots the average outstanding loans of the treatment group and the control group around the experiment. Outstanding loans are defined as the sum of unpaid principals

Figure 3

The Dynamics of Consumption Around the Experiment



This figure illustrates the average magnitude of relative changes in consumption around the experiment. The points on the graphic reflect the average difference in total e-commerce consumption for treatment individuals versus control individuals in the matched sample. Vertical bands represent 95% confidence interval of each point estimate.

Table I

Performance Measures of Consumption Classification

This table presents the performance measures of three consumption classification tasks in the test sample. Accuracy is the number of correct predictions in the test sample divided by 4000. Precision is the number of true positives divided by the sum of true positives and true negatives. Recall is the number of true positives divided by the sum of 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 consumption category and then averaged across categories.

	Accuracy	Precision	Recall	F1-score
CEX Categories	86.2%	85.2%	82.0%	83.4%
Gaming and Non-Gaming	95.7%	93.8%	91.4%	92.5%
Addictive and non-addictive	97.0%	94.5%	91.4%	92.9%

Table II

Summary Statistics

Panel A reports the summary statistics for personal information and loan characteristics for the full sample. This sample contains all the 2,322 borrowers who disclosed to the cash loan platform all the Alibaba e-commerce transactions happened before Aug 9, 2016. It also includes all the 5,810 loans borrowed by these borrowers within the 8 fortnights before the experiment or the 8 fortnights after the experiment. *Treat* is a dummy variable with the value of 1 for treatment group individuals. *Male* is a dummy variable for males. *# Age* is the borrower's age in 2016. *Loansize* is the CNY value of the loan size. *Maturity* is the months of the loans' maturity. *Rate* is the interest rate category of the loans. *Overdue* is a dummy variable with the value of 1 for loans that have ever been overdue for seven or more days. *Default* is a dummy variable with the value of 1 for loans that have ever been overdue for 60 or more days. Panel B presents the summary statistics of the consumption variables for 37,152 individual-fortnight observations in the full sample. This sample comprises all the 2,322 individuals in the full sample, with the 8 fortnights before the experiment and the 8 fortnights after the experiment. Total consumption and all categories of consumption are winsorized at 1% and 99% level. Overdue% is defined as the proportion of seven or more days overdue repayments among all the repayments that are due in the fortnight for the individual. Default% is defined as the proportion of 60 or more days overdue repayments among all the repayments that are due in the fortnight for the individual. Panel C presents the proportion of CEX categories of consumption in e-commerce consumption and household consumption. The proportion of each consumption category in E-commerce consumption is calculated as dividing the consumption category by the sum of all the seven categories of consumption. The proportions of six consumption categories in household consumption are calculated by using the consumption data of 3,449 households from 2014 CFPS survey, with hospital treatment, vehicle purchase, and cash contribution data excluded.

Panel A. Borrower Information and Loan Characteristics

	N	Mean	Std	Min	Q1	Median	Q3	Max
Treat	2322	0.332	0.471	0.000	0.000	0.000	1.000	1.000
Male	2322	0.792	0.406	0.000	1.000	1.000	1.000	1.000
Age	2322	27.370	5.757	18.000	23.000	26.000	30.000	56.000
Loansize	5810	1264.400	1407.180	20.000	400.000	800.000	1600.000	30000.000
Maturity	5810	6.719	4.088	1.000	3.000	6.000	12.000	24.000
Rate	5810	2.259	0.857	1.000	2.000	2.000	3.000	10.000
Overdue	5810	0.213	0.409	0.000	0.000	0.000	0.000	1.000
Default	5810	0.063	0.242	0.000	0.000	0.000	0.000	1.000

Panel B. Consumption Variables

	N	Mean	Std	Min	Q1	Median	Q3	Max
Consumption	37152	424.528	954.022	0.000	0.000	99.800	365.920	6458.800
CEX Categories								
Food	37152	15.016	58.808	0.000	0.000	0.000	0.000	422.470
Housing	37152	149.024	389.918	0.000	0.000	24.100	119.880	2776.700
Apparels	37152	63.963	185.798	0.000	0.000	0.000	9.800	1253.480
Entertainment	37152	38.699	154.550	0.000	0.000	0.000	0.000	1189.000
Transportation	37152	17.665	97.625	0.000	0.000	0.000	0.000	779.500
Healthcare	37152	1.909	12.205	0.000	0.000	0.000	0.000	101.000
Others	37152	62.992	258.586	0.000	0.000	0.000	0.000	2000.000
Gaming, Non-Gaming, Addictive, and Non-addictive								
Gaming	37152	73.265	332.679	0.000	0.000	0.000	0.000	2521.980
Non-Gaming	37152	327.169	725.406	0.000	0.000	86.235	298.995	4967.160
Addictive	37152	19.119	95.403	0.000	0.000	0.000	0.000	758.780
Non-addictive	37152	383.914	859.165	0.000	0.000	96.830	334.695	5796.650
Loan Delinquency								
Overdue%	9846	0.062	0.227	0.000	0.000	0.000	0.000	1.000
Default%	9846	0.013	0.109	0.000	0.000	0.000	0.000	1.000

Panel C E-commerce Consumption and Household Consumption

	E-commerce Consumption	Household Consumption
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%

Table III

Propensity Score Matching

Panel A presents the difference in the mean value of key variables for treatment group individuals versus control group individuals in the pre-match sample and the corresponding t-statistics. The treatment group contains 771 individuals that were selected by the platform to increase credit lines in the experiment. The control contains 1,552 individuals that were not selected in the experiment. *Male* is a dummy variable for male borrowers. *Age* is the age of individuals in 2016. Lntimes is the logarithem of one plus the times of borrowing before 04/19/2016. *WithOverdue* is a dummy variable for the individuals who had not repaid all the due loans at 04/19/2016. *PastConsumption* is the CNY value of the total expenditure on Alibaba e-commerce platforms within the eight fortnights before the experiment. *AddictiveConsumption* is the CNY value of the total expenditure on the addictive consumption within the eight fortnights before the experiment. Panel B presents the coefficients and z-statistics of Probit regressions in the pre-matched sample and post-matched sample. The post-matched sample is generated by applying propensity score matching algorithm to the pre-matched sample with respect to the covariates of *Male*, *Age*, *Lntimes*, *OverdueLoans>0*, *OutstandingLoans*, *PastConsumption*, *AddictiveConsumption*. Panel C presents the difference in the mean value of key variables for treatment group individuals versus control group individuals in the post-match sample and the corresponding t-statistics. ***, **, * denote the significance at 1%, 5%, or 10%, respectively.

Panel A. Key Variables for the Pre-match Sample

	Treat		Control		Treat-Control	
	N	Mean	N	Mean	Diff	T
Male	771	0.763	1551	0.806	-0.043**	-2.361
Age	771	26.947	1551	27.580	-0.633**	-2.503
Lntimes	771	0.373	1551	0.699	-0.326***	-9.720
WithOverdue	771	0.016	1551	0.049	-0.033***	-4.730
OutstandingLoans	771	813.582	1551	1224.934	-411.352***	-5.304
PastConsumption	771	3753.664	1551	3027.612	726.052***	3.225
AddictiveConsumption	771	163.553	1551	149.587	13.966	0.632

Panel B. Probit Regression

	Prob(Treat=1)	
	Pre-match	Post-match
	(1)	(2)
Male	-0.115*	0.082
	(-1.713)	(1.098)
Age	-0.013***	0.004
	(-2.753)	(0.685)
Lntimes	-0.352***	0.044
	(-6.932)	(0.659)
WithOverdue	-0.301*	-0.189
	(-1.678)	(-0.773)
OutstandingLoans	0.000	-0.000*
	(1.635)	(-1.704)
PastConsumption	0.000***	0.000
	(3.922)	(0.329)
AddictiveConsumption	-0.000	-0.000
	(-0.973)	(-1.576)
Constant	0.113	-0.135
	(0.785)	(-0.802)
Observations	2,322	1,542
p-value	0.000	0.277
Pseudo-R2	0.038	0.004

Panel C. Key Variables for the Post-match Sample

	Treat		Control		Treat-Control	
	N	Mean	N	Mean	Diff	T
Male	771	0.763	771	0.742	0.021	0.944
Age	771	26.947	771	26.739	0.208	0.739
Lntimes	771	0.373	771	0.404	-0.031	-0.875
Overdue>0	771	0.016	771	0.023	-0.008	-1.106
Outstanding	771	813.582	771	986.762	-173.180*	-1.818
Consumption	771	3753.664	771	3977.063	-223.399	-0.778
AddictiveConsumption	771	163.553	771	210.603	-47.050	-1.538

Table IV

Expanding Credit Access on Total Consumption

This table presents the results of the Did analysis on the effect of increasing credit lines on total consumption. The sample contains 24,672 individual-fortnights observations, including 1,542 individuals in the post-match sample and 16 fortnights around (8 fortnights before and 8 nights after) the experiment. The dependent variable is the total consumption on the Alibaba e-commerce platforms in the given fortnight. Treat is a dummy variable for treatment group individuals. *Before(3-4)* is the dummy variable with the value of 1 for the third and the fourth fortnights before the experiment. *Before(1-2)* is the dummy variable for the first two fortnights before the experiment. *After(1-2)* is the dummy variable with the value of 1 for the first two fortnights after the experiment. *After(3-4)* is the dummy variable for the third and fourth fortnights after the experiment. *After(5+)* is the dummy variable for the fifth fortnight after the experiment or later. T-statistics are reported in parentheses. ***, **, * denote the significance at the 1%, 5%, 10% level respectively.

	(1) consumption	(2) consumption
Treat*Before(3-4)		25.126
		(0.544)
Treat*Before(1-2)		39.554
		(0.856)
Treat*After(1-2)	105.737**	121.907***
	(2.506)	(2.638)
Treat*After(3-4)	-10.916	5.254
	(-0.259)	(0.114)
Treat*After(5+)	9.738	25.908
	(0.298)	(0.687)
Treat	66.833***	50.663*
	(3.541)	(1.899)
Before(3-4)		40.481
		(1.239)
Before(1-2)		88.311***
		(2.703)
After(1-2)	-44.312	-12.114
	(-1.485)	(-0.371)
After(3-4)	2.861	35.059
	(0.096)	(1.073)
After(5+)	12.350	44.548*
	(0.534)	(1.670)
Constant	415.244***	383.046***
	(31.117)	(20.305)
Observations	24,672	24,672
R-squared	0.002	0.003

Table V

Expanding Credit Access on Gaming Consumption

This table presents the results of the Did analysis on the effect of increasing credit lines on total consumption. The sample contains 24,672 individual-fortnights observations, including 1,542 individuals in the post-match sample and 16 fortnights around (8 fortnights before and 8 nights after) the experiment. The dependent variables are the gaming consumption and the non-gaming consumption in the given fortnight. *Treat* is a dummy variable for treatment group individuals. *After(1-2)* is the dummy variable with the value of 1 for the first two fortnights after the experiment. *After(3-4)* is the dummy variable for the third and fourth fortnights after the experiment. *After(5+)* is the dummy variable for the fifth fortnight after the experiment or later. T-statistics are reported in parentheses. ***, **, * denote the significance at the 1%, 5%, 10% level respectively.

	Gaming (1)	Non-Gaming (2)
Treat	-10.296	6.633
	(-1.568)	(0.478)
Treat*After(1-2)	31.289**	51.985*
	(2.130)	(1.677)
Treat*After(3-4)	-7.698	26.688
	(-0.524)	(0.861)
Treat*After(5+)	7.914	23.051
	(0.696)	(0.960)
After(1-2)	-0.099	-19.886
	(-0.010)	(-0.907)
After(3-4)	3.282	-11.355
	(0.316)	(-0.518)
After(5+)	11.014	-15.019
	(1.369)	(-0.884)
Constant	85.076***	360.979***
	(18.318)	(36.820)
Nobs	24,672	24,672
R2	0.001	0.000

Table VI

Expanding Credit Access and Addicted Individuals

This table presents estimate the difference in the effect of increasing credit lines on consumption for the more addicted individuals versus the less addicted individuals. The sample contains 15,420 individual-fortnights observations, including 1,542 individuals in the post-match sample and 10 fortnights around (8 fortnights before and 2 nights after) the experiment. The dependent variables are the total Alibaba e-commerce consumption, gaming consumption, and the non-gaming consumption in the given fortnight. *Treat* is a dummy variable for treatment group individuals. *Addicted* is a dummy variable with the value of 1 if the borrower's gaming related consumption within the eight fortnights before the experiment is in the highest quartile. *After(1-2)* is the dummy variable with the value of 1 for the first two fortnights after the experiment. *After(3-4)* is the dummy variable for the third and fourth fortnights after the experiment. *After(5+)* is the dummy variable for the fifth fortnight after the experiment or later. T-statistics are reported in parentheses. ***, **, * denote the significance at the 1%, 5%, 10% level respectively.

	(1) Consumption	(2) Gaming	(3) Non-Gaming
Addicted*Treat*After(1-2)	288.801***	70.602**	101.514
	(2.994)	(2.128)	(1.397)
Treat	13.472	8.378	9.861
	(0.628)	(1.135)	(0.610)
After(1-2)	25.873	18.897*	13.461
	(0.778)	(1.652)	(0.537)
Treat*After(1-2)	56.026	16.629	32.504
	(1.168)	(1.008)	(0.899)
Addicted	611.840***	248.186***	229.506***
	(19.318)	(22.783)	(9.619)
Addicted*Treat	-276.510***	-118.913***	-59.612*
	(-6.411)	(-8.016)	(-1.835)
Addicted*After(1-2)	-356.992***	-86.153***	-151.240***
	(-5.041)	(-3.537)	(-2.835)
Constant	362.226***	30.352***	310.375***
	(24.356)	(5.934)	(27.704)
Observations	15,420	15,420	15,420
R-squared	0.034	0.048	0.011

Table VII

Expanding Credit Access and Loan Delinquency

This table presents the results of the Did analysis on the effect of increasing credit lines on total consumption. For this analysis, we construct a sub-sample by dropping any individual-fortnight when there are no due repayments in the given fortnight for the given individual from the post-matched full sample. The sub-sample contains 5,166 individual-fortnight observations. *Overdue%* is defined as the proportion of repayments that are overdue for seven or more days among all the repayments that are due in the fortnight for the individual. *Default%* is defined as the proportion of repayments that are overdue for 60 or more days among all the repayments that are due in the fortnight for the individual. *Treat* is a dummy variable for treatment group individuals. *After(1-2)* is the dummy variable with the value of 1 for the first two fortnights after the experiment. *After(3-4)* is the dummy variable for the third and fourth fortnights after the experiment. *After(5+)* is the dummy variable for the fifth fortnight after the experiment or later. Individual Fixed effects and fortnight fixed effects are controlled in the regressions. T-statistics are reported in parentheses. ***, **, * denote the significance at the 1%, 5%, 10% level respectively.

	(1)	(2)
	Overdue%	Default%
Treat*After(1-2)	-0.032*	-0.025***
	(-1.776)	(-2.862)
Treat*After(3-4)	-0.042**	-0.028***
	(-2.538)	(-3.530)
Treat*After(5+)	0.004	-0.016**
	(0.270)	(-2.282)
Borrower Fixed Effects	Y	Y
Week Fixed Effects	Y	Y
Observations	5,166	5,166
R-squared	0.530	0.606