Individual Consumption Response to Credit Supply Shock: Evidence from an Online Cash Loan Platform

February 2018

Abstract

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

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

JEL Classification: D12, G21, I31

I. Introduction

Understanding the determinants of consumption decision 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 constraint on consumption (Johnson et al. 2006; Agarwal et al., 2007; Agarwal and Qian, 2014; Guerrieri and Lorenzoni, 2017). One particular stream of research is dedicated to investigate the impact on consumption of credit constrained borrowers from relaxing liquidity constraint through expanding credit access (Gross and Souleles, 2002; Karlan and Zinman, 2010; Cuffe and Gibbs, 2017).

The major challenge generally faced by these researchers in identifying the effect of credit access on consumption is to accurately measure individual consumption. Existing literature has heavily relies on indirect measures, such as the change of debt in credit card, survey data or data that are not at individual consumption level. In this paper, we use a proprietary dataset on individual consumption and borrowing behavior with a unique experiment to study the impact of increased access to credit on consumption.

To measure individual borrowers' consumption, we use borrowers' full spending transaction level records from Alibaba ("Taobao" and "Tmall"), which accounts for market share of approximately 70% in China e-commerce industry[1]. Similar to the Amazon in US, online shopping has becoming an important mediums of disposable consumption in China, and approximately 18% of personal consumption in the country is purchased online. Our consumption measures have following key advantages: first, these measures are calculated

[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).

from the real individual consumption transactions with timestamp, which may provide more accuracy and higher frequency compared to the survey data; second, the data is on the individual level, which allows us to track down the financial information of same individuals in our proprietary dataset provided by a leading cash loan platform in China[1], so that we can measure the individual specific information such as age, sex, borrowing and repayment history; finally, for each transaction, we have the details for each purchased items, therefore by employing textual analysis on items 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 an online cash loan platform on their existing and new cash loan borrowers between Apr, 20 2016 and Apr, 30 2016. As part of platform's trial and error initiatives, the cash loan provider randomly selected a set of borrowers from its user base during that time period and permanently increased the borrowers' credit limits. This credit supply shock substantially increased the credit access of the borrowers. We noticed that the average loan size increased significantly after the shock. Combined with detailed consumption information from each individual, this experiment provides us a rare opportunity to investigate the direct association of expanding credit access with individual consumption.

We use the above event and construct a matching sample between the borrowers before the credit expand and borrowers after the credit expand according to credit rating, age, historical borrowing amount, so that we can compare the consumption difference between

[1] The data provider is a leading cash loan platform in China. Until Apr 2017, 2.2 billion loans had been facilitated to its borrowers.

the borrowers before the event and the borrowers after the event. We find that expanding credit access has positively correlated with borrowers' consumption in the short term. Within a month after obtaining cash loans, the after-event borrowers who may have access to increased credit limit have significantly increased their consumption online by RMB 127 compared to the consumption from before-shock borrowers, suggesting a 75% of marginal propensity to consume out of borrowing amount. However, 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 addiction related products such as games. We showed that the effect of expanding credit access on gaming related consumption is most prominent for borrowers with gaming related spending history in the highest quartile from our sample. If gaming is addictive and attracts individuals to engage in utility-destroying temptation consumptions (Fisher, 1994; Gul and Pesendorfer, 2007; O'Donoghue and Rabin, 2007), expanding credit access could make constrained borrowers worse off.

Researchers have examined the effect of income shock (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; Porteba 2000; Lettau and Ludvigson, 2004), and interest rate (e.g. Weber, 1970; Bolskin, 1978; Gross and Souleles, 2002) on consumptions. We contribute to the vast literature by documenting how consumption in different categories responses to credit access expanding.

This paper also contributes to the long debate of the welfare effect from increased credit to borrowers. We showed that increased credit to the borrowers with addiction may attract them to engage in utility-destroying temptation consumption and may put on extra financial burden. Little consensus exist whether access to consumer credit necessarily provides a benefit to individual. Previous studies find that an increase of consumer credit access may have both positive and negative welfare effect on borrowers. On one hand, consumer credit access may have 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), improves food consumption, economic self-sufficiency, mental health, and outlook (Karlan and Zinman, 2010), increases self-employment (Herkenhoff et al., 2016). On the other hand, access to consumer credit may have negative effect on number of behavioural reasons, such as cognitive biases (Betrand and Morse, 2011), time-inconsistency (Laibson 1997), and exponential growth bias (Stango and Zinman, 2009). For example, accessing to more credit increases hardship in paying mortgage, rent, and utilities bills (Melzer, 2011), impairs military readiness (Carrell and Zinman, 2010), increases involuntary bank account closures (Campbell et al., 2012) and bankruptcy rates (Morgan et al., 2012).

The rest of the paper proceeds as follows. Section II presents the institutional background including 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 institutions other than banks. Cash loan market is an important credit market for credit constrained individuals in many countries. In the U.S., one type of cash loans, the payday lending transaction volume was on average $50 billion in each year (Morse, 2011). In 2010, twelve 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 €3.7 billion (around $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 lending[1].

Academics argue that two possible reasons may explain the fast growing cash loan market with borrowers underserved by traditional banks (Stegman, 2007). First, the transaction costs 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, 2011). 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 US, payday loans are usually made for a maturity of 7 to 30 days with less than $300

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

amount and extremely high APRs over 400%. The credit application and funding procedure are used to happen in a payday loan shop but now more and more payday loan providers are moving to online platform[1]. A typical funding procedure for 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). In 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. The Chinese cash loan providers operate in a very similar way as the US payday loan providers: the payday loan provider offer small and short-term credit to credit constrained individuals. The major difference between the cash loan in China and payday loan in US is that the maturity of cash loan is longer, approximately 3-6 months compared to two weeks of majority of the US payday loans. According to an official industry report, a payday loan is a small-size loan with the maturity 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[2].

B. The cash loan platform and our data provider

Our cooperating cash loan platform and our data provider, a leading cash loan platform, was founded in 2014 and grows substantially in the 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]

[1] Typical examples of online cash loan lenders are Lendup, Opportun, Elevate, and Insikt.

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

The funding procedure 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 askes the loan applicant to upload the photocopies of his ID card and verify 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 authorize the computer system to collect his personal information, which may contain full transaction records on Alibaba e-commerce platforms (see Section II.C for details of these e-commerce platforms), mobile phone call records, and other personal information. After that, the system collects the personal information, calculates the credit score, and decides the credit limit for the applicant. 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 staff of the platform will review the application and make a decision to approve the loan or not. The cash will be sent to the applicant's bank account after the approval of the loan. Generally, the whole funding process takes less than 1 day from downloading the app.

[Insert Figure 2 About Here]

To test the effect of expanding credit assess on consumption, we identify an exogenous credit supply shock on the borrowers of the cash loan platform. Between Apr 20, 2016 and Apr 30, 2016, the cash loan platform conducted an experiment by selecting a random set of borrowers from its user base and permanently increasing their credit limits. This credit supply shock prominently expanded the credit access on the platform's borrowers. In Figure 2, we illustrates that the average loan size increased sharply after the experiment.

Per discussion with the platform's management team and learning from other news source, this experiment can be part of the trial and error initiative to promote the business and test their risk control strategy.

C. 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 transactions.

The online shopping has been growing tremendously in China in the recent years compare to the rest of the world. Between 2014 and 2016, the online shopping volume had a 35.9% annual growth rate in China[1], compared to the around 25% annual growth rate in the world[2].Alibaba has been one of the biggest winners of the all. In the 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 Chinese population[3]. Alibaba online shopping platforms have a wide coverage of most of the consumption goods and services in China, including food, apparels, housing items, traffic tickets, vehicles maintenance, healthcare products, over-the-counter medicines, video games, entertainment services, books, and other common goods and services. Therefore, our measurements of the

[1] The data is collected from the National Bureau of Statistics of the People's Republic of China.
[2] https://www.statista.com/statistics/288487/forecast-of-global-b2c-e-commerce-growt/
[3] 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.

consumption using data from Alibaba are generally representative and are in line with the CFPS survey. (China Family Panel Studies[1]) But we want to point three differences between online shopping from Alibaba and the household consumption in general. First, in-hospital treatment is prohibited to sell on e-commerce platforms. Second, vehicles are usually purchased offline through the 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 contain the information of a randomly selected sample of 9,998 borrowers from those who had at least borrowed one loan on the cash loan platform before the date of data collection (July, 9 2017). More than 75% of the borrowers have disclosed the full transaction records on Alibaba e-commerce platforms up until the time of their credit application. For each of the 1,816,791 consumption transaction records in our dataset, the information contains transaction volume (dollar amount and number of the products/services), transaction time, and item description. Rather than observing consumption behaviour indirectly (Gross and Souleles, 2002; Karlan and Zinman, 2010) or

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

using store-level consumption data (Cuffe and Gibbs, 2017), our unique data of e-commerce transaction records allow us to construct individual-level consumption measures based on real time transactions.

This datasets also contain loan information offered to these 9,998 borrowers and borrowers' personal information. Total of 55,500 loans offered to these 9,998 borrowers before the data collection date. The loan information includes the amount, term, interest rate category, facilitation date, repayment records, and the current loan status (repaid, overdue, or default which is defined as 60-day plus past due). The personal information includes the sex and age.

B. The Measure of Consumption

According to CEX (Consumption Expenditure Survey), we classify each of 1,816,791 e-commerce transactions of borrowers into one of the following ten consumption categories, namely food, apparels, communication expenses, mobiles and computers, other housing, transportation, healthcare, video game, other entertainment, and others. The definition of these categories is primarily inherited from the CEX. In order to identify gaming related expenditures, we made the following minor adjustment of the CEX categories: first we separated the gaming related expense from entertainment category of CEX; and second we separate expenditure on mobiles and computers and expenditure on communication[1] from housing category of CEX.

We employ textual analysis methods on each transaction's good description so that we can classify them into one of the above 10 categories. Our textual analysis takes the

[1] The communication fees include the spending on mobile services and internet services

following steps. First, we build a world list for each consumption category following the textual analysis methodology from literature (e.g. Tetlock, 2007; Loughran and Madonald, 2011; You, Zhang and Zhang, 2017): we calculate the frequency of words in all goods/service descriptions and select the 1,000 words with the highest frequency. For each word, we manually identify its related consumption categories and delete it if it is related to no category or multi-categories. In addition, we collect the key words of each consumption category from the websites of the two Alibaba e-commerce platforms and we re-check the words one-by-one manually and build the word lists.

Second, we do a trail test on the word list and modify it according to the new rules to get our final word lists. The detail procedures are in the following: we classify all the e-commerce transaction records based on the word lists above. Each transaction is classified into one particular consumption category if its description contains one or more words in the category's word list. For transactions contain no words in the word lists, we classify it into others category. Then we re-examine the transaction records that are classified into multi-categories or other categories, design more complex rules for classification and update the word lists. Then we make a final classification based on the updated word lists and rules.

In order to examine the validity of our textual analysis, we construct a test sample by randomly selecting 1,000 transaction records from our sample and manually classify these records into one of the consumption categories. We find that our final-step classification algorithm has 87.0% accuracy in our test sample, higher than the out-of-sample accuracy (73.2%~82.6%) of machine learning methods documented in Chen et al (2018).

C. Summary Statistics

From the information related to 9,998 borrowers that we obtained from our data provider, we construct a sample that contains 7,566 borrowers whose consumption information on Alibaba's online shopping platforms is available in our dataset. These 7,566 borrowers obtained 48,907 loans in total, with the dollar value of 10.1 million USD. This sample covers 75.6% of the total number of the borrowers, 88.1% of the total number of the loans, and 89.3% of the dollar value in our dataset. This sample is called "full sample" hereafter.

[Insert Table I About Here]

Table I Panel A reports the summary statistics of the 7,566 borrowers and 48,907 loans in the full sample. The average borrower was born in 1989, or around 28 years old when we collected the data. Males constitute 78.0% of the borrowers in the full sample. This suggests that most of the cash loan borrowers are young males. For each borrower, the cash loan platform rates his credit grade, ranging from excellent to poor as A to F. Borrowers whose credit grade are "A", "B" and lower than "B" account for 21.0%, 19.8%, and 59.8%, respectively.

For all 48,907 loans in our consumer sample, the average size is CNY 1303.81 (around $200) and the average maturity is 3.31 months. The first loan in the sample is obtained at March, 2014[1]. Approximately half of loans are facilitated in 2017. As to loan performance, 42.0% of the loans have experienced overdue payments while 8.0% of the loans are in default.

[1] As most funding processes happen in one day, we do not distinguish between the date of applying a loan and the date of obtaining a loan.

We construct a sample of 580,916 borrower-fortnight observations to analyze the consumption behaviour of the full sample borrowers. This sample comprises all the 7,566 borrowers and all the consumption within fortnights between January, 6 2014 and July, 2 2017. For each borrower, we exclude the fortnights after the facilitation date of the borrowers' last loan from this sample, because the system usually collects information from e-commerce platforms at the loan facilitation date and may not collect consumption transactions after the facilitation date of the latest loan. The sample contains ten consumption variables, each of which measures the expenditure on the corresponding consumption category.

Table I Panel B presents the descriptive statistics of consumption variables. In Panel B, we find that the average fortnight consumption online from a cash loan borrower is CNY 157.89 (Approximately $25), approximately 20% of the fortnightly household consumption per capita in China in 2016[1], which indicates that the consumption data from our sample is consistent with the industry average. On average quarterly consumption is 77.8% of the average loan size, suggesting that the expenditure from online shopping is significant in comparing to the size of the cash loans. On average for every two weeks, borrower spends CNY 48.85 on apparels, CNY 61.5 on housing, including CNY 27.48 on communication and CNY 11.07 on mobiles or computers every fortnightly. We also find that the entertainment consumption amounts to CNY 15.29, of which CNY 6.19 is on video games. The above results indicate that housing and apparels constitute the largest components in cash loan borrowers' online consumption.

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

In order to validate whether our consumption measures are representative, we compare the composition of the cash loan borrowers' 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 valid response of household spending. The data contain 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.

[Insert Table II About Here]

In Table II, we present the share of each consumption category for e-commerce consumption in the first column and for household consumption in the second column. Though the percentage of spending on food and apparels is different in e-commerce consumption and household consumption, we find that housing, entertainment, transportation, and others categories accounts for similar proportions. Hence, our online consumption measures are in general reasonable proxies to represent the daily individual consumption in China.

D. Empirical Strategy

We design our empirical strategy around the experiment that the cash loan platform randomly selected some users and offered to increase their credit limit permanently between Apr, 20 2016 and Apr, 30 2016. To leverage this exogenous positive credit supply shock, we restrict the full sample into a subsample that comprises borrowers who were offered loans before the credit supply shock and after the credit supply shock (Hereafter, we call this subsample "around-shock sample"). The sample comprises two groups of borrowers[1]: the after-shock group contains 697 borrowers who were offered loans in the after-shock period, or dates between May, 1 2016 and May, 30 2016; the before-shock group contains 620 borrowers who were offered loans in the before-shock period, or dates between March, 21 2016 and Apr, 19 2016.

[Insert Table III About Here]

Table III Panel A reports the means of the key variables in both the after-shock group and the before-shock group and tests the difference. We show that the average loan size increases significantly by CNY 354.12 or over 25% after the shock, suggesting that the credit supply shock has substantial effect on credit access of borrowers. In addition, we find that these two groups are significantly different in terms of interest rate, credit grade, and past two-month consumption, although sex ratio, past borrowing amount, and terms are similar between the two groups.

In order to address the concern that difference in observable covariates may bias our empirical results, we employ propensity score matching algorithm. We first estimate a pre-match Probit model based on all the 1,317 borrowers in the around-shock sample. The dependent variable, Aftershock, is equal to one if the borrower belongs to the after-shock group. The independent variables include the dummy variables of grade A, grade B, and male borrowers, born year, interest rate category, the natural logarithm of the amount of past borrowing, and the natural logarithm of consumption within 56 days before the date of

[1] To keep continuous consumption records for each borrower, we require each borrower in the around-shock sample to obtain a loan more than 168 days after being offered the loan in the around-shock period. We retain only the first loan for each borrower in the corresponding time period.

obtaining a loan.

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 indicated by a pseudo-R2 of 2.95% 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 nearest-neighbor propensity score matching algorithm with replacement allowed. The propensity matching process generates the matched sample that contains 697 pairs of borrowers.

We conduct two diagnostic tests to verify that the after-shock group and before-shock group in the matched sample are similar in the observable covariates. First, we 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 0.789, 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 after-group borrowers and before-group borrowers. The results are reported in Table III Panel C. most of the observable characteristics are not significantly different between the after-shock group borrowers and the before-shock group borrowers except that the amount borrowed before and after the shock is statistically different. The above results imply that the propensity score matching algorithm is likely to remove the effect of difference in observable covariates. Later, we also use the borrowers fixed effects to control for the unobservable characteristics of the borrowers.

We construct a "consumption sample" that contains 33,456 borrower-fortnight level observations to examine the cash loan borrowers' consumption around the credit supply shock. This sample contains all 697 pairs of borrowers in the matched around-shock sample. For each borrower in the after-shock (before-shock) group, the sample contains 12 fortnights after the facilitation date of the cash loan in the after-shock (before-shock) period (for simplicity, we use "the loan facilitation date" for this date hereafter) and 12 fortnights before the facilitation date.

To identify the effect of credit access on consumption variables, we perform the following regressions.

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

where C_{it} denotes any consumption variable, $Aftershock_i$ is a dummy variable which takes the value of 1 if the borrower i is in after-shock group and takes the value of 0 if the borrower i is in before-shock group, $After1_{it}$ is the dummy variable with the value of 1 if the fortnight t is within the first two fortnights after the loan facilitation date. $After2_{it}$ is a dummy variable for the third and fourth fortnights after the loan facilitation date, $After3_{it}$ is for the fifth fortnight or later after the loan facilitation date. γ_1 denotes the effect of expanding access to credit on the consumption variable in the first two fortnights after the loan facilitation date. γ_2 denotes the effect in the third and the fourth fortnights after the loan facilitation date. γ_3 denotes the effect in the fifth fortnights and later.

IV. Results

A. Credit Access and Total Consumption

We begin by examining the effect of expanding access to credit on the total e-commerce consumption on Alibaba platforms. By using the total consumption of a given borrower in a given fortnight as the dependent variable, we run an OLS regression to estimate the coefficients of specification (1). We cluster the standard errors at the borrower level to control for the possible correlation of consumption at different times of a given borrower.

[Insert Table IV About Here]

The results are reported in the first column of Table IV. The coefficient of *Aftershock*Fortnight (1-2)* is 63.359 with a t-statistic of 2.320. It indicates that after-shock group borrowers increase their total consumption significantly more than the before-shock group borrowers. That is to say, expanding access to cash loan credit has significantly positive correlation with borrowers' total consumption in the first two fortnights after the loan facilitation date.

The effect on total consumption also has economic significance. The coefficient of *Aftershock*Fortnight (1-2)* implies that, within the first month after the loan facilitation date, the after-shock group borrowers consume CNY 126.718 (=63.359*2) more than the before-shock group borrowers Recall the results in Table III Panel C that the average loan size of the after-shock group borrowers is CNY 168.84 larger than the before-shock group borrowers. It suggests that the marginal propensity to consume out of borrowing amount is approximately 75% (=126.718/168.82) in the first month. In other words, obtaining one more dollar cash loan could induce 0.75 dollar more consumption within the first month. However, both the coefficients of *Aftershock*Fortnight (3-4)* and *Aftershock*Fortnight (5+)* are not significantly different from zero. This suggests that the credit access may not have long term effect on total consumption.

In the second column, the regression includes the borrower fixed effects to account for the effect of unobserved borrower characteristics. As total consumption is a continuous variable left censored at zero, we use a Tobit regression to estimate specification (1) and report the results in the third column. The results show that expanding the credit access has increased the consumption significantly in the short term even controlling for the borrowers' unobservable characteristics.

Our finding that increasing credit access has positive effect on total consumption in the short term is consistent with the economic intuition that credit-constrained individuals may consume more after relaxing the credit constraint. It is also similar to the findings of Gross and Souleles (2002) that exogenous credit limit increases raise consumption, especially for consumers near the credit limit.

B. Credit Access and addiction related Consumption

"There is ample evidence to suggest that people are spending more time playing games….also spending more on them[1]." As is documented by psychologists (e.g. Fisher, 1994), video games are addictive. Researchers argue that addictive consumption impairs self-control ability and in turn may reduce consumers' welfare (Gul and Pesendorfer, 2007). Therefore, understanding the relationship of expanding credit access on addiction related

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

consumption such as spending on the gaming may contribute to the debate on whether access to consumer credit has positive or negative welfare effect.

To test the effect of expanding credit access on gaming related spending, we construct the variable of gaming related consumption by summing the expenditure on video games and the expenditure on mobiles and computers. Expenditure on mobiles and computers is likely to be closely related to video games since video games are usually played on mobiles or computers. We use the CNY value of gaming related consumption as the dependent variable and re-run the OLS regression 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 *Aftershock*Fortnight (1-2)* is 41.604 with a t-statistic of 4.414, implying that after-shock group borrowers increase their gaming related consumption by the magnitude CNY 83.208 (=41.604*2) more than before-shock group borrowers within the next month after the loan facilitation date. For gaming related consumption, the marginal propensity to consume out of borrowing amount is 49.3% (=83.208/168.82). That is to say, obtaining one dollar more cash loan induces 0.493 dollar more gaming related spending. Hence, expanding access to cash loans borrowers has both statistically and economically significant correlation with gaming related consumption in the first month after the loan facilitation date.

In terms of the effect in the long term, we find that both the coefficients of *Aftershock*Fortnight (3-4)* and *Aftershock*Fortnight (5+)* are not significant from zero, suggesting that expanding cash loan credit access has little effect on consumption after four weeks.

Our findings suggest that expanding credit access may have negative welfare effect as it raises addictive consumption. This is consistent with some previous studies (e.g. Betrand and Morse, 2011; Carrell and Zinman, 2010; Campbell et al 2012) that document the negative impact of consumer credit access.

Our results are robust to controlling for borrower fixed effects and using Tobit regression. In the second column of Table V, we include borrower fixed effects in the regression to account for the unobservable characteristics of borrowers. We also estimate the coefficients by using a Tobit regression to account for that the gaming related consumption variable is left-censored at zero and present the results in the third column. The sign and significance of these two regressions are similar to the regression in the first column, implying the robustness of our findings.

We also investigate the correlation between expanding credit access and the other eight categories of consumption. We use the eight categories of consumption as the dependent variables and run OLS regressions respectively. In each regression, we control for borrower fixed effects to remove the effect of unobserved borrower characteristics.

[Insert Table VI About Here]

The coefficients and t-statistics are reported in Table VI. In most of the regressions, the coefficients of *Aftershock*Fortnight (1-2), Aftershock*Fortnight (3-4),* and *Aftershock*Fortnight (5+)* are not significantly different from zero. However, the results in the second column of Table VI show that expanding credit access has positive effect on other housing consumption. It is indicated that the effect of expanding credit access on total consumption may primarily concentrated on gaming related consumption and other housing consumption.

C. Expanding Credit Access and gaming addicted borrowers

Next, we test whether expanding credit access has different effects on borrowers with different levels of gaming-related consumption. Borrowers with larger gaming related consumption are more likely video game addicts, which are more likely to have weaker self-control (Oh 2003; Kim et al, 2008). As weaker self-control implies overconsumption when accessing to more cash (Morse, 2011), our hypothesis is that the effect of expanding credit access on consumption is more prominent in gaming addicted borrowers, or borrowers with larger gaming-related consumption.

To test this hypothesis, we estimate the coefficients of the following specification.

$$\mathrm{C_{it}} = \alpha + \gamma_1 * \mathrm{HighGame_i} * \mathrm{Aftershock_i} * \mathrm{Fortnight}(1-2)_{\mathrm{it}} + \gamma_2 * \mathrm{HighGame_i} * \mathrm{Aftershock_i} * \mathrm{Fortnight}(3-4)_{\mathrm{it}} + \gamma_3 * \mathrm{HighGame_i} * \mathrm{Aftershock_i} * \mathrm{Fortnight}(5+)_{\mathrm{it}} + \text{Interaction Term}_{\mathrm{it}} + \text{Borrower Fixed Effect}_{\mathrm{i}} + \varepsilon_{\mathrm{it}} \tag{2}$$

where C_{it}, $Aftershock_i$, $Fortnight(1-2)_{it}$, $Fortnight(3-4)_{it}$, $Fortnight(5+)_{it}$ are defined in Section III.D. $\mathrm{HighGame_i}$ is a dummy variable with the value of 1 if the borrower i spent over CNY 62.5 (the 75th percentile of the borrowers in the matched around-shock sample) within eight weeks before the loan facilitation date. $\text{Interaction Terms}_{\mathrm{it}}$ comprises the other interaction terms generated by $\mathrm{Aftershock_i}$, $Fortnight(1-2)_{it}$, $Fortnight(3-4)_{it}$, $Fortnight(5+)_{it}$, and $HighGame_i$. ε_{it} is the error term. γ_1, γ_2, γ_3 represent the difference of the effect of expanding credit access on consumption between borrowers with higher gaming related consumption and borrowers with lower gaming related consumption.

[Insert Table VII About Here]

Table VII reports the OLS estimates of specification (2). In the first column, we use total consumption as the dependent variable. The coefficient of *HighGame*Aftershock*Fortnight(1-2)* is 103.690 with a t-statistics of 1.370 and the coefficient *HighGame*Aftershock*Fortnight(3-4)* is 114.417 and significant at 10% level, implying that the expanding credit access are more positively correlated with borrowers with larger gaming related consumption.

In the second column of Table VII, we use gaming related consumption as the dependent variable. The coefficients of *HighGame*Aftershock*Fortnight(1-2)* is 78.966 and significant at 1% level. It suggests that, in the first month, the average effect of the credit expansion on gaming related consumption is 157.932 (=78.966*2) larger among borrowers with high gaming related consumption than the rest. Since the average marginal effect on gaming related consumption is 83.208, the credit expansion may have economically significantly different effect among borrowers with different levels of gaming related consumption.

These results suggest that credit expansion has larger positive association with gaming related consumption for borrowers with high past gaming related consumption. As larger gaming related consumption may have negative welfare effect on consumers, it is likely that the negative welfare effect of credit access is more prominent for borrowers who are more likely to be game addicts.

To examine whether the effect of expanding credit access on the other eight categories of consumption is different among borrowers with different levels of gaming related consumption, we use these eight categories consumption as the dependent variables and re-run regressions of specification (2). The results are reported in Column (3)-(11) of Table VII. In these columns, most of the coefficients of *HighGame*Aftershock*Fortnight(1-2)*, *HighGame*Aftershock*Fortnight(3-4)* , and *HighGame*Aftershock*Fortnight(5+)* are insignificant. When using other housing consumption as the dependent variable, *HighGame*Aftershock*Fortnight(3-4)* and *HighGame*Aftershock*Fortnight(5+)* are significantly positive at 5% significance. It is indicated that the expanding credit access is more associated with other housing consumption for borrowers with larger gaming related consumption. For the other seven categories of consumption, the effect is not significantly different among borrowers with different gaming related consumption.

D. Expanding Credit Access and Borrowers' Repayment

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 the high interest payment. We intend to exam whether expanding credit assess is associated with increased loan delinquency.

To test this, we use two proxies for loan delinquency. The first one is *Overdue*, a dummy variable with the value of 1 if the borrower does not repay the loan on time. The second one is *Default*, a dummy variable with the value of 1 if the loan is 60-day plus past due. Using 1,394 borrowers in the matched around-shock sample, we run a series of Probit regressions with these two proxies as the dependent variables.

[Insert Table VIII About Here]

The results are reported in Table VIII. In the first column of Panel A, we regress *Overdue* on *Aftershock*. The coefficient of *Aftershock* is not significant different from zero, suggesting that expanding credit access has no significant average effect on the overdue rate. The marginal effect is -1.86%, relatively small comparing to the 42% overdue rate in our sample. In the second column, we add *HighGame* to the right-hand side variables to examine whether past gaming related spending is related to the likelihood of overdue payments. The coefficient of *HighGame* is also insignificant and the marginal effect is also small. To examine whether expanding credit access has different effect among borrowers with different levels of gaming related consumption, we include the interaction of *HighGame and Aftershock* in the regression. The coefficient of the interaction term is also not significant from zero, suggesting that the credit expansion has no heterogeneous effect among borrowers with different levels of gaming related consumption.

In the Panel B, we use *Default* to replace *Overdue* as the dependent variable and re-run the Probit regressions. In the first column, we find that expanding credit is positively correlated with the default rate at 10% significance. The marginal effect is 1.50%, 19% of the full sample default rate which is 8.0%. In the second column, we include *HighGame* in the regression to test whether past gaming related consumption is positively related to default rate. We find that *HighGame* is positively related to higher default rate, with the marginal effect of 2.86%, over one third of the average full sample default rate. When we include the interaction term in the third column, the coefficient of the interaction term is not significantly different from 0, suggesting that the effect on default rate is not significantly different across borrowers with different level of gaming related consumption.

Overall, increased credit access is positively correlated with increased default rate. However, the association on default rate is not significantly different across borrowers with different level of gaming related consumption. Borrowers with high gaming related consumption are more likely to default their loans.

V. Conclusion

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

In this paper, we investigate the effect of expanding credit access on consumption by using a unique and comprehensive datasets combined with a rare exogenous credit supply shock. Our datasets contains 9,998 randomly selected borrowers and their full transaction records on Alibaba e-commerce platforms. Using textual analysis on item description of each spending transaction, we measure consumption in each of ten categories at borrower level based on real transactions. Leveraging the event that the cash loan platform increased the credit lines of a randomly-chosen set of borrowers, we are able to have a few interesting findings: First, expanding credit access is positively correlated with the total expenditure on e-commerce platforms in the first month after the loan facilitation date, with the marginal propensity to consume out of borrowing amount around 75%. Second, expanding credit access is significantly positively correlated with the gaming related consumption in the first month after the loan facilitation date. For gaming related consumption, the marginal propensity to consume out of borrowing amount is 49.3%. However, credit expanding does not have long term effect on both total consumption and gaming related consumption. Third, the correlation of expanding credit access and gaming related consumption is more prominent for borrowers with higher gaming related consumption. Fourth, the effect of expanding credit access has little effect on the other categories of consumption except for expenditure on other housing. Finally, we find that credit expansion is positively associated with both loan size and default rate.

As the policy maker around the world try to keep up with this fast growing online unsecured lending industry, this paper may shed some light for regulators when considering the response from different type of individual who faces the increase of the credit access.

Reference

ACCA. Payday lending: fixing a broken market. 2014

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, Wenlan Qian. 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.

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.

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.

Guerrieri V, Lorenzoni G. Credit crises, precautionary savings, and the liquidity trap[J]. Quarterly Journal of Economics, 2017, 132(3): 1427-1467.

Hayashi F. The effect of liquidity constraints on consumption: a cross-sectional analysis[J]. Quarterly Journal of Economics, 1985, 100(1): 183-206.

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.

Laibson D. Golden eggs and hyperbolic discounting[J]. Quarterly Journal of Economics, 1997, 112(2): 443-478.

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.

Mian A, Rao K, Sufi A. Household balance sheets, consumption, and the economic slump[J]. Quarterly Journal of Economics, 2013, 128(4): 1687-1726.

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.
Laibson D. Golden eggs and hyperbolic discounting[J]. Quarterly Journal of Economics, 1997, 112(2): 443-478.
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.

Oh W O. Factors influencing internet addiction tendency among middle school students in Gyeong-buk area[J]. Journal of Korean Academy of Nursing, 2003, 33(8): 1135-1144.

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.

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.

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.

Zeldes S P. Consumption and liquidity constraints: an empirical investigation[J]. Journal of Political Economy, 1989, 97(2): 305-346.

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.

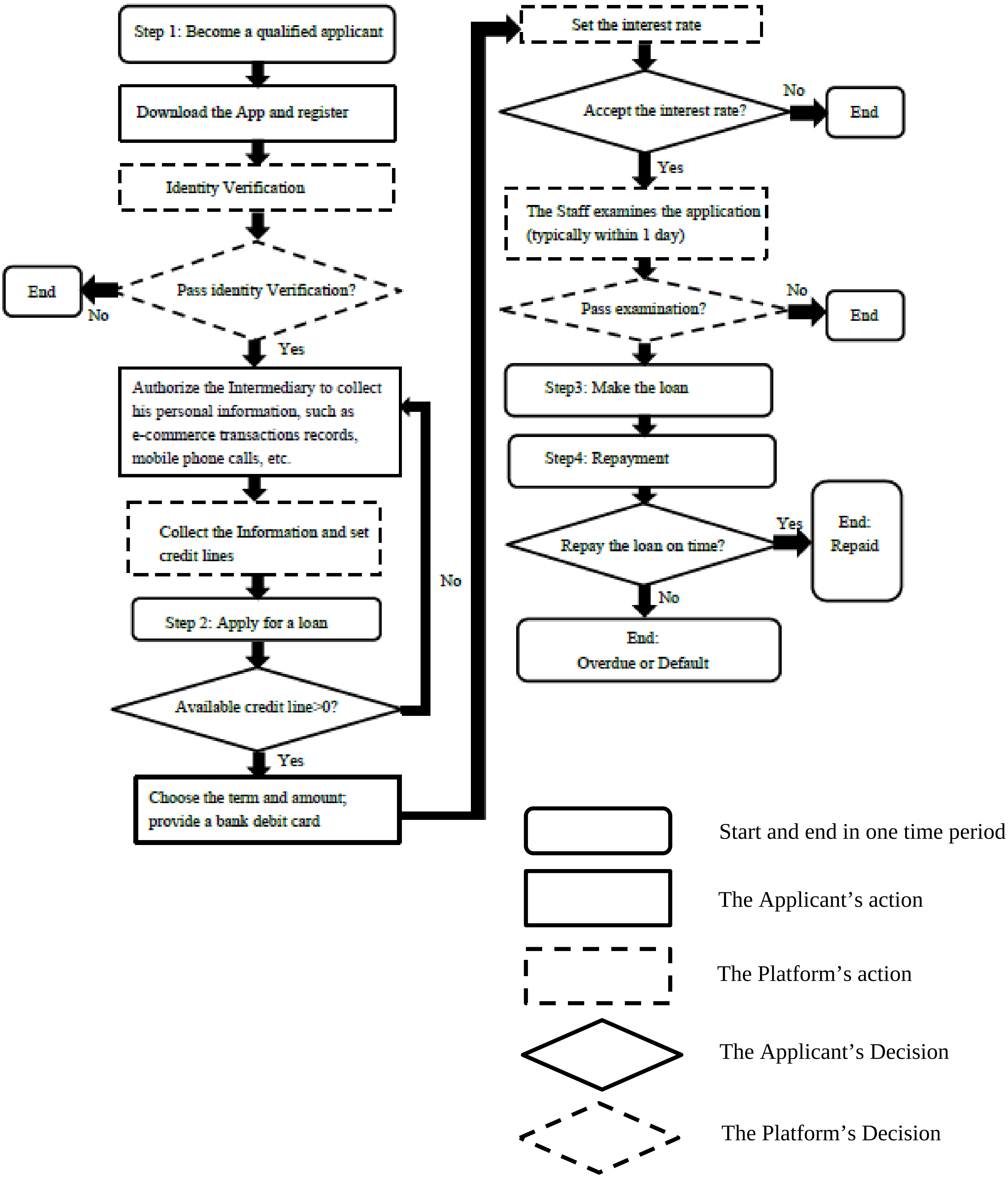

Figure 1 Flow Chart of the Lending Procedure on the Platform

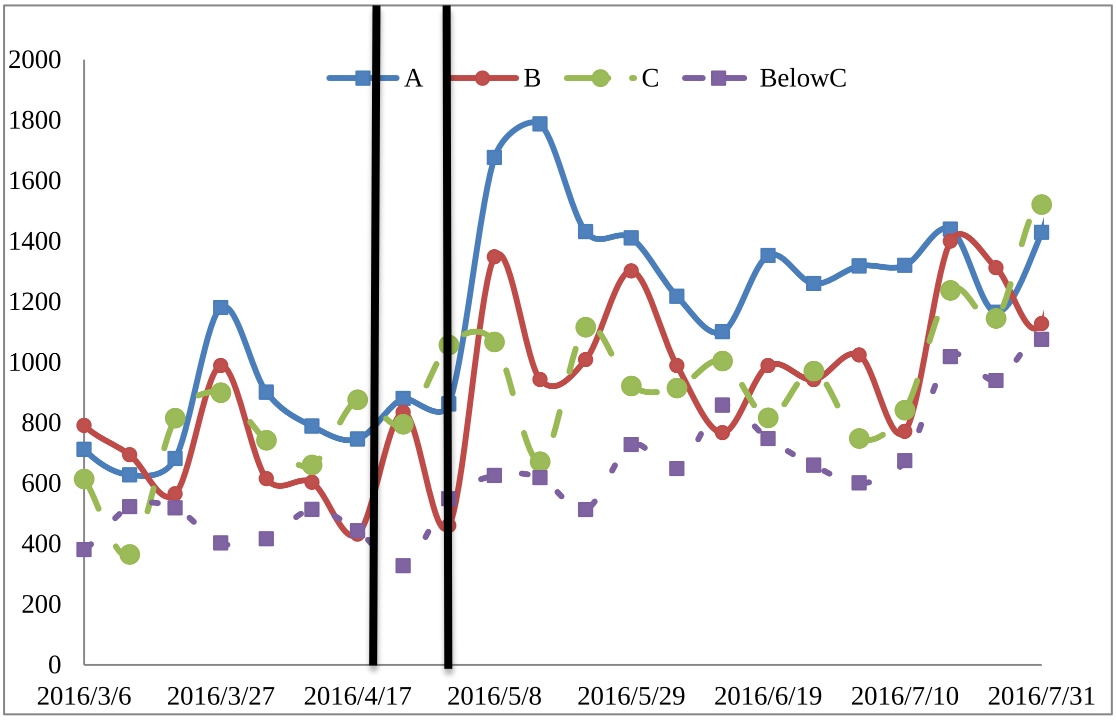

Figure 2 Loan Size Around the Experiment. This figure plots the average CNY value of cash loans on the Chinese cash loan platform each week between 03/06/2016 and 07/31/2016. The two solid vertical lines in the middle of the figure denote the beginning date (04/20/2016) and the end date (04/30/2016) of the experiment.

Table I Summary Statistics

Panel A reports the summary statistics for personal information and loan characteristics for the full sample. This sample contains all the 7,566 borrowers whose consumption information on Alibaba's online shopping platforms is available in our dataset. It also includes all the 48,907 loans that these borrowers obtained before data collection. *Bornyear* is the year of born. *Male* is a dummy variable for male borrowers. *# Loans* is the number of loans that the borrower obtained before data collection. *Grade A, Grade B, and Grade lower than B* are dummy variables for borrowers who are rated A, B, or lower than B by the platform, respectively. *Amount* is the CNY value of the loan size. *Maturity* is the months of the loans' maturity. *Rate Category* is the interest rate category of the loans. *Facilitation date* is the date of loan facilitation. *Overdue* is a dummy variable with the value of 1 for loans not repaid on time. *Default* is a dummy variable with the value of 1 for loans which are 60-day plus past due. Panel B presents the summary statistics of the consumption variables by using a sample of 580,916 borrower-fortnight observations. This sample comprises all the 7,566 borrowers in the full sample and all the consumption within fortnights between January, 6 2014 and July, 2 2017. The fortnights after the facilitation date of each borrower's last loan are excluded. *Consumption* is the total expenditure on the Alibaba e-commerce platforms. *Food, Housing, ComExp, MobCom, OtherHou, Apparel, Entertainment, VideoGame, OtherEnter, Transportation, Healthcare, Others* are the expenditure on the corresponding consumption categories. We winsorize the expenditure on each of the ten consumption categories mentioned in Section III.B at 1% and 99% level before calculating the rest of the consumption variables.

Panel A. Borrower Information and Loan Characteristics

	N	Mean	Std	Min	Q1	Median	Q3	Max
Bornyear	7566	1989.81	5.328	1962	1987	1991	1994	1999
Male	7566	0.780	0.414	0	1	1	1	1
# Loans	7566	6.46	7.84	1	1	3	9	98
Grade_A	7566	0.210	0.407	0	0	0	0	1
Grade_B	7566	0.198	0.399	0	0	0	0	1
Grade lower than B	7566	0.591	0.492	0	0	1	1	1
Amount	48907	1303.81	1026.05	0.95	600.00	1000.00	1700.00	25380.00
Maturity	48907	3.31	3.21	1.00	1.00	2.00	4.00	18.00
Rate Category	48907	4.80	2.16	1.00	4.00	4.00	5.07	10.00
Facilitation date	48907	2016/10/29	187.08	2014/3/4	2016/6/28	2016/12/26	2017/3/26	2017/7/3
Overdue	48907	0.42	0.49	0.00	0.00	0.00	1.00	1.00
Default	48907	0.08	0.27	0.00	0.00	0.00	0.00	1.00

Panel B. Consumption Variables

	N	Mean	Std	Min	P5	Q1	Median	Q3	P95	Max
Consumption	580916	157.89	320.67	0	0	0	0	173.96	809.94	3935.23
Consumption>0	580916	0.49	0.50	0	0	0	0	1	1	1
Food	580916	5.76	28.82	0	0	0	0	0	26	216.9
Housing	580916	50.55	115.99	0	0	0	0	49.5	297.12	1350.92
ComExp	580916	27.48	63.98	0	0	0	0	19.7	169.61	349.3
MobCom	580916	11.07	65.13	0	0	0	0	0	32	576
OtherHou	580916	12.00	55.80	0	0	0	0	0	61	425.62
Apparel	580916	48.85	153.84	0	0	0	0	0	315	1017.15
Entertainment	580916	11.97	46.62	0	0	0	0	0	84.4	509.98
VideoGame	580916	6.19	36.27	0	0	0	0	0	9.49	300.3
OtherEnter	580916	5.78	28.03	0	0	0	0	0	27.41	209.68
Transportation	580916	2.20	15.78	0	0	0	0	0	0	138.5
Healthcare	580916	0.48	3.91	0	0	0	0	0	0	35.5
Others	580916	38.09	151.60	0	0	0	0	0	200	1154.08

Table II E-commerce Consumption and Household Consumption

This table presents the proportion of six CEX categories of consumption in e-commerce consumption and household consumption. *Food, Housing, Apparel, Entertainment, Transportation, Healthcare, and Others* are the proportion of expenditure on the corresponding CEX categories. The proportions of six consumption categories in E-commerce consumption are calculated by using a sample that comprises all the 7,566 borrowers in the full sample and all the consumption within fortnights between January, 6 2014 and July, 2 2017. The fortnights after the facilitation date of each borrower's last loan are excluded. We winsorize the expenditure on each of the ten consumption categories mentioned in Section III.B at 1% and 99% level before calculating the proportions of the six CEX categories. The proportions of six consumption categories in household consumption are calculated by using the consumption data of 3,449 households from 2014 CFPS survey. Hospital treatment, vehicle purchase, and cash contribution are excluded from the CFPS survey data.

	E-commerce Consumption	Household Consumption
Food	3.6%	8.2%
Housing	32.0%	36.5%
Apparel	30.9%	13.5%
Entertainment	7.6%	9.6%
Transportation	1.4%	1.0%
Healthcare	0.3%	2.4%
Others	24.1%	28.8%

Table III The Around-shock Sample and Propensity Matching

Panel A compares the features for the before-shock group borrowers and the after-shock borrowers in the unmatched sample. The before-shock group contains 620 borrowers that obtained one or more loans between March, 30 2016 and April, 19 2016. The after-shock group contains 697 borrowers that obtained one or more loans between May, 1 2016 and May, 30 2016. *Bornyear* is the year of born. *Male* is a dummy variable for male borrowers. *Grade A, Grade B, and Grade lower than B* are dummy variables for borrowers who are rated A, B, or lower than B by the platform, respectively. *Amount* is the CNY value of the loan size. *Maturity* is the months of the loans' maturity. *Rate Category* is the interest rate category of the loans. *Pastborrowing* is the CNY value of loans obtained before the loan facilitation date. *Pastconsumption* is the CNV value of consumption within 56 days before the loan facilitation date. Panel B presents the coefficients and z-statistics of Probit regressions in the unmatched sample and matched sample. The matched sample is generated by applying propensity score matching algorithm to the unmatched sample with respect to the covariates of *Grade_A, Grade_B, male, Bornyear, Rate Category, Maturity, ln(Pastborrowing), and ln(Pastconsumption)*. Panel C compares the features for the before-shock group borrowers and the after-shock borrowers in the matched sample. ***, **, * denote the significance at 1%, 5%, or 10%, respectively.

Panel A. Unmatched Around-shock Sample

	Before-shock Group		After-shock Group		After-Before	
	N	Mean	N	Mean	Diff	T-stat
Amount	620	1351.59	697	1705.71	354.12***	4.34
Male	620	0.78	697	0.77	-0.01	-0.32
Bornyear	620	1989.35	697	1989.15	-0.20	-0.64
Grade A	620	0.47	697	0.52	0.05*	1.77
Grade B	620	0.21	697	0.21	-0.00	-0.13
Grade lower than B	620	0.32	697	0.28	-0.05	-1.81
Rate Category	620	6.86	697	6.27	-0.59***	-4.59
Term	620	7.04	697	6.98	-0.06	-0.28
ln(Pastborrowing)	620	6.21	697	6.08	-0.13	-0.61
ln(PastConsumption)	620	5.88	697	6.19	0.31**	2.39

Panel B. Probit Regressions

Dependent Variable:	Dummy = 1 if in the after-shock group; = 0 if in the before-shock group.	
	(1)	(2)
	Pre-match	After-match
Male	-0.002	0.073
	-0.02	0.91
Bornyear	-0.006	0.002
	-0.98	-0.691
Grade A	0.070	-0.112
	0.83	-1.36
Grade B	0.013	-0.059
	0.13	-0.58
Rate Category	-0.156***	-0.004
	-6.51	-0.17
Term	0.061***	0.002
	4.42	0.15
ln(PastBorrowing)	-0.022**	0.008
	-2.22	0.9
ln(Pastconsumption)	0.029*	0.016
	1.94	1.07
Observations	1317	1394
Pvalue of Chi2	0.000	0.7894
Pseudo R2	0.030	0.002

Panel C Matched Around-shock Sample

	Before-shock		After-shock		After-Before	
	N	Mean	N	Mean	Diff	T-stat
Amount	697	1536.87	697	1705.71	168.84**	2.08
Male	697	0.75	697	0.77	0.02	0.94
Bornyear	697	27.00	697	26.85	-0.15	-0.50
Grade A	697	0.55	697	0.52	-0.03	-1.18
Grade B	697	0.20	697	0.21	0.01	0.27
Grade lower than B	697	0.25	697	0.28	0.03	1.09
Rate category	697	6.31	697	6.27	-0.04	-0.35
Term	697	7.02	697	6.98	-0.04	-0.18
ln(Pastborrowing)	697	5.88	697	6.08	0.20	0.98
ln(Pastconsumption)	697	6.10	697	6.19	0.10	0.81

Table IV Expanding Credit Access and Total Consumption

This table presents the estimation results from regressions relating to expanding credit access and total consumption. The sample contains 33,456 observations at borrower-fortnight level. It includes 679 pairs of borrowers in the matched sample. For each borrower, the sample includes 12 fortnights before the loan facilitation date and 12 fortnights after the facilitation date. The dependent variables are the total consumption of the given borrower at the given fortnight. Before computing the total consumption, we winsorize the expenditure on the ten consumption categories mentioned in Section III.B at 1% and 99% level. *Aftershock* is a dummy variable with the value of 1 if the borrower is in the after-shock group. *Fortnight(1-2)*, *Fortnight(3-4)*, and *Fortnight(5+)* are dummy variables with the value of 1 for the 1-2 fortnights, 3-4 fortnights, or >=5 fortnights after the loan facilitation date. T-statistics are reported in parentheses. ***, **, * denote the significance at the 1%, 5%, 10% level respectively.

	(1)	(2)	(3)
	OLS	OLS	Tobit
	Consumption	Consumption	Consumption
Aftershock	-3.320	-9.375	1.719
	(-0.140)	(-0.844)	(0.054)
Fortnight(1-2)	14.296	14.296	25.481
	(0.662)	(0.654)	(0.877)
Fortnight(3-4)	31.005	31.005	29.372
	(1.055)	(1.041)	(0.786)
Fortnight(5+)	12.020	12.020	25.561
	(0.696)	(0.688)	(1.065)
Aftershock*Fortnight(1-2)	63.259**	63.259**	70.597**
	(2.320)	(2.290)	(2.000)
Aftershock*Fortnight(3-4)	19.299	19.299	44.446
	(0.594)	(0.587)	(1.076)
Aftershock*Fortnight(5+)	14.826	14.826	7.407
	(0.780)	(0.770)	(0.280)
Borrower FE		Y	
Observations	33,456	33,456	33,456
R-squared	0.001	0.372	0.000

Table V Expanding Credit Access and Gaming related Consumption

This table presents the estimation results from regressions relating to expanding credit access and gaming related consumption. The sample contains 33,456 observations at borrower-fortnight level. It includes 679 pairs of borrowers in the matched sample. For each borrower, the sample includes 12 fortnights before the loan facilitation date and 12 fortnights after the facilitation date. The dependent variables are the gaming related consumption, which equals to the expenditure on video games plus the expenditure on mobiles and computers. Before computing the gaming related consumption, we winsorize the expenditure on video games and the expenditure on mobiles and computers at 1% and 99% level. *Aftershock* is a dummy variable with the value of 1 if the borrower is in the after-shock group. *Fortnight(1-2)*, *Fortnight(3-4)*, and *Fortnight(5+)* are dummy variables with the value of 1 for the 1-2 fortnights, 3-4 fortnights, or >=5 fortnights after the loan facilitation date. T-statistics are reported in parentheses. ***, **, * denote the significance at the 1%, 5%, 10% level respectively.

	(1)	(2)	(3)
	OLS	OLS	Tobit
	GamingRelated	GamingRelated	GamingRelated
Aftershock	0.310	-2.140	23.872
	(0.068)	(-0.613)	(0.927)
Fortnight(1-2)	-9.671	-9.671	-52.966
	(-1.414)	(-1.395)	(-1.314)
Fortnight(3-4)	12.564	12.564	26.513
	(1.275)	(1.258)	(0.669)
Fortnight(5+)	14.548**	14.548**	52.549**
	(2.471)	(2.440)	(1.969)
Aftershock*Fortnight(1-2)	41.604***	41.604***	149.259***
	(4.414)	(4.357)	(3.312)
Aftershock*Fortnight(3-4)	10.234	10.234	48.763
	(0.896)	(0.884)	(1.096)
Aftershock*Fortnight(5+)	-6.194	-6.194	-38.680
	(-1.017)	(-1.004)	(-1.378)
Borrower Fixed Effects		Y	
Observations	33,456	33,456	33,456
R-squared	0.002	0.124	0.000

Table VI Expanding Credit Access and Other Categories of Consumption

This table presents the estimation results from OLS regressions relating to expanding credit access and other eight categories of consumption. The sample contains 33,456 observations at borrower-fortnight level. It includes 1,394 borrowers in the matched sample. For each borrower, the sample includes 12 fortnights before the loan facilitation date and 12 fortnights after the facilitation date. The dependent variables, *Food, OtherHou, ComExp, OtherEnter, Apparels, Healthcare, Transportation, Others,* are the expenditure on the corresponding consumption categories. Each of them is winsorized at the 1% and 99% level. *Aftershock* is a dummy variable with the value of 1 if the borrower is in the after-shock group. *Fortnight(1-2)*, *Fortnight(3-4)*, and *Fortnight(5+)* are dummy variables with the value of 1 for the 1-2 fortnights, 3-4 fortnights, or >=5 fortnights after the loan facilitation date. T-statistics are reported in parentheses. ***, **, * denote the significance at the 1%, 5%, 10% level respectively.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Food	OtherHou	ComExp	OtherEnter	Apparel	Healthcare	Transportation	Others
Aftershock	-0.565	-2.208	0.745	0.474	-7.761*	0.178	0.174	1.728
	(-0.505)	(-0.865)	(0.464)	(0.512)	(-1.845)	(1.209)	(0.222)	(0.260)
Fortnight(1-2)	-2.788	-5.404	3.371	1.809	10.556	0.150	2.002	14.270
	(-1.235)	(-1.016)	(1.059)	(0.752)	(1.250)	(0.337)	(0.933)	(0.974)
Fortnight(3-4)	1.286	4.388	-0.658	3.076	-4.934	0.272	4.808*	10.202
	(0.489)	(0.637)	(-0.177)	(0.961)	(-0.667)	(0.704)	(1.718)	(0.437)
Fortnight(5+)	-2.198	5.422	0.104	1.844	-11.820*	0.114	1.962	2.046
	(-1.252)	(1.145)	(0.034)	(1.131)	(-1.871)	(0.485)	(1.153)	(0.193)
Aftershock*Fortnight(1-2)	0.105	16.178**	0.685	0.062	2.795	-0.216	-0.456	2.501
	(0.040)	(2.536)	(0.175)	(0.022)	(0.271)	(-0.420)	(-0.199)	(0.137)
Aftershock*Fortnight(3-4)	-2.357	7.250	6.049	0.482	1.929	0.248	-2.555	-1.980
	(-0.786)	(0.933)	(1.464)	(0.138)	(0.205)	(0.500)	(-0.870)	(-0.079)
Aftershock*Fortnight(5+)	1.757	2.558	-3.534	-1.189	10.197	-0.214	1.681	9.764
	(0.921)	(0.505)	(-1.122)	(-0.691)	(1.439)	(-0.899)	(0.951)	(0.812)
Borrower FE	Y	Y	Y	Y	Y	Y	Y	Y
Observations	33,456	33,456	33,456	33,456	33,456	33,456	33,456	33,456
R-squared	0.202	0.155	0.272	0.133	0.293	0.130	0.169	0.291

Table VII Gaming Addicted Borrowers V.S. Non Addicted Borrowers

This table presents the estimation results from OLS regressions relating to expanding credit access and consumption for gaming addicted borrowers and non-gaming addicted borrowers. We use the past gaming related consumption as a proxy for whether a borrower is gaming addicted or not. The sample contains 33,456 observations at borrower-fortnight level. It includes 1,394 borrowers in the matched sample. For each borrower, the sample includes 12 fortnights before the loan facilitation date and 12 fortnights after the facilitation date. The dependent variables are the total consumption, gaming related consumption, and the other eight categories of consumption. Before calculating the total consumption and gaming related consumption, we winsorize the expenditure on each of the ten consumption categories mentioned in Section III.B at 1% and 99% level. *HighGame* is a dummy variable with the value of 1 if the borrower's gaming related consumption within the 56 days before the loan facilitation date is in the highest quartile. *Aftershock* is a dummy variable with the value of 1 if the borrower is in the after-shock group. *Fortnight(1-2)*, *Fortnight(3-4)*, and *Fortnight(5+)* are dummy variables with the value of 1 for the 1-2 fortnights, 3-4 fortnights, or >=5 fortnights after the loan facilitation date. T-statistics are reported in parentheses. ***, **, * denote the significance at the 1%, 5%, 10% level respectively.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
	Consumption	Gamingrelated	Food	OtherHou	ComExp	OtherEnter	Apparel	Healthcare	Transportation	Others
HighGame*Aftershock*Fortnight(1-2)	103.690	78.966***	0.797	9.830	-7.890	-13.678*	28.681	-1.328	5.227	3.085
	(1.370)	(2.994)	(0.141)	(0.576)	(-0.922)	(-1.834)	(1.166)	(-0.931)	(1.299)	(0.062)
HighGame*Aftershock*Fortnight(3-4)	114.417*	10.071	0.526	43.158***	3.824	5.222	27.161	-0.639	4.003	21.090
	(1.662)	(0.307)	(0.086)	(2.691)	(0.444)	(0.677)	(1.186)	(-0.524)	(0.737)	(0.456)
HighGame *Aftershock*Fortnight(5+)	32.939	-20.173	7.249	25.812**	-4.190	0.090	35.497*	-0.509	-7.572**	-3.265
	(0.758)	(-0.955)	(1.625)	(2.180)	(-0.609)	(0.020)	(1.922)	(-0.758)	(-2.101)	(-0.120)
Interaction Term	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
Borrower FE	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
Observations	33,456	33,456	33,456	33,456	33,456	33,456	33,456	33,456	33,456	33,456
R-squared	0.372	0.125	0.202	0.156	0.274	0.134	0.294	0.131	0.169	0.292

Table VIII Expanding Credit Access and Loan Delinquency

This table presents the results from the Probit regressions relating expanding credit access and loan delinquency. The sample includes 1,394 borrowers in the matched after-shock sample. The dependent variable in Panel A is *Overdue,* a dummy variable for the loans not paid on time. The dependent variable in Panel B is *Default,* a dummy variable for loans which are 60-day plus past due. *HighGame* is a dummy variable with the value of 1 if the borrower's gaming related consumption within the eight weeks before the loan facilitation date is in the highest quartile. *Aftershock* is a dummy variable with the value of 1 if the borrower is in the after-shock group. Marginal Effect is computed at the average value of the other explanatory variable (if any). Z-statistics are reported in parentheses. ***, **, * denote the significance at the 1%, 5%, 10% level respectively.

Panel A. Expanding Credit Access and Overdue

	Prob(Overdue =1)				
	(1)		(2)		(3)
	Coefficient	Marginal Effect	Coefficient	Marginal Effect	Coefficient
Aftershock	-0.047	-1.86%	-0.049	-1.91%	-0.005
	(-0.703)		(-0.720)		(-0.064)
HighGame			0.049	1.93%	0.14
			-0.631		-1.245
Aftershock*HighGame					-0.175
					(-1.122)
Observations	1,394		1,394		1,394
Pseudo-R2	0.000		0.000		0.001

Panel B. Expanding Credit Access and Default

	Prob(Default=1)				
	(1)		(2)		(3)
	Coefficient	Marginal Effect	Coefficient	Marginal Effect	Coefficient
Aftershock	0.222*	1.57%	0.220	1.50%	0.283*
	-1.662		-1.631		-1.657
HighGame			0.355**	2.86%	0.455**
			-2.571		-2.139
Aftershock*HighGame					-0.171
					(-0.612)
Observations	1,394		1,394		1,394
Pseudo-R2	0.007		0.023		0.024