Association for Information Systems

AIS Electronic Library (AISeL)

ICIS 2022 Proceedings | Digital and Mobile Commerce

Dec 12th, 12:00 AM

Brake or Step On the Gas? Empirical Analyses of Credit Effects on Individual Consumption

Jiayan Han
Fudan University, jyhan20@fudan.edu.cn

Yingjie Zhang
Peking University, yingjiezhang@gsm.pku.edu.cn

Tian Lu
Carnegie Mellon University, lutian@asu.edu

Yiheng Sun
Tencent Weixin Group, elisun@tencent.com

Wen Huang
Tencent Weixin Group, aawenhuang@tencent.com

Follow this and additional works at: https://aisel.aisnet.org/icis2022

Recommended Citation

Han, Jiayan; Zhang, Yingjie; Lu, Tian; Sun, Yiheng; and Huang, Wen, "Brake or Step On the Gas? Empirical Analyses of Credit Effects on Individual Consumption" (2022). *ICIS 2022 Proceedings*. 1.
https://aisel.aisnet.org/icis2022/digital_commerce/digital_commerce/1

This material is brought to you by the International Conference on Information Systems (ICIS) at AIS Electronic Library (AISeL). It has been accepted for inclusion in ICIS 2022 Proceedings by an authorized administrator of AIS Electronic Library (AISeL). For more information, please contact elibrary@aisnet.org.

Brake or Step On the Gas? Empirical Analyses of Credit Effects on Individual Consumption

Completed Research Paper

Jiayan Han
Fudan University
Shanghai, China
jyhan20@fudan.edu.cn

Yingjie Zhang
Peking University
Beijing, China
yingjiezhang@gsm.pku.edu.cn

Tian Lu
Arizona State University
Tempe, United States
lutian@asu.edu

Yiheng Sun
Tencent
Shenzhen, China
elisun@tencent.com

Wen Huang
Tencent
Shenzhen, China
aawenhuang@tencent.com

Abstract

Understanding the effects of credit on consumption is crucial for guiding users' consumption behavior, designing financial marketing strategies, and identifying credit's value in stimulating the economy. Whereas several studies have endeavored on this issue, most simply utilize observations of a single credit channel and/or focus on an overall effect without considering the potentially heterogeneous short-term and long-term consumption changes. This study, leveraging a quasi-experimental design with high-resolution transaction data, examines how people respond to credit in both short- and long-term periods. Results show that credit users' consumption amount significantly expand by 51.74% after getting access to credit in the short term. However, they ultimately cut their consumption by 4.02% to cope with financial constraints in the long term. We also reveal and quantify the spillover effects of credit on consumption with savings channels. We draw on regulatory focus theory to rationalize the changes on users' consumption behavior after credit activation.

Keywords: Consumer Credit, Consumption Patterns, Long-Term Effect, Spillover Effect, Regulatory Focus Motive

Introduction

Credit and credit cards have been widely accepted by the public, especially in developed countries. Recently we have witnessed, in the train of the newly emerging financial technologies (FinTechs), rapid growth of credit products, a number of digital credit products among them (Bhutta et al. 2016, Buchak et al. 2018).

Credit card payment takes up as high as 27% of all individual/household payments in the US in 2020.[1] Over the past few years, credit products especially those FinTech credit products have been growing even faster in developing regions, as more and more people therein are drawn to the perceived benefits of credit spending(White 2012). Digital credit products allow users to apply, use, and repay credit conveniently via online (mobile) channels. What's more, credit has been documented to play a crucial role in stimulating economy via affecting consumption (Agarwal et al. 2018). Industry practice and the academic literature have aggregated empirical evidence of a positive relationship between credit and consumption (D'Acunto et al. 2020; Gross and Souleles 2002).

However, most existing studies have considered the impacts of credit on consumption expansion from a static perspective, namely quantified a simple overall effect, without breaking down to inspect the respective short-term patterns and long-term dynamic changes. Yet, the increase in consumption after receiving credit may not endure. One the one hand, as prior studies suggest, accessing to credit may lead to peoples' overspending, incurring financial constraints (Sotiropoulos and d'Astous 2012). People often exhibit resilience when encountering financial constraints (Thompson et al. 2020): They would react positively to cope with financial constraints by using their money more prudently and cutting down unnecessary expenditures (Hamilton et al. 2019). On the other hand, credit may lead to impulsive consumption (Thomas et al. 2011). Such indulgent behavior can invoke negative emotions such as remorse, guilt, or regret, which results in a subsequent reversal of preferences and behavior (Kivetz and Keinan 2006). Hence, consumption expansion after accessing to credit is likely to wane over time. Therefore, it is necessary to empirically examine both the short-term and the long- term effects of credit on multi-dimensional individual consumption (e.g., amount, frequency, stability, and diversity). It enables a comprehensive and elaborative understanding of how people respond to credit.

In addition, after accessing to credit, people would have two payment options of credit and the money sourced from savings channels (e.g., debit card) for consumption (Bhutta et al. 2016). We thus also wonder how credit would spill over to savings channels. Prior empirical literature is majorly constrained by the observations from a single credit channel (Agarwal and Qian 2014), which might fall into the fallacy of over- or underestimating the value of credit. Disentangling the effects of credit on utilizing other money sources helps identify to what extent the consumption changes are stemmed from the newly activated credit and how people choose between credit and savings channels for consumption.

Given the need for more insights into the impacts of credit, we seek to answer the following questions: (1) Whether and how does the access to credit affect users' consumption behavior? If so, how will this effect diverse over time? (2) Will the effects of credit spill over to consumption financed by savings channels? (3) What are the underlying mechanisms?

To answer empirically the above questions, we collaborate with Tencent. In specific, our study is based on WeChat Pay, a leading Chinese mobile payment service offered by Tencent. It was documented that in 2019, the percentage of mobile payments in China reached 86%,[2] among which WeChat Pay took approximately 40% of the payment market share.[3] Given WeChat Pay's mass user base, we believe that partnering with it would be an effective way of analyzing individual users' consumption patterns. Tencent launched its own consumer loan product, *Fenfu*, in March 2020. WeChat users can choose to use such loan service anytime.

Whether to activate this service is endogenously decided by individual users. To address the potential self-selection bias, we first use Propensity Score Matching (PSM) to construct the matched sets of borrowers and non-borrowers with comparable characteristics. We then adopt a widely-used econometric model, the difference-in-difference (DID), to quantify the before-after changes in consumption patterns between borrowers (i.e., users who are given the access to credit and activated the service during our data period) and non-borrowers (i.e., users who did not use this credit service). Regarding the overall effect, our results show that post-activation periods can be divided into two frames (i.e. the short- and long-term time windows) separated by week 15 after activation. In the short term, compared with non-borrowers, borrowers extend all their consumption patterns. However, this increase trend becomes moderate over time and continues for 15 weeks. In the long term, all patterns return to roughly the same level as non-borrowers

[1] Data source: https://www.atlantafed.org/-/media/documents/banking/consumer-payments/diary-of-consumer-paymentchoice/2020/2020-diary-of-consumer-payment-choice.pdf. Accessed on April 22, 2022.

[2] https://tech.ifeng.com/c/7lrWoMzw6OL. Accessed on April 18, 2022.

[3] http://www.jjckb.cn/2021-02/03/c_139717235.htm. Accessed on April 18, 2022.

except for diversity. Similar to the overall effect, the spillover effects on savings channels can also be divided into short and long-term windows. Different consumption dimension, however, shows diverse patterns.

To explain these patterns, especially with respect to time-varying changes and between-channels switching, we suggest that the regulatory focus theory is one plausible explanation. Inspired by this stream of literature (Forster et al. 1998, Higgins et al. 2020), we propose that users of distinct types (i.e., promotion- and prevention- focused) drive the dynamics of credit effects.

Literature Review

This paper stems from the following four streams in the literature.

Credit and Consumption

Our study builds on the literature of how users respond to access to credit. There has been already vast literature analyzing effects of credit on consumers' consumption behavior. For example, using data from five countries, Bacchetta and Gerlach (1997) find that mortgage credit and consumer credit are correlated with consumption of non-durable goods and services. Prior studies leverage different sources of context and data, and their findings are mixed regarding the relationship between credit and consumption. A large body of studies present empirical evidence of positive correlations. For example, using U.S. aggregate data, Ludvigson (1999) shows that consumption growth is positively related to the predictable consumer credit growth. Using credit card data, Gross and Souleles (2002) provides evidence that increasing credit card limits stimulate people to spend more, and this effect is stronger for people who spend close to their overdraft limits. On the contrary, Ekici and Dunn (2010), using detailed monthly credit card data and consumption data, find that consumption growth is negatively related to credit card debt due to debt burden.

More recently, some studies adopt a randomized research design to detect causal impacts of credit consumption. For example, Karlan and Zinman (2010) shows that randomly assigned marginal loans produce a positive effect on food consumption. And leveraging a large-scale field experiment, Aydin (2022) reveals that consumption behavior is positively related to a credit limit increase. The recent rise of Fintech provides a unique opportunity to explore the effects of credit on consumption using transaction-level data. D'Acunto et al. (2020) studies a Fintech application and investigates consumers' spending responses toward an overdraft facility and the findings indicates a permanent increase in consumers' spending. Meanwhile, Li et al. (2018) find that increasing credit limit leads to an expansion on overall consumption amount and addictive product consumption.

Our contributions to this stream of literature are twofold. First, existing studies only have access to coarse-grained data, which limit their research scope to a short-term (static) perspective. Our study focuses on the trend dynamics by incorporating a long-term period and distinguishes diverse mechanisms. Second, the literature focuses on overall consumption, paying scant attention to the channels of money used to finance consumption. This study takes a further step to identify the causal spillover effects driven by access to credit.

Short-term and Long-term Effects of Exogenous Shocks on Consumption

Consumption behavior has been for a long time attracted great attentions in the academic literature. Studies aim to stimulate consumption from diverse perspectives. Due to the complexity of behavior itself as well as the data availability, many studies have examined the effect of exogenous shocks within a rather short time window. For example, Misra et al. (2022) studies effects of CARES acts using a 20-day period and Liu et al. (2021) examines the context of digital coupons also within an approximately 20-day data window. Other studies investigate the effects with a relatively longer period (e.g., Agarwal et al. (2007) considers nine months). An important question in studying effects of stimulus on consumption is to identify whether and why there exist differences of the consumption trends over time. In other words, will consumers behave differently in a short period vs. in a long run? For example, during the COVID-19 outbreaks, consumers first decreased consumption levels when the pandemic was declared but recovered their spending over time due to stimulus payment (Chetty et al. 2020; Horvath et al. 2021). Besides, psychologically, consumers also behave differently in the short term and long term. As Gerend and Cullen (2008) points out, consumers' temporal focus varies from short-term to long-term outcomes due to their different time discounting preferences. Moreover, when resource availability decreases over time, consumers' spending decisions also change because of the increase in the pain of paying (Soster et al. 2014). Under the impulsive consumption scenario, consumers may firstly yield to the temptation to consume impulsively. However, with the passage of time, they might alternate their preference to resist the temptation due to regrets (Schelling 1992). Taken together, this stream of literature suggests that consumers' behavior would not stay constant over time.

Spillover Effects on Money Channels

To the best of our knowledge, extant research is relatively silent in the spillover effects across channels. This stream of literature focuses on the substitution patterns between different channels (Koulayev et al. 2016; Wisniewski et al. 2021) or the investigation of how consumers make payment choices among channels (Stavins 2017; Stavins 2020; Wang and Wolman 2016). However, their findings cannot fully explain consumption responses across different channels when consumers have access to a new channel. Agarwal and Qian (2014) highlights the dynamics of consumption response across different channels, suggesting that previous research based on a single payment channel likely underestimates the consumption response to unanticipated income shocks. The present study aims to bridge this gap.

Regulatory Focus Motives

Our study not only quantifies effects of credit in both the short and long terms, but also investigate the mechanisms explaining consumption behavior. Specifically, we draw on the regulatory focus theory to explain the dynamics in consumption patterns after receiving credit. Regulatory focus theory proposes that people can obtain their goals by adopting either a promotion-focused strategy or a prevention-focused strategy (Higgins 1998; Higgins and Spiegel 2004). It has been demonstrated that promotion focus emphasizes positive outcomes and benefits (i.e. advancement, attainment, and accomplishment) whereas prevention focus emphasizes negative outcomes and losses (i.e. caution and avoidness) (Sengupta and Zhou 2007; Shah et al. 1998). Although both motivations are said to coexist within a person, one or the other may be chronically or situationally induced (Crowe and Higgins 1997). Consumers with these two distinct focuses tend to behave differently and show different preferences (Pennington and Roese 2003).

Regulatory focus theory has been widely adopted to explain consumer behavior. For example, compared to prevention-focused individuals, promotion-focused persons are more likely to have larger consideration sets in decision making (Tuan Pham and Chang 2010), to accept new options (Liberman et al. 1999), to feel more intense urges, and more capable to resist them (Dholakia et al. 2006). In the finance context, (Zhou and Pham 2004) find that promotion and prevention focuses also cast influence on consumers' investment decisions: consumers prefer financial products that align with their focus orientation. (Mishra et al. 2010) shows that consumer preferences shift as a function of time intervals since they last received a paycheck.

According to the regulatory focus theory, we postulate that after receiving credit, users with different regulatory focus motives may perform heterogeneous consumption patterns and distinct usage patterns between credit and savings channels for payment in a long run.

Empirical Background

WeChat Pay and Credit Service

We conducted our empirical study in the context of WeChat Pay, a mobile payment and digital wallet service embedded in WeChat, which is the largest free instant messaging and calling app in China.[4] WeChat Pay, with 910 million active users, had an 84.3% market penetration rate in China's mobile payment market in 2019.[5] Given the dominating role of mobile payments in China, WeChat Pay has become users' main means of payment.[6] Users regularly use WeChat Pay for daily activities including shopping, catering, public transportation, and other household expenditures. Similar to Venmo in U.S., users can store information of multiple cards (including either debit or credit cards) in WeChat Pay. Thus, when making payments, users can directly enjoy WeChat Pay's quick payment service while being able to freely choose (switch among) any money sources (channels) via either pre-stored debit or credit cards.

[4] The dataset in this paper was properly sampled only for testing purposes and does not imply any commercial information. All users' sensitive (personally identifiable) information was removed. Also, our analyses were conducted domestically on Tencent's (WeChat's) server by its employees, who strictly followed data protection regulations.

[5] https://ltl-beijing.com/wechat-pay-vs-alipay/. Accessed on March 31, 2022.

[6] https://daxueconsulting.com/payment-methods-in-china/. Accessed on March 31, 2022.

Tencent recently launched its own embedded consumer loan product, called Fenfu, in March 2020. Similar to credit cards released by traditional banks, this credit service allows users to spend money first and pay it back later. Users can repay at any time after consumption and before the self-selected payment due date each month. Users can also repay by installments, but are required to pay with the minimum repayment per period of 10% plus interest. In short, Fenfu offers an alternative and convenient source of payments. WeChat users can choose to use Fenfu anytime. This business allows us to observe an additional (credit) money source for payment. More importantly, users' first usage of Fenfu (or not) provides us with a unique quasi-experimental opportunity to identify causal effects of credit service on consumption patterns.

Data

The sample consists of 10,376 credit borrowers and 15,345 non-borrowers who are randomly selected from the entire WeChat Pay user pool in China. We define "borrowers" as those who had first used Fenfu in November 2020, and define "non-borrowers" as those who had never used Fenfu throughout our research period.

We obtain a unique data set of the above users with large-scale and fine-grained granular consumption information from August 1, 2020 to June 30, 2021. The consumption information is obtained from WeChat Pay and involves daily transactions carried out via WeChat Pay by users. The data set contains detailed transaction-level consumption records, including encrypted user ID, transaction time, transaction/consumption amount, consumption category,[7] and money source. Besides, although we did not have the exact Fenfu activation date, we could infer it by the date when a user first used Fenfu for a transaction. The dataset also contained each sampled user's demographic information, including age, gender, education level, and living city. Given that our data period covers COVID-19 outbreaks, we collected statistics on COVID-19 (including weekly infection, recovery, and mortality rates of each city) to control for pandemic effects on users.

Variables

We aggregate the data to construct a user-week panel. We finally obtain a balanced panel of 25,721 user' weekly consumption patterns spanning 40 weeks in total.

We followed prior studies and consider multiple dependent variables, namely weekly consumption amount (Amount), weekly consumption frequency (Frequency), weekly average consumption amount (AverageAmount), weekly consumption variability (Variability), and weekly consumption diversity (Diversity), to capture consumption behavior as exhaustively as possible. In particular, Amount is user i's total spending (in RMB) in week t and AverageAmount is user i's average spending (in RMB) per transaction in week t. To capture repeated consumption patterns, we code Frequency as the number of transaction occurrence user i has in week t. To account for consumption volatility, we consider Variability measured as the changes in total consumption amounts between two consecutive weeks (Kerr et al. 2002). Last, we define Diversity using the concept of entropy to capture the scope of category-level consumption differences. In particular, we apply the standard definition of entropy and calculate it based on proportion of total consumption amounts per category (Tovanich et al. 2021).

Our main empirical strategy follows a DID design. We consider three independent variables in our analyses. We define a binary variable, $Treat_i$, to indicate whether user i is in the treatment group (=1 for borrower, 0 for non-borrower). We consider two dummies, $Short_t$ and $Long_t$ to capture the short- and long-term trends, respectively. In particular, $Short_t = 1$ if week t is after the availability of credit and within a short-term window while $Long_t = 1$ if week t is considered a time window long after Fenfu service adoption.

Matching Design

Though WeChat Pay platform randomly selected users to offer authentication of Fenfu service, whether to activate the service is a self-selected decision. Users' such decision could be influenced by unobserved factors. For example, some users are more risk-taking and therefore are more prone to adopt the service. This could give rise to the self-selection bias. To alleviate the potential endogeneity issue, we adopt

[7] WeChat Pay platform pre-defines 12 categories for all transactions. The 12 categories include transportation, public affairs, education, entertainment, travel, health, life necessities, food, family affairs, clothes and beauty, charity, and investment.

Propensity Score Matching (PSM) before any formal empirical analyses and estimations (Rishika et al. 2013; Rubin 2006).

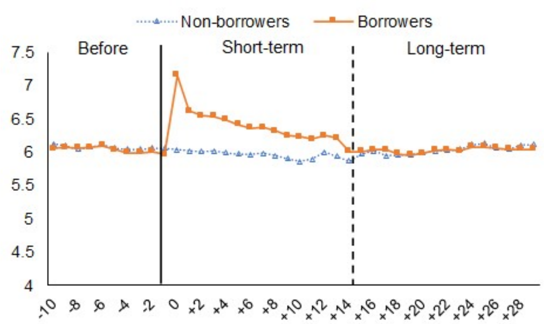
We employ variables of demographic characteristics (e.g., age, gender, education level) and consumption features (e.g., average weekly consumption amount, frequency, and diversity in the pre-adoption period), and 1-on-1 matching and sampling with replacement in PSM. After validated successful matching, our final panel data contains 9,790 borrowers and 9,790 non-borrowers. We assign the treated borrowers' activation time to the matched counterpart non-borrowers.

Model-free Evidence

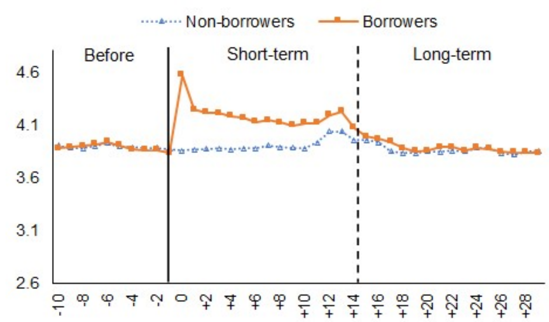
After matching, we plot the consumption trends using the matched samples. As discussed previously, the main focuses of the present study are two-folds: a comparison between short-term and long-term effects of Fenfu adoption, and identification of spillover effects.

Figure 1 first illustrates the consumption trends averaged among all treated or control users. We demonstrate the trends within the 40-week time window (10 weeks before and 30 weeks after the adoption). Note that our before period is intentionally shorter than the after period to avoid the effects of COVID-19 pandemic on consumption and credit activation. For each individual, we define week 0 as the week of the day when he/she activated the service. And week -10 to week -1 is the pre-activation period. It is worth noting that non-borrowers did not have an adoption date, but since we applied a one-to-one matching strategy, we assign the "adoption" date of non-borrowers with the same date of the matched counterpart borrowers.

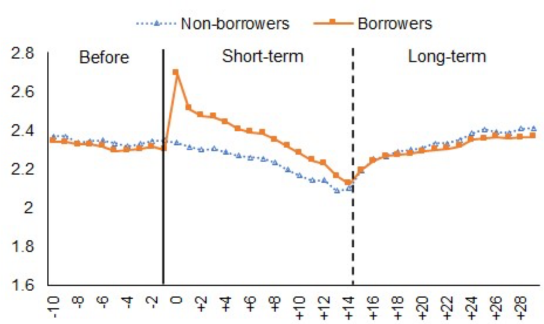
Figure 1 covers all the five dependent variables we described before. All variables show similar patterns: First, in the pre-activation period (i.e., left panel of the solid vertical lines in all five sub-figures), the two groups of users have similar (or parallel) trajectories. This suggests the matched samples are comparable without adoption. Second, borrowers show sharp increases right after activating the service in all the five dimensions. The increasing trends, however, diminished over time and last for approximately 15 weeks.

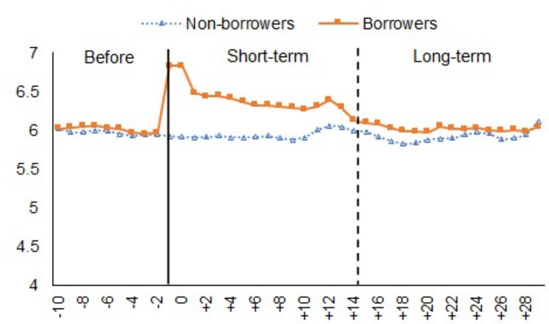


(a) Weekly Consumption Amounts

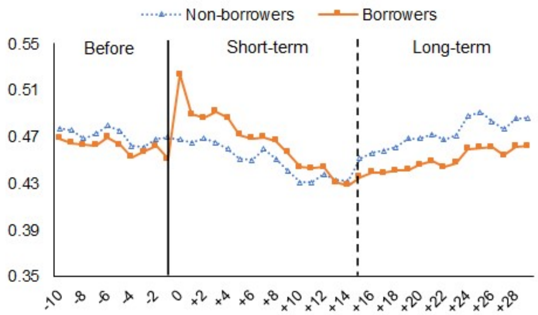


(b) Weekly Average Amounts per Transaction





(c) Weekly Consumption Frequency



(d) Weekly Consumption Variability

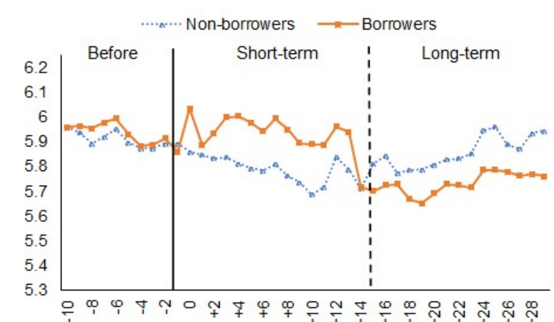
(e) Weekly Consumption Diversity

Figure 1. Comparison of Consumption Patterns after Service Adoption. Values in all figures are log-transformed.

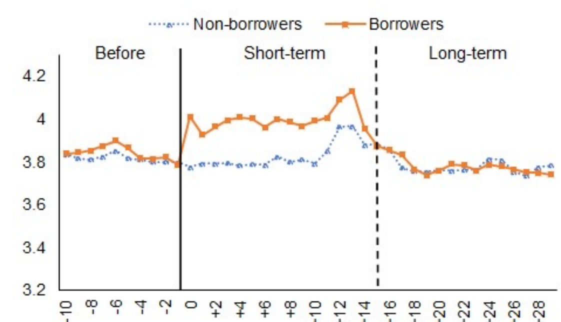
Hence, we divide the post-activation periods into two frames: short- and long-term windows, separating by week 15 after activation (denoting with the dotted vertical lines). We observe from the figures that in the long-term windows, borrowers' consumption patterns return to a similar or even lower trend as nonborrowers. The patterns are different among dependent variables. For example, pattern metrics such as consumption amounts and frequencies were elevated shortly after the service activation. But in the long run, borrowers cut down their consumption amounts and frequencies to a similar level as non-borrowers. On the contrary, though borrowers also lifted their consumption diversity in the short term, diversity decremented to the level even lower than non-borrowers in a relatively long period.

Collectively, Figure 1 not only implies the validity of our matching results, but also suggests the needs in separating the effects between short- and long-term analyses, as well as in taking into accounts different dimensions to describe users' behavior after Fenfu activation.

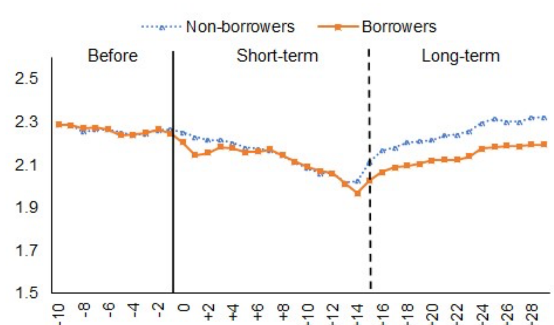
We next explore the existence of spillover effects on savings channels and we present the corresponding

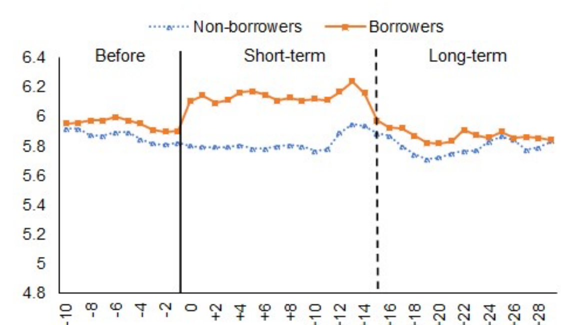


(a) Weekly Consumption Amounts

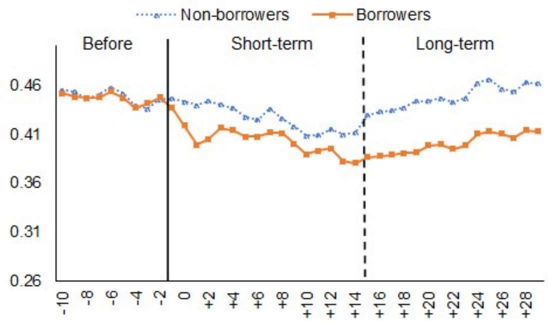


(b) Weekly Average Amount per Transaction





(c) Weekly Consumption Frequency



(d) Weekly Consumption Variability

(e) Weekly Consumption Diversity

Figure 2. Comparison of Consumption Patterns in the Savings Channel after Service Adoption. Values in all figures are log-transformed.

model-free evidence in Figure 2. Savings is an accumulation of financial resources set aside for future consumption (Xiao 2015). Savings is often kept in the form of cash or cash equivalents (Furnham 1999). In WeChat Pay setting, there are, in general, two types of payment channels, namely credit channels and savings channels. The savings channels include debit card, balance account itself and money in the investment product offered by WeChat Pay. Similar to Figure 1, in addition to separating time frames into pre- and post-activation periods, we also observe two diverse patterns in the short- and long-term windows. Still, two groups of users have similar trajectories in all consumption patterns in the pre-activation stage, suggesting that when limiting transactions to savings-channel related, our matched samples are comparable.

Yet unlike the consistent patterns incorporating all transactions, Figure 2 present divergent trends among all of the five dependent variables. For example, we present a significant increase in consumption amounts and variability in the savings channel among borrowers shortly after activating Fenfu. In the long run, however, the increasing trends disappeared and even worse, the weekly consumption amounts were lower than those of non-borrowers. This implies borrowers might be accustomed to using credit as a payment instrument, therefore crowding out consumption financed by the savings channel. Another interesting finding is regarding consumption frequency. Since the service activation, we observe that borrowers' consumption frequency in the savings channel was lower than non-borrowers, whereas the gap enlarged as time goes on.

Notably, we find that the consumption pattern in Figure 2 is not continuous and there is a shock in week 13 and 14. This might be due to the holiday effect because the Chinese New Year holiday for the year 2021 fell on that period. Previous studies have identified that public holidays are associated with increases in consumption in certain types (Foster et al. 2015; Richards 1998). Therefore, the consumption patterns are likely to fluctuate during week 13 and 14.

In sum, our model-free evidence confirms the existence of spillover effects on the savings channel, and such effects have diverse patterns in different dimensions. Our model-free results are robust to other matching strategies. We do not report these detailed results due to the space limit. We offer in-depth discussions in the next section.

Empirical Strategies and Results

Based on the above model-free supports, this section adopted multiple econometric approaches to quantify the effects as well as to identify potential underlying mechanism.

Short-term vs. Long-term Effects

To quantify the effects of Fenfu on consumption patterns, we apply the Difference-in-Difference (DiD) econometric model. This model is an increasingly popular approach to quantify the causal effects (Bertrand et al. 2002) by comparing outcome differences before and after an exogenous shock of a treatment group to that of a control group, which is not affected by the exogenous shock. In our setting, we consider the service activation as the shock because the authorization was a random assignment decided by WeChat Pay platform. Though whether to activate the service is self-selected by users, our PSM-based matched sample could alleviate this concern as we showed in Figures 1 and 2 that the two groups follow similar trends in the pre-activation period. We specify our model as follows:

$$y_{it} = \beta_0 + \beta_1 \cdot Treat_i \cdot Short_t + \beta_2 \cdot Treat_i \cdot Long_t + \beta_3 \cdot Controls_{it} + \eta_i + \tau_t + \epsilon_{it}, \tag{1}$$

where y_{it} denotes the dependent variables of user i in week t. As discussed before, we consider five dimensions in defining the dependent variables. Due to their skewness, we log-transform all the five variables. $Treat_i$ is a dummy variable that equals one if user i is a borrower who receives credit. Notably, following the findings in the model-free evidence, we separate the post-activation period into two stages. In specific, $Short_t$ equals one if week t is within the short-term period, which ranges from the week of the first access date to the 14th week post the activation date. $Long_t$ defines the long-term period and it equals one if week t ranges from the 15th to 29th weeks after activation. η_i and τ_t capture user fixed effect and time fixed effect, respectively. ϵ_{it} is the idiosyncratic error term. The parameters of interest are β1 and β2, which measure the effects of Fenfu on consumption for borrowers. We consider two sets of controls in the regression. The first set includes COVID-19 related statistics, including weekly infection, recovery, and mortality rates of the user's living city. This set of control would alleviate potential concerns that the pandemic might alter users' regular consumption patterns. Second, we also control users' historical consumption. In specific, for each dependent variable of user i in week t, we calculate the its historical consumption as the average weekly consumption from week 0 to week $t - 1$. We cluster the standard errors by users.

Table 1 presents the regression results for our DID analysis. We estimate Equation (1) with the five dependent variables, separately. As a whole, the estimates are in line with the model-free evidence in fig. 1. First, the coefficients of $Treat_i \cdot Short_t$ document the short-term effects after service activation. All the five dimensions describe consistent consumption patterns that the adoption of an additional credit channel would boost users' consumption in both volumes and diversity. Statistically speaking, our estimates suggest that the total consumption amount per week increases by 51.7% (exp(0.417) − 1, Column 1), and the consumption frequency rises by approximately 16.2% (exp(0.150) − 1, Column 3). This suggests that with the extra channel, users not only consume more frequently, but also purchase more per visit. Meanwhile, the estimate in Column 5 is positive and significant, but the magnitude is relatively smaller than other estimates. This implies that the ability is limited of an additional channel in expanding consumption diversity.

Table 1. Effects of Fenfu on Consumption Patterns

	(1)	(2)	(3)	(4)	(5)
DV	Amount	Average amount	Frequency	Variability	Diversity
$Treat_i \cdot Short_t$	0.417***	0.265***	0.150***	0.407***	0.026***
	(0.014)	(0.010)	(0.006)	(0.014)	(0.002)
$Treat_i \cdot Long_t$	-0.041**	-0.001	-0.019**	0.017	-0.014***
	(0.019)	(0.013)	(0.008)	(0.019)	(0.002)
Controls of COVID-19	Yes	Yes	Yes	Yes	Yes
Controls of Historical Consumption	Yes	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes	Yes
User FE	Yes	Yes	Yes	Yes	Yes
R-squared	0.352	0.243	0.369	0.252	0.096
Observations	783,200	783,200	783,200	783,200	783,200

Notes: Standard errors clustered by users in parentheses. ***p<0.01; **p<0.05; *p<0.10

Consistent with our model-free evidence, though the stimulation effects of Fenfu on consumption are instant, such effects did not last for a long time as we observe insignificant or even negative estimates of $Treat_i \cdot Long_t$. This set of coefficients captures the long-term effects defined as 15 weeks after service activation.[8] For example, we observe that the total consumption amounts per week slightly dropped by 4.02% (exp(−0.041)−1, Column 1) in the long-term stage. Notably, though the effect is significant, the magnitude of this effect is trivial, especially when compared to the short-term effect. Similar patterns are present with respect to the average consumption amount, consumption frequency, and variability. Interestingly, however, we notice that the change in diversity in the long-term is non-negligible with 1.39% (exp(−0.014) − 1, Column 5) decreases. In sum, our estimates confirm that, with Fenfu, borrowers in general expand consumption in the short term but return to normal or even depress consumption diversity in the long term. This supports our previous argument in the beginning of this paper the necessity of separating short- and long-term effects when analyzing the links between credit channels and consumption behavior.

To assess the validity of DiD mode and to measure the effect of credit over time, we estimate a relative time model. There results justify our separation of short- and long-term patterns. Similarly, the estimates of the post-treatment interaction terms of the effects also are consistent with our main findings. We do not report these detailed results due to the space limit.

Spillover Effects on Savings Channels

We next quantify the spillover effects using a similar empirical approach specified in Equation (1). The impacts of credit on the savings channels have long been overlooked in prior studies. Considering savings channels is important to provide rigorous assessment of effects of credit and ascertain whether the consumption boosting comes at the expense of savings channels. Therefore, when estimating Equation (1), we compute the dependent variables, y_{it} using consumption records financed by savings channels only. We then present in Table 2 estimations results, which are consistent with our model-free evidence in Figure 2.

First, different from the estimates in Table 1, in the short term, spillover effects on savings channels diverse in the five dimensions. Column (1) shows that borrowers' total consumption amounts per week, on average, exceeded non-borrowers' by 13.5% (exp(0.127) − 1). But we do not observe a significant change in consumption frequency. This finding suggests that when users have access to an alternative finance channel, they would not change the frequencies of using savings money for purchases. But they are highly likely to consume more per purchase. This is reasonable, especially when the additional channel is in a form of credits, because users might unconsciously think they have more finance sources allowing them to purchase more. However, Fenfu and traditional savings accounts are two different channels, reflecting user' different purchase preferences. And thus, in a short run, they are less likely to transform their frequency tendencies in using savings channels. We provide more comprehensive discussions and theorize our findings in the next sub-sections. At the meantime, we observe that the consumption pattern become more fluctuate as consumption variability increases by 25.1% (exp(0.224) − 1, Column 4) and the access to Fenfu shrinks

Table 2. Spillover Effects of Fenfu on Consumption Financed by Savings Channels

	(1)	(2)	(3)	(4)	(5)
DV	Amount	Average amount	Frequency	Variability	Diversity
$Treat_i \cdot Short_t$	0.127***	0.143***	-0.007	0.224***	-0.020***
	(0.014)	(0.010)	(0.006)	(0.014)	(0.002)
$Treat_i \cdot Long_t$	-0.132***	-0.032**	-0.082***	-0.026	-0.042***
	(0.018)	(0.013)	(0.008)	(0.018)	(0.002)
Controls of COVID-19	Yes	Yes	Yes	Yes	Yes
Controls of Historical Consumption	Yes	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes	Yes
User FE	Yes	Yes	Yes	Yes	Yes
R-squared	0.316	0.177	0.368	0.233	0.094
Observations	783,200	783,200	783,200	783,200	783,200

Notes: Standard errors clustered by users in parentheses.

[8] We test different thresholds of the short- and long-term windows and results remain consistent.

***p<0.01; **p<0.05; *p<0.10

consumption diversity related to savings channels by 2.0% (exp(−0.020) − 1, Column 5).

On the contrary, the long-term trends are relatively universal across the five dimensions, which present significantly negative or insignificant estimates of $Treat_i \cdot Long_t$. In regard to consumption volumes, we find that in the long run, users with access to Fenfu would get used to this new channel and reduce the frequencies of consumption financed by savings accounts, while their consumption per visit as well as the consumption variability would be back to normal. It is worth noting that even though the estimate in Column (2) is significantly negative but the magnitude is much smaller than the short-term effect. Meanwhile, our estimate in Column (5) presents a surprising observation that in the long run, the decrease even enlarged in consumption diversity related to savings channels. Combining with findings in Table 1, this implies that the enriched overall diversity is mainly caused by Fenfu. That is, users are likely to have changed the consumption structure.

Mechanism Theorization and Empirical Tests

In this section, we theorize and empirically test the underlying mechanisms behind our findings. We borrow the idea of regulatory focus theory (Cole et al. 2008; Mishra et al. 2010) as the main explanation. This theory states two distinct strategies (i.e., promotion- and prevention-focused) to achieve satisfaction (Mishra et al. 2010). A promotion focus pays more attention to the positive side by actively pursue advancement or accomplishment, whereas a prevention focus emphasizes negative outcomes with more cautions and prevention (Higgins and Tykocinski 1992; Sengupta and Zhou 2007).

Prior studies have revealed that socioeconomic status predicts self-regulatory orientation (Baumeister and Vohs 2007). High socioeconomic status, especially high economic capacity and financial liquidity, is positively associated with the form of promotion-focused preference (Xue 2017). Contrastingly, low economic status is correlated with avoidance motivation (Gilbert et al. 2022). Hence, we applied financial constraints as a proxy for users' regulatory focus tendency. In particular, users with more financial constraints tended to be prevention-focused, while the rest (with less financial constraints) tended to be promotion-focused users. Empirically, if we observed diverse patterns between users with more/less financial constraints, we could potentially match our findings with the theoretical foundations to justify the validity of the observed time-varying and spillover consumption patterns.

We partition borrowers and their matched non-borrowers into subgroups based on the levels of their liquidity constraints. Note that we do not observe their actual assets. We follow (Ji et al. 2019) to account for both the supply- and demand-side liquidity to identify users' actual liquidity condition. Specifically, supply-side liquidity is credit supply (Agarwal et al. 2018; Aydin 2022) and we proxy it using the credit quota offered by Fenfu. On the other hand, credit demand, also denoted as demand-side liquidity, captures users' liquidity needs (Aydin 2022), and we proxy it using the average monthly amounts borrowed from Fenfu in six months. Note that we argue that liquidity constraints infer users' perceived liquidity increases. To support this claim, we consider the ratios rather than the absolute value when computing both the credit supply and demand. That is, we divide the credit quota or monthly amounts borrowed by the average total spending per month in three months prior to credit. We then jointly involve both credit supply and demand when deciding a user's liquidity condition. For example, users with lower supply and higher demand are more likely to be liquidity-constrained than users with low supply and lower demand. Empirically, for the purpose of computational convenience, we classify two levels of credit demand and supply, using the median values. If a borrower's credit demand (supply) is higher (lower) than the median demand (supply), we assign he/she with a high-(low-)level of credit demand (supply). In particular, we adopt a two-stage approach. We first partition users into two subgroups using the median value of credit supply among all users. Next, within each of the two subgroups, we split borrowers again with the median value of credit supply calculated among all borrowers within the subgroup. In this way, we obtain four subgroups of borrowers and their matched non-borrowers. We rerun our main analyses with the four groups of users, separately.

We first test the mechanisms of the comparisons between short-term vs. long-term effects and report estimates in Table 3. Note that we apply a two-stage approach to segment users, thus we compare borrowers within each supply level. We observe that, with respect to consumption volumes (measured by consumption amount, average amount, frequency, or variability), more liquidity-constrained borrowers (i.e., Groups 2 and 4) consume more in the short term but cut down their consumption in the long run, when compared to borrowers with less constraints (i.e., Groups 1 and 3, respectively). This supports our above hypothesis justified using promotion- and prevention-focused strategies in explaining the changes of consumption patterns. As for diversity, conversely, we find that less liquidity-constrained borrowers (i.e., Groups 1 and 3) enhance the diversity more in the short term and their diversity yet continue to expand in the long run. On the one hand, findings in table 1 and table 2 illustrate that borrowers utilize credit on the categories they have never tapped into. On the other hand, existing literature has documented that users shift to discretionary consumption after using credit (D'Acunto et al. 2020; Li et al. 2021). Therefore, we infer that credit enable borrowers to update their consumption by optimizing the consumption structure. For less liquidity-constrained borrowers, they have more spare money and thus more likely to increase diversity by upgrading the consumption. More liquidity-constrained borrowers, on the contrary, consume mainly utilize credit to sustain their previous consumption structure and therefore less likely to amplify diversity.

We next examine empirically the mechanisms behind spillover effects on consumption financed by savings channels and report estimates in Table 4. We follow the similar approach by separating users into four subgroups with different levels of liquidity constraints. As suggested by regulatory focus theory, prevention-focused strategies play an important role among borrowers who are more liquidity constraints (Mishra et al. 2010). This tendency would be enhanced when they realize they have excessive consumption due to an exogenous offer with the access to Fenfu. Furthermore, the prevention-focused preference should not limit to a certain channel and is expected to spread across all available financing sources. Thus, we presume that borrowers with lower liquidity are more likely to have more pronounced negative spillover

Table 3. Mechanism Detection: Short-term vs. Long-term Effects

		Lower Supply			Higher Supply		
		(1)	(2)		(3)	(4)	
DV	Coeff	LS & LD	LS & HD	P-Value	HS & LD	HS & HD	P-Value
Amount	$Treat_i \cdot Short_t$	0.184***	0.309***	0.000	0.546***	0.583***	0.000
		(0.025)	(0.028)		(0.026)	(0.031)	
	$Treat_i \cdot Long_t$	0.005	-0.268***	0.000	0.318***	-0.229***	0.000
		(0.033)	(0.038)		(0.034)	(0.042)	
	R-squared	0.300	0.323		0.173	0.309	
AvgAmount	$Treat_i \cdot Short_t$	0.065***	0.198***	0.000	0.360***	0.411***	0.000
		(0.018)	(0.020)		(0.018)	(0.021)	
	$Treat_i \cdot Long_t$	-0.044*	-0.155***	0.000	0.249***	-0.056**	0.000
		(0.024)	(0.025)		(0.024)	(0.028)	
	R-squared	0.130	0.301		0.010	0.282	
Frequency	$Treat_i \cdot Short_t$	0.107***	0.120***	0.000	0.170***	0.190***	0.000
		(0.011)	(0.012)		(0.012)	(0.013)	
	$Treat_i \cdot Long_t$	0.041***	-0.082***	0.000	0.080***	-0.114	0.000
		(0.014)	(0.017)		(0.015)	(0.018)	
	R-squared	0.351	0.334		0.300	0.322	
Variability	$Treat_i \cdot Short_t$	0.092***	0.282***	0.000	0.501***	0.702***	0.000
		(0.026)	(0.027)		(0.021)	(0.031)	
	$Treat_i \cdot Long_t$	-0.063*	-0.232***	0.000	0.396***	-0.060	0.000
		(0.033)	(0.038)		(0.034)	(0.043)	
	R-squared	0.141	0.265		0.046	0.270	
Diversity	$Treat_i \cdot Short_t$	0.030***	0.019***	0.000	0.034***	0.020***	0.000
		(0.004)	(0.004)		(0.004)	(0.004)	

$Treat_i \cdot Long_t$	0.014***	-0.027	0.000	0.009**	-0.047***	0.000
	(0.004)	(0.005)		(0.005)	(0.005)	
R-squared	0.003	0.110		0.005	0.189	
Obs	195,760	195,840		195,760	195,840	

Notes: Standard errors clustered by users in parentheses.
***p<0.01; **p<0.05; *p<0.10
LS: low supply; LD: low demand; HS: high supply; HD: high demand

effect on consumption financed by savings channels in the long run. And in accordance with our prediction, we observe significantly negative estimates of $Treat_i \cdot Long_t$ among all the five dimensions in Columns 2 and 4 (denoting borrowers with more liquidity constraints), when compared to borrowers in subgroups 1 and 3 (denoting borrowers with less constraints).

Surprisingly, the results are diverse among estimates of $Treat_i \cdot Short_t$, suggesting that the mechanisms would be different and regulatory focus motive alone might not fully rationalize the spillover effects on savings channels. Comparing estimates of $Treat_i \cdot Short_t$ between Columns 1 and 2, we show that less liquidity-constrained borrowers behaved relatively consistent with the time before service activation, as we observe that (1) the changes in purchase per visit and consumption variability were less than those of borrowers with more constraints, (2) consumption frequency remained unchanged, and (3) they tend to stick with their current payment methods while borrowers with more constraints would switch to other channels and reduce consumption frequency with savings channels significantly by 4.8%. All these findings imply that less liquidity-constrained borrowers mainly spend more of their savings and less likely to tap into the new Fenfu channel.

Table 4. Mechanism Detection: Spillover Effects

		Lower Supply			Higher Supply		
		(1)	(2)		(3)	(4)	
DV	Coeff	LS & LD	LS & HD	P-Value	HS & LD	HS & HD	P-Value
Amount	$Treat_i \cdot Short_t$	0.068***	0.040	0.000	0.265***	0.126***	0.000
		(0.026)	(0.027)		(0.027)	(0.030)	
	$Treat_i \cdot Long_t$	-0.082**	-0.300***	0.000	0.146***	-0.262***	0.000
		(0.033)	(0.036)		(0.033)	(0.039)	
	R-squared	0.243	0.303		0.140	0.301	
AvgAmount	$Treat_i \cdot Short_t$	0.043**	0.105***	0.000	0.233***	0.186***	0.000
		(0.019)	(0.019)		(0.019)	(0.020)	
	$Treat_i \cdot Long_t$	-0.066***	-0.152***	0.000	0.170***	-0.069***	0.000
		(0.024)	(0.025)		(0.024)	(0.027)	
	R-squared	0.065	0.239		0.005	0.228	
Frequency	$Treat_i \cdot Short_t$	0.027**	-0.049***	0.000	-0.036***	-0.042***	0.000
		(0.011)	(0.012)		(0.012)	(0.013)	
	$Treat_i \cdot Long_t$	-0.011	-0.136***	0.000	-0.003	-0.167***	0.000
		(0.014)	(0.016)		(0.015)	(0.017)	
	R-squared	0.342	0.353		0.291	0.341	
Variability	$Treat_i \cdot Short_t$	0.060**	0.113***	0.000	0.350***	0.362***	0.000
		(0.027)	(0.027)		(0.027)	(0.030)	
	$Treat_i \cdot Long_t$	-0.090***	-0.253***	0.000	0.310***	-0.065*	0.000
		(0.039)	(0.036)		(0.034)	(0.099)	
	R-squared	0.131	0.240		0.041	0.253	

Diversity	$Treat_i \cdot Short_t$	0.003	-0.031***	0.000	-0.010***	-0.042***	0.000
		(0.004)	(0.004)		(0.004)	(0.004)	
	$Treat_i \cdot Long_t$	-0.006	-0.056***	0.000	-0.025***	-0.080***	0.000
		(0.005)	(0.005)		(0.005)	(0.005)	
	R-squared	0.003	0.111		0.017	0.178	
	Obs	195,760	195,840		195,760	195,840	

Notes: Standard errors clustered by users in parentheses.
***p<0.01; **p<0.05; *p<0.10
LS: low supply; LD: low demand; HS: high supply; HD: high demand

Conclusions and Discussions

This paper investigates the impacts of credit adoption on consumption patterns. We find that the post-activation period can be divided into short- and long-term frames. Specifically, borrowers in general expand consumption in the short term but return to normal or even depress consumption diversity in the long term. We also find the existence of spillover effects on the savings channel, and such effects have diverse patterns in different dimensions. Finally, we suggest the regulatory focus to explain our findings. We test this mechanism by studying distinct types (i.e., promotion- and prevention- focused) drive the dynamics of credit effects.

Our research offers multifold non-trivial theoretical contributions to the literature of (micro)credit, FinTech, consumption, and consumer behavior. First, to our knowledge, this study is among the first to distinguish the short-term and long-term effect of credit on multi-dimensional consumption behaviors. Second, we are also among the first to decompose the consumption responses into different channels and test the spillover effects. Third, we provide theoretical explanations for users' consumption patterns change over time.

Based on our findings, we also offer insightful practical implications. First, for credit providers, ascertaining users' reactions to credit helps tailor their marketing and operation effort to obtain more profit and lower the risk. Second, this study reminds borrowers of not only focusing on the short-term gains from over-spending but also paying attention to the financial constraint caused by overspending. Third, for policymakers, precise estimation of the impact of credit on consumption is conducive to designing the credit-based effective expansionary policy.

Our study is subject to several limitations that yet offer fruitful avenues for potential future research. First, our empirical strategy and findings rely on Fenfu, one specific product designed and released by WeChat Pay. This setup could potentially limit the generalizability of our findings to other types of credit products or contexts. Second, WeChat Pay is one dominant payment method, but users can also consume through other payment methods, such as Alipay and UnionPay. Therefore, caution is needed in interpreting the results of our study. Third, we acknowledge the limitations existing in our empirical test of underlying mechanisms. We have no access to borrowers' income data or card-level information. Therefore, we could only proxy borrowers' liquidity condition through consumption data. This could incur some potential endogeneity issues, though we try our best to alleviate this concern by separating users into two groups based on whether they have ever defaulted within our data period.

References

Agarwal, S., Chomsisengphet, S., Mahoney, N., and Stroebel, J. (2018). "Do banks pass through credit expansions to consumers who want to borrow?," *The Quarterly Journal of Economics* (133:1), pp. 129–190.

Agarwal, S., Liu, C., and Souleles, N. S. (2007). "The reaction of consumer spending and debt to tax rebates—evidence from consumer credit data," *Journal of political Economy* (115:6), pp. 986–1019.

Agarwal, S. and Qian, W. (2014). "Consumption and debt response to unanticipated income shocks: Evidence from a natural experiment in Singapore," *American Economic Review* (104:12), pp. 4205–30.

Aydin, D. (2022). "Consumption response to credit expansions: Evidence from experimental assignment of 45,307 credit lines," *American Economic Review* (112:1), pp. 1–40.

Bacchetta, P. and Gerlach, S. (1997). "Consumption and credit constraints: International evidence," *Journal of Monetary Economics* (40:2), pp. 207–238.

Baumeister, Roy F, Kathleen D Vohs. 2007. Self-regulation, ego depletion, and motivation. Social and personality psychology compass 1(1) 115–128.

Bertrand, M., Mehta, P., and Mullainathan, S. (2002). "Ferreting out tunneling: An application to Indian business groups," *The Quarterly Journal of Economics* (117:1), pp. 121–148.

Bhutta, N., Goldin, J., and Homonoff, T. (2016). "Consumer borrowing after payday loan bans," *The Journal of Law and Economics* (59:1), pp. 225–259.

Buchak, Greg, Gregor Matvos, Tomasz Piskorski, Amit Seru. 2018. Fintech, regulatory arbitrage, and the rise of shadow banks. Journal of financial economics 130(3) 453–483.

Chetty, R., Friedman, J. N., Hendren, N., Stepner, M., and Team, T. O. I. (2020). *How did COVID-19 and stabilization policies affect spending and employment? A new real-time economic tracker based on private sector data,* vol. 27431. National Bureau of Economic Research Cambridge, MA.

Cole, C., Laurent, G., Drolet, A., Ebert, J., Gutchess, A., Lambert-Pandraud, R., Mullet, E., Norton, M. I., and Peters, E. (2008). "Decision making and brand choice by older consumers," *Marketing Letters* (19:3), pp. 355–365.

Crowe, E. and Higgins, E. T. (1997). "Regulatory focus and strategic inclinations: Promotion and prevention in decision-making," *Organizational behavior and human decision processes* (69:2), pp. 117–132.

D'Acunto, F., Rauter, T., Scheuch, C. K., and Weber, M. (2020). *Perceived precautionary savings motives: Evidence from fintech*. Tech. rep. National Bureau of Economic Research.

Dholakia, U. M., Gopinath, M., Bagozzi, R. P., and Nataraajan, R. (2006). "The role of regulatory focus in the experience and self-control of desire for temptations," *Journal of Consumer Psychology* (16:2), pp. 163– 175.

Ekici, T. and Dunn, L. (2010). "Credit card debt and consumption: evidence from household-level data," *Applied Economics* (42:4), pp. 455–462.

Forster, Jens, E Tory Higgins, Lorraine Chen Idson. 1998. Approach and avoidance strength during goal attainment: regulatory focus and the" goal looms larger" effect. Journal of personality and social psychology 75(5) 1115.

Foster, S., Gmel, G., Estévez, N., Bähler, C., and Mohler-Kuo, M. (2015). "Temporal patterns of alcohol consumption and alcohol-related road accidents in young Swiss men: seasonal, weekday and public holiday effects," *Alcohol and alcoholism* (50:5), pp. 565–572.

Furnham, A. (1999). "The saving and spending habits of young people," *Journal of economic Psychology* (20:6), pp. 677–697.

Gerend, M. A. and Cullen, M. (2008). "Effects of message framing and temporal context on college student drinking behavior," *Journal of Experimental Social Psychology* (44:4), pp. 1167–1173.

Gilbert, Karen M, Andrew J Elliot, Bonnie M Le. 2022. Economic status and avoidance motivation: a meta-analysis. Motivation and Emotion 1–14.

Gross, D. B. and Souleles, N. S. (2002). "Do liquidity constraints and interest rates matter for consumer behavior? Evidence from credit card data," *The Quarterly journal of economics* (117:1), pp. 149–185.

Hamilton, R. W., Mittal, C., Shah, A., Thompson, D. V., and Griskevicius, V. (2019). "How financial constraints influence consumer behavior: An integrative framework," *Journal of Consumer Psychology* (29:2), pp. 285–305.

Higgins, E. T. (1998). "Promotion and prevention: Regulatory focus as a motivational principle," in *Advances in experimental social psychology,* vol. 30. Elsevier, pp. 1–46.

Higgins, E Tory, Emily Nakkawita, James FM Cornwell. 2020. Beyond outcomes: How regulatory focus motivates consumer goal pursuit processes. Consumer Psychology Review 3(1) 76–90.

Higgins, E. T. and Spiegel, S. (2004). "Promotion and prevention strategies for self-regulation," *Handbook of self-regulation: Research, theory, and applications,* pp. 171–187.

Higgins, T. and Tykocinski, O. (1992). "Seff-discrepancies and biographical memory: Personality and cognition at the level of psychological situation," *Personality and Social Psychology Bulletin* (18:5), pp. 527– 535.

Horvath, A., Kay, B. S., and Wix, C. (2021). "The COVID-19 shock and consumer credit: Evidence from credit card data," *Available at SSRN 3613408*.

Ji, Y., Wang, X., Huang, Y., Chen, S., Wang, F., and Zhu, G. (2019). "Fintech consumer credit, liquidity constraints, and consumption: Evidence from a randomized experiment in China".

Kahneman, D., Knetsch, J. L., and Thaler, R. H. (1991). "Anomalies: The endowment effect, loss aversion, and status quo bias," *Journal of Economic perspectives* (5:1), pp. 193–206.

Karlan, D. and Zinman, J. (2010). "Expanding credit access: Using randomized supply decisions to estimate the impacts," *The Review of Financial Studies* (23:1), pp. 433–464.

Kerr, W. C., Fillmore, K. M., and Bostrom, A. (2002). "Stability of alcohol consumption over time: evidence from three longitudinal surveys from the United States." *Journal of studies on alcohol* (63:3), pp. 325–333.

Kivetz, R. and Keinan, A. (2006). "Repenting hyperopia: An analysis of self-control regrets," *Journal of Consumer Research* (33:2), pp. 273–282.

Koulayev, S., Rysman, M., Schuh, S., and Stavins, J. (2016). "Explaining adoption and use of payment instruments by US consumers," *The RAND Journal of Economics* (47:2), pp. 293–325.

Li, E., Liao, L., Wang, Z., and Xiang, H. (2018). "Individual Consumption Response to Expanding Credit Access: Evidence from online cash loan platform," *PBCSF-NIFR Research Paper*.

Li, J., Song, Q., Wu, Y., and Huang, B. (2021). "The effects of online consumer credit on household consumption level and structure: Evidence from China," *Journal of Consumer Affairs* (55:4), pp. 1614–1632.

Liberman, N., Idson, L. C., Camacho, C. J., and Higgins, E. T. (1999). "Promotion and prevention choices between stability and change." *Journal of personality and social psychology* (77:6), p. 1135.

Liu, Q., Shen, Q., Li, Z., and Chen, S. (2021). "Stimulating consumption at low budget: Evidence from a large-scale policy experiment amid the COVID-19 pandemic," *Management Science* (67:12), pp. 7291–7307.

Ludvigson, S. (1999). "Consumption and credit: a model of time-varying liquidity constraints," *Review of Economics and Statistics* (81:3), pp. 434–447.

Mishra, H., Mishra, A., and Nayakankuppam, D. (2010). "How salary receipt affects consumers' regulatory motivations and product preferences," *Journal of Marketing* (74:5), pp. 93–103.

Misra, K., Singh, V., and Zhang, Q. (2022). "Frontiers: Impact of Stay-at-Home-Orders and Cost-of-Living on Stimulus Response: Evidence from the CARES Act," *Marketing Science*.

Pennington, G. L. and Roese, N. J. (2003). "Regulatory focus and temporal distance," *Journal of Experimental Social Psychology* (39:6), pp. 563–576.

Richards, G. (1998). "Time for a holiday? Social rights and international tourism consumption," *Time & Society* (7:1), pp. 145–160.

Rishika, R., Kumar, A., Janakiraman, R., and Bezawada, R. (2013). "The effect of customers' social media participation on customer visit frequency and profitability: an empirical investigation," *Informationsystems research* (24:1), pp. 108–127.

Rubin, D. B. (2006). *Matched sampling for causal effects,* Cambridge University Press.

Samuelson, W. and Zeckhauser, R. (1988). "Status quo bias in decision making," *Journal of risk and uncertainty* (1:1), pp. 7–59.

Schelling, T. C. (1992). *Self-command: A new discipline*. Russell Sage Foundation.

Sengupta, J. and Zhou, R. (2007). "Understanding impulsive eaters' choice behaviors: The motivational influences of regulatory focus," *Journal of Marketing Research* (44:2), pp. 297–308.

Shah, J., Higgins, T., and Friedman, R. S. (1998). "Performance incentives and means: how regulatory focus influences goal attainment." *Journal of personality and social psychology* (74:2), p. 285.

Soster, R. L., Gershoff, A. D., and Bearden, W. O. (2014). "The bottom dollar effect: the influence of spending to zero on pain of payment and satisfaction," *Journal of Consumer Research* (41:3), pp. 656–677.

Sotiropoulos, V. and d'Astous, A. (2012). "Social networks and credit card overspending among young adult consumers," *Journal of Consumer Affairs* (46:3), pp. 457–484.

Stavins, J. (2017). "How do consumers make their payment choices?".

Stavins, J. (2020). "Credit card debt and consumer payment choice: what can we learn from credit bureau data?," *Journal of Financial Services Research* (58:1), pp. 59–90.

Thaler, R. (1980). "Toward a positive theory of consumer choice," *Journal of economic behavior & organization* (1:1), pp. 39–60.

Thomas, M., Desai, K. K., and Seenivasan, S. (2011). "How credit card payments increase unhealthy food purchases: Visceral regulation of vices," *Journal of consumer research* (38:1), pp. 126–139.

Thompson, D. V., Banerji, I., and Hamilton, R. W. (2020). "Scarcity of choice: The effects of childhood socioeconomic status on consumers' responses to substitution," *Journal of the Association for Consumer Research* (5:4), pp. 415–426.

Tovanich, N., Centellegher, S., Seghouani, N. B., Gladstone, J., Matz, S., and Lepri, B. (2021). "Inferring psychological traits from spending categories and dynamic consumption patterns," *EPJ Data Science* (10:1), p. 24.

Tuan Pham, M. and Chang, H. H. (2010). "Regulatory focus, regulatory fit, and the search and consideration of choice alternatives," *Journal of Consumer Research* (37:4), pp. 626–640.

Wang, Z. and Wolman, A. L. (2016). "Payment choice and currency use: Insights from two billion retail transactions," *Journal of Monetary Economics* (84), pp. 94–115.

White, A. M. (2012). "Credit and human welfare: Lessons from microcredit in developing nations," *Wash. & Lee L. Rev.* (69), p. 1093.

Wisniewski, T. P., Polasik, M., Kotkowski, R., and Moro, A. (2021). "Switching from cash to cashless payments during the COVID-19 pandemic and beyond," *Available at SSRN 3794790*.

Xiao, J. J. (2015). "Consumer economic wellbeing," in *Consumer economic wellbeing,* Springer, pp. 3–21.

Xue, Cindy. 2017. On the origins of chronic regulatory focus: The role of socioeconomic status.

Zhou, R. and Pham, M. T. (2004). "Promotion and prevention across mental accounts: When financial products dictate consumers& investment goals," *Journal of consumer research* (31:1), pp. 125–135.