Fintech Access and Consumption Smoothing*

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Abstract

We identify and quantify the effect of access to Fintech consumer credit service on consumption using granular data from a nearly one billion consumer population on China's leading digital payment platform. We find that, despite sharp declines in consumption following the pandemic shock, consumers who used Fintech credit maintained a 28.7% higher monthly consumption in the six months afterward, indicating a consumption-smoothing effect. The effect persists at 22.0% on average over the two-year period. We explain the effect with two channels: the income channel, where the consumption-smoothing effect is stronger among low-income consumers and those from less developed regions, and the financial literacy channel, with a more significant effect for consumers with lower financial literacy. Fintech credit users do not show high delinquency rates but invest less in their wealth management account. Additionally, we find that the Fintech credit usage helps explain city-level variations in retail sales.

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Over the last decade, the fintech development, coupled with the democratization of financial services, has been a defining trend. The proliferation of mobile payments and the advancements in big data and AI have enabled financial service providers to offer credit service for a broader customer base, while scalable and automated systems have significantly reduced the cost. According to the World Bank's Global Financial Inclusion survey, the worldwide credit card user base swelled by about 87% from 2011 to 2021, an increase of approximately 659 million, with 514 million from developing countries and 348 million from China alone.[1] Then a critical question emerges: what are the real impacts of increased accessibility to financial services on consumers' welfare, and how significant are these impacts? This is the question our article aims to answer.

The welfare implications of more inclusive credit services remain unclear (Zinman, 2015; Banerjee, Hanna, et al., 2024). On the one hand, credit access can relax credit constraints, supporting consumers in smoothing consumption, overcoming hardships, and investing in human capital, which could lead to increased welfare.[2] Conversely, the lack of financial literacy and behavioural bias may drive excessive consumption or over-borrowing, worsening consumers' financial situations.[3] One main challenge in answering this question is the difficulty of tracking consumers' long-term consumption payments. Most existing research relies on survey data or administrative data from a single institution to represent consumers' consumption, which may not reflect the full picture of consumer spending.

China's rapid transition to a cashless economy, coupled with the fact that most consumers now use consolidated digital payment platforms, has made it possible for the detailed, long-term observation of consumer spending behaviors. Using de-identified administrative data from Alipay, a leading digital payment platform in China, we analyze the welfare effect of a fintech credit service provided by the payment platform and used by 500 million consumers. Specifically, our dataset includes the monthly records of consumer spending across different categories and payment tools through Alipay from 2017 to 2021, along with information on fintech credit usage, personal characteristics, and investment activities on the platform. We estimate the effect of accessing Fintech credit on consumers' consumption after the pandemic shock in January 2020, to the end of 2021.

[1] Worldwide, the percentage of individuals aged 15 and above who owns credit cards increased from 15% in 2011 to 24% in 2021. The percentage of developing economies increased from 7% to 17%, and in China from 8% to 38%. From the data provided in Demirgüç-Kunt et al. (2022).

[2] Banerjee and Duflo (2010) provide a review on the value of microcredit to households. Some recent research provides evidence on the value of credit for consumption smoothing (Hundtofte, Olafsson, and Pagel, 2019), accumulating human capital (Stein and Yannelis, 2020; Choi et al., 2023), obtaining necessary insurance coverage (Cole et al., 2013), and coping with negative shocks such as disasters (Lane, 2024).

[3] Accessing consumer credit can lead to overspending or overborrowing because of behaviour bias (Medina, 2021), limited attention (Stango and Zinman, 2014), or utility-based biases in beliefs(Brunnermeier and Parker, 2005). Various evidence of negative consequences of consumer credit are found in the literature, see Ausubel (1991) on credit cards, Melzer (2011) on payday lending, Di Maggio and Yao (2021) on fintech lending, deHaan et al. (2024) on Buy-now-pay-later, and Garber et al. (2024) on a pay-roll backed credit expansion program.

The challenges of identifying the effect of credit access on consumption include, first, the endogeneity of fintech credit service usage and, second, measurement error. Since fintech credit is an innovative credit payment service, consumers who are more inclined to use it likely differ from those who do not in their attitudes toward digital payments and spending patterns. Although fixed effects can account for the time-invariant heterogeneity of individuals, consumers' preferences for payment may change over time. For example, using the credit service provided by the payment platform may likely result in an increased tendency to complete more transactions through it. Second, China's digital payment market exhibits a duopoly structure. Although we can observe consumer payment data through Alipay, one of the primary platforms, this still does not capture all consumer transactions, leading to unavoidable a measurement error in our data.

We overcome the challenges first by leveraging our access to a large consumer sample. With access to the full population of nearly one billion consumers, we apply strict criteria for activeness levels among both users and non-users of the credit service to ensure that our sample consists of consumers who rely heavily on Alipay, suggesting that most of their daily spending occurs on this platform. Additionally, our data includes a rich set of personal information and long-term pre-shock spending data. Utilizing this detailed dataset, we employ matching methods to construct highly similar treatment and control groups, we employ a matching method to construct treatment and control groups who, aside from the use of Fintech credit service, are highly similar. Specifically, we construct a one-to-one matched control group based on the consumers' consumption before the shock and a rich set of individual characteristics, including age, gender, region, and the time they started using digital payment. We use the two years of consumption data before the shock and an additional set of personal information variables to validate the matching outcomes. Then, after obtaining the matched samples, we estimated the treatment effect on consumption in the two years after the shock.

Our main finding is that Fintech credit access results in a 28.71% higher monthly consumption in the first half year of 2020, 25.42% in the year of 2020, and 21.99% for the two-year period by the end of 2021 (as shown in Table 3). We examine the differences in the treatment effect based on the severity of the shock. Based on the variation in lockdown duration across different cities in 2020, ranging from 5 to 16 weeks, we find that the intensity of the shock has a profound impact on the treatment effect. Doubling the duration of the lockdown leads to a 5% increase in the consumption difference between the groups.

Then, we explain the estimated treatment effect through two channels. First is the income channel. We utilize two aspects measuring consumers' income: (1) The total consumption expenditure of consumers in the two years before the shock and (2) the regional economic disparities of the cities in which they reside. After dividing consumers into ten groups based on their consumption from 2018 to 2019, the estimated treatment effect shows a strictly decreasing pattern from the lowest to

the highest consumption levels (Figure 6). In addition, the long-run treatment effect of consumers living in less developed areas is 26.21%, while 18.55% is for consumers living in big cities (Table 6).

The second channel is the financial literacy. We start with education level as a proxy, supported by extensive research indicating a robust link between education level and financial literacy.[4] Our findings across different levels of education reveal a clear trend: the more educated the consumer group, the less pronounced the treatment effect, from 26.06% for consumers with high school or below to 6.05% for consumers with a graduate degree. Moreover, we develop a Financial Sophistication Index from two unique payment methods within Alipay as a proxy for financial literacy: a typical balance account and an interest-generating wallet. Since the two payment tools are equally convenient, consumers who are more open to innovation and financially sophisticated would keep their balance in the interest-generating wallet for payments. In fact, only 27.4% of consumers did so in 2019, and we use this variation to represent consumers' understanding of the fintech platform. Our results indicate a smaller treatment effect for more sophisticated consumer groups (Table 8).

Given the large consumer base of the credit service we study, one would expect this effect to be reflected in aggregate variables. We study the macroeconomic impact of fintech credit on consumption at the city level. Using city-level monthly retail data, and a representative sample of one million fintech credit users, we find that associated fintech credit payments per capita are associated with higher retail sales. A 1% increase in fintech credit payments is linked to a 0.35% rise in retail sales per capita in the short term and a 0.17-0.26% rise in the long term; the effects are driven by fintech credit usage rather than the total digital payment. These results highlight fintech credit's potential to drive sustained consumption increases.

To examine whether this higher level of consumption is sustainable and whether it has led to overconsumption or excessive borrowing, we analyze two aspects: first, the sources of consumers' funds, and second, the delinquency rate. While we lack data on consumers' total savings and income, we examine their investment behaviours on Alipay's wealth management platform. Comparing the treatment group with the control group, we found that fintech credit users held lower balances in mutual funds and money market funds. This lower asset accumulation, while not entirely accounting for their higher consumption, indicates that fintech credit users may be saving less. This finding has positive policy implications for China's traditionally high savings and low consumption economy.

We analyze the delinquency rate of fintech credit users from 2020 to 2021. On average, 0.29% of users in the treatment group had monthly overdue balances, with a peak of 0.52% in 2020/02 when the shock was at its most severe. The average overdue balance was 3,458 *yuan*, against a monthly fintech credit spending of 8,682 *yuan* of the delinquent consumers. Consistent with studies on similar

[4] See the seminal findings in Bernheim, Garrett, and Maki (2001), and surveys in Hastings, Madrian, and Skimmyhorn (2013) and Finke and Huston (2014).

fintech services, our results suggest that big tech platforms, by offering integrated payment, credit and investment services and building an ecosystem, increase the potential default cost and, therefore, promote lower delinquency.

We also conduct a heterogeneity analysis regarding age, gender, and occupation. The long-run treatment effect is strongest in the age group of 26 to 30 years, stronger for males, and stronger for the blue-collar worker group. Additionally, we considered that after the shock, control group consumers might adopt the fintech credit, and existing users may stop using it. After adjusting for the entry of new users and exit of existing users, the estimations of the treatment effect increase, suggesting that the baseline estimates do not overestimate the effect.

Our paper contributes to four strands of literature. First, there has been a significant amount of research on the *financial inclusion* promoted by fintech services. With the rise of cashless payment, new lending models arise with the newly feasible or complementary alternative data in credit risk assessment (Berg, Burg, Gombović, et al., 2020; Vissing-Jorgensen, 2021; Lee, Yang, and Anderson, 2023) and screening technology (Ghosh, Vallee, and Zeng, 2023). The Fintech credit expansion on firms and households covers those who were historically outside of the financial system, especially in developing economies (Frost et al., 2019; Agarwal, Alok, et al., 2019; Maggio, Ratnadiwakara, and Carmichael, 2022; Liu, Lu, and Xiong, 2022; Ouyang, 2023; Berg, Fuster, and Puri, 2022; Agarwal, Ghosh, et al., 2024). There are studies on the effect of Fintech credit on firms' growth (Hau et al., 2024; Eca et al., 2023) and the ability to reduce volatility (Chen, Huang, et al., 2022). Yet, evidence remains scarce on the effects of such credit expansions on household well-being. In this regard, our research identifies and quantifies the real effect of a Fintech credit service that has been used by half a billion consumers, providing new evidence of how Fintech promotes financial inclusion by expanding credit access.

Second, the literature on *consumption response to an income shock*, which lies in the core of household finance. Facing unanticipated income changes such as the COVID-19 pandemic, consumers would respond with a change in consumption patterns (see the theoretical framework and a survey on early works in Jappelli and Pistaferri (2010)). Our work highlights the value of consumer credit in helping individuals smooth consumption in the aftermath of a shock. The literature has studied the rule of various institutions in consumption smoothing, including accumulation of assets (Rosenzweig and Wolpin, 1993), informal lending and gift (Townsend, 1994), and unemployment insurance (Gruber, 1997). More recently, some studies have explored the role of credit constraints in shaping how consumption behavior responds to shocks, but the conclusions remain inconclusive.

On the one hand, Baker (2018) finds that heterogeneity in consumption elasticity with respect to income can be explained entirely by credit and liquidity. Agarwal and Qian (2014) shows that consumers respond to a future positive income shock by increasing consumption via credit cards. Baker and Yannelis (2017) and Gelman et al. (2020) both find that following the 2013 federal government

shutdown, an unanticipated income shock while having no direct effect on permanent income, federal government workers decreased their consumption, and credit constraints played a significant role in driving the decrease in spending. On the other hand, Ganong and Noel (2019) also shows spending drops sharply following a predictable decrease in income from the exhaustion of unemployment insurance benefits and finds no significant use of credit cards to smooth consumption during unemployment. Baugh et al. (2021) finds households do not reduce consumption spending following making the tax payment, and even for those carrying credit card debt, inconsistent with the liquidity constraint explanation. Hundtofte, Olafsson, and Pagel (2019) finds that individuals do not use borrowing to smooth consumption when they experience a transitory income shock of unemployment. In this regard, our study utilizes a large-scale, long-term, near-comprehensive dataset on consumption, providing new evidence on the role of credit in determining how consumption reacts to shocks.

Third, The credit service we study shares the nature of buy-now-pay-later (BNPL) service, a market experiencing high growth recently, but little research has been done. Maggio, Williams, and Katz (2022) shows that Buy-now-pay-later access increases both total spending levels and the retail share in total spending. deHaan et al. (2024) finds that BNPL users experience rapid increases in their bank overdraft charges and credit card interest and fees, leading to over-borrowing problems. Bian, Cong, and Ji (2023) studies the effect of the BNPL option in Alipay on credit expansion and consumer spending. We provide evidence on how BNPL service can help consumers during the shock and whether it leads to excessive borrowing.

More broadly, we contribute to the study of the impact of the COVID-19 pandemic on households. Kim, Parker, and Schoar (2020) finds that revenues of small businesses in the US have declined by 40 percent in the first two months following the National Emergency. However, the decrease in consumption was limited due to the liquidity buffer and federal subsidies. Using payment data in China, Chen, Qian, and Wen (2021) finds that consumption decreased by 32% in the 12 weeks following the lockdown. Parker et al. (2022) studies the effect of the Economic Impact Payments of 2020 on household consumption. Chetty et al. (2023) detailed the reduction, composition, and recovery of consumer spending in the United States. In contrast, our research, tracking consumers' spending two years following the shock, presents a comparative perspective on the evolution of consumption levels among Chinese consumers.

The remainder of the paper proceeds as follows. We describe the data and methodology in Section 1, including the background of the focal fintech credit service, data descriptions, the sample creation process, and how we construct the matched sample. Section 2 reports the main results of the treatment effect of fintech credit access and the effects for various consumption categories. In Section 3, we provide additional robustness analysis for the baseline results. Second 4 propose two channels to explain the treatment effect: the income channel and financial literacy. In Section 5, we

discuss the macroeconomic implication of the fintech credit service, the delinquency rates, and also analyze the potential sources on consumers' balance sheets for the higher spending, then we provide additional heterogeniety analysis regarding gender, age, and occupations of consumers.

1 Data and Methodology

Given the critical dependence of our methodology on the unique aspects of our data source from Alipay, we will start this section by detailing the users and services of Alipay and Huabei. Then, we will explain how we design our empirical strategy based on these data characteristics, followed by the details of the sampling procedure, the variables, and the specifics of the matching method.

1.1 Alipay and Huabei

Alipay is a payment platform that provides customers and merchants with online and mobile payment services. As of June 2020, Alipay is used by 1.3 billion users and 80 million merchants. It was created in 2004 by Alibaba to provide a trustworthy third-party payment method for e-commerce buyers and sellers. With the adoption of QR code payment in 2014, it has quickly expanded from online e-commerce to offline face-to-face use cases[5], becoming a universally accepted payment tool in China. Alipay is the largest payment platform in the mobile payment market in China, with about 45% market share, followed by WeChat Pay and UnionPay.[6]

Huabei, meaning *just spend* in Chinese, is a consumption credit service that Alipay has offered to its Chinese customers since December 2014. Although without a physical card, consumers can use Huabei as a payment method in their digital wallet. The usage is similar to a typical credit card. Within a monthly billing cycle, consumers can spend as they wish within their credit limit. After the closing date, they can choose to pay everything back before the due date to avoid interest or make install payments over 3 to 12 months with an annual interest rate (APR) of approximately 15%.[7] Furthermore, it was also one of the earliest to offer the "buy now, pay later" option, typically used for large purchases, allowing consumers to directly select the payment period at the time of payment.

[5]This expansion particularly accelerated after 2016, when the People's Bank of China formally introduced industry standards for QR code payments. During the period of our study, from 2017/01 to 2021/12, we observed a steady rise in the average monthly expenditure for face-to-face payments before 2019. However, the growth in online payments remained relatively stable throughout this period. The proportion of expenditure not related to e-commerce steadied at around 75% after 2019.

[6]According to multiple reports of iResarch and Statista, Alipay's market share in China's mobile payment market decreased from approximately 80% in 2014 to about 50% in 2022, but it has remained the largest payment platform.

[7]Typically, the bill closing date is the 1st of the following month, and the payment is due by the 9th of that month, resulting in a maximum interest-free period of 40 days. Choices for instalment payments include durations of 3, 6, 9, and 12 months, with Annual Percentage Rates (APR) of 14.94%, 15.27%, 15.34%, and 15.96%, respectively. It was the largest consumer credit service in China both in credit balance and number of consumers.

By June 2020, Huabei was used by about 500 million users, with an average outstanding balance of 2,000 *yuan*, and the credit line was as low as 20 *yuan*.[8]

Our analysis makes use of the de-identified payment data provided by Luohan Academy and Ant Group, the parent company controlling both Alipay and the credit service Huabei. Generated from transaction-level data, our final dataset provides monthly information on consumers' payments between January 2017 and December 2021. We also use individual information, including age, gender, education, residential cities, etc. We will first explain the empirical strategy and then get into the details of the data and our sample.

1.2 Empirical strategy

We use the lockdown caused by the COVID-19 pandemic in 2020H1 as a negative impact on consumer income to study how access to fintech credit can help alleviate the income shock. In the several months following the lockdown of Wuhan on January 23, 2020, almost all the cities in China experienced different levels of lockdowns. The lockdown and mobility restriction measures were gradually relaxed from late February to June. As a result, the total consumption decreased by 19% and 3.9% in the first and second quarters of 2020 on a year-over-year basis.[9]

The main challenge for our identification is that having access to Huabei and the consumption after shock may be affected by unobserved confounding factors. We fully exploited the two advantages of our data source to resolve this problem.

The first feature of the data source is its large user base, which allows us to select a considerably large sample even after applying restrictive conditions. One hypothesis is that consumers who started using Alipay earlier or use it more frequently are more likely to utilize the credit service. Those who have not used the credit service tend to be inactive on the digital payment platform. The large user base allows us to select a sample of 5 million consumers, given the constraint that they are using digital payment for six consecutive months while not using the credit service.

The second is that our data includes rich individual characteristics that are of economic significance. We have accurate information on gender, age, education, birth city, residential city, and the time to start using digital payment, and a rich set of information predicted by algorithms such as occupation, car ownership, and real property ownership. Therefore, we can construct a control group that is almost identical to the treatment group *ex-ante*, and use additional variables to verify the quality of the match.

[8] See Ant Group's prospectus of its proposed IPO at the Hong Kong Stock Exchange on October 26, 2020: https://www1.hkexnews.hk/listedco/listconews/sehk/2020/1026/2020102600165.pdf

[9] Using high-frequency daily transaction data, Chen, Qian, and Wen (2021) find that the consumption decreased by 32% in the 12 weeks following the lock-down. According to China's National Bureau of Statistics, the total retail sales of consumer goods decreased by 19% and 3.9% in the first and second quarters of 2020 on a year-over-year basis (see https://www.gov.cn/xinwen/2020-07/16/content_5527279.htm).

These two features allow us to construct the control group with the matching method. After having the control and treatment group, we use the following specification as our baseline estimation:

$$Y_{it} = \alpha + \beta \cdot (Treatment_i \times Post_t) + \delta_t + \lambda_i + \epsilon_{it} \tag{1}$$

where Y_{it} denote the *log(consumption+1)* of consumer i in month t, $Treatment_i$ is a dummy variable indicating whether consumers have access to credit service before the shock, $Post_t$ is the dummy indicating the time is after the shock, δ_t is the time fixed effect, λ_i is the induvial fixed effect capturing all the time invariant characteristics. The purpose of our matching is to find two groups with similar consumptions and individual characteristics, and the pre-shock treatment effect, therefore is nil. Then, in the specification we focus on the coefficient β indicating the treatment effect.

1.3 Data

We construct our sample from the Alipay consumers who are active in each of the six months in the second half of 2019 (henceforth 2019H2). We first randomly selected 1,000,000 consumers who had used Huabei at least once in 2019H2 (treatment) and 5,000,000 consumers who had not used Huabei before the end of 2019 (control). Then, we exclude those individuals with excessively high or low consumption, lack individual information, and individuals who are not within the age range of 18 to 60 years, as Huabei is unable to offer services to them[10]. Among these consumers, we then randomly draw 500,000 and 3,000,000, respectively, as the treatment and control samples.

Variables. The data we use is from January 2017, shortly after Alipay widely promoted its QR code payment and went from online payment into a widely accepted payment in both online and face-to-face transactions, and ended in December 2021, two years after the COVID-19 shock. The variables include (1) consumers' payment information with Alipay, including payment methods, merchant types, and the respective amount and number of payments at the monthly level; (2) individual characteristics, including age, gender, education, occupation, residential cities, the date starting using digital payment; and (3) balance and gains of investment in mutual funds and money market funds on Alipay's wealth management platform.

Table 1 shows the summary statistics of the original sample of 3,500,000 consumers, including age, gender, the quarter in which consumers started using Alipay, and the consumption of each year. In 2019, individuals in the treatment and control groups spent an average of 31,888 *yuan* and

[10] We first select a random sample of 1 million consumers who have used Huabei at least once in 2019H2, and 5 million consumers who have not used Huabei before the end of 2019. In the sample, 94% got matched with complete individual information. Then we drop those consumers (1) whose age was below 18 or above 60 in 2019; (2) whose total consumption in 2019H2 is at the bottom 5% (with a threshold of *yuan* 1,005); (3) whose monthly consumption is over *yuan* 100,000. Then we have a treatment group of 882,618 consumers and a control group of 3,063,787. Among these consumers, we randomly draw 500,000 and 3,000,000, respectively, as the treatment and control samples.

22,222 *yuan*, respectively. Meanwhile, official statistics indicate that urban residents' per capita consumption expenditure was 28,063 *yuan*, and rural residents was 13,328 yuan for the same year (the base of which includes children and the elderly). This suggests that the spending captured via Alipay constitutes a substantial share of the total consumption among these consumers. Furthermore, the statistics show that there are differences in the composition and consumption levels of the two groups.

Supplemental data. In addition to our primary data set, we incorporated several public datasets for further analysis. (1) We obtained the asset balance and gains on two types of assets, mutual fund and money market fund, of consumers in the matched sample who invest with Alipay's wealth management platform. (2) For a sub-sample, we obtained the total credit limit from financial institutions recorded in the central bank's credit reporting system through the payment platform. (3) We gathered information on the 2020 lockdown measures implemented in response to the pandemic from the official announcements of different provinces, with pandemic data sourced from the Chinese Center for Disease Control and Prevention public releases. (4) We use city-level information, such as population, GDP, and retail sales, from the China Statistical Yearbook and CEIC.

1.4 Matching

We use one-to-one matching to construct the control and treatment groups and then estimate the treatment effect (Abadie and Imbens, 2006; Imbens, 2015)). Given the large size, long period, and rich set of characteristics of the data, we can select a number of matching variables to obtain a balanced match. Meanwhile, we don't exploit too much and leave enough variables to validate the matching quality. Specifically, we use the three aspects of variables to construct comparable treatment and control groups that are balanced with respect to observable characteristics.

(a) **consumption**: the logarithm of consumption in the first, second, third, and fourth quarters of 2019, as well as in December 2018. We use the quarterly consumption of 2019 to control the consumption level, hence the income level of consumers. Consumers with the same income level may consume differently between the usual time and festivals; we add the consumption in December 2018 to control the spending pattern in the festival of consumers.

(b) **demographic information**, including *gender*, *age*, and *region*. We use gender and age to account for fundamental consumer demographics. In our dataset, the geographical information for consumers is accurate up to the city level. However, aligning solely on the city level would drastically diminish the number of successful matches. On the other hand, matching at the broader provincial level is overly generalized. To find a middle ground, we first identify major cities, including super cities such as Beijing and Shanghai, provincial capitals, and the leading economic cities within a

province that aren't the capital, adding up to 40 cities[11]. Then, we group the areas excluding these major cities into a single region for each province. This approach leads to the definition of 70 distinct regions.

(c) **digital age**, when individuals started using digital payment, measured in quarters, *time enter*. A potential source of endogeneity in the decision to use fintech credit is consumers' familiarity with digital payments. Age, consumption level, and place of residence alone are insufficient to control consumers' payment habits in the digital economy. Furthermore, the penetration of digital payments might differ across regions, and all the transactions we observed in our study were made through digital payments. To address this issue, we control for the time when a consumer first adopted digital payments to mitigate this endogeneity. Since the widespread adoption of digital payments in China started around 2016, we do not differentiate among those who began using it before 2017.

To summarize, we have used the following nine variables in the matching process:

- consumption amount in the first, second, third, and fourth quarters of 2019, and in December 2018;
- demographic information, including *gender*, *age*, and *region*;
- *enter time*, the quarter when individuals started using digital payment.

We apply exact match on *gender*, *region*, and *enter time* and nearest match with Mahalanobis' distance for other variables with a caliper equal to 0.2.[12] Before matching, the treatment group consists of 500,000 consumers, and the control group has 3,000,000 consumers. The matching ratio is 1:6. In total, 217,199 consumers in the treatment group are matched with one pair in the control group, with a success rate of 43.4%.

To check whether the matching successfully balances the sample, Table A3 shows the univariate comparisons of individual characteristics between Huabei users and the control group before and after matching. The left side shows the means for the two groups before matching. The consumers in the treatment group are younger, have a higher proportion of males, and are less likely to be in large cities. In any given year, the consumption of treatment group consumers is higher than that of the control group consumers. After matching, the ages between the two groups became very similar.

[11]Specifically, the 40 big cities include 4 provincial-level municipalities: Beijing, Shanghai, Tianjin, Chongqing; the capitals of 27 provinces; 5 sub-provincial cities: Shenzhen, Ningbo, Qingdao, Dalian, Xiamen; and four non-provincial capital cities that rank first in GDP within their respective provinces: Suzhou, Quanzhou, Tangshan, and Ordos.

[12]The standard caliper used in the literature is 0.25 (Lunt, 2014). However, given our large sample size, we chose a lower caliper, to further reduce the bias of the two groups. The drawback of a smaller caliper is more subjects would not be matched. Our analysis of different calipers shows the decrease is acceptable.

There were no significant differences in the consumption of the two groups in each of the three years before the shock (2017 to 2019).[13]

From the initial matched sample, we observe an imbalance in the two groups leaving the payment platform after the shock. The number of consumers who stopped using Alipay as their payment method is higher than the treatment group, which creates an imbalance in the observability and measurement error. Therefore, we drop those consumers with more than six months zero consumption in the 24 months period after shock. We also drop the consumers with more than three consecutive months of zero payment as we want to ensure the two groups consistently use Alipay as their primary payment platform. When dropping one consumer, the matched consumer is also dropped. The procedure left us with a final sample of 159,519 pairs of consumers, that is 73.4% of the initial matched sample. The purpose of the clean of activeness is to present an accurate estimation of the actual treatment effect from using fintech credit. We discuss the impact on estimates of applying different criteria in Section B. Without this procedure, the results lead to an overestimation of the treatment effect.

From now on, we will focus on the sample after dropping inactive pairs. Hence, we note it as the *matched sample*. The summary statistics and covariates of the matched sample are reported in Table 2. Besides the two variables *gender* and *region* we apply an exact match on, other main variables used in the match do not show significant differences between the two groups. We also divide the consumption into consumption from the e-commerce platform and offline consumption; the difference is not significant, either, showing the two groups of consumers are behaving similarly in their purchasing habits.

In addition, Figure 4 presents the distribution of other individual characteristics we have not included in the matching. Variables include the year they started using Taobao, an e-commerce platform, education level, occupation, car ownership, and whether they are living as native residents. All distributions show no significant difference, suggesting the matching eliminates meaningful observable differences in covariates between the two groups of consumers.

We also carry out various robustness checks regarding different matching specifications, as presented and discussed in Appendix B. In determining which specification is used as the baseline estimation, we face the bias-variance trade-off commonly seen in the research with matching (Smith, 1997; Imbens and Rubin, 2015). Given the large size and matching ratio in our analysis, we consider minimizing bias as our priority in choosing among matching methods. Therefore, we choose the *single* nearest neighbour matching *with a caliper* (Caliendo and Kopeinig, 2008). The other decision is about choosing the match with or *without replacement*. The value of using replacement is significant when the sample size is relatively small (Caliendo and Kopeinig, 2008). Therefore, we implement

[13]The monthly differences of consumption in the two groups are in Figure A5 In each month from 2017 to 2019, consumption differences between the two groups are not significant.

the matching without replacement and ensure the ordering is randomly done (Augurzky and Kluve, 2007).

2 Main Results

Next, we report the baseline estimation of the treatment effect in the matched sample. We then decompose the effect into various consumption categories.

2.1 Baseline estimation

Our main findings are conveyed by Figure 2, which plots the difference between the mean of the logarithmic monthly consumption of treatment and control groups. (1) After January 2020, a significant difference in consumption emerged between the two groups, peaking in February 2020. Note the lockdown policy started on January 23, 2020, and stated to relax in most areas in April, 2020. After May 2020, this difference gradually stabilized and remained significant till the end period. (2) Consumption data from December 2018 to December 2019 was used for our matching process; hence, the difference between the two groups is non-significant by construction during this period. (3) There is no significant difference in the period before the shock and not used in constructing the matching, i.e., from January 2017 to November 2018.

Table 3 shows the baseline treatment effect of accessing fintech credit on consumption. We note the short-term treatment effect in the three months after the lockdown, from February to April 2020, which is 39.66%. From April 2020, most areas in China had relaxed the restrictions on traffic and economic activities. We report the treatment effect within the first half year of 2020, 28.71%. These effects shows the value of fintech credit in consumption smoothing. As time went on, the effect gradually decreased but remained significant, with 24.52% in the year 2020 and 19.45% in the year 2021. Within two years after the shock, the average treatment effect is 21.99%.

In terms of the effect on the consumption spending amount, Figure 1 gives the average monthly consumption of the two groups. We see a sharp decrease in consumption following the shock. In the three months following the shock, the average spending of consumers in the two groups decreased by 10.1% on a year-on-year basis and by 23.8% compared to the annual average of 2021, despite an upward trend in total digital payment spending.[14] In the period of 2020/2-4, treatment consumers have 251 *yuan* higher monthly spending than the control groups, 210 *yuan* in 2020H1, and 256 *yuan* within 2020. Throughout the two-year period following the shock, the treatment group, on average, spent 257 *yuan* more per month than the Control group.

[14]The decrease is larger for control group consumers, with a 14.5% decrease compared to the same period last year, and 27.5% compared to the average of 2021. The decreases in treatment group consumption are 5.6% and 20.1%, respectively.

2.2 Decomposition of Consumption

For the consumption payment not on the e-commce platform, we have the information of the Merchant Category Code (MCC) of the payment (see Appendix A.1). Therefore we can future decomposite the treatment effect in different types of consumption. Following the method in Ganong and Noel (2019) and Lusardi (1996), we use the MCC data to categorize spending into 19 mutually exclusive and comprehensively exhaustive categories, and then summarize as Durable, Non-Durable, and Strictly Non-Durable expenditures. Table 4 presents the treatment effect in different time horizons for each category with its respective share in the total expenditure, ranked from highest to lowest based on the short-term treatment effect.

Firstly, in both the short and long term, the highest treatment effects are seen in categories of relatively non-essential non-durables, such as "Food Away From Home" (restaurant expenditures) and "Retail Durable". This indicates that fintech credit access allows consumers to sustain their spending on these items, maintain spending on these items after the shock, and, in the long run, stimulate even more spending in these categories.

Secondly, the treatment effects for Non-Durable expenditure on necessities, such as Groceries, Department Stores, and Ground Transportation, are relatively low. This suggests that, while consumers in the control group are decreasing spending across all categories in short run, it is more difficult to reduce expenses in these essential categories. Meanwhile, for non-essential Durables categories like retail durables, home improvement, and hotels & rental cars, the long-term effect shows a decline. This implies that, in the short term, consumers in the control group reduced spending on these items more sharply than those in the treatment group. Over the longer term, however, Fintech access has a more pronounced effect on increasing spending in Non-Durables than in Durables.

For unavoidable expenses such as medical copays and drugstore purchases, there is no significant difference in spending between the two groups. Even following the shock, consumers were unable to save on these items, regardless of access to additional credit. In the long term, while fintech credit does not significantly affect spending on medical visits and treatments, it does lead to higher expenditure on medications, suggesting a potential role in enhancing consumer health.

3 Robustness Analysis

Next, we discuss the robustness checks of our baseline estimation. First, our hypothesis is that the differences in consumption of the two groups are triggered by the shock. We use the variation in lockdown duration across different regions after the shock to examine the relationship between the treatment effect and the intensity of the shock. We also discuss the criteria of the sample selection process, alternative measures on consumption, and considering adoption and exit.

3.1 The intensity of shocks

During the COVID-19 pandemic, the duration of lockdowns varied across different regions, ranging from 5 to 16 weeks(Wu et al., 2023), resulting in varying consumer impacts. The provincial government determines the lockdown duration depending on the province's epidemic control situation. While the lockdown policy implements strict traffic restrictions and feasible economic activities, we consider this variable to capture the intensity of the shock on consumers' income and the expectations on future income.

Table 5 shows the treatment effect and its interactions with lockdown days in a region. In Panel A, we find that the intensity of the shock has a profound impact on the treatment effect. Doubling the duration of the lockdown leads to a 4.5%-5.3% increase in the consumption difference between the groups.

The intensity of shocks' marginal effect on treatment should be different among consumers with different income levels. For consumers with lower income, the same level of shocks implies a larger impact on their liquidity constraint and daily life, than that of the higher income consumers. In panel B, we divide the cities into three groups. based on their consumption levels in 2019. From the lowest income group to the highest income group, the marginal effect on treatment effect gradually decreases by half. The highest group of consumers are affected less by the lockdown.

3.2 Alternative measures of consumption

In the baseline estimation, we use the logarithmic of consumption as the main variable. As pointed out by Chen and Roth (2024), the logarithmic transformations would be problematic when interpreting as percentage effects. Applying to our case, when the consumption increases from zero to nonzero for a treat group consumer, the interpretation of percentage change is not well defined. To address this issue, we dropped those matched pairs including inactive consumers, as their consumption data include a non-negligible number of zeros. In addition, the $log(1+Y)$ transformation, or the total of spending amount, disproportionately amplifies the impact of higher-spending consumers within the dataset. Furthermore, we propose an alternative approach of defining the consumption variable and plotting the difference in the mean of treatment and control groups.

To address this concern, we define the ratio relative to the average monthly consumption in 2019. For each consumer i , note her average monthly consumption in 2019H2 as base y_0^i, then define the ratio of consumer i in month t as $r_t^i = y_t^i/y_0^i$. We can consider r_t^i as the growth rate of consumer's spending compared to the benchmark in 2019. By employing the ratio that equalizes the variance in consumption behaviours across individuals, we more accurately capture the mean impact of the treatment effect across both groups. Figure 5.A shows the difference in the mean of ratio in the two groups. The pre-shock pattern is similar to the baseline, not significantly different. The difference

after shock remains persistent. Although it is lower than the baseline estimation, on average, the effect is significant and higher than 10%, meaning that the growth rate of consumption for the treated consumers is ten percentage higher than that of the control group.

To better mitigate the impact of zero values on the results and to eliminate volatility in consumption, we also examined the outcomes under two other period definitions, bimonthly and quarterly, as shown in Figure. The results under both specifications are consistent with the baseline estimation.

3.3 Adoption and Exit

One concern with our baseline estimate is that we only controlled for whether the two groups of consumers had access to fintech credit at the start of the shock. However, after the shock, it's possible that consumers in the control group could start using fintech credit, while those in the non-control group might stop using it. Figure 8 shows how consumers in the control group started to use fintech credit after the shock. From the control group consumers, almost one-third had adopted Fintech credit by the end of 2021 (Figure 8.A), and the activeness of these new users in using fintech credit is steady (Figure 8.B).

Given that fintech credit usage might increase consumer spending, considering control group users who adopt fintech credit as treated would likely increase our estimate of the treatment effect. To assess this impact, we consider control group consumers who adopt fintech credit as treated, starting from the month they began using fintech credit. Column (2) in Table 9 shows a long term treatment effect of 24.06% under such specification, higher than the baseline effect.

Meanwhile, some consumers in the treatment group may stop using fintech after the shock. This could lead to an underestimation of the actual treatment effect in our baseline estimate. It should be noted, however, that a consumer's non-use of credit does not necessarily mean that the credit limit has no value to them. To examine the impact of exits on our estimates, we defined an exit indicator: if a consumer stopped using fintech credit from a given month through to the end of our data in 2021/12, the consumer is considered as having exited fintech credit for that month. Column (3) in Table 9 shows the long term treatment effect is 32.14% after considering the exit, significantly higher than the baseline.

In addition, in column (4) we consider both the adoption and exit, providing a more precise control over the effect of using fintech credit.. The treatment effect is 28.75%, approximately 30% higher than the baseline estimation. This further supports our claim that the baseline estimate does not overstate the effect.

3.4 Access to the Fintech credit service

There are several potential reasons why controlled consumers lack access to credit services: (1) they could access but choose not to use it, (2) they might not be aware of the service, or (3) they want to use it, but the platform does not offer them the service. Our data includes a tag indicating that these consumers, if willing, could activate credit services. In total, 82,240 of the 159,514 consumers (51.6%) in the control group are granted to the credit service before the shock.

Table 10 shows the estimation for the subsample only consider consumers in the control group who could access Huabei but did not activate the service. The treatment group are the matched pairs. The estimations are consistent with the baseline, with slightly lower values, 25.66% in the six months after shock and 17.86% for two years.

4 Mechanisms

The baseline estimates show that consumers with Fintech credit access had a 21.99% higher consumption than those without it after an income shock. Moreover, the effect persists over the long term. We propose two mechanisms causing this impact: the income channel and financial literacy.

4.1 Income Channel

The shock affects consumers with various income levels differently. The immediate economic impact of lockdowns varying from one to three months on consumers is recuding their income by restricting labor mobility (Wu et al., 2023). The lockdown also led to the temporary closure of many small and medium-sized enterprises, directly impacting a large portion of the workforce that relies on these businesses for employment (Dai et al., 2021). After a negative income shock, higher-income consumers presumably have more savings to sustain their spending, reducing their reliance on supplementary credit.

On the other hand, lower-income consumers face tighter liquidity constraints. The differences in the liquidity constraint faced by consumers will affect their marginal propensity to consume after getting a credit service. Gross and Souleles (2002) find that the "MPC out of liquidity wealth" is the largest for people having binding liquidity constraints. In our context, if consumers with tighter liquidity constraints can access to Fintech credit, they would more likely utilize it to smooth their consumption. We validate this argument with two measures: (1) use the consumption spending in the two years prior to the shock as a proxy of income, and (2) the level of development in the consumer's residential area.

4.1.1 Consumption Level

First, we use the total consumption observed in 2018 and 2019 as a proxy for consumers' income.[15] We categorize consumers into ten brackets according to their 2018-2019 consumption—from the lowest (group 1) to the highest (group 10). Then, estimate the treatment effect for each bracket. Figure 6 shows the treatment effect in the one-year (Figure 6.A) and two-year (Figure 6.B) period after the shock. In both results, the treatment effect strictly decreases as moving to a high consumption level. The variation is large. The long-term treatment effect, for example, varies from a high of 51.7% in the bottom 10% of consumers to a slight negative effect of -2.3% in the top 10% group. This indicates that the highest-income group likely has access to other credit channels and assets, making the availability of Fintech credit not as impactful for them.

4.1.2 Regional Development

Regional development could also contribute to the treatment effect. Faced with income shocks, consumers living in large cities have better expectations for future income declines compared to those living in less developed areas. As a result, the incentive to smooth consumption for consumers in large cities is lower. Table 6 shows the treatment effect for big cities, 18.55%, and less developed regions, 26.21%.

In addition, we divide the 327 cities into five groups based on the per capita GDP of in 2019, with equal residential population. Then, we estimate the treatment effect for consumers in each group of cities, as shown in Figure 7. From the least developed group to the most developed group, the treatment effect shows a strictly monotonic decrease, with notable variation observed across the groups.

4.2 Financial literacy

Considering the innovative nature of the focal fintech credit service, it requires a certain level of financial literacy to become aware of it, be inclined to apply, make use of it effectively, and ensure timely repayment. Therefore, financial literacy is another potential mechanism behind the treatment effect. In the literature, the term financial literacy can be used to indicate the consumers' awareness or sophistication in each decision-making process associated with using fintech credit, and it is also influential in other household financial decisions(Campbell, 2006; Lusardi and Mitchell, 2014).

In our case, the the differences in consumers' literacy to utilize fintech credit can be summarized in two aspects. First, their acceptance of consumer credit, which aligns with traditional financial

[15] We excluded the year 2017 because it was still in the phase of massive promotion of Cashless Payment, and after 2018, consumers' usage habits became more stable.

literacy. Second, their literacy about fintech products. As pointed out in recent studies (Buchak, Hu, and Wei, 2021; Bian, Cong, and Ji, 2023; Hong, Lu, and Pan, 2023), in pursuit of synergies across various businesses, fintech companies typically offer multiple financial services on their platforms, such as payments, credit, and wealth management. When consumers engage with product design, marketing, and algorithms that are crafted for synergy, they often develop greater financial literacy about other products in the process.

We use educational level as a proxy to address the first aspect. For the second, we develop a new indicator utilizing consumers' literacy on an innovative payment method to measure consumers' literacy on fintech credit services.

4.2.1 Educational Level

We first use the education level as a proxy for financial literacy. It is widely studied that general education is influential in many financial decisions. For instance, research has found that individuals with college degrees are more likely to own stocks (Haliassos and Bertaut, 1995) and less likely to use high-cost borrowing methods (Lusardi and Scheresberg, 2013).

In the data, we have four education levels: high school education or below (70.09%), post-secondary degree (6.8%), college degree (19.4%), and graduate degree (3.7%).[16] Table 7 shows the treatment effect across different levels of education. As education level increases, the treatment effect strictly decreases, from 26.06%, 20.44%, 9.21%, to 6.05%.

To interpret the results, we should point out that we used *exact match* on education in constructing the matched sample. Consumers in each pair have the same educational level. So, the difference in treatment effects between the two educational levels is determined by two parts. We consider increasing the educational level of a matched pair. First, for the treatment consumer who has accessed fintech credit, how much does higher education affect the ability to use the service, and other financial tools, to mitigate the shock? Second, for the control group consumer, who lacks access to fintech credit, how does his capacity for using other financial tools improve in helping to alleviate the impact of shocks?

If the first effect is larger, we will see an increase in treatment effect when increasing the educational level. However, the estimations suggest the second effect is larger. This implies that, among consumers who have already used fintech credit services, the additional benefits derived from higher education levels are not significant. Alternatively, it means that the benefits gained from using fintech credit are greater for lower-education groups relatively.

[16] The information on education level is accurate. We combine the consumers with a master's degree (3.54%) and those with a doctoral degree (0.15%).

4.2.2 Financial Sophistication Index

Moreover, we develop a Financial Sophistication Index from two unique payment methods within Alipay as a proxy for financial literacy. One is Yu'e Bao, an innovative e-wallet linked to the money market fund. Consumers deposit money into it and can use it for payment at any time. At the same time, they earn a daily return from the money market fund, with annual interest rates ranging from 2% to 7%. In addition, Alipay also offers a traditional balance payment option, where consumers can transfer money into the balance and use it for payment, but it does not have interest. Since both payment methods are equally convenient, the returns from the money market fund can be considered risk-free. Ideally, rational consumers should opt for Yu'e Bao instead of using balance payments. However, we observed that only 27.4% of consumers did this in 2019. The distribution of usage between Yu'e Bao payments and balance payments is relatively even.

For each consumer i, we define the financial sophistication index as the share of "interest generated balance" used in all transactions in 2019:

$$FS_i = MMF_i/(MMF_i + Balance_i) \tag{2}$$

where FS=1 means very sophisticated, and the consumer is actively taking advantage of the interest generated service. Fig A7 shows the distribution of FS index for each educational level. High-education group has a larger share of financially sophisticated consumers. However, even in high education groups, a significant amount of consumers are not financially sophisticated, suggesting the Financial Sophistication Index and educational level are not entirely aligned. The Table A5), and not significant.

Table 8 shows the relationship between treatment effect and FS index. Panel A shows the regression results using the Financial Sophistication Index (FS) as an interaction term. The results indicate that a 0.1 increase in FS index will reduce the treatment effect by 3.1 to 3.4 percentage. In Panel B, we divide consumers into four groups based on the range of the FS index. The treatment effect decreases sequentially as the FS Index increases from low to high, with a treatment effect of 27.2% for consumers who only use balance payments and 27.4% for sophisticated consumers who only use Yu'e Bao.

This interpretation aligns with our understanding of educational effects. For those with lower financial literacy on fintech platforms, using fintech credit provides stronger consumption smoothing and a more significant improvement in their financial situation.

5 Discussions

5.1 Impact on Aggregate Economy

Considering the significant impact fintech credit has on consumption, along with the extensive user base, it is reasonable to expect that the utilization of fintech credit could have an impact on macroeconomic variables.

We utilized our initial random sample of nearly one million fintech credit consumers to examine the relationship between fintech credit activities and retail sales at the city level. First, we calculate the monthly *per capita Fintech credit payment* for consumers in each city, which we use as a monthly indicator of Fintech credit usage intensity among cities. Then we get the city-level retail sales data as reported by municipal governments[17] and calculate the *retail per capita* based on the residential population. We then apply the following specification with the city-month level panel data:

$$log(y_{jt}^{\text{Retail}}) = \gamma \cdot log(y_{jt}^{\text{Fintech credit}}) + \delta_t + \lambda_j + \epsilon_{jt} \tag{3}$$

where λ_j is the city fixed effect, capturing the city-specific fundamentals associated with retail sales, and δ_t is the fixed effect. Due to the limitations of the observations and the relatively longer time unit in this analysis, we do not distinguish the impacts of the pandemic over different cities besides the time-fixed effect. In addition, we assume the effect on social retail is time-invariant, which might be violated, particularly when the acceptance of fintech credit in different cities is changing at different paces over time.

Table 11 shows the fintech credit payment is significant in explaining the variations in retail sales at the city level for both monthly and quarterly available data. One percentage increase in consumers' fintech credit payment results in a 0.35 percentage increase in the retail sales per capita in the half-year period following the shock, while a 0.17 to 0.26 increase in the long term.

In column (2), we add the digital payment amount in the regression. It is not significant and does not weaken the effect of fintech credit, therefore ruling out the possibility that the effect mainly comes from digital payment methods rather than fintech credit. However, we are not suggesting that digital payment adoption has no effect on consumption. Recently, Agarwal, Ghosh, et al. (2024) found an increase in household consumption by about 2.38% for an additional 10 percentage points in prior cash dependence when adopting mobile payments. Jack and Suri (2014) also find an effect on consumption smoothing of mobile money adoption. In our setting, both control and treatment consumers have intensive digital payment usage, and the payment system has become highly digitalized. Therefore, building on these results, our findings emphasise the role of fintech credit in

[17] The data is from the CEIC database. Between 2019 and 2021, 291 cities have reported the retail sales data. Of these, 137 cities reported monthly while the other cities reported quarterly. The sales in January and February are combined due to the Spring Festival holiday, and we apply a similar process to the consumer data.

increasing consumer spending. Considering China's digital payment advancements (Didier et al., 2022), our analysis could serve as a reference for other economies rapidly transitioning to digital payments.

While the short-term rise in consumption can be attributed to consumption smoothing, the persistent long-term increase remains unexplained. Previous studies have demonstrated that payment methods can impact consumer spending; for instance, consumers tend to spend more with credit cards than with cash (Hirschman, 1979), one potential reason is the delayed payment (Raghubir and Srivastava, 2008). Although Fintech credit functions much like credit cards, the actual user experience may differ. Maesen and Ang (2024) find that adoption of BNPL installment payment plans of merchants increases purchase incidence by 9% and purchase amount by 10%. reducing perceived financial constraints. The effect is stronger for credit card shoppers than for debit card shoppers. The mechanism is through reducing perceived financial constraints by reducing perceived costs and facilitating budget control.

5.2 Delinquency Rate

The welfare consequences of offering consumer credit to individuals are controversial, especially considering that many of the consumers using fintech credit services are relatively young, lack solid financial planning and awareness, and have lower creditworthiness. Since we only have the repayment data for the treatment group, we are unable to conduct a rigorous analysis on whether the use of fintech credit has led to excessive consumption or excessive borrowing. We will report the observed delinquency level and then compare it with similar studies.

In our sample, from 2020 to 2021, on average 0.29% of consumers in the treatment group had overdue balances each month. Figure 10 plots the share of consumers having overdue payments in each month. The share is between 0.21% and 0.52%, where the highest is in 2020/2, the month following the shock. Among all consumers who have overdue payments, the average overdue balance is 3,458 *yuan*, while their Huabei spending bill in that month averages 8,682 *yuan*. The total overdue amount is about 0.25% of the total consumption expenditure in the two years.[18]

The finding is in line with a study on the consumers of the same Fintech credit services by Dong et al. (2024), where the 30-day delinquency rate is 0.012 over a one-year period. It is also consistent with Berg, Burg, Keil, et al. (2023), who find the default costs of consumers using BNPL payment are moderate. These contrast with Di Maggio and Yao (2021), who find fintech consumer credit loans are significantly more likely to be in default compared to the loans granted by traditional institutions.

[18] We should point out that, until September 2021, the regulatory framework for Fintech was not clearly defined, allowing Huabei delinquencies to go unreported to the central bank's credit system. This reduced the default liability for consumers (Dong et al., 2024). Although we lack data to address the policy change on delinquency, since the policy will increase the delinquency cost, one should expect the delinquency rate to decrease after the change.

One non-negligible factor is that different from the fintech loan providers in many studies, the focal fintech credit service is provided by a big tech platform. Its payment system, investment platform and its own credit rating agency are all widely used by the fintech credit users. As a result, the cost of severe default might result in an exclusion from the platform, which is substantial for users, therefore leading to lower default rates.

5.3 Where Does the Money Come From?

Following the shock, fintech credit consumers not only show increased spending in the short term but sustain higher monthly expenditures over a relatively long period. At the aggregate level, we see a macroeconomic effect from the fintech credit usage. Meanwhile, delinquency and default rates remain low. Naturally, this raises the question: where does the money come from?

One possible answer is that these consumers are saving less. Since we don't have information on their balance sheets, or data on their income and savings, we can't provide a definitive answer. However, we have acquired data about consumers' investments on Alipay's wealth management platform, and we attempt to derive insights from this data to address the question.

As studied in Hong, Lu, and Pan (2024), the platform-based distributions of mutual funds in China have quickly risen since 2012, when the regulation allowed tech firms to distribute mutual funds. By June 2020, the wealth management platform we studied had total assets under management (AUM) of 4.1 trillion[19] *yuan*. The major investments on the platforms are Mutual Funds and Money Market Funds.[20] For our research, we obtain the end-of-month balances for the two types of assets, and the total gains consumers have earned from each asset type since they began participating on the platform.

Figure 11 shows the balances, participations, and gains of two groups in each asset type. Over the two-year period in 2020-21, the number of control group consumers who have non-zero balances in mutual funds is 36.6% less than that of the treatment Group. However, their average asset balance was 56.1% higher (8,294 versus 5,313 *yuan*). For the Money Market Fund, Control Group participation was 5.2% lower, though their average asset holdings were 28.6% higher (7,800 and 6,063 *yuan*). The treatment group, on average, had 4,718 *yuan* less in assets than the control group. As a result of the lower balance, the control group consumers earned 185 *yuan* more in returns for the two types of assets than the treatment group consumers.

The fact that by the end of 2021, 31.7% consumers in the treatment group held some Mutual Funds, and 67.8% had balances in Money Market Funds, the lower asset holding cannot account for the 257 *yuan* higher monthly consumption. Nevertheless, there is reason to hypothesize that individuals who invest less in these types of funds may also have lower savings, which might fully explain

[19] Same source as in footnote 8.

[20] There are also time deposits and gold investment products, but they account for relatively small shares.

the long-term differences in consumption expenditure we have observed.

5.4 Additional Heterogeneity Analysis

The rich set of individual characteristics allows us to look at the treatment effect across different demographic groups. Table 12 shows the treatment effect regarding age, gender, and occupation.

Table 12.A shows the estimation for gender, revealing that the treatment effect is larger for males (25.00%) than females (19.25%). One reason for the gap is that, in our data, male consumers spend less than female consumers. In the matched sample, female consumers showed 6.8% higher monthly consumption in 2018-19. This implies that female consumers are more inclined to adopt new fintech payment technologies.

Table 12.B examines the effect for different age groups. First the effect is highest for the 26 to 30 age group. This could be connected to the fact that individuals in this age group are among the most likely to experience limited liquidity. We provide two possible explanations: first, older consumers are more likely to have already used or be accustomed to using credit cards. Consequently, the additional effects of using fintech credit for them are lower.

Table 12.C shows the effect for different occupations. The information on occupation is an algorithmic prediction rather than an exact value. Nonetheless, we observe that professions with relatively stable income show smaller treatment effects, around 10%, such as public company employees, civil servants, teachers, and white-collar workers. Their income is less likely to be impacted by shocks. Following the shock, medical personnel experienced considerable changes in both their work and lifestyle, leading to increased volatility. We observe a moderate treatment effect for this group. Blue-collar workers, though less represented in our analysis than white-collar workers, show a highest treatment effect of 35%. These results are in line with our analysis from the perspectives of income and financial literacy.

6 Conclusion

In the context of rapid fintech development over the past decade, significantly enhancing financial inclusion, we utilize large-sample consumer data from a world-leading fintech company to demonstrate the real impact of fintech credit on consumers. By examining consumption smoothing in the aftermath of shocks, we identified substantial short-term and long-term effects of accessing Fintech credit on consumption, which persisted for up to two years.

We then explain the findings from two perspectives. The first is that consumers with lower income levels have a greater need for liquidity following a shock. Then, accessing the Fintech credit service results in more pronounced consumption smoothing effects. Second, for consumers with

lower financial literacy, the availability and ability to use external financial services are relatively limited. Therefore, the advent of fintech credit greatly improves their welfare.

Our research also sheds new light on policy discussions on whether current financial inclusion developments are beneficial to society. We found no evidence of a notably higher rate of overdue consumer credit payments within these groups. Additionally, we found no evidence indicating that these consumers are over-borrowing.

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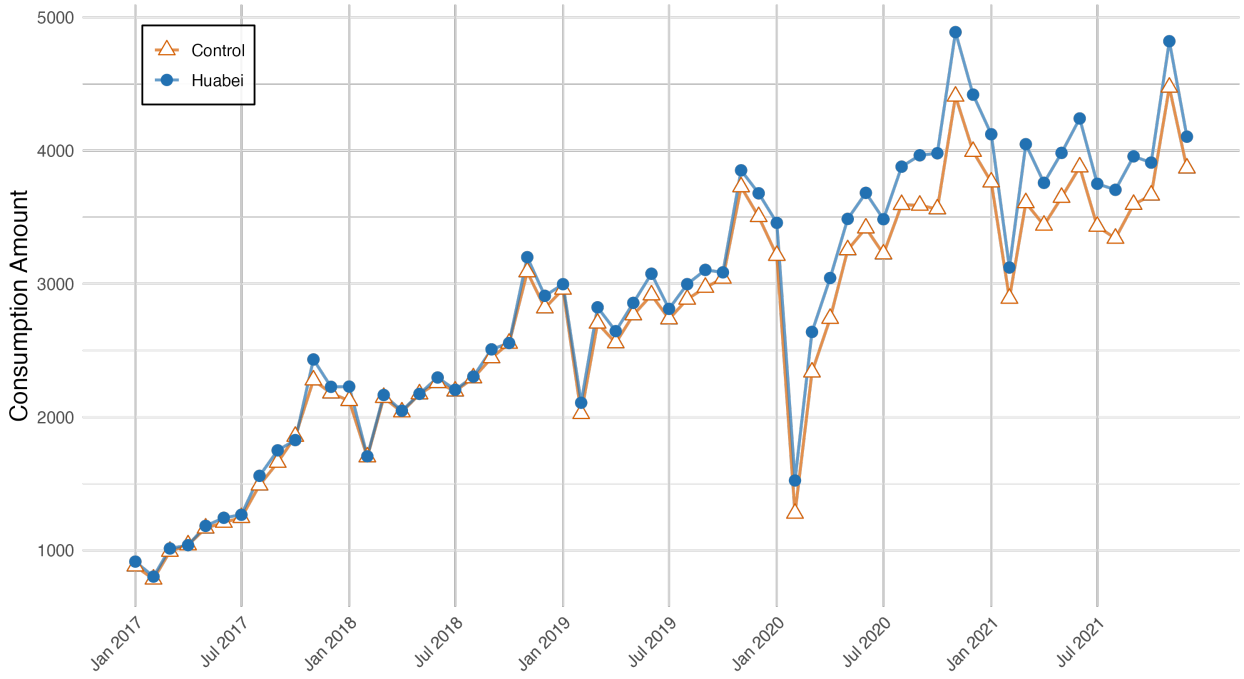
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Figures

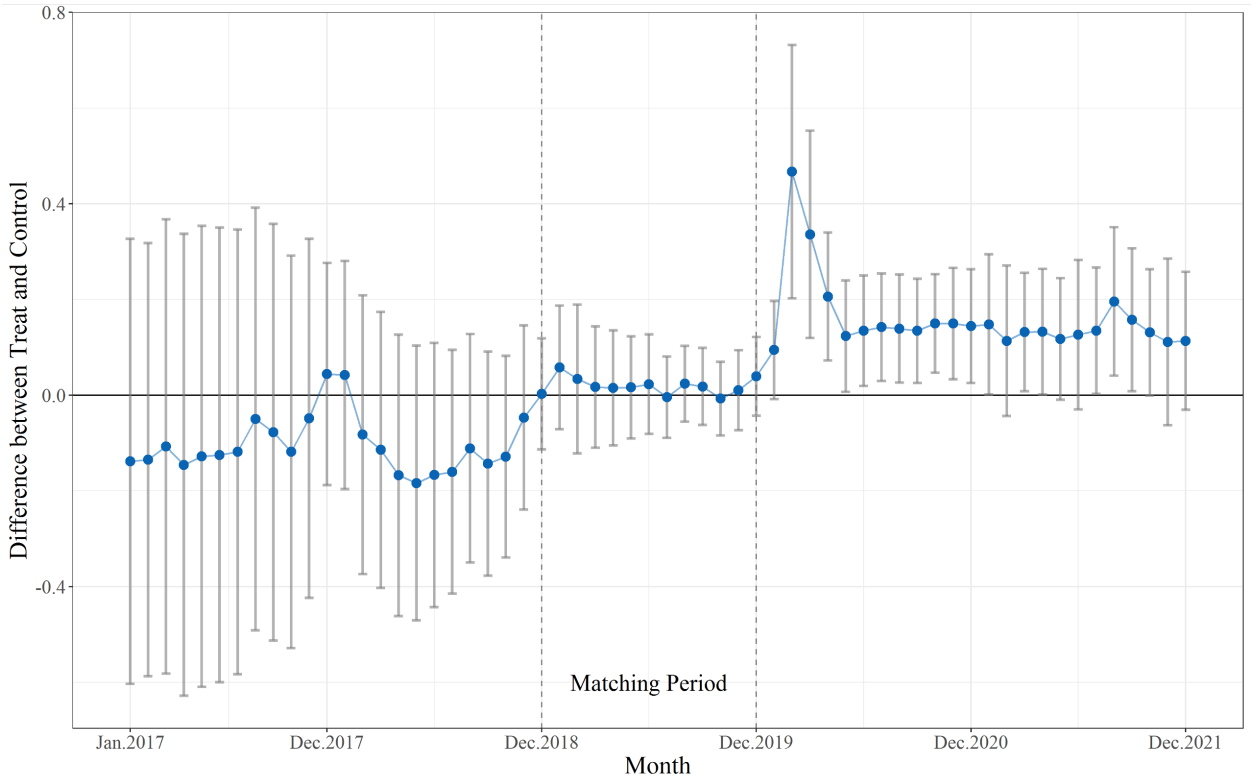
Figure 1: The Monthly Consumption of Consumers in the Matched Sample (2017 – 2021)



Note: This figure plots the monthly consumption between treatment and control groups from Jan. 2017 to Dec. 2021. We use the consumption from Dec. 2018 to Dec. 2019 to construct the matching. Alipay's adoption surged rapidly after the promotion of offline QR code payments in 2016, with the number of payment scenarios also increasing, until it gradually stabilized between 2018 and 2019. A sharp decline occurred in February 2020 following the pandemic shock. In each year, the consumption amount peaks in November, primarily due to the large promotional events on e-commerce platforms during that month in China.

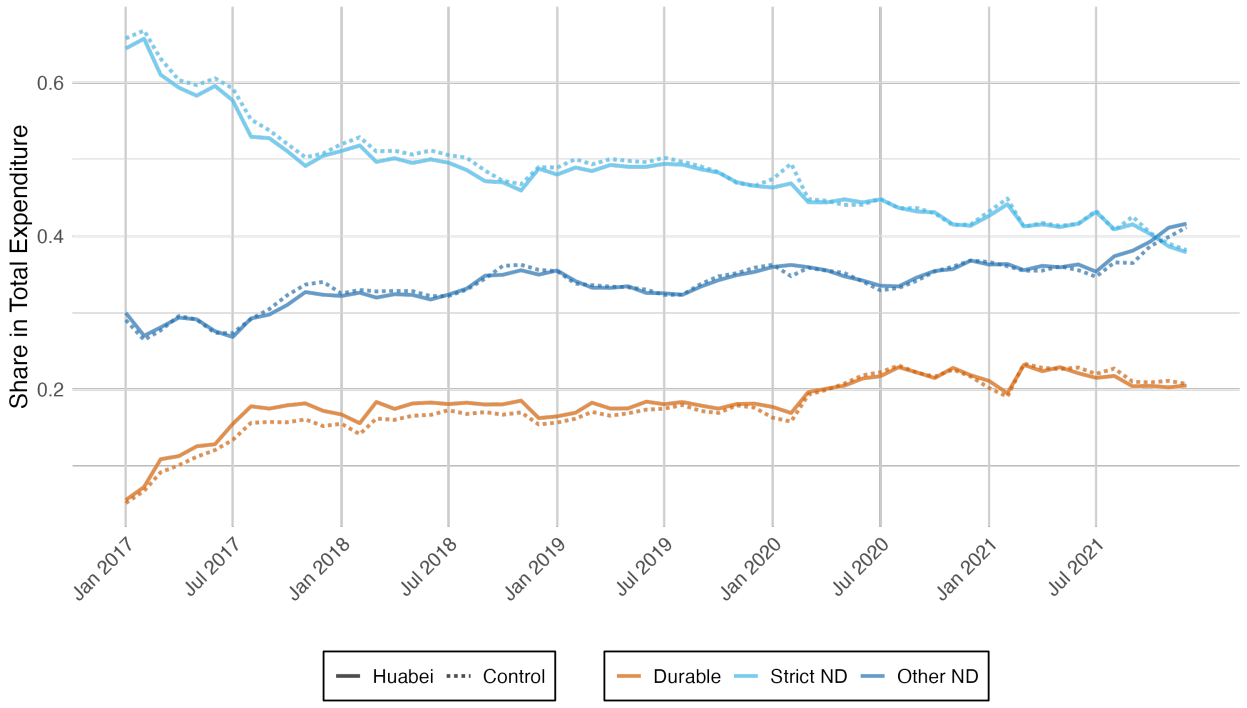
From 2017 to 2021, the sample's average monthly consumption was 1,306, 2,423, 3,130, 3,560, and 4,007 *yuan*, respectively. The average monthly difference in consumption between the Huabei group and the control group was 5.3, -61.3, 27.0, 256.3, and 257.4 *yuan*, respectively.

Figure 2: The Difference of Consumption between Treatment and Control Group



Note: This figure plots the difference of the average logarithm of monthly consumption between treatment and control groups from Jan. 2017 to Dec. 2021, with standard errors at 90% confidence level, clustered at *region* level. After Jan. 2020, there is a significant difference in consumption between the two groups, peaking in Feb. 2020. After May 2020, this difference gradually stabilizes and remains significant over the next two years. We use the consumption information in the the matching period to construct the matched sample, specifically, the matching variables include consumption of Dec. 2018, Q1 2019, Q2 2019, Q3 2019 and Q4 2019 . The non-significant differences in consumption from Jan. 2017 to Nov. 2018 validate the similarity of the two groups.

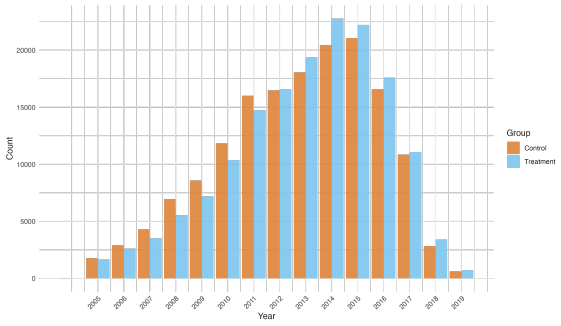
Figure 3: Decomposition of Consumption Expenditure



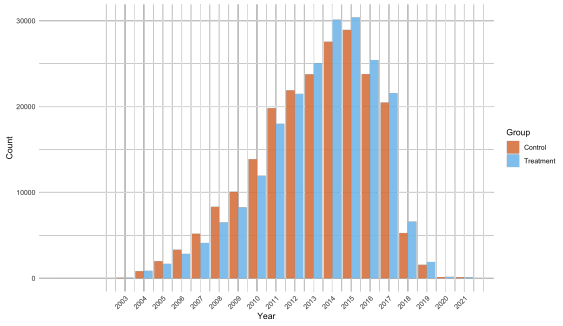
Note: This figure shows the average share of consumer spending on three consumption categories between 2017 and 2021. We categorize spending into Durable, Non-Durable, and Strictly Non-Durable following the method in Ganong and Noel (2019) and Lusardi (1996). On average, spending on Durable goods and services is 12.4%, Strictly Non-Durable at 58.7%, and Other Non-Durable at 28.9%. Following the shock, there was a incresea in Strictly Non-Durable spending for the control group, with decreases in the share of other two types of spending. In general, the share of spending on Strictly Non-Durable goods and services has shown a downward trend, suggesting an expansion in the use cases for digital payments, as they increasingly shift from non-durable consumption to deeper adoption in durable consumption.

As a benchmark, the share of nondurable expenditure is approximately 60% and SND is 47% of total expenditure, in Lusardi (1996). The Strict ND category includes: Food away from home, Groceries, Transportation, Professional & personal services, Telecom, Utilities, and Flights. The Other ND category includes Discount stores, Department stores, Other retail, Drug stores, Online, and Medical copay.

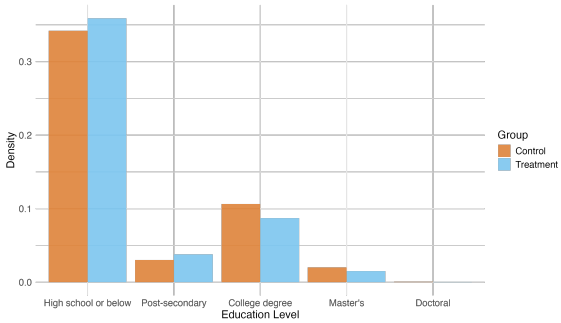
Figure 4: Distribution of Individual Characteristics in the Matched Sample



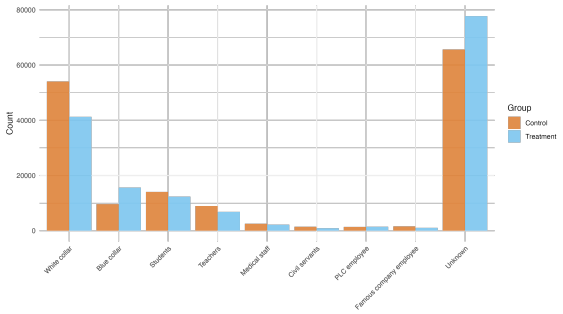
A: Year of Alipay Registration



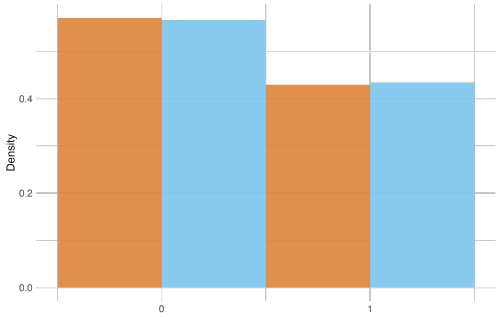
B: Year of Taobao Registration



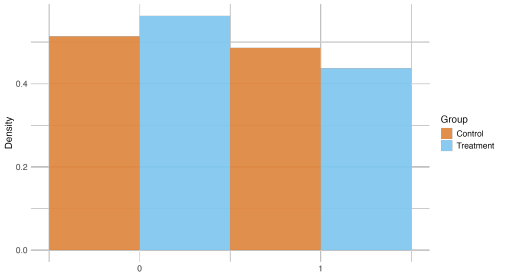
C: Education Level



D: Occupation



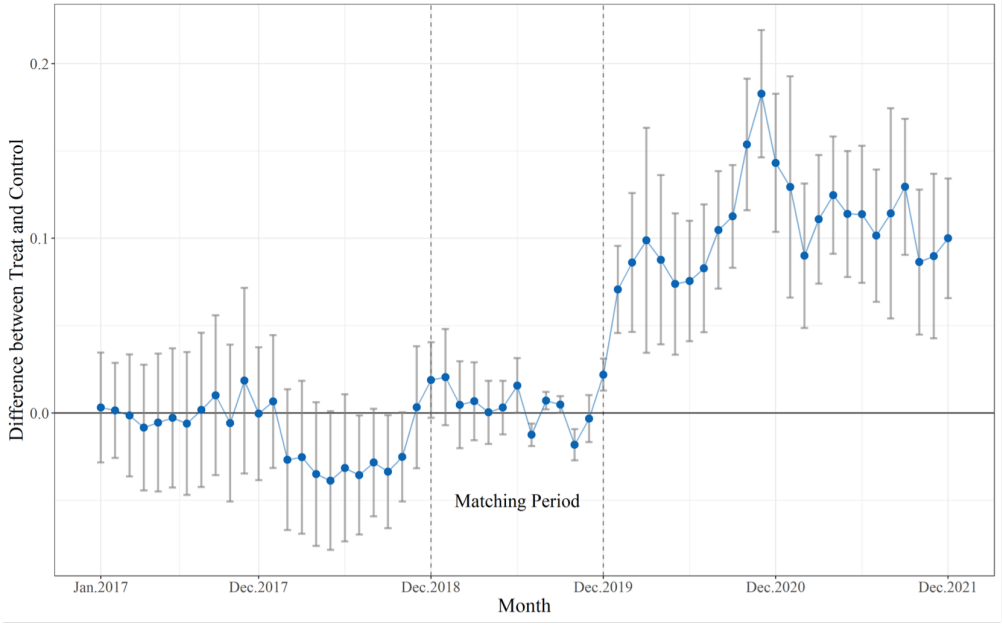
E: Car Ownership



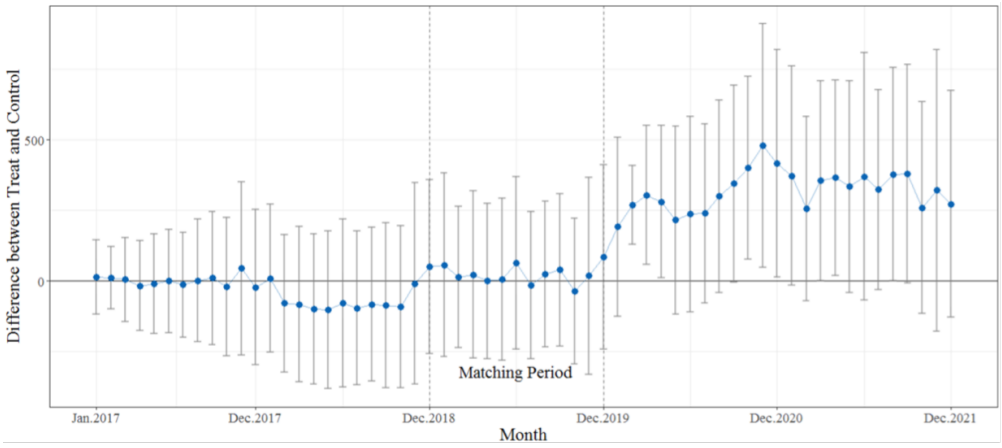
F: Resident Native to the City

Note: This figure shows the distribution of individual characteristics in the matched sample. Panel A is the year started using Alipay, Panel B is the year started using Taobao. Panel C shows the distribution of education level. Panel D distribution of the occupation. Panel E is about car ownership, and Panel F shows whether individuals live as native residents. All variables in panels B to F are not used in the matching process.

Figure 5: Robustness Check with Alternative Dependent Variable



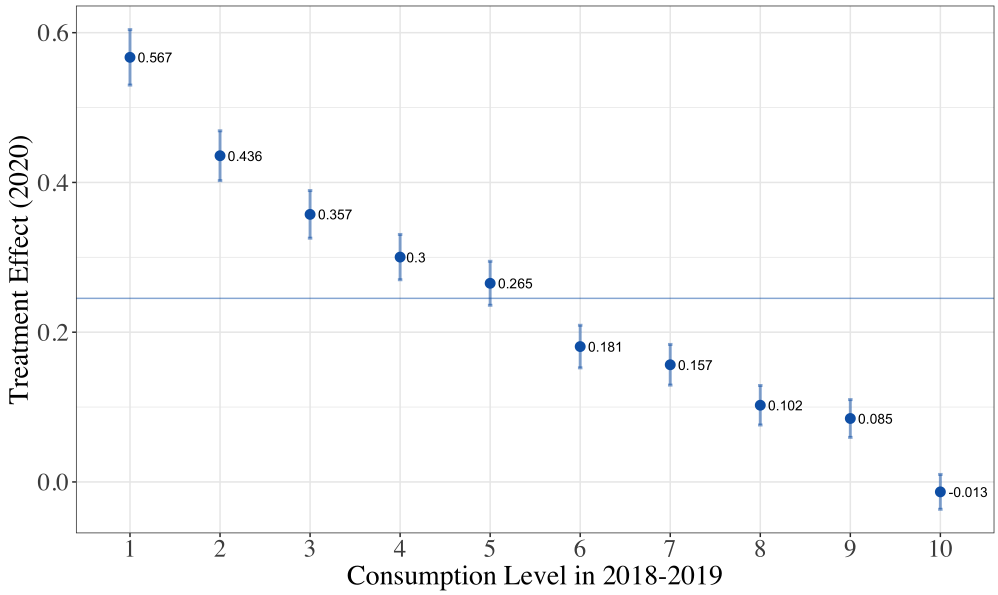
A: The Ratio Relative to Individual Average Monthly Consumption in 2019



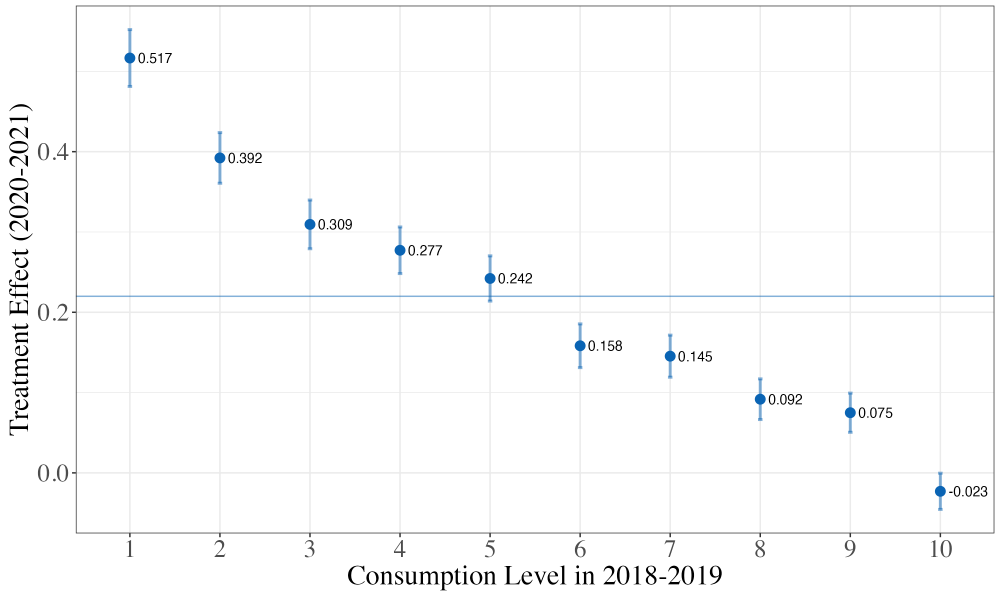
B: Monthly Consumption Amount (*yuan*)

Note. This figure shows two alternative approaches to defining the consumption variable and plotting the difference in the mean of treatment and control groups. Panel A shows the ratio relative to the average monthly consumption in 2019. For each consumer i, note her average monthly consumption in 2019H2 as base y_0^i, then define the ratio of consumer i in month t as $r_t^i = y_t^i / y_0^i$. In panel B, we simply use the amount of consumption in *yuan*. The standard error is at the 90% confidence level, clustered at the region level.

Figure 6: Treatment Effect and Income Level



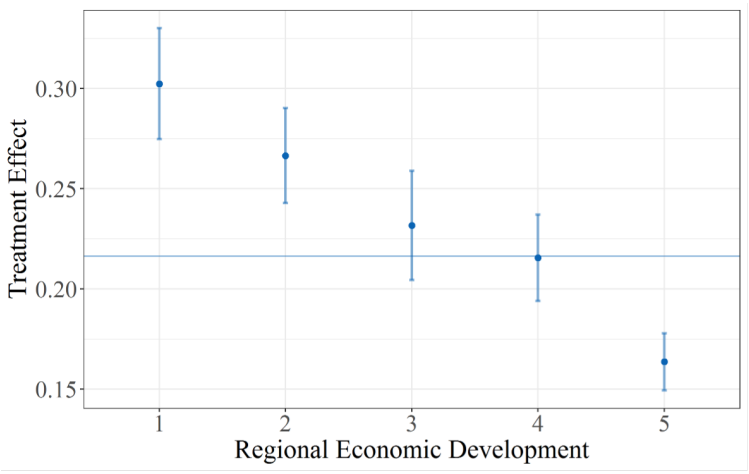
A: Treatment Effect in the Year 2020



B: Treatment Effect in 2020-21

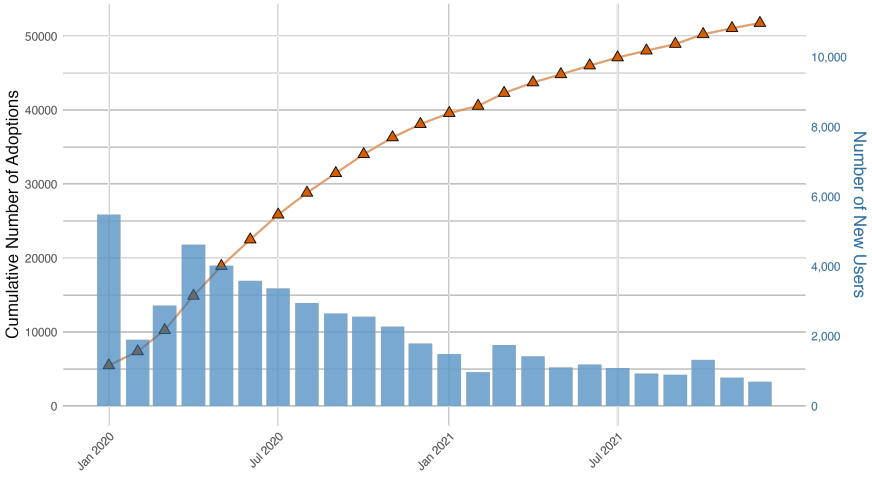
Note. This figure shows how the treatment effect varies with income levels. We categorize consumers into ten brackets according to their 2018-2019 consumption—from the lowest (group 1) to the highest (group 10). Then, estimate the treatment effect for each bracket. Figure A presents the Treatment Effect for the year 2020. The horizontal blue line represents the treatment effect of the full sample, 0.2452. Figure B shows the long-run treatment effect across 2020 and 2021, with a baseline estimation of 0.2199.

Figure 7: Treatment Effect and Regional Development

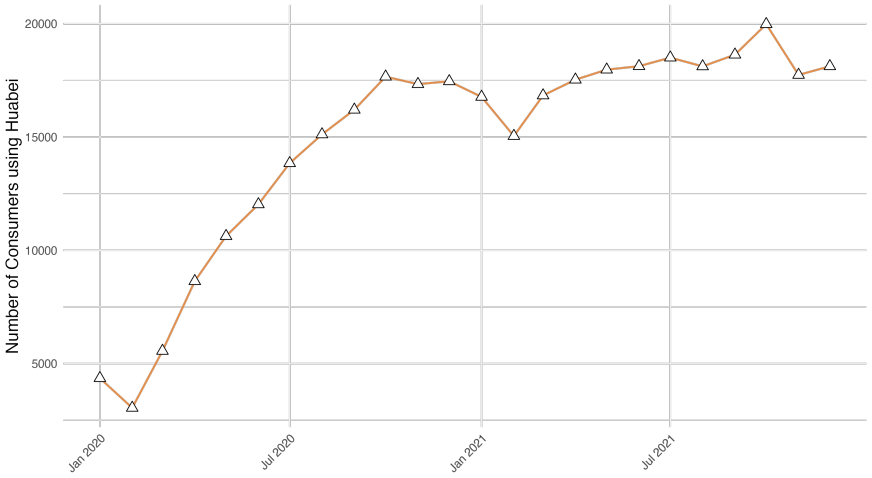


Note: This figure demonstrates the relationship between the treatment effect and regional development. Cities were divided into five groups based on their GDP per capita in 2019, from the lowest (group 1) to the highest (group 5). Then, we estimate the Treatment Effect over two years (2020-2021). The Treatment Effect is highest in the least developed group and decreases monotonically.

Figure 8: Post-Shock Fintech Credit Adoption in the Control Group



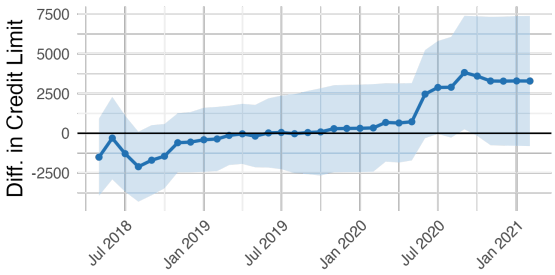
A: Number of Adoptions in the Control Group



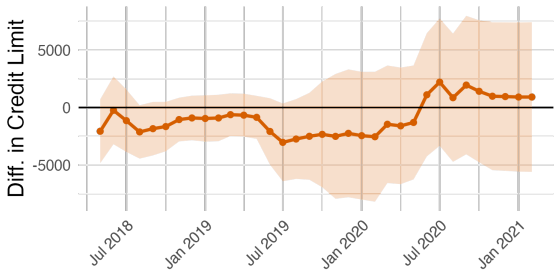
B: Monthly Active Adoptions in the Control Group

Note: This figure illustrate how consumers in the control group adapted to using Fintech Credit after the shock. In Panel A, the focus is on the monthly count of new Fintech credit users. Of the overall 159,514 consumers in the control group, 51,765 consumers had adopted Fintech credit by the end of 2021. Panel B shows the engagement levels, highlighting the frequency of Fintech credit payment usage among control group consumers on a monthly basis.

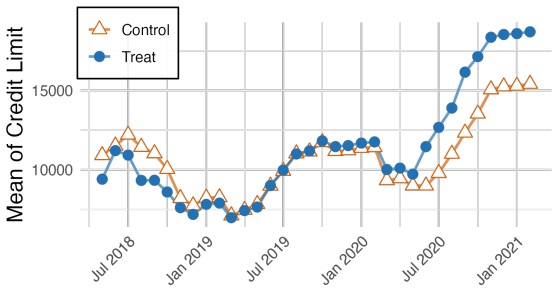
Figure 9: Credit Limit of a Sub-sample



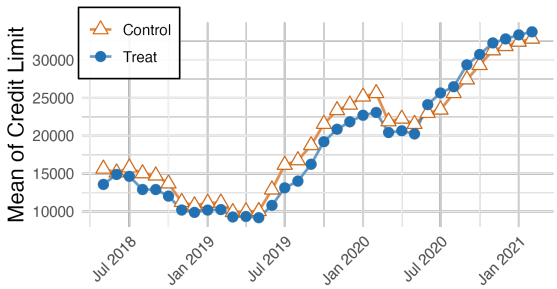
A: Fintech Credit Limit



B: External Credit Limit



C: Average Fintech Credit Limit



B: Average External Credit Limit

Note: This figure shows the credit limit for a sub-sample, where we have information on Fintech credit and total external credit for both consumers in the same matched pairs. It include 33,050 consumers of 16,525 pairs, approximately 10.4% of the matched sample. The total external credit include credit limit of credit cards from banks and the credit limits from other digital payment services. This data is only available from May 2018 to February 2021.

The proportion of consumers in this sub-sample that falls into each of our five defined consumer groups is 24.3%, 20.6%, 19.5%, 17.8%, and 17.7%, from low to high. It indicates the representitiveness of the sub-sample.

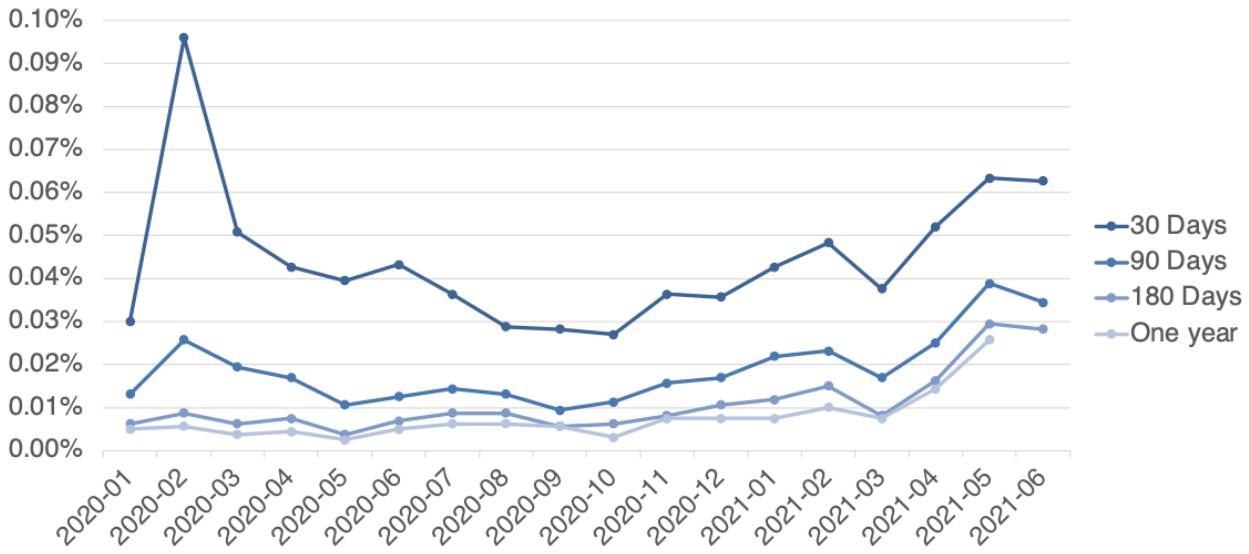
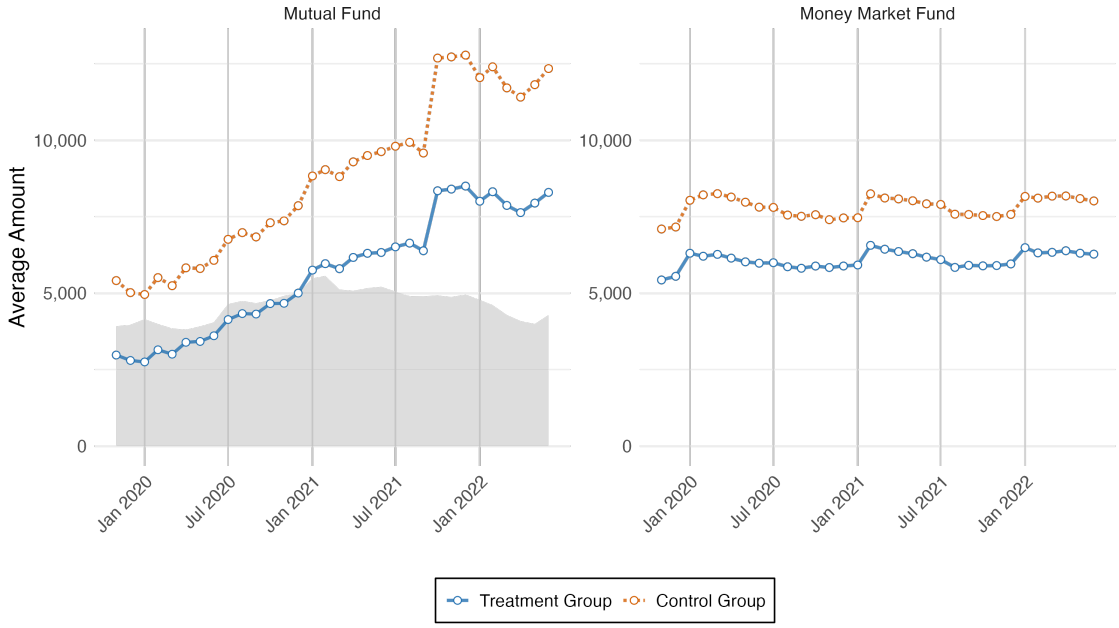


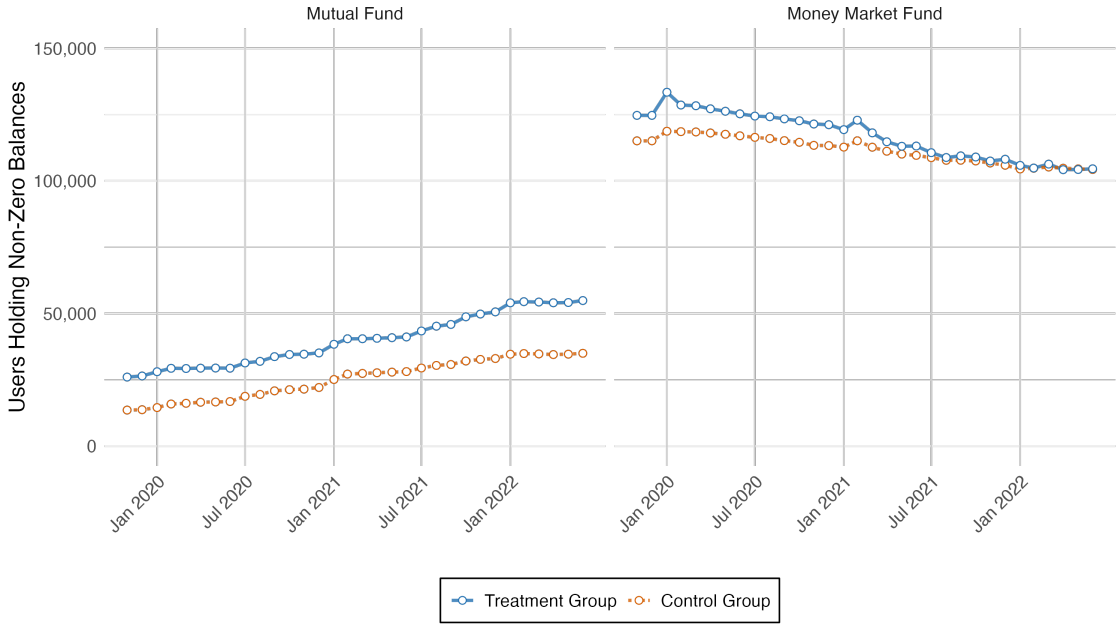
Figure 10: Share of Delinquent Consumers

Note: This figure plots the share of consumers having overdue payments in each month. On average, from 2020 to 2021, 0.29% of consumers in the treatment group had overdue balances each month. The rate is between 0.21% and 0.52%, where the highest is in 2020/2, the month following the shock. Among all consumers who have overdue payments, the average overdue balance is 3,458 *yuan*, while their Huabei spending bill in that month averages 8,682 *yuan*.

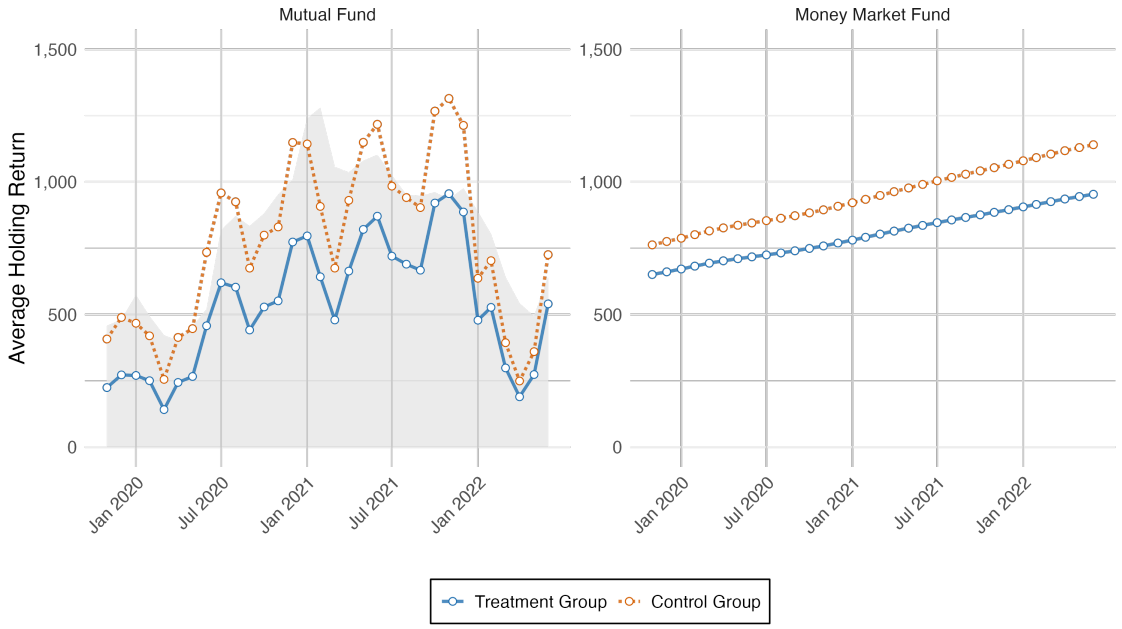
Figure 11: Asset Management on the Digital Payment Platform



A. Average End-of-Month Asset Balances



B. Number of Consumers with Non-zero Balances



C. Gains of Investment

Note: This figure illustrates the asset management activities on the digital payment platform of consumers in two groups. Panel A shows the average month-end balances in two main types of investment assets: Mutual Funds and Money Market Funds. The left panel depicts the average end-of-month balances invested in Mutual Funds, with the shaded area representing the *Shanghai and Shenzhen 300 Index*. The right panel shows the month-end balances in Money Market Funds, which can be used for real-time payments through the Yu'e Bao service. Panel B illustrates the monthly number of consumers holding a positive balance in these assets. Overall, more consumers in the treatment group participate in investments, but their average holding was lower. Panel C presents the cumulative returns obtained by consumers on the platform by they end of each month, with the shaded area again reflecting the change in *Shanghai and Shenzhen 300 Index*.

Between January 2020 and December 2021, control group consumers had an average Mutual Fund balance of 8,294 *yuan*, whereas treatment consumers held 5,313 *yuan*. For Money Market Funds, the average balances were 7,800 *yuan* for the control group and 6,063 *yuan* for the treatment group. The treatment group, on average, had 4,718 *yuan* less in assets than the control group. Over the two-year period, the control group earned 746 *yuan* from Mutual Funds and 279 *yuan* from Money Market Funds, while the treatment group earned 616 *yuan* and 224 *yuan*, respectively. In total, control group consumers earned 185 *yuan* more in returns than treatment group consumers.

Tables

Table 1: Summary Statistics of the Random Samples

A. Control sample (non-Huabei users)

	Mean	SD	P10	P50	P90	N consumers
Age	36.3	10.2	23	36	50	3,000,000
Gender (Is male)	0.525	0.499	0	1	0	3,000,000
Enter time (quarters from 2017)	3.97	3.15	1	3	9	3,000,000
Consumption 2018/12	2,053	4,692	0	543	5,298	3,000,000
Consumption 2019Q1	6,670	10,647	111	3,073	16,835	3,000,000
Consumption 2019Q2	7,439	9,498	563	4,012	18,731	3,000,000
Consumption 2019Q3	8,254	10,358	600	4,513	20,874	3,000,000
Consumption 2019Q4	5,308	9,132	75	2,285	13,217	3,000,000

B. Treatment sample (Huabei users)

	Mean	SD	P10	P50	P90	N consumers
Age	31.1	9.15	20	30	45	500,000
Gender (Is male)	0.548	0.498	0	1	2	500,000
Enter time (quarters from 2017)	2.86	2.19	1	2	6	500,000
Consumption 2018/12	2,555	4,851	77	1,198	5,786	500,000
Consumption 2019Q1	7,449	10,247	746	4,335	16,846	500,000
Consumption 2019Q2	8,204	9,050	1,276	5,204	18,855	500,000
Consumption 2019Q3	9,553	10,201	1,564	6,169	21,890	500,000
Consumption 2019Q4	6,682	9,710	511	3,723	15,279	500,000

Note: This table shows the summary statistics of the original random sample. The two samples include 3,500,000 consumers who are active in each month of 2019H2. Consumers in the control group did not use Huabei as a payment method before the end of 2019. The treatment group has used Huabei at least once in 2019H2. The *age* variable represents the consumer's age in 2019. The age variable is recorded by the end of 2019 and only includes those who are aged 18-60. The *enter time* variable represents the quarter in which consumers started using Alipay, with the first quarter of 2017 marked as Quarter 1. Anyone who began using Alipay before 2017 is assigned as a quarter 1. *Consumption* is the total amount consumers pay with Alipay in *yuan*. The types of transactions include online e-commerce, online payment, and QR code payment. Money transfers are not included in this variable.

Table 2: Comparison of Treatment and Control in the Matched Sample

	Before Matching (T=500,000, C=3,000,000)			Matched Sample (T=159,514, C=159,514)			P-value (clustered)
	Treated	Control	Difference	Treated	Control	Difference	
A. Individual Characteristics							
Age	31.1	36.3	-5.2	30.2	30.3	-0.092	0.769
	(9.17)	(10.20)		(7.91)	(7.84)		
Gender (Male=1)	0.547	0.525	0.022	0.476	0.476	/	/
	(0.498)	(0.499)		(0.499)	(0.499)		
Region (Big City=1)	0.457	0.568	-0.111	0.551	0.551	/	/
	(0.498)	(0.495)		(0.497)	(0.497)		
B. Consumption							
Consumption 2017	9,667	8,340	1,327	15,708	15,644	63	0.964
	(18,155)	(17,697)		(21,780)	(20,849)		
Consumption 2018	20,818	18,119	2,699	28,703	29,439	-736	0.712
	(29,014)	(29,613)		(29,937)	(29,423)		
Consumption 2019	31,877	28,138	3,739	37,722	37,398	324	0.872
	(30,179)	(31,743)		(29,432)	(29,019)		
Online Payment (2017-2019)	20,134	14,345	5,789	29,815	27,682	2133	0.256
	(31,771)	(28,330)		(37,512)	(34,998)		
Offline Payment (2017-2019)	42,228	40,251	1,977	52,317	54,799	-2482	0.515
	(49,088)	(54,134)		(50,093)	(52,587)		

Note: This table shows the mean of individual characteristics and consumption variables on the control and treatment in the original sample and the *analysis sample*, which implements the activeness requirement after the shock in the matched sample. We report the difference in mean and p-value after matching, except for *gender* and *region*, on which we apply an exact match. The p-value is clustered at the region level.

Table 3: Baseline Estimation of the Treatment Effect on Consumption

	(1) Two years 2020-2021	(2) Three months 2020/02-04	(3) Six months 2020H1	(4) First year Year 2020	(5) Second year Year 2021
Treat × *Post*	0.2199***	0.3966***	0.2871***	0.2452***	0.1945***
	(0.0049)	(0.0073)	(0.0057)	(0.0051)	(0.0054)
Individual FE	Yes	Yes	Yes	Yes	Yes
Year-Month FE	Yes	Yes	Yes	Yes	Yes
R^2	0.432	0.495	0.486	0.469	0.466
Obs.	19,141,680	12,442,092	13,399,176	15,313,344	15,313,344

Note: This table shows the baseline treatment effect of using Huabei on log consumption. Columns 1-5 represent the treatment effect in different periods. The effect is strongest in the three months following the shock, as shown in column 2. Over a longer period, the effect gradually decreases, moving from column 3 to column 4. The effect in the second year after the shock is weaker than in the first year, as illustrated in columns 4 and 5. Standard errors in parentheses. * p<0.10, ** p<0.05, *** p<0.01

Table 4: Treatment Effect by Consumption Category

Spend-ing	Category	3-Months	2020H1	2020	2020-2021	Share
SND	Food Away From Home	17.95***	17.17***	16.94***	14.52***	19.77%
		(0.30)	(0.24)	(0.18)	(0.15)	
ND	Misc. Nondurables	14.33***	13.76***	14.30***	15.15***	12.51%
		(0.51)	(0.41)	(0.31)	(0.25)	
ND	Retail Nondurables	13.14***	11.89***	12.23***	14.41***	15.08%
		(0.39)	(0.32)	(0.24)	(0.19)	
D	Entertainment	9.66***	8.91***	11.49***	13.45***	3.07%
		(0.74)	(0.59)	(0.43)	(0.35)	
D	Retail Durables	9.42***	8.10***	8.60***	8.86***	4.76%
		(0.67)	(0.53)	(0.39)	(0.34)	
SND	Prof. & Pers. Services	9.30***	9.08***	9.51***	11.53***	6.94%
		(0.44)	(0.36)	(0.27)	(0.23)	
D	Home Improvement	9.18***	6.78***	7.23***	6.24***	4.00%
		(1.09)	(0.88)	(0.67)	(0.56)	
D	Hotels & Rental Cars	8.48***	6.75***	4.60***	3.12***	2.41%
		(1.39)	(1.06)	(0.74)	(0.59)	
SND	Groceries	6.94***	7.64***	9.33***	8.98***	13.17%
		(0.28)	(0.23)	(0.18)	(0.14)	
D	Insurance	5.21	5.00	3.35	3.36	0.87%
		(7.16)	(5.45)	(3.41)	(2.75)	
ND	Department Stores	4.76***	3.77***	3.01***	3.07***	2.15%
		(1.02)	(0.84)	(0.64)	(0.54)	
SND	Ground Transportation	3.84***	4.07***	3.35***	3.23***	4.55%
		(0.39)	(0.31)	(0.23)	(0.19)	
D	Auto Repair	3.59***	2.49***	3.22***	3.93***	2.54%
		(1.19)	(0.96)	(0.71)	(0.60)	
SND	Flights	2.16	2.45	−2.44	−1.58	0.07%
		(2.74)	(2.25)	(1.72)	(1.61)	
SND	Utilities	−0.76	0.33	4.30***	4.64***	0.30%
		(2.41)	(2.04)	(1.62)	(1.42)	
ND	Drug Stores	−0.78	−0.53	1.70***	3.19***	1.41%
		(0.66)	(0.55)	(0.43)	(0.36)	
ND	Medical Copay	−1.00	−0.40	0.32	0.01	3.87%
		(1.11)	(0.90)	(0.66)	(0.54)	
D	Misc. Durables	−4.28*	−1.19	−2.85**	−2.65**	1.79%
		(2.35)	(1.84)	(1.28)	(1.08)	
SND	Telecom	−9.61***	−7.38***	−0.77	0.51	0.75%
		(2.83)	(2.38)	(1.84)	(1.48)	

Table 5: The Intensity of Shocks

A.Effects from Various Duration of Lockdown Policy

	(1) Baseline	(2) Average lockdown days in a region	(3) Weighted by population
$Treat \times Post$	0.2199***	0.1095***	0.1287***
	(0.0049)	(0.0073)	(0.0073)
$Treat \times Post \times log(Lockdown\ days)$		0.0531***	0.0449***
		(0.0027)	(0.0027)
Individual FE	Yes	Yes	Yes
Year-Month FE	Yes	Yes	Yes
R^2	0.432	0.432	0.432
Num. Obs.	19,141,680	19,117,200	19,117,200

B. For Different Income Groups

	(1) Bottom 1/3	(2) Middle 1/3	(3) Top 1/3
$Treat \times Post$	0.1674***	0.1463***	0.0986***
	(0.0142)	(0.0120)	(0.0106)
$Treat \times Post \times log(Lockdown\ days)$	0.0512***	0.0439***	0.0286***
	(0.0052)	(0.0035)	(0.0041)
Individual FE	Yes	Yes	Yes
Year-Month FE	Yes	Yes	Yes
R^2	0.419	0.366	0.343
Num. Obs.	6,342,840	6,365,640	6,408,720

Note: Panel A shows the treatment effect and its interactions of lockdown days in a *region*. The city government determines the lockdown duration. In our definition, the *'region'* may encompass several cities when consumers are not in big cities. So there might e variations in the timing of lifting the lockdown among cities in one *region*. The lockdown duration used in column (2) is the average of these cities' lockdown durations. In column (3), we use the population of the cities as weights to calculate the lockdown duration for that region.
Panel B shows the treatment effect and its interactions with lockdown duration for consumers from different income levels. We categorised consumers into three groups based on their consumption levels in 2019. The treatment effect gradually decreases from the lowest to the highest income group. Moreover, the impact of the pandemic on the treatment effect also diminishes accordingly.
Standard errors in parentheses. * p<0.10, ** p<0.05, *** p<0.01

Table 6: Treatment Effect and Regional Development

	(1) Baseline	(2) Big cities	(3) Other regions
$Treat \times Post$	0.2199***	0.1855***	0.2621***
	(0.0049)	(0.0060)	(0.0078)
Individual FE	Yes	Yes	Yes
Year-Month FE	Yes	Yes	Yes
R^2	0.432	0.407	0.458
Num. Obs.	19,141,680	10,551,960	8,589,720

Note: This table shows the treatment effect and the level of regional development. Column (1) shows the baseline regression of the full sample; column (2) shows the groups that live in big cities, including 40 cities in China; column (3) includes consumers living in other places. The treatment effect in big cities is smaller than the effect for consumers in less developed areas. Standard errors in parentheses. * p<0.10, ** p<0.05, *** p<0.01

Table 7: Treatment Effect and Education

	(1) High school or below	(2) Post-secondary	(3) College	(4) Graduate
$Treat \times Post$	0.2606***	0.2044***	0.0921***	0.0605***
	(0.0060)	(0.0158)	(0.0103)	(0.0193)
Individual FE	Yes	Yes	Yes	Yes
Year-Month FE	Yes	Yes	Yes	Yes
R^2	0.444	0.420	0.418	0.330
Num. Obs.	7,476,760	2,903,520	6,666,480	1,272,480
Share of Obs.	40.81%	15.85%	36.39%	6.95%

Note: This table displays the treatment effect across different levels of education. Column 1 is for individuals with high school education or below, Column 2 is for those with post-secondary education, Column 3 is for consumers with a college degree, and Column 4 is for consumers with a graduate degree, including master's or doctoral degrees. A noticeable trend is the diminishing treatment effect with rising educational levels. Standard errors in parentheses. * p<0.10, ** p<0.05, *** p<0.01

Table 8: Treatment Effect and the Financial Sophistication Index

A. Financial Sophistication Index as an Interaction Term

	(1) 2020-2021	(2) 2020/02-04	(3) 2020H1	(4) Year 2020	(5) Year 2021
$Treat \times Post$	0.4191***	0.6165***	0.4895***	0.4533***	0.3848***
	(0.0081)	(0.0117)	(0.0092)	(0.0083)	(0.0088)
$Treat \times Post \times FS$	−0.3258***	−0.3415***	−0.3249***	−0.3380***	−0.3137***
	(0.0089)	(0.0130)	(0.0102)	(0.0092)	(0.0098)
Individual FE	Yes	Yes	Yes	Yes	Yes
Year-Month FE	Yes	Yes	Yes	Yes	Yes
R^2	0.427	0.489	0.480	0.464	0.459
Num. Obs.	15,789,600	10,263,240	11,052,720	12,631,680	12,631,680

B. Different Financial Sophistication Levels

	(1) $FS = 0$	(2) $FS \in (0, 0.5]$	(3) $FS \in (0.5, 1)$	(4) $FS = 1$
$Treat \times Post$	0.2934***	0.2084***	0.1884***	0.1816***
	(0.0124)	(0.0134)	(0.0092)	(0.0081)
Individual FE	Yes	Yes	Yes	Yes
Year-Month FE	Yes	Yes	Yes	Yes
R^2	0.454	0.433	0.420	0.411
Num. Obs.	3,549,000	2,518,080	4,733,400	6,132,120
Share of Obs.	21.0%	14.9%	28.0%	31.2%

Note: This table shows the treatment effect and the level of financial sophistication. For each consumer i, define the financial sophistication index as the share of "interest generated balance" used in all transactions in 2019:

$$FS_i = MMF_i / (MMF_i + Balance_i)$$

$FS = 1$ means very sophisticated, and the consumer actively takes advantage of the interest-generated service. Panel A shows the regression results using the Financial Sophistication Index (FS) as an interaction term. The results indicate that an increase in FS from 0 to 1 significantly reduces the treatment effect. In Panel B, consumers are divided into four groups based on the FS Index. The treatment effect decreases sequentially as the FS Index increases from low to high. Standard errors are shown in parentheses. * p<0.10, ** p<0.05, *** p<0.01.

Table 9: The Adoption and Exit of Fintech Credit

	(1) Baseline	(2) Treatment including new adoption	(3) Treatment excluding exit	(4) Entry & Exit
Treat × *Post*	0.2199***	0.2406***	0.3214***	0.2875***
	(0.0049)	(0.0047)	(0.0078)	(0.0042)
Individual FE	Yes	Yes	Yes	Yes
Year-Month FE	Yes	Yes	Yes	Yes
R^2	0.432	0.432	0.432	0.432
Num. Obs.	19,141,680	19,141,680	19,141,680	19,141,680

Note: This table presents the estimations considering consumers in the control group adopting Fintech credit and the treatment group not using it. Panel A introduces the definitions of "enter" and "exit". In column 2, we consider entry, where treatment is denoted as 1 for the months including and after a consumer in the control group started using Huabei. In column 3, we consider exit, where treatment is denoted as 0 after a consumer in the treatment group is not using Huabei until the end of 2021. Column 4 includes both entry and exit. Standard errors in parentheses. * p<0.10, ** p<0.05, *** p<0.01.

Table 10: The Feasibility of Using Fintech Credit

	(1) 2020-21	(2) 2020/2-4	(3) 2020H1	(4) Year 2020	(5) Year 2021
Treatment × *Post*	0.1786***	0.3576***	0.2566***	0.2127***	0.1445***
	(-0.0068)	(-0.0101)	(-0.0078)	(-0.0070)	(-0.0075)
Individual FE	Yes	Yes	Yes	Yes	Yes
Year-Month FE	Yes	Yes	Yes	Yes	Yes
R^2	0.421	0.485	0.476	0.459	0.454
Num. Obs.	9,868,800	6,414,720	6,908,160	7,895,040	7,895,040

Note: This table shows the treatment effect of the sub-sample in which the control group could access Fintech credit if they apply. We restrict the control group to those who could have the service but did not activate it, intentionally or unintentionally. Then we estimated the treatment effect for different periods. There are 82,240 of the 159,514 consumers in the control group who can access Huabei (but do not open the service). Standard errors in parentheses. * p<0.10, ** p<0.05, *** p<0.01.

Table 11: The Effect on City-Level Retail Sales

	Dependent Variable: log(*Retail per capita*)			
	2020-21		2020H1	
	(1)	(2)	(3)	(4)
$\log(y_{\textit{Fintech Credit}})$	0.25***	0.26***	0.35***	0.38***
	(0.03)	(0.03)	(0.05)	(0.06)
$\log(y_{\textit{Total Payment}})$		−0.02		−0.04
		(0.02)		(0.04)
City FE	Yes	Yes	Yes	Yes
Year-Month FE	Yes	Yes	Yes	Yes
R^2 Adj.	0.967	0.967	0.976	0.976
Num. Obs.	2700	2700	611	611

(a) Monthly, 130 Cities

	2020-21		2020H1	
	(1)	(2)	(3)	(4)
$\log(y_{\textit{Fintech Credit}})$	0.18***	0.17***	0.36***	0.35***
	(0.04)	(0.05)	(0.10)	(0.11)
$\log(y_{\textit{Total Payment}})$		0.00		0.01
		(0.03)		(0.01)
City FE	Yes	Yes	Yes	Yes
Year-Month FE	Yes	Yes	Yes	Yes
R^2 Adj.	0.972	0.972	0.983	0.983
Num. Obs.	1834	1834	405	405

(b) Quarterly, 291 Cities

Note: This table shows the effect of fintech credit consumption on variations of retail sales at the city level. Among the 337 cities in the population, 130 cites have monthly time series of retails sales and 291 cities report quarterly. We construct the fintech credit and total payment per user for each city with the random sample of 943,874 consumers drawn from all users who have used fintech credit in 2019H2. * p<0.05, ** p<0.01, *** p<0.001.

Table 12: Heterogeneity Analysis: Age, Gender, and Occupation

	(1) Baseline	(2) Male	(3) Female
Treat × *Post*	0.2199***	0.2500***	0.1925***
	(0.0049)	(0.0074)	(0.0065)
Individual FE	Yes	Yes	Yes
Year-Month FE	Yes	Yes	Yes
R^2	0.432	0.437	0.427
Num. Obs.	19,141,680	9,107,040	10,034,640

(a) Gender

	(1) Under 25	(2) 26-30	(3) 31-35	(4) 35-40	(5) 41-45	(6) 45+
Treat × *Post*	0.1842***	0.2683***	0.2384***	0.2292***	0.1756***	0.1578***
	(0.0082)	(0.0090)	(0.0113)	(0.0154)	(0.0218)	(0.0223)
Individual FE	Yes	Yes	Yes	Yes	Yes	Yes
Year-Month FE	Yes	Yes	Yes	Yes	Yes	Yes
R^2	0.425	0.387	0.431	0.461	0.499	0.522
Obs.	6,060,120	5,032,920	3,705,660	2,184,300	1,151,700	1,193,700

(b) Age (in 2019)

	(1) White Collar	(2) Blue Collar	(3) Students	(4) Teachers	(5) Civil Servants	(6) Medical Staff	(7) Public Co. Employee
Treat × *Post*	0.1084***	0.3502***	0.1066***	0.1185***	0.1003***	0.2451***	0.0722*
	(0.0081)	(0.0176)	(0.0182)	(0.0206)	(0.0617)	(0.0389)	(0.0313)
Indiv. FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year-Month FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
R^2	0.369	0.491	0.482	0.388	0.404	0.400	0.378
Obs.	9,894,120	3,749,160	2,974,560	1,639,440	221,880	532,320	598,320
Share	51.7%	19.6%	15.5%	8.6%	1.2%	2.8%	3.1%

(c) Occupation

Note: This table shows the treatment effect across different demographic characteristics. Standard errors in parentheses. * p<0.10, ** p<0.05, *** p<0.01.

A Consumption Data Cleaning and Classification

As we are using observed payments from Alipay as a proxy variable of consumers' consumption expenditure, it is necessary to provide a detailed explanation of the composition of these payments, consumers' usage patterns, and the criteria and procedures we applied in selecting the transaction data.

A.1 Payments for Consumption

There are three main categories of consumers' payment activities on Alipay: online payments, in-person payments, and transfers.

(1) *Online payments*.

So-called online payments include payments made via mobile devices or PC browsers, where merchants use Alipay's API to facilitate payments through the mobile app or web platform. After initiating a transaction, the consumer is redirected to the Alipay app or web platform to complete the payment process. Typical usage scenarios include e-commerce platforms, on-demand delivery services, ride-sharing services, and other digital transactions.

(2) *In-person payments*

In-person payments include scenarios where consumers are physically present during the transaction, using mobile devices or biometric authentication. When making a payment, consumers can scan the merchant's QR code or allow the merchant to scan their payment barcode if a scanner is available. With compatible point-of-sale equipments, consumers may also complete the payment through NFC contact or facial recognition. QR code payments are the most widely utilized among these options, primarily because merchants require only a plastic QR code card, which payment platforms typically provide for free.

(3) *Transfers*

Transfers involve consumers sending money to other Alipay accounts or bank account. This type of payment typically occurs between acquaintances serving purposes such as social gifting or splitting a bill. The main difference of transfer with the previous two categories is that consumers cannot use credit card or fintech credit in transfer.

For the first two payment types, recipients needs proper authorization to receive payments. If the recipient is a business entity, they are assigned a Merchant Category Code (MCC) specific to their industry. Since digital payments are extensively utilized by small individual businesses, often informal and without formal registration, the platform develops algorithms to distinguish business transactions from personal ones[21]. For these two types of transactions, we directly use the MCC labels

[21]The main goal behind creating the algorithms was to identify merchants and, based on their business activity, offer them micro-loans. We utilize the outcomes of this algorithm to filter consumption transactions. These algorithms

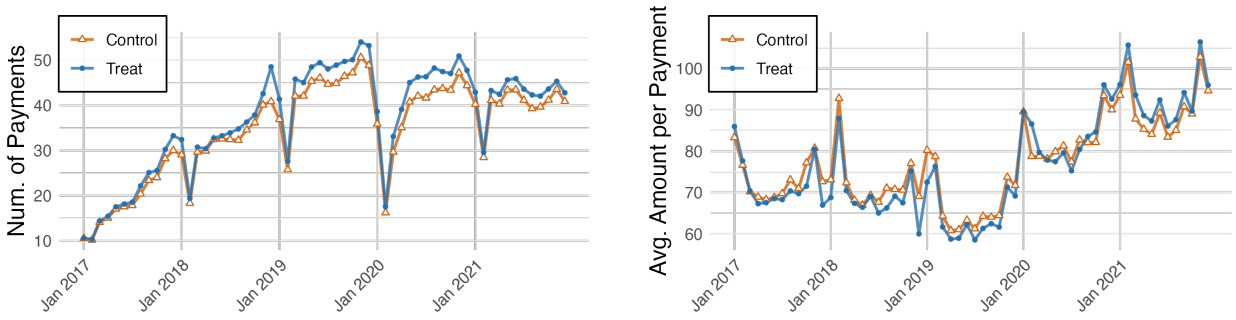
or the algorithm's classification of long-tail merchants to classify transactions into their respective consumption categories.

For transfers, we decide based on whether the recipient is classified as a merchant by the algorithm and filtered out non-commercial transactions. Firstly, their share of the total payment volume is very small (less than 0.1%), and secondly, we have insufficient information on these payments.

Among the 411 MCC classifications, Table A1 lists the 17 MCC categories with transaction shares exceeding 1%. Restaurants top the list in terms of both transaction volume and count, followed by miscellaneous personal services and grocery stores, each accounting for the next largest share of transaction volume and frequency.

Figure 1 illustrates the average monthly spending amount, while Figure A1 provides the monthly transaction count and the average amount per payment of consumers in the matched sample. Over the five years from 2017 to 2021, the data covers an average of 37.0 payments per month per consumer, with each payment averaging 76.0 *yuan* ($11). As a comparison, the annual Diary of Consumer Payment Choice report conducted by the Federal Reserve recorded that a representative U.S. consumer made an average of 36.6 monthly payments during the same period[22].

Figure A1: The Payment Usage of Consumers in the Matched Sample



A. Number of Payment

B. Amount of Each Payment

Note: This figure shows the consumers' payment usage. Panel A plots the number of payments made by consumers in treatment and control groups from Jan. 2017 to Dec 2021. Panel B, plots the average amount of each payment in the two groups.

analyze transaction network patterns, payment amounts, and transaction frequency. For merchants, the algorithms also predict the industry of the recipient.

[22]The survey is conducted in each October. In our sample, the average number of payments in each October is 39.6. For the details of the report, see https://www.frbservices.org/news/research/2024-findings-from-the-diary-of-consumer-payment-choice

A.2 Method of Payment

The methods of payment include credit card, debit card, Huabei, balance, and Yu'e Bao. Consumers can set up and rank their preferred methods or cards in advance. When a payment is initiated, the consumer's payment page displays a default payment method, which is the highest-ranked option that the merchant accepts. Alternatively, consumers can take an additional step to choose another accepted payment method.

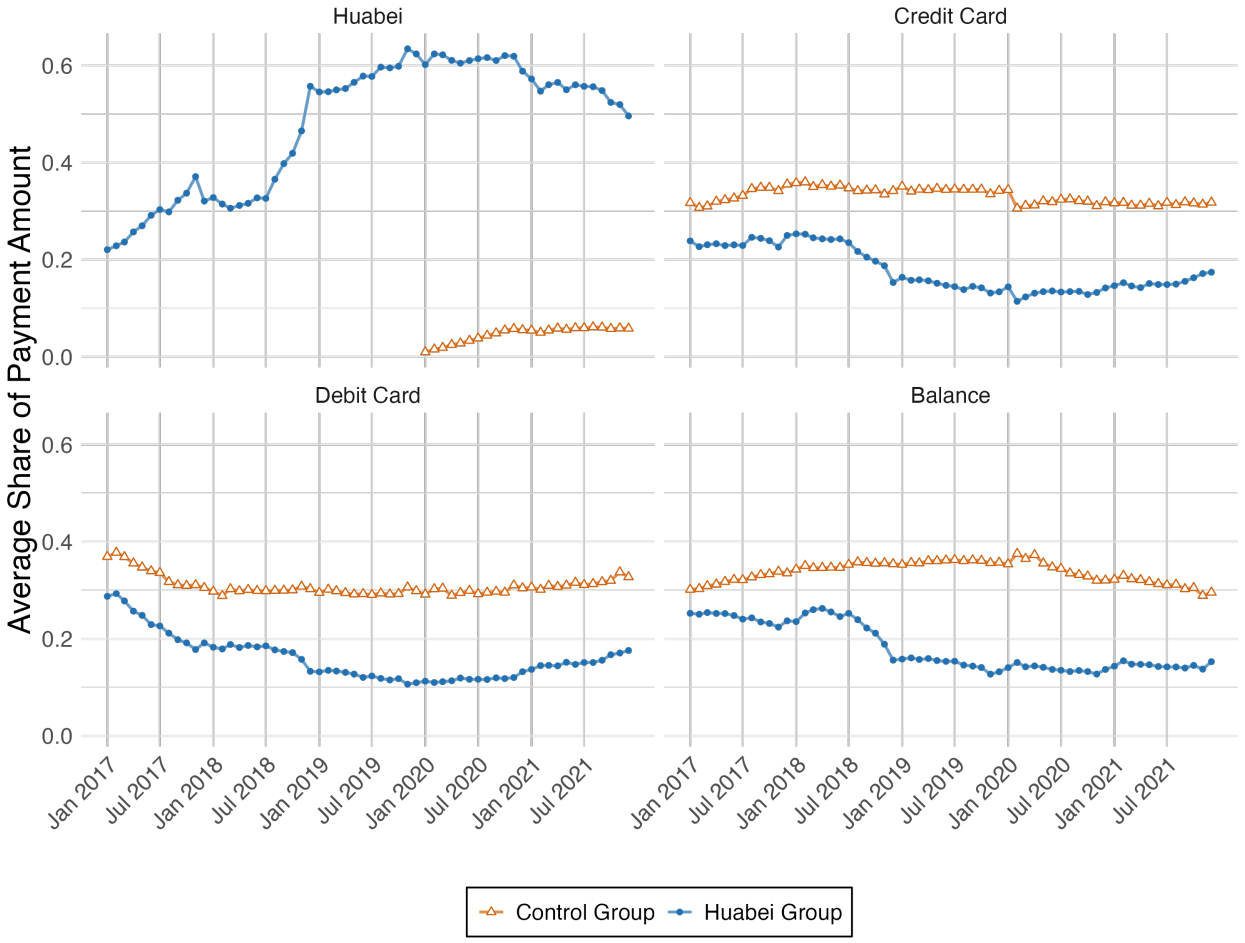


Figure A2: Usage across Different Payment Methods

Note: This figure shows the average share of amounts made with various payment methods in each group. The control group consumers use the three payment methods in roughly equal proportions. The treatment group consumers use fintech credit significantly higher htan the other three methods, the share is over 60% in 2020.

Non-credit payment methods, including debit card, balance payment, and Yu'e Bao, are universally accepted for all payments. The use of credit-based payments, Huabei and credit cards, however,

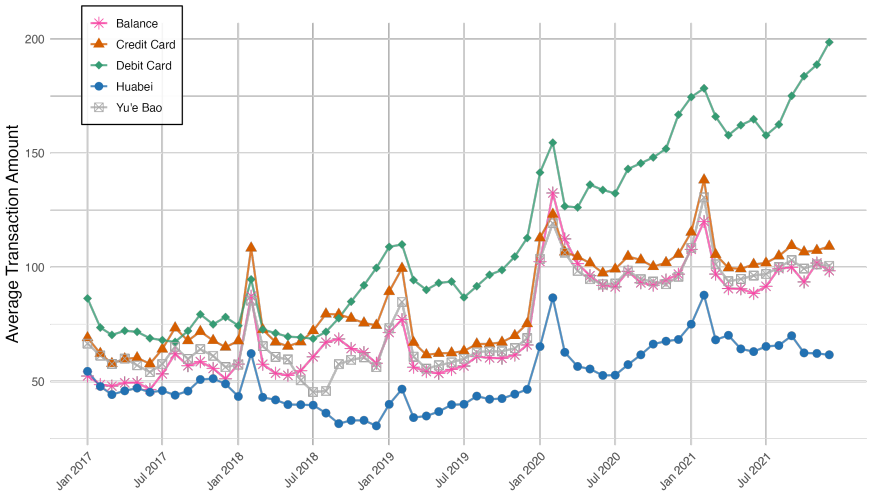


Figure A3: Per-transaction Amount by Different Payment Methods

Note: This figure shows the average amounts per transaction made with various payment methods. The per-transaction amount for debit card payments is relatively large. In contrast, Fintech credit transactions are significantly lower than all other payment methods, indicating that it is widely used for small, everyday purchases that traditional payment systems do not cover.

is subject to the merchant's acceptance. Some merchants may not accept Huabei or credit card payments because Alipay or the banks may impose withdrawal fees or transaction fees on these payment types. Some merchants may be unwilling to accept credit cards or fintech credit due to the additional processing fees, which generally range from 0.6% to 0.8% of the payment amount.

A.3 Representativeness of Consumption

To ensure the representativeness of consumption data in the matched sample, we applied two procedures. First, in the random sample selection, we required consumers to be active on the digital payment platform every month in the second half of 2019. Second, after obtaining the initial matched sample, we added further criteria on the activitness following the shock.

In Table A2, we use the annual per capita consumption expenditurefrom National Bureau of Statistics (NBS) for each year in 2017-21, and for 2018, we also reference survey data from the China Family Panel Studies (CFPS), as comparable benchmarks. Since our study excludes individuals under age 18 and over 60, we adjusted the sample annual consumption by the population proportion of those aged 18 to 59 for each year. Columns (5) and (6) show that, from 2018 to 2021, the sample consumption ranges from 90% to 126% of the national average and 72% to 99% of the average consumption by urban residents. The exception is 2017, a year in which digital payments were still experiencing rapid adoption.

In addition, the median consumption of 2018-2019 is 25,308, with a median-mean ratio of 0.76. According to the NBS report, in 2019, the median-mean ratio of national, urban, and rural disposable income per capita was 0.86, 0.92, and 0.89, respectively. Considering that the low-income group has a higher MPC, the median-mean ratio of consumption would be smaller. It suggests that the matched sample is a reasonable sample distribution.

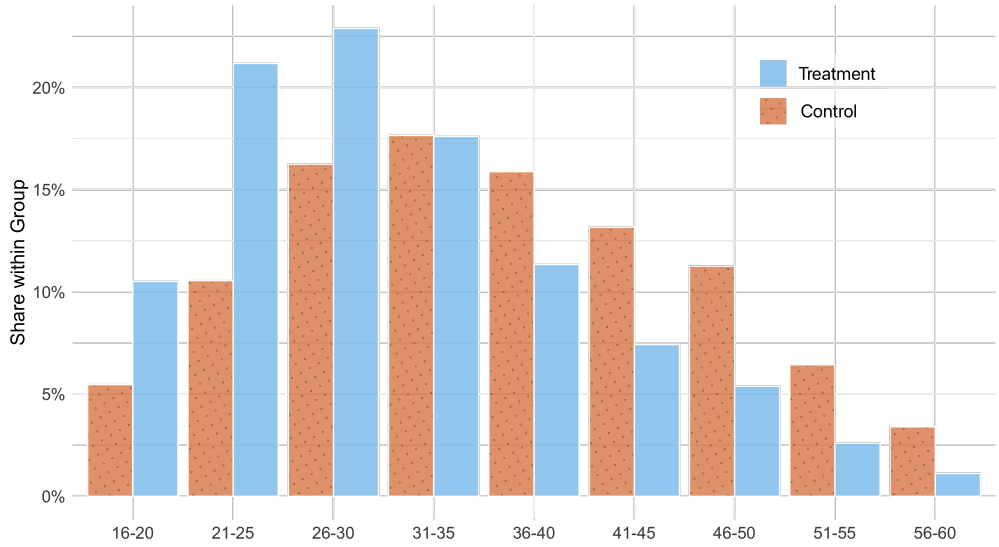
B Robustness Check of Matching

B.1 The selection of active consumers

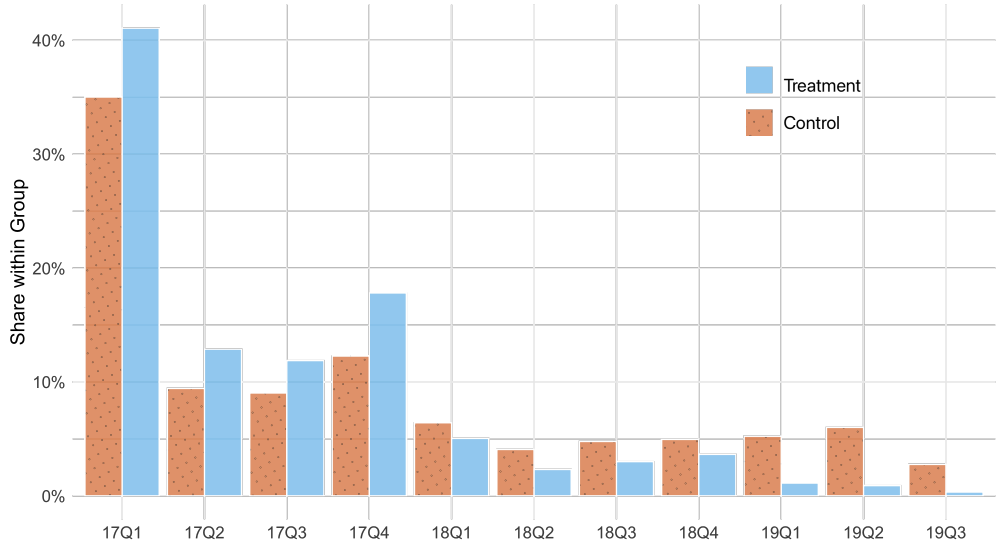
To control the two groups having similar payment preferences over the usage of the payment platform after the shock, we eliminate those consumers who were not active in the two years following the shock. The treatment effect in the two years period is 40.66%, much higher than the baseline estimation. Figure A5 plots the difference in the average logarithm of monthly consumption between treatment and control groups in this sample. Compared to the baseline in Figure 2, the difference after shock is consistently larger. Since the treatment group in this sample is more active than the consumers in the control group after the shock, it amplified the estimate of the treatment effect.

Regarding our selection criteria, stricter standards reduce the treatment effect while increasing the consistency of observed payment information between the two groups. Table A4 shows the treatment effect of various selection criteria. We chose a relatively strict one among these criteria, so we consider our baseline results to represent a lower bound of the treatment effect.

Figure A4: Distribution of Age and Digital Payment Adoption Time in Random Samples



A. Distribution of Age



B. Distribution of Digital Payment Adoption Time

Note: This figure shows the distribution of age and the time of using digital payment in the sample before matching. Figure A displays the distribution age, where we can observe that the Treatment (Huabei) group has a younger age distribution than the control group. Figure B shows the distribution of the time of using digital payment. The treatment group has a higher proportion of early users than the control group.

Table A1: Top MCC Merchants Types in Payments

No.	MCC code	Amount	Count	Group	Category	Merchant Type
1	5812	16.8%	25.3%	SND	Food Away From Home	Eating places and Restaurants
2	7299	8.8%	4.9%	ND	Misc. Nondurables	Miscellaneous Personal Services
3	5411	7.9%	11.9%	SND	Groceries	Grocery Stores, Supermarkets
4	5699	4.4%	1.5%	ND	Retail Nondurables	Misc. Apparel and Accessory Shops
5	5399	3.2%	2.2%	ND	Retail Nondurables	Misc. General Merchandise
6	8062	2.6%	0.8%	ND	Medical Copay	Hospitals
7	5422	2.5%	5.4%	SND	Groceries	Meat Provisioners - Freezer and Locker
8	5712	2.5%	0.6%	D	Home Improvement	Furniture, Home Furnishings, and Equipment Stores
9	5311	1.9%	0.9%	ND	Department Stores	Department Stores
10	5732	1.8%	0.5%	D	Retail Durables	Electronic Sales
11	7011	1.8%	0.4%	D	Hotels & Rental Cars	Lodging - Hotels, Motels, Resorts, Central Reservation Services
12	4121	1.6%	5.0%	SND	Ground Transportation	Taxicabs and Limousines
13	7994	1.6%	1.1%	D	Entertainment	Video Game Arcades/Establishments
14	7531	1.4%	0.5%	D	Auto Repair	Automotive Body Repair Shops
15	7298	1.4%	0.5%	SND	Professional & Personal Services	Health and Beauty Shops
16	5331	1.2%	2.7%	ND	Retail Nondurables	Variety Stores
17	5122	1.1%	0.7%	ND	Drug Stores	Drugs, Drug Proprietors, and Druggist's Sundries

Notes: This table shows merchant types with a transaction amount share greater than 1% of all payments. Among all payments records, 8.879% of the transaction amount (5.814% of the transaction count) was directed to recipients without an assigned MCC code. Out of 407 MCC codes, we successfully matched 369, and 0.018% of the total transaction amount was unmatched (0.016% of the transaction count).

Table A2: Representativeness: Consumption Data Compared to External Benchmark

Year	Sample	National	Urban	Rural	Ratio(%) $\frac{(1)\cdot adj.}{(2)}$	Ratio(%) $\frac{(1)\cdot adj.}{(3)}$	Source
	(1)	(2)	(3)	(4)	(5)	(6)	
2017	15,672	18,322	24,445	10,955	56.3	42.2	NBS
2018	29,076	19,853	26,112	12,124	95.6	72.7	NBS
		15,882	20,890	9,699	90.6	90.8	CFPS
2019	37,560	21,559	28,063	13,328	111.5	85.7	NBS
2020	42,720	21,210	27,007	13,713	125.9	98.9	NBS
2021	48,084	24,100	30,307	15,916	124.7	99.2	NBS

Note: This table shows a comparison of the annual consumption amounts of two groups of consumers in our matched sample, along with data from other sources. We use the annual per capita consumption expenditure from National Bureau of Statistics (NBS), and for 2018, we reference survey data from the China Family Panel Studies (CFPS). Since our study excludes individuals under age 18 and over 60, we adjusted the ratios in columns 5 and 6 according to the population proportion of those aged 18 to 59 for each year. The adjustment ratios for the five years are as follows: 65.9%, 65.3%, 65.3%, 64.0%, and 62.5%.

Table A3: Covariates Table of Matched Sample without Controlling Activeness

	Before Matching (T=500,000, C=3,000,000)			After Matching (T=228,062, C=228,062)			P-value (clustered)
	Treatment	Control	Difference	Treatment	Control	Difference	
A. Individual Characteristics							
Age	31.1	36.3	-5.2	30.4	30.5	-0.090	0.779
	(9.17)	(10.20)		(8.13)	(8.07)		
Gender (Is male)	0.547	0.525	0.022	0.479	0.479	/	/
	(0.498)	(0.499)		(0.500)	(0.500)		
Region: Is big city	0.457	0.568	-0.111	0.506	0.506	/	/
	(0.498)	(0.495)		(0.500)	(0.500)		
B. Consumption							
Consumption 2017	9,667	8,340	1,327	13,926	13,875	52	0.969
	(18,155)	(17,697)		(20,486)	(19,839)		
Consumption 2018	20,818	18,119	2,699	25,879	26,316	-437	0.825
	(29,014)	(29,613)		(28,197)	(27,602)		
Consumption 2019	31,877	28,138	3,739	34,684	34,366	317	0.875
	(30,179)	(31,743)		(28,711)	(28,269)		
Online Payment (2017-2019)	20,134	14,345	5,789	26,945	25,333	1,612	0.378
	(31,771)	(28,330)		(35,243)	(33,438)		
Offline Payment (2017-2019)	42,228	40,251	1,977	47,544	49,224	-1,680	0.656
	(49,088)	(54,134)		(48,164)	(50,410)		

Note: This table shows the mean of individual characteristics and consumption variables on the control and treatment before and after matching. We report the difference in mean and p-value after matching, excepted for *gender* and *region*, on which we apply exact match. The p-value is clustered at region level.

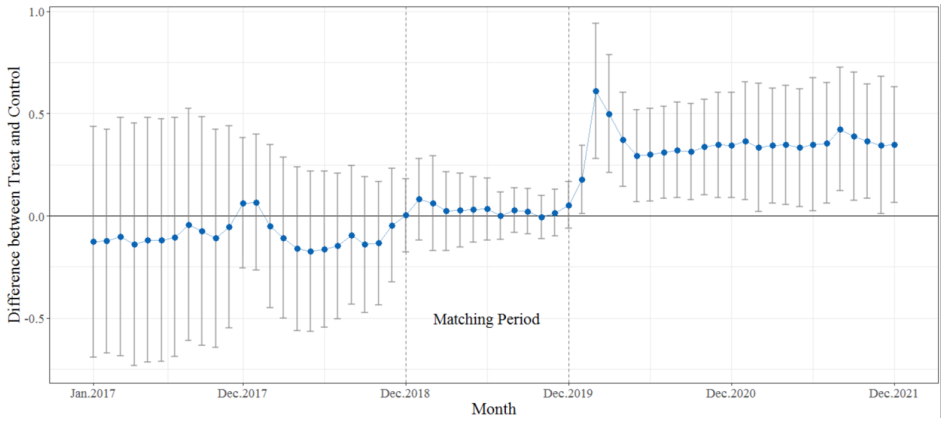


Figure A5: Baseline Results for Matched Sample without Controlling Activeness

Criteria:	Consecutively Inactive	≥ 6	≥ 5	≥ 4	≥ 3
	Treatment Effect	31.85	29.48	26.5	22.15
	Share in Sample	87.9%	84.5%	79.1%	69.6%
Criteria:	Total Inactive	> 6	> 5	> 4	> 3
	Treatment Effect	22.59	21.04	19.28	17.06
	Share in Sample	76.2%	71.9%	66.6%	60.2%

Table A4: Various Criteria for Dropping Inactive Consumers

Note: This table shows the estimated treatment effect based on different criteria for dropping inactive consumers. We tested two methods: filtering based on consecutive inactive months and total inactive months in 2020-21. The method shown here excludes the match of two consumers if either of there satisfies the inactive creiterion. If only dropping those inactive consumers, the treatment effect is 3–4 percentage points higher. In the baseline specification, we selected a criterion of dropping those with more than 3 consecutive inactive months or more than 6 total inactive months, by match.

C Financial Sophistication Index

To better measure the financial literacy associated with fintech credit usage, we develop a Financial Sophistication Index utilizing two unique payment methods within Alipay.The two payment methods are Balance payment and Yu'e Bao One is Yu'e Bao, as briefly introduced in section A.2.

Yu'e Bao is an innovative e-wallet linked to the money market fund. Consumers deposit money into it and can use it for payment at any time. At the same time, they earn a daily return from the money market fund, with annual interest rates ranging from 2% to 7%. In addition, Alipay also offers a traditional balance payment option, where consumers can transfer money into the balance and

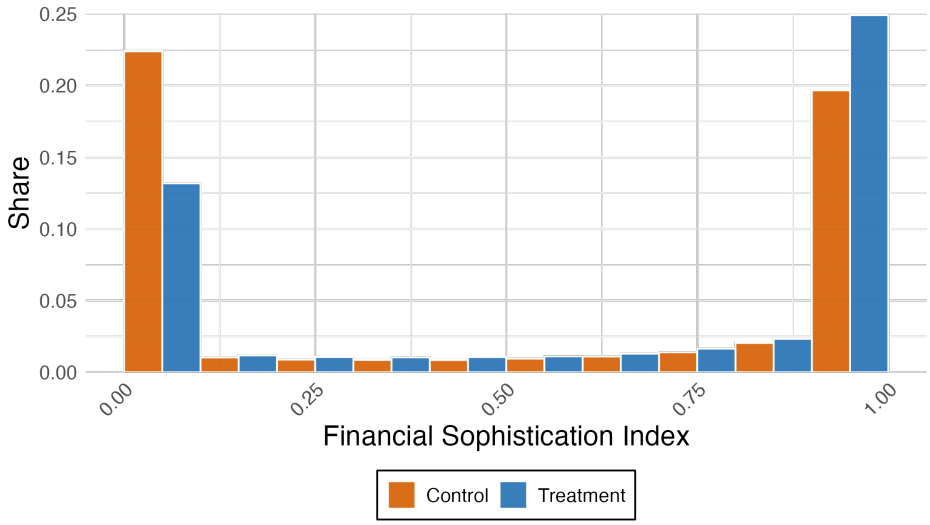


Figure A6: Distribution of Financial Sophistication Index

use it for payment, but it does not have interest. Figure A3 shows that the average per transaction amount of these two methods are similar, suggesting that the two payment methods are equally convenient. However, since the returns from the money market fund can be considered risk-free, saving money put in Yu'e Bao is strictly dominant than saving money in a balance account and using it in the payment if consumers fully understand and accept the financial innovation. Ideally, rational consumers should opt for Yu'e Bao instead of using balance payments. However, we observed that only 27.4% of consumers did this in 2019. There are 27.2% consumers who strictly prefer in using balance to Yu'e Bao.

For each consumer i, we define the financial sophistication index as the share of "interest generated balance" used in all transactions in 2019:

$$FS_i = MMF_i/(MMF_i + Balance_i) \tag{4}$$

Therefore, $FS = 1$ means very sophisticated, and the consumer is actively taking advantage of the innovative financial payment method. And $FS = 0$ means unsophisticated. Our interpretation in this situation is that these consumers either lack awareness of the interest advantages provided by the payment method, or they are aware but choose not to use this innovative payment method due to distrust or other conservative considerations.

Among the 77.8% consumers who have a well-defined FS index in 2019, Figure A6 plots the distribution of the index of two groups. The treatment group consumers are more sophisticated than control group under this measure. However, in both groups we found that the index shows a higher proportion at the extremes of 0 and 1, while the middle range displays a relatively even distribution.

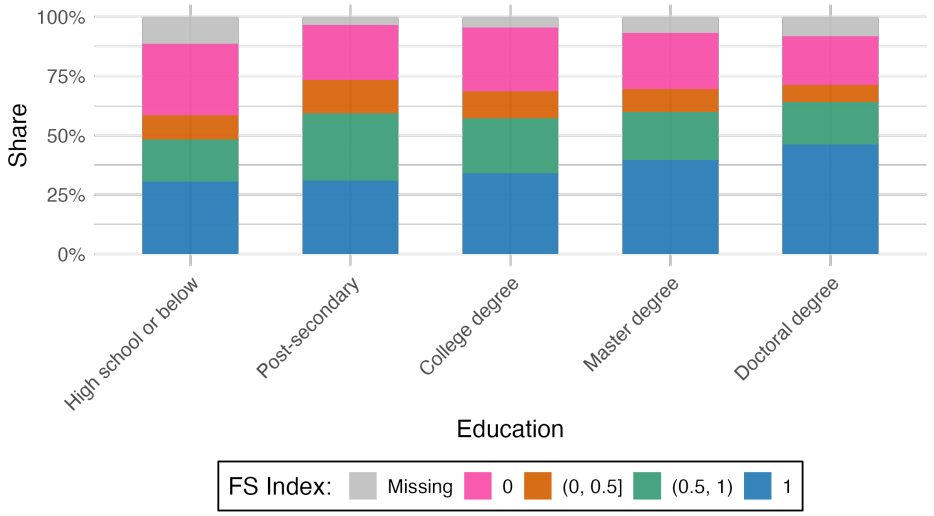


Figure A7: Distribution of Financial Sophistication Index

Note: This plot shows the distribution of the Financial Sophistication Index in each education group. First, the high education group has a larger share of consumers with $FS = 1$. However, in each education group, the distribution from 0 to 1 is similar, showing that the FS index and education are not completely correlated.

As shown in Fig A7, the high-education group has a larger share of financially sophisticated consumers. In consumers with a doctoral or master's degree, the proportion of $FS = 1$ is 46% and 40%, respectively, while 30% in the high school or below group. On the other hand, even in high education groups, a significant amount of consumers are not financially sophisticated, suggesting the Financial Sophistication Index and educational level are not entirely aligned. Therefore, our newly defined index highlights the consumer's understanding and acceptance of different payment methods within the fintech payment platform, offering a new dimension in measuring financial literacy.

	Age	Big City	Education	Consumption	FS Index	Treatment
Age	1	-0.025	-0.466	0.198	-0.032	-0.018
Big city		1	0.127	0.103	0.02	0.008
Education			1	-0.109	0.062	-0.046
Consumption				1	0.024	0.019
FS Index					1	0.164
Treatment						1

Table A5: Correlation of Variables Used in Heterogeneity Analysis

Note: This table shows the correlation between the variables used in heterogeneity analysis. Education is denoted as 1 to 4, to represent the four levels of education: high school education or below, post-secondary, college, and those with graduate degrees. FS index refers to the Financially Sophistication Index.