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Keywords: consumption; traditional bank credit; FinTech credit; COVID-19

JEL Classification: D12; D81; G51

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Jiayin Hu[†], Yiping Huang[‡], Jialin Liu[§]

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We investigate the changing pattern of consumer credit usage following a large, adverse shock. Using a unique dataset comprising the consumption, payment, and investment activities of nearly 100,000 users of a leading Big Tech platform in China, we find that consumers who have access to both FinTech and traditional bank credit reduce their bank credit card usage while increasing their FinTech credit usage. Moreover, FinTech credit works as a complement rather than a substitute for traditional bank credit on the same Big Tech platform, as the amount of FinTech-credit-enabled payments is much lower. This impact is more pronounced among female consumers, younger consumers, and consumers who invest more money in the Big Tech platform. Hence, the rise of FinTech credit is potentially driven by (1) the consumption downgrading (i.e., shifting from large amounts and service consumption to small amounts and daily necessity consumption) in the post-COVID era, when people's income and growth expectations have been reduced and the uncertainties they face have increased, and (2) payment convenience, as people become less likely to access banks after the outbreak of COVID. Our findings provide novel evidence regarding the relationship between FinTech and traditional bank credit and the interplay between consumption and consumer credit, with implications for consumption resilience in the post-COVID-19 era.

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1. Introduction

The slow recovery of consumption is a major concern in many countries, including China, during the post-COVID era. Adverse shocks as large as that of the COVID-19 pandemic may have a long-lasting impact on consumption and borrowing activities, as they greatly reduce people's incomes and weaken expectations for future growth. While many studies have shown that consumer credit, especially FinTech lending, is helpful for households in smoothing consumption levels and increasing household resilience to negative shocks, little is known about how these shocks impact household adoption of FinTech credit and traditional bank credit.

In this paper, we investigate the changing face of consumer credit after a large, exogenous adverse shock, i.e., the COVID-19 pandemic. We investigate the impact of adverse shocks on consumer credit using proprietary data from a leading Chinese Big Tech platform. This platform owns one of the two largest mobile payment tools in China and provides a wide range of financial services to ordinary households. Our unique dataset consists of nearly 100,000 randomly drawn consumers from 280 cities, and it includes their consumption, payments, and borrowing activities over the period of January 2019 to December 2021. We adopt a difference-in-differences (DID) regression approach using geographical variations in the severity of COVID-19 across cities. Our individual-month panel data cover the periods before and after the outbreak of the COVID-19 pandemic in January 2020 in China, thus enabling us to analyze the short- and medium-term impacts of the shock.

We find that, on average, consumers increased their FinTech credit usage while reducing their bank credit usage after the COVID shock. Specifically, the Big Tech platform enables mobile payment functions for both online and offline consumption; consumers can pay for goods and services through the payment options provided by the Big Tech platform: its digital wallet (e-wallet), its money market fund (i.e., Yu'ebao MMF), its Buy Now Pay Later (BNPL) credit, and the bank credit cards or debit cards that users have connected to the Big Tech platform. We refer to the BNPL credit provided by the Big Tech platform as FinTech credit and that provided by a bank credit card as traditional bank credit. To exclude confounding factors that affect people's access to bank credit cards, i.e., FinTech credit users may be fundamentally different from traditional bank clients, we focus on consumers who have access to both traditional bank credit and FinTech credit. We find that compared to those in cities that were less hit by the COVID-19 pandemic, consumers in cities that faced greater COVID-19 severity increased their FinTech credit usage while reducing their traditional bank credit usage, indicating an increase in FinTech choices after the COVID-19 shock.

Interestingly, we find that the rising pattern of FinTech is more likely due to a shrinkage and downgrading of consumption and payment convenience than a result of a substitutional relationship between FinTech credit and traditional bank credit. First, there was a large decline in the total amount of consumption in our sample after the COVID-19 outbreak, especially for service goods, which suggests a consumption downgrading phenomenon. Most importantly, the consumption amount via FinTech credit is significantly smaller than that via bank credit cards; hence, the two types of credit work more like complements for each other rather than substitutes. Therefore, the rising pattern of FinTech credit usage is potentially driven by consumption downgrading (i.e., shifting from large consumption amounts and a service consumption type to small consumption amounts and daily necessity consumption) in the post-COVID era, when people's income and growth expectations have been reduced and their level of uncertainty has increase. Second, we find that traditional financial services access still has value in the FinTech era: consumers in cities with more bank branches expanded their traditional credit usage and reduced their FinTech credit usage after the COVID-19 shock, suggesting that these brick-and-mortar facilities provide certain amenities to consumers that help to strengthen customer loyalty after adverse shocks.

We further conduct heterogeneity analyses to investigate the differentiated impact of the adverse shock. First, we find that heterogeneity in personal characteristics plays a larger role than variations in geographical locations: Younger, female consumers, those with higher levels of trust in the Big Tech platform and those with lower levels of wealth are more likely to increase their FinTech credit usage, but there are no statistically significant differences in this phenomenon detected among different regions (i.e., east, middle, and west.) This result is consistent with the literature in that FinTech adoption is found to overcome geographical barriers and help promote financial inclusion.

This paper mainly contributes to three strands of literature. First, the results demonstrate the connection between consumption and consumer credit and the resilience of both FinTech and general consumption in the face of crises. Consumer credit alleviates liquidity constraints and makes it easier for residents to smooth consumption even in the face of negative income shocks (Huang et al., 2023). The development of FinTech provides more people with financial services that are based on advanced technologies, such as big data, artificial intelligence, and cloud computing. Thus, FinTech consumer credit serves as an effective alternative service for those who are underserved by traditional banks, thus boosting consumption and reducing consumption inequality (Yang and Zhang, 2022). Meanwhile, the development of FinTech lenders has led to alternative borrowing that accounts for a larger proportion of credit markets, effectively reducing discrimination (Tantri, 2021; Lyons et al., 2022; Hu et al., 2023) and improving access and consumption (Jack et al., 2013; Yang and Zhang, 2022).

When there are unexpected adverse shocks, such as monetary policy shocks or economic uncertainty, the level of information asymmetry becomes more severe between borrowers and lenders, leading traditional lenders to reduce their credit supply to avoid risks (Hülsewig et al., 2006).[5] However, Bao and Huang (2021) find that after the COVID-19 pandemic, FinTech lenders expand their credit to people who are new users with low income, while banks offer more credit to preexisting borrowers, thus demonstrating the extensive characteristics of FinTech lending. Meanwhile, most recent

[5] Classical literature has already shown that information asymmetry is a crucial factor in the access to credit (Stiglitz and Weiss, 1981). Bordo et al. (2016) also find that a higher degree of information asymmetry makes banks become more reluctant to provide loans. What's more, in more recent studies, for example, Jiménez et al. (2012) also find that worse economic conditions significantly reduce the level of loan granting from the perspective of firms.

studies claim that crises and uncertainties also impact consumption due to precautionary saving motives (Benito, 2006; Bahmani-Oskooee and Xi, 2011; Bahmani-Oskooee et al., 2015; Binder, 2017a; Christelis et al. 2020). Like this response to precautionary saving motives, borrowing behaviors are also affected by uncertainty (Bloom et al., 2007). Ben-David et al. (2018) find that higher uncertainty is associated with more caution in consumer borrowing behaviors. Additionally, Erel and Liebersohn (2022) explore the demand for FinTech from a small business perspective and find that it is used more in counties that faced more severe economic effects from the COVID-19 pandemic. Suri et al. (2021) state that FinTech loans help those households that are less likely to reduce their expenses when facing negative shocks. Fu and Mishra (2022) study FinTech adoption and usage during the COVID-19 pandemic and document the fact that the large-scale shift in FinTech adoption may have helped many households mitigate the short–term decrease in productivity and economic growth that was caused by COVID-19. In the context of China, Huang et al. (2023) use the CFPS dataset to show that FinTech adoption also helps alleviate credit constraints to mitigate the negative effects of economic uncertainty on household consumption, especially regarding service goods consumption.

The most relevant paper is that of Chen et al. (2021), which uses high-frequency payment data in China to document how the COVID-19 pandemic has affected consumer spending offline, particularly for categories such as dining, entertainment, and travel. Several other studies have also explored consumer spending amid the COVID-19 pandemic in different countries or regions (Chronopoulos et al., 2020; Andersen et al., 2022; Baker et al., 2020). Our paper complements this literature by offering an examination of people's online consumer credit and consumption over a much longer horizon to investigate the medium-term impact of the COVID-19 shock. We find that when facing adverse shocks, consumers increase their FinTech credit usage and reduce their bank credit card usage on the same Big Tech payment platform. While this pattern can also be interpreted as a substitution effect, we find that the payment amount via BNPL credit is much smaller than that via bank credit cards; hence, switching toward BNPL credit mainly demonstrates a move towards consumption downgrading. Our results indicate that the same consumer's allocation between the different categories of consumer credit reflects not only their preferences regarding credit but also consumer consumption choices. Our results have some new policy implications regarding the new situation in the consumer market during and after the pandemic. We need more concrete means to increase income, improve expectations, and boost consumer spending, as epidemic prevention has entered a new stage.

Second, our results contribute to the heated debate over the relationship between FinTech lenders and traditional banks (Thakor, 2020), with some studies finding evidence that FinTech functionality is complementary to that of banks (Fuster et al., 2019; Tang, 2019), while others claim that FinTech lenders generally serve those who are not able to obtain service provided by traditional banks (Hau et al., 2019; Jagtiani and Lemieux, 2018; Claessens et al., 2018; Agarwal et al., 2020a; Frost et al., 2019). The debate is focused on loans and payments. For example, a few studies claim that FinTech lenders have a technology advantage over traditional banks (Buchak et al., 2018) and have less of a reliance on traditional financial information (Gambacorta et al., 2023) in offering loan service. Some studies suggest that the competition provided by FinTech payment providers may have a negative impact on bank payments, bank loan services (Parlour et al., 2022; Bian et al., 2023), and bank deposit services (Buchak et al., 2021), or it may have a positive spillover effect on banks (Beck et al., 2022). While previous literature mainly considers only a single type of consumer credit, our unique dataset enables us to compare consumer usage of different credit sources. By comparing different consumption patterns through BNPL FinTech credit and traditional bank credit, we find that there is a rising pattern of FinTech credit usage. However, this pattern does not necessarily indicate FinTech substitution; rather, we show that FinTech credit is more likely to serve as a complement to traditional bank credit on the same Big Tech platform by catering to different payment amounts. We show that the rising pattern of BNPL credit is closely related to consumption downgrading, as FinTech credit is often used to purchase goods and services with much lower prices than those purchased with bank credit. The increased usage of FinTech credit may simply reflect consumption downgrading. Our paper thus complements the literature on the implications of FinTech lending for the credit market and its relationship with bank lending.

Third, our paper adds to the literature on the adoption of FinTech credit, particularly the burgeoning literature on BNPL. The existing studies on FinTech adoption can be grouped into those focused on (1) network effects, (2) individual-level determinants, (3) country-level predictors, and (4) shocks. The first group suggests that FinTech adoption on the demand side has spillover effects on FinTech adoption on both the supply side and the demand side (Higgins, 2019). The second group of studies is focused on individual-level determinants and tend to emphasize digital literacy (Carlin et al., 2017; Cong et al., 2021) or digital trust (Gertler et al., 2022). Recently, several studies have also revealed that credit also behaves as liquidity insurance, which affects FinTech adoption. For example, Telyukova (2013) finds that consumers choose to use credit cards before using liquid assets because liquid assets have broader uses and customers prefer to save them for future urgent needs. The third group mainly includes studies that use country-level data to analyze the predictors of FinTech adoption, such as regulation level (Claessens et al., 2018), bank competition (Frost et al., 2019), financial service demand, and demographics (Frost, 2020). The fourth group claims that sudden negative shocks may induce people to adopt FinTech services (Crouzet et al., 2019), but technology shocks do not exert this effect (Agarwal et al., 2020b).

The remainder of this paper proceeds as follows: Section 2 presents the institutional background and theoretical analysis. Section 3 introduces our empirical specification and data. Section 4 reports the estimated baseline empirical results on consumer credit. Section 5 offers an examination of the mechanism channel. Section 6 presents the heterogeneity analysis. Section 7 concludes.

2. Background and Testable Hypotheses

2.1 Institutional Background

Consumer credit provided by Big Tech firms has grown rapidly in the past decade. Recently, “buy now, pay later” (BNPL) has become one of the most common forms of FinTech consumer credit, both in China and around the world (Ji et al., 2023). Similar to a credit card in that it provides credit to consumers, BNPL evaluates applicants on the basis of soft information (e.g., payment history, digital footprint, and online social networks) rather than hard information (such as applicant education backgrounds, work experience, and income) and thus helps to promote financial inclusion (Grennan and Michaely, 2021; Ji et al., 2023).

Our study is focused on Huabei, which is a widely recognized BNPL product provided by Alipay, one of the largest FinTech payment platforms in China.[6] As a leading player in the FinTech BNPL credit market, Huabei primarily caters to individual borrowers in financing their small- and medium-sized consumption.[7] While providing lines of credit to consumers in a similar fashion as bank credit cards, Huabei is not required to report the borrowing history and credit records of its users to the central bank, as traditional banks are required to, until mid-2021.

The BNPL lending process is as follows: After receiving applications from consumers, Huabei’s risk control department investigates creditworthiness based on applicant information and FinTech credit score (i.e., the Sesame Credit), which measures an applicants’ creditworthiness using cloud computing, machine learning and other financial technologies. The BNPL lender then approves or rejects the application through an automated algorithm and notifies the credit line if the borrowing request is approved.

2.2 Theoretical Analysis and Propositions

The outbreak of COVID-19 caused significant damage to economic growth and thus adversely affected future expectations, which has led to an increase in economic uncertainty. In parallel to the corporate finance theories claiming that negative shocks and uncertainty affect firm investment, consumers may also become more cautious and reduce their consumption levels, especially for service goods, given the risks associated with uncertain income prospects (Ben-David et al., 2018). This leads to a consumption downgrading phenomenon and a reduction in consumer credit adoption.

However, people’s demand for consumer credit may also increase as a means to

[6] Specifically, Huabei is managed by Chongqing Ant Consumer Finance Co., Ltd, which is a FinTech firm fully controlled by Alipay.

[7] The funding of Huabei is mainly sourced from the owned assets of FinTech firms and ABS bond issue. In the early stages of development, FinTech firms relied heavily on their technological advantages to differentiate themselves from other lenders with high leverage. However, in order to maintain healthy development within the industry, China’s regulation authority began defining the financing leverage ratio for FinTech firms in 2017, implementing strict regulations that limit these companies' financing capabilities. As a result, many FinTech firms have begun collaborating with banks to provide credit service.

meet their daily consumption needs. On the one hand, consumer credit serves as an extra source of liquidity for individuals. On the other hand, according to the theories of liquidity insurance and precautionary saving motives, people may turn to borrowing to preserve their liquid assets for supporting future consumption due to uncertainty regarding the availability of borrowing in the next period (Fulford, 2015). Thus, we have:

Proposition Ia: Consumer credit usage increased after the outbreak of COVID-19.
Proposition Ib: Consumer credit usage decreased after the outbreak of COVID-19.

Due to the distinct characteristics between traditional credit and FinTech credit, their behavior may differ in response to the outbreak of COVID-19. First, FinTech credit is more accessible and can be more widely used online than traditional credit, such as a credit card, thus leading to a decline in credit card usage (Bian et al., 2023). Second, in terms of consumption structure, FinTech consumer credit and credit cards are likely to be used disproportionately for various types of consumption. For example, FinTech credit is typically used for smaller consumption amounts, such as daily necessities, while credit cards are commonly used for larger transactions, such as entertainment, tourism or durable goods (housing and furniture). Third, from the supply side, unlike traditional banks that reduce loan supply during times of high uncertainty, FinTech lenders may still provide credit to borrowers (Bao and Huang, 2021). This is because FinTech lenders conduct credit investigations based on more inclusive information than that on traditional financial situations, which are the main concern of traditional banks. The abundance of information reduces the level of market information asymmetry and minimizes default rates (Berg et al., 2020), thus allowing FinTech firms to supply loans to applicants without increasing their delinquency rates (Allen et al., 2022). Thus, we have:

Proposition II: Traditional bank credit usage and FinTech credit usage behave differently in response to the outbreak of COVID-19.

The COVID-19 pandemic may exert a heterogeneous impact on different types of consumers. Most studies have found that uncertainty causes different expectations in households (Ben-David et al., 2018), and the response of individuals to uncertainty varies across income or wealth distributions (De Bruin et al., 2011). For example, people with higher levels of wealth and income have sufficient financial resources to support their consumption compared to those with lower levels of wealth and income. Lower-income consumers are also more likely to experience high levels of uncertainty (Binder, 2017a; Binder, 2017b). As a result, higher levels of wealth and income may lead to a decrease in consumer credit demand and adoption. Other characteristics, such as age, gender (De Bruin et al., 2011; Binder, 2017a; Chen et al., 2023), and risk preference, may also play key roles in determining borrowing responses to the pandemic.

Furthermore, there is significant regional variation in consumer behavior across China. For example, individuals residing in less developed areas often experience severe shocks and may have a higher level of demand for consumer credit during periods of high levels of uncertainty. Additionally, the development of traditional finance also impacts consumer credit adoption. If traditional finance is well developed, people may not need to adopt FinTech credit. Moreover, people living in areas with lower levels of FinTech development may be less likely to adopt FinTech credit even if they are offered such services due to lower levels of acceptance or trust. Thus, we have:

Proposition III: The impact of COVID-19 on consumer credit usage varies by individual characteristics and across regions and may be more pronounced among consumers with greater exposure to BNPL credit.

3. Empirical Methodology and Data

3.1 Empirical Methodology

Our empirical analysis is conducted to investigate the impact of the COVID-19 pandemic on consumption and consumer credit adoption. Specifically, we adopt the following difference-in-difference (DID) regression model to exploit the cross-sectional variations in the severity of the COVID-19 shock:

$$\ln(Y_{ijt}) = \alpha + \beta_1 Covid_t * Confirmed_{ij} + \gamma X_{ijt-1} + \mu_i + \eta_t + \varepsilon_{ijt} \qquad (1)$$

where Y_{ijt} denotes consumer i's consumer credit usage (and its two categories: traditional and FinTech credit usage) or consumption (and its three categories: services goods, durable goods, and nondurable goods) in period t. $Covid_t$ is a dummy variable indicating post-COVID periods that equals 1 for periods in or after January 2020 and equals 0 otherwise. $Confirmed_{ij}$ captures the pandemic exposure of city j, which is the residence city of consumer i, as measured by the number of confirmed COVID-19 cases per 100 people in the city during the first quarter of 2020.

The coefficient of interest is β_1, which is used to capture the differentiated impact on consumption and consumer credit adoption across consumers exposed to different levels of shock from the COVID-19 pandemic. Our control variables X_{ijt-1} include lagged time-variant characteristics (Digital_assets) and lagged city-level macroeconomic variables such as GDP (log), population (log), the share of secondary industry in GDP (Second), and the share of tertiary industry in GDP (Third). μ_i represents the individual fixed effects used to control for consumers' time-invariant characteristics (such as age, risk preferences, and gender). η_t represents the year-month fixed effects used to control for macroeconomic trends that do not vary cross-sectionally. ε_{ijt} is the error term. The standard error is clustered at the city level.

Additionally, we exploit individual and regional variations to analyze the heterogeneous response of consumer credit demand. We add dummy variables that represent individual and regional characteristics and their interactions with $Covid_t * Confirmed_{ij}$ in the baseline regression. Our triple differences (DDD) regression model is the following:

$$\ln(Y_{ijt}) = \alpha + \beta_1 Covid_t * Confirmed_{ij} + \beta_2 Covid_t * Confirmed_{ij} * Indichar + \beta_3 Confirmed_{ij} * Indichar + \beta_4 Covid_t * Indichar + \gamma X_{ijt-1} + \mu_i + \eta_t + \varepsilon_{ijt} \quad (2)$$

where $Indichar$ refers to the specific individual-level or city-level characteristic of interest. The coefficient of the triple interaction term β_2 is used to capture individual and regional variations in the impact of the COVID-19 shock on consumer behaviors.

3.2 Data

3.2.1 Individual-level Data

We use individual-level data regarding personal characteristics, consumption, and borrowing records to estimate Models (1) to (2). Our main data come from Alipay[8], one of the largest Big Tech companies in China. We conducted our analysis remotely through the Ant Open Research Laboratory[9] in an Ant Group Environment. The data were sampled and desensitized by the Ant Group Research Institute and stored at the Ant Open Research Laboratory. The laboratory is a sandbox environment where the authors can only remotely conduct empirical analysis and individual observations are not visible.

We randomly selected 100,000 users from all Alipay users who had at least one consumption payment record each month since January 2018 and constructed a dataset with individual-month level data covering the period of January 2019 to December 2021. The dataset contains (1) basic individual characteristics, such as gender, age, and risk preference; (2) consumption and consumption categories, such as service goods consumption, durable goods consumption, and nondurable goods consumption; (3) payment instruments, such as e-cash, credit card, FinTech credit, and monetary fund (similar to bank deposit); and (4) financial indicators, such as total financial assets, assets allocation, and return on risky assets.

Our data have several unique advantages compared to traditional household data. First, our dataset combines individuals' consumption, borrowing, and financial investment behaviors, thus enabling us to explore the connections between consumer borrowing demand and consumer consumption level. The large sample size also provides sufficient power for empirical tests. Second, our dataset provides high-frequency and accurate information regarding consumption and consumer credit, while commonly used survey data are collected at annual frequency. This detailed monthly dataset enables an examination of the dynamic changes in consumption and consumer credit usage around the unexpected outbreak of COVID-19. Third, our dataset distinguishes between different types of consumer credit (such as bank credit cards and BNPL credit), thus enabling us to compare the differences between traditional and FinTech credit and test whether they serve as complements or substitutes for each other.

[8] Alipay is a third-party mobile and online payment platform, established by the Alibaba Group that was subsequently rebranded as Ant Financial Services Group in October 2014 and Ant Group in June 2020.

[9] https://www.deor.org.cn/index

3.2.2 COVID-19 Data

We obtained COVID-19 data from the National Health Commission of the People' Republic of China (NHC, http://www.nhc.gov.cn/) and supplemented it with manually collected information from the Sina website (https://news.sina.cn/zt_d/yiqing0121?vt=4). [10] As shown in Figure 1, COVID-19 broke out in January 2020, and newly confirmed cases peaked in February 2020. According to the NHC, there were 81,554 cumulative confirmed cases as of March 2020.

The COVID-19 outbreak has undergone several high peaks, with the initial shock being the most severe. The first case emerged in Wuhan city, Hubei Province, and quickly spread to other areas. By the end of March 2020, there were 50,007 cases in Wuhan city, accounting for 0.55% of its total population.

Our dataset provides the number of daily confirmed COVID-19 cases for 280 cities in China. To examine the impact of the pandemic on consumer behavior across different cities, we use the ratio of cumulative confirmed cases to the total population of one city during the period ranging from January 2020 to March 2020 to represent pandemic severity. By merging the city-level COVID-19 infection dataset with the individual dataset according to the administrative code of each city, we are able to identify the differences in consumer behavior across cities of varying levels of COVID-19 exposure.

3.2.3 City-level Macroeconomic Data

The macroeconomic data for each city comes from the National Bureau of Statistics (http://www.stats.gov.cn/) and the China City Statistical Yearbook 2001-2022. A higher gross domestic product (GDP) generally indicates a city's higher level of economic development, which in turn can lead to higher resident income and consumption levels. Thus, we consider the economic condition difference by controlling the log value for GDP. Similarly, the industry structure of a city relates to employment and income levels, with cities that rely heavily on secondary and tertiary industries often exhibiting more job opportunities and higher consumption levels. Additionally, the population of a city also plays a role in determining job opportunities and economic conditions, so we include this variable in our models. By controlling for these variables, we are able to better understand the impact of the COVID-19 pandemic on consumer behavior across different cities.

[10] Some studies, such as Gao et al. (2022), use the infection data from China Stock Market & Accounting Research Database (CSMAR). We check these two datasets and find that they are basically the same.

3.3 Key Variables

3.3.1 Measurement of Pandemic Exposure

In the baseline specification, we use the cumulative confirmed COVID-19 cases per 100 people in city *j* (where individual *i* resides) during the first quarter of 2020 as a proxy for consumer pandemic exposure. Additionally, we use the number of confirmed COVID-19 cases as an alternative measure of city-level COVID-19 exposure for robustness tests.

3.3.2 Measurement of Consumption Behavior

Based on the classification of the Ant Group dataset, total consumption can be divided into three types: (1) services, which include enjoyment expenditures such as transportation, culture and leisure, hotel and tourism, education and training, and food and beverage; (2) durable goods, which include home furnishings, digital appliances, and other long-lasting items; and (3) nondurable goods, which include recurring expenditures such as clothing and shoes, daily necessities, and pets. Figure 2 demonstrates the trend of total consumption and its components. We find that consumption sharply decreases after the COVID-19 outbreak in early 2020.

To capture consumers' borrowing behavior, we use the ratio of credit card payment (BNPL) to total consumption to measure the adoption and usage of traditional bank credit (FinTech credit). The upper panel of Figure 3 shows the amount of these two types of consumer credit adoption during our sample period. We find that the total amount of FinTech credit used for consumption is higher than that of traditional credit. For an average consumer, the total amount of consumption using FinTech credit is greater than 2000 yuan per month, while that using traditional credit is less than 2000 yuan per month.

The lower panel of Figure 3 displays the trend of consumer credit usage for consumption. We find that consumer credit accounts for over 60% of total consumption, indicating that it plays a significant role in supporting consumption. Regarding the specific forms of consumer credit, we find that FinTech credit usage accounts for 50% of total consumption, while tradition credit usage accounts for less than 20%. Thus, FinTech credit has become the most commonly used payment method in China.

Figure 4 reports the amount per payment of credit during the sample period. The average transaction amount paid by traditional credit (averaged over more than 400 yuan per payment) is much higher than that paid by FinTech credit (averaged over less than 200 yuan per payment).

3.3.3 Measurement of Other Variables

For individual characteristics, we use a dummy variable *Female,* which equals 1 if the consumer is a woman and 0 otherwise. Similarly, we collected information on people's risk preferences and divided it into six levels (with higher levels indicating higher risk preference). We then constructed five dummy variables to proxy for different levels of consumer risk preference. Based on the age distribution among samples, we categorized consumers into two cohorts by age: those under 31 years old (the median age) and those older than 31 years old. We also use a dummy variable to proxy for age group, which equals 1 if the consumer is 31 years old or older and 0 otherwise. Individual financial conditions include total financial assets, which is log-transformed to proxy for the level of digital assets.

For city-level macro variables, we use GDP (log value) and population (log value) as proxies for economic conditions. Additionally, we use the share of second industry (the second industry GDP ratio of GDP) and the tertiary industry (the tertiary industry GDP ratio of GDP) to proxy for industry structure. All continuous variables are winsorized at 1% and 99%, respectively.

3.4 Sample and Summary Statistics

We focus on the online consumption of Alipay users between January 2019 and December 2021. We exclude users who do not report their gender or risk preferences. Our final sample contains 99,239 consumers in 280 cities. We construct balanced panel data for our main regressions, i.e., there is complete 36-period data for each consumer used in the regression sample.[11]

Table 1 provides the summary statistics of our key variables. In our sample, 38% of the users are female; the ages of users range from 21 to 80, with an average age of 33. The average holding of digital assets of consumers is 34,929 yuan, suggesting that the sample has a high level of acceptance or trust toward the FinTech platforms and therefore sampled participants are comfortable using the platform to manage their financial assets.

The average consumption amount in our sample is 6,234 yuan. Among the three categories of consumption, nondurable goods and service goods make up the largest proportion, with averages of 2,767 yuan and 2,515 yuan, respectively. Durable goods consumption has the lowest proportion, with an average of only 582 yuan. In terms of consumer credit adoption, we can see that total consumer credit accounts for 64.60% of total consumption, while credit card usage accounts for 13.20% and BNPL usage accounts for 51.39%.

The distribution of confirmed COVID-19 cases across different regions after the initial outbreak in 2020 exhibited significant differences. The average number of confirmed cases in each city was 1,571. On average, there were approximately two cases per 10,000 people, with a standard error of 0.0905.

The economic conditions and industry structure in different cities also have significant differences. The average GDP of China's 280 cities is 898.9 billion. In the developed cities of eastern provinces such as Beijing, Shanghai, Guangzhou, and Shenzhen, the GDP was above 2,362 billion during our sample period. However, the cities of western provinces such as Xizang, Qinghai, and Ningxia had a GDP of less than 500 billion during our sample period. Regarding industry structure, on average,

[11] However, the individual level dataset and city level dataset contain missing values. Thus, the observation of our baseline results is not the product of period and user numbers (99239*36=3572604).

secondary and tertiary industries account for 40.44% and 53.67% of gross domestic product, respectively.

4. The Impact on Consumer Credit

4.1 Baseline Regression Results

Table 2 presents the results of assessing the impact of the COVID-19 outbreak on consumer credit. We estimate the coefficients as specified in Model (1) to quantify the magnitude and statistical significance of the impact of the pandemic on consumer credit. We find that consumers located in cities with higher levels of COVID-19 exposure experienced a significant increase in consumer credit usage after the initial outbreak in early 2020. We estimate Model (1) using consumer credit usage as the dependent variable. As shown in Column (1) of Table 2, the coefficient is not statistically significant. In Column (2), we continue to add time-varying individual-level control variables such as digital assets and city-level variables such as GDP, population, the second industry share, and the tertiary industry share to account for any observable differences among consumers and cities. We find that the coefficient becomes significantly positive, which means that the outbreak of COVID-19 increases people's borrowing, as one newly confirmed case for every 100 people in a month leads to an increase of approximately 0.43% in total consumer credit usage for a resident consumer in the city. We also control for individual and year-month fixed effects to exclude the impact of time-invariant individual characteristics and macroeconomic trends.

We then explore the impact of the COVID-19 outbreak on different types of consumer credit and find that increased borrowing is driven by changes in FinTech credit usage. Columns (3)-(4) of Table 2 show that after the COVID-19 outbreak, consumers who locate in cities with a higher level of exposure to the shock underwent a significant decrease in traditional bank credit usage. As shown in Column (4), each newly confirmed case per 100 people in a month, on average, leads to a 0.64% decrease in consumers' traditional leverage. However, Column (6) of Table 2 shows that after the COVID-19 outbreak, consumers locate in cities with a higher level of exposure to the shock experienced a significant increase in FinTech credit usage. One newly confirmed case for every 100 people in a month, on average, leads to a 1.07% increase in FinTech credit.

Combining the results of total consumer credit and its categories, we conclude that the leverage of consumers increased after the COVID-19 outbreak and experienced a larger rise as exposure to the COVID-19 outbreak increased, and this increase was mainly driven by FinTech credit usage.

4.2 Dual-Access Sample

To address the endogeneity in consumer access to different types of credit, we focus on a subsample of consumers who have access to both bank credit and BNPL credit. In Columns (1)-(2) of Table 3, the coefficients of *Covid*Confirmed* are significantly negative, indicating that consumers decreased their traditional bank credit usage after the outbreak of COVID-19. As shown in Column (2), one newly confirmed case in every 100 people in a month, on average, implies a decrease of 0.82% in traditional bank credit usage in the city.

However, for FinTech credit usage, as shown in Columns (3)-(4), the regression coefficient is significantly positive at the 1% level, which means that FinTech credit usage increases by approximately 1.16% in response to a newly confirmed case per every 100 people in a month. These results indicate that consumers were more willing to borrow from FinTech lenders than traditional banks following the COVID-19 shock, and they demonstrate the intensive margin effects of FinTech credit.

We use the following dynamic DID specification to test whether the parallel trend assumption holds in the pre-COVID-19 period:

$$\ln(Y_{ijt}) = \alpha + \sum_{i=-4}^{-2} \beta_{5+i} Covid_{t+i} * Confirmed_{ij} + \beta_4 Covid_t * Confirmed_{ij} + \sum_{i=1}^{6} \beta_{4+i}\, Covid_{t+i} * Confirmed_{ij} + \gamma X_{ijt-1} + \mu_i + \eta_t + \varepsilon_{ijt} \quad (3)$$

where $Covid_{t+i}$ are year-month dummies. We set the month before the outbreak of COVID-19 as a benchmark by excluding the dummy for $Covid_{t-1}$ from our regression.

Figure 5 and Figure 6 plot the regression coefficients of the dynamic DID with total consumer credit usage, traditional credit usage, and FinTech credit usage set as the dependent variables. Before the COVID-19 shock, there was no obvious consistent trend observed in credit usage between consumers located in cities that were more affected and those located in cities that were less affected. That is, parallel trends existed during the pre-COVID-19 period. However, after the outbreak of COVID-19, the total consumer credit usage and FinTech credit usage of consumers located in more affected cities increased significantly. We also find that such an increase in FinTech credit usage is temporary, as this effect lasts for 2 months.

4.3 No-Access to FinTech Sample

We continue by exploring whether this FinTech effect is extensive. Specifically, we filter out people who did not access to FinTech credit before the pandemic and then explore their consumer credit usage after the outbreak of COVID-19. Table 4 reports the results. In Column (2) of Table 4, we find that the coefficient of *Covid*Confirmed* is not significant after controlling for macroeconomic variables, suggesting that there is no obvious difference in traditional bank credit usage for those who did not use FinTech credit before the pandemic. However, in Column (4) of Table 4, we find that the coefficient is significantly positive for FinTech credit usage. That is, consumers who do not access to FinTech credit before the outbreak increased their FinTech credit adoption afterwards, indicating the resilience of FinTech credit to a sudden adverse shock.

Thus, the rise of FinTech credit adoption is likely to be associated with a complementary rather than a substitution relationship between BNPL and bank credit.

5. Mechanism Analysis

5.1 Consumption Downgrading Patterns

Our previous empirical results have shown that consumers located in areas with a higher level of exposure to the shock tended to increase their total consumer credit, especially FinTech credit, after the outbreak. Consumer credit is often considered a valuable tool for promoting consumption, especially for those who face credit constraints. Thus, we conjecture that credit usage for FinTech BNPL credit is associated with changes in consumption.

Table 5 reports the impact of COVID-19 on consumption. We find that consumers residing in cities with a higher level of COVID-19 exposure experienced a significant decline in consumption after the initial outbreak in early 2020. As shown in Column (1), on average, one newly confirmed case in every 100 people in a month results in a reduction of approximately 23.79% in consumption for a consumer residing in the city. An alternative interpretation is that a one-standard-error increase in pandemic exposure leads to a reduction of 2.15% in consumption. In Column (2), we also control for individual-level and city-level variables. We find that the impact of COVID-19 exposure on consumption deepens, as one newly confirmed case in every 100 people in a month leads to a reduction of approximately 38.22% in consumption for a consumer located in the city. An alternative interpretation is that a one-standard-error increase in pandemic exposure will lead to a reduction of 3.46% in consumption.

The COVID-19 pandemic has had a significant impact on people's lives, and this impact has led to increased uncertainty about the future. As a result, we expect people to first reduce their nonessential consumption. Columns (3)-(5) report the category consumption results for service goods, durable goods, and nondurable goods. We find that consumption in all three categories decreased significantly. In terms of economic significance, one newly confirmed case in every 100 people in a month leads to an average reduction of approximately 52.95% in service consumption (a 4.79% reduction if there is a one-standard-error increase in pandemic exposure), 18.64% in durable goods consumption (a 1.69% reduction if there is a one-standard-error increase in pandemic exposure), and 55.22% in nondurable goods consumption (a 5.00% reduction if there is a one-standard-error increase in pandemic exposure) for a consumer located in the city.

These findings are consistent with the consumption downgrading hypothesis that the COVID-19 pandemic exacerbates the level of economic uncertainty regarding the future for consumers, since many people lost their jobs and are experiencing greater uncertainty about their future income due to the lockdowns, which leads to changes in consumption patterns. Our results also echo prior studies showing that when consumers face uncertainty caused by the COVID-19 shock, they tend to decrease their service good consumption (Chen et al., 2021; Huang et al., 2023).

In the previous sections, we show that consumption decreases when consumers are exposed to the COVID-19 shock. One possible explanation for this is that the frequency decreases, but the total amount of each transaction remains unaffected. Another possibility involves our use of the city-level population to scale COVID-19 exposure, and the population may dampen or strengthen the impact. However, we find that both arguments are highly unlikely. First, we use consumption payment numbers (log values) as our dependent variable. Second, we use the log value for COVID-19 cases to replace the previous method to measure COVID-19 exposure.

Panels A and B in Table 6 report the regression results of the dependent variable and independent variable being measured via alternative methods, respectively. We find that these results are consistent with our baseline regression results. In addition, as shown in Panel A, one newly confirmed case in every 100 people in a month leads to an average reduction of approximately 46.82% (a 4.24% reduction if there is a one-standard-error increase in the pandemic exposure) in consumption payment numbers. By comparing the magnitude, we document that not only has the total consumption amount decreased but that the average consumption amount of each payment decreased as well. As shown in Panel B, the coefficients are mostly negative and significant even when an alternative method is used to measure COVID-19 exposure. Therefore, our findings are robust to alternative measurements of the main variables.

We further explore whether the consumption downgrading pattern results in changes in credit usage. As shown in Figure 4, the average transaction amount paid by traditional credit (averaged over more than 400 yuan per payment) is much higher than that paid by FinTech credit (averaged over less than 200 yuan per payment). Therefore, credit card payments are more likely to be associated with large-amount consumption, such as service or durable goods. In contrast, FinTech credit is always used when people pay for small-amount consumption. Table 7 reports the change in the average payment amounts of the two credits after the shock. We find that the average amount of each traditional bank credit card payment significantly decreases (as shown in Columns (1)-(2)), while the average amount of each FinTech credit payment shows no obvious change (as shown in Columns (3)-(4)).

According to our analysis, consumers reduced their consumption levels after the shock, especially in regard to more expensive consumption categories. Note that the average transaction amount paid by credit cards is significantly higher than that paid by BNPL credit, and the former obviously declined after the shock. Thus, we interpret the rise of FinTech credit as a byproduct of consumption downgrading in the post-COVID era. Therefore, the rising pattern of FinTech credit is likely to be associated with the change in consumption structure rather than being indicative of a substitutional relationship between BNPL and bank credit.

5.2 Payment Convenience

Another argument can be made claiming that people might use both credit cards and FinTech credit to support their small-amount consumption. Although we compare the usage of bank credit cards and FinTech based on a Big Tech platform, people may still face problems with payment devices when making a payment. Thus, payment convenience may also play an essential role in borrowing choice. If so, people will opt to use FinTech credit more when the use of FinTech credit is more convenient than the use of credit cards. Thus, although we cannot obtain an adequate measure of payment convenience for FinTech credit due to data limitations, we instead try to measure the payment convenience of using bank credit cards. Usually, traditional financial service access is highly and positively associated with payment convenience for bank credit cards. Thus, we expect that people use credit cards less often than FinTech credit when accessing traditional financial services is more difficult. Here, we emphasize that the payment convenience advantage of FinTech over bank credit is more obvious after the outbreak of COVID-19.

We obtain the numbers of bank branches per kilometer square to represent the traditional financial service access for every county of China. Then, we construct a county-level dummy variable that equals 1 if the level of traditional financial service access is above its median. By merging the county-level dummy variable and our individual-level datasets, we obtain the results of estimation, as shown in Table 8. The coefficients of the interaction term are significantly positive for traditional bank credit in Column (1), suggesting that consumers located in cities with higher traditional financial access used traditional bank credit more than FinTech credit after the outbreak of COVID-19. This effect increases when we control for macroeconomic variables. For FinTech credit usage, we find that the coefficients of the interaction term are significantly negative when we control for macroeconomic variables.

These results show that payment convenience affects consumer choice regarding credit types. People located in cities with more developed traditional finance find it easier to obtain traditional financial services; thus, the payment convenience of FinTech credit is not as obvious as that of bank credit cards. This is consistent with recent findings that FinTech consumer lending and adoption has generally penetrated areas that tend to not qualify for traditional bank lending (Jagtiani and Lemieux, 2018; Erel and Liebersohn, 2022). This effect is more obvious during high-risk periods (Liu et al., 2022).

6. Heterogeneity Analysis

We find that the impact of the COVID-19 pandemic on consumer credit varies significantly across consumers who experienced different levels of COVID-19 shock. In this section, we further explore whether the response of FinTech and traditional bank credit usage to COVID-19 exposure is heterogeneous across consumers and regions.

6.1 Age

We start by examining the heterogeneity across consumer age ranges. Previous studies find that younger people are less likely to access to bank credit cards because they have lower and more unstable income. However, we here consider consumers who have access to both bank credit cards and FinTech credit to exclude that argument and then explore whether there is a difference in credit usage between younger and older people.

We categorized people into two cohorts by age: under 31 years and older than 31 years. Thus, we have a dummy variable *Age>= 31* representing older groups, and we estimate the triple differences (DDD) regression model. As shown in Table 9, when we control for individual and year-month fixed effects, the coefficient on the interaction term between *Covid*Confirmed* and *Age>= 31* is significantly positive for traditional bank credit usage (as shown in Columns (1)-(2)) and negative for FinTech credit usage (as shown in Columns (3)-(4)). Combined with the coefficient of *Covid*Confirmed*, we find that consumers older than 31 years old used more traditional bank credit and less FinTech credit than younger consumers after the outbreak of COVID-19.

These findings are consistent with our consumption downgrading hypothesis and further reflect the different degrees of consumption downgrading among consumers of different ages. Older people are better able to maintain their large-amount transactions and still experience a slighter consumption downgrading than younger people, despite their experiencing the same negative shock. Moreover, according to Yang and Zhang's (2022)[12] findings, younger people are more familiar with and more receptive to FinTech credit. Therefore, older people may have less demand for FinTech credit than younger people.

6.2 Gender

Recent studies focusing on gender inequality in the post-COVID-19 era show that females are disproportionately impacted due to poverty and a lower level of job opportunity (Agur et al., 2020). Thus, the income shocks faced by men and women are also different. Here, we further examine whether gender impacts credit adoption following the outbreak of COVID-19.

Specifically, we interact the *Covid*Confirmed* variable with a dummy variable *female,* which indicates whether the consumer is female. In Columns (1)-(2) of Table 10, the coefficients of the interaction term are significantly negative for traditional bank credit usage, which indicates that after the COVID-19 shock, women reduced their bank credit card payment share of total consumption more than men, reflecting a gender gap in traditional bank credit usage. However, there is an obvious increase in FinTech credit usage among women compared to that among men, as the coefficients of the interaction term in Columns (3)-(4) are significantly positive.

The different borrowing behaviors of women and men imply that the gender gap also remained in traditional bank credit usage, where even women with the same access to bank credit as men experienced different income shocks and underwent different consumption changes. For example, women had fewer job opportunities than men and had to cut more services or durable goods out of their budgets after the pandemic. Thus, women also reduced their credit card usage more than men. Our results complement previous studies on gender differences in risk-taking (e.g., Byrnes et al., 1999; Croson and Gneezy, 2009), banking services (Demirgüç-Kunt and Singer, 2017), and household finance management (Guiso and Zaccaria, 2023) (including borrowing

[12] In Yang and Zhang (2022)'s study, they find that younger cohorts are more likely to consume online and Fintech is expected to affect consumption inequality more among younger cohorts.

behaviors) under uncertainty.

Furthermore, several studies show that FinTech is used differently by women and men and that FinTech falls short of addressing this gender gap (Chen et al., 2023). Our results indicate that female consumers are more likely to use FinTech credit to buy small-amount goods.

6.3 Region

In addition to individual characteristics, regional variations may also impact consumer credit demand. Here, we continue to explore the impact of regional characteristics. In China, the central region and the western region are relatively backward compared to the eastern region in terms of economic and digital financial development. Therefore, we explore borrowing response across different administrative regions.

We construct 2 dummy variables, *Central* and *Western,* to proxy for whether consumers are located in the central or western region, and we interact these proxies with pandemic exposure. As shown in Table 11, the coefficients of the interaction term between *Central* and *Covid*Confirmed* are significantly negative for traditional bank credit usage, as shown in Column (1). However, the negative effect is not significant when we control for macroeconomic variables. For FinTech credit, we also find that the coefficients of both interaction terms are not significant when we control for macroeconomic variables, as shown in Column (4). Combining these two results, we conclude that consumers living in different administrative regions experienced no obvious heterogeneities in the level of consumer credit adoption.

These findings show that with the development of digital technology and mobile payment, physical distance has no limitation on either FinTech or traditional financial service access.

6.4 Trust in Big Tech Platforms

Previous studies find that the acceptance of FinTech or Big Tech is an essential factor impacting the usage of FinTech services. We then explore whether it also plays an important role when we compare traditional financial services and FinTech services on the same Big Tech platform.

We compare the difference in consumer credit usage between consumers with a low level of trust and those with a high level of trust in Big Tech platforms after the COVID-19 outbreak. Unfortunately, there is no direct variable for measuring trust in our dataset. We assume that people who are more likely to trust the Big Tech platforms offered by Big Tech companies would like to conduct digital wealth management on these platforms. Here, we divide the individuals into two groups according to their average (log) holdings of total assets on the platform during the first half of 2019, and we obtain a dummy variable $High\_trust$, which equals 1 if this value is above its top 25% quantiles and 0 otherwise, to represent a high or low level of trust in Big Tech platforms. Table 12 reports the results. We find that the coefficients on the interaction term between $High\_trust$ and *Covid*Confirmed* are not significant, as shown in

Columns (1)-(2), indicating that the traditional borrowing behavior of consumers with high trust in Big Tech platforms has no obvious heterogeneity with consumers with lower levels of trust.

For FinTech credit usage, the coefficient of the interaction term is significantly positive in Columns (3)-(4), which indicates that there is an obvious difference in consumer credit usage between people with high levels of trust and people with low levels of trust in Big Tech platforms. That is, people with higher levels of trust more readily adopt FinTech credit.

Therefore, the acceptance of FinTech or Big Tech also plays an essential role in financial service on the same Big Tech platform.

6.5 Wealth

As previous studies find that the marginal propensity to consume is dependent on wealth distribution (Carroll et al., 2017) and that financial conditions are one of the most important factors that impact the level of uncertainty in economic expectations (Ben-David et al., 2018), we would expect there to be a difference among people of various wealth levels in credit usage following the outbreak of COVID-19.

Unfortunately, we are unable to obtain the total income or wealth of individual consumers due to the Act of Data privacy. Rather, we obtain the average total deposit of the household sector of a city during the first half of 2019 in our sample and divide the individuals into two groups according to city-level wealth. We obtain a dummy variable $high\_wealth$, which equals 1 if the wealth level is above its median and 0 otherwise. As shown in Table 13, we find that the coefficient of the interaction term between *High_wealth* and *Covid*Confirmed* is significantly positive for traditional bank credit usage. This indicates that high-wealth consumers also increase their levels of borrowing from traditional banks.

For FinTech credit usage, the coefficient of the interaction term is significantly negative, while the coefficient of *Covid*Confirmed* is significantly positive, suggesting that people with high wealth cut their FinTech borrowing, while people with low wealth increase their Fintech borrowing.

Our results concerning the low-wealth group echo prior studies that find FinTech credit has extensive margin effects (Ji et al. 2023). Consumers with high levels of wealth find it easier to maintain service or durable consumption through the use of credit cards. However, consumers with low levels of wealth may need more credit usage to support essential consumption, particularly when their income or wealth faces negative shocks.

7. Conclusion

In this paper, we document the changing patterns of consumption and consumer credit usage following the COVID-19 pandemic using data from nearly 100,000 users on a leading Big Tech platform in China. We find that the consumers in cities hit harder by the pandemic experienced a larger decline in overall consumption (particularly for service consumption) and an increase in consumer credit usage. Interestingly, consumers with both credit cards and BNPL FinTech credit were more inclined to borrow from FinTech credit (via BNPL) than from traditional banks (via credit cards) during this period. These effects are more pronounced among consumers who are female, younger, less wealthy, and who invest more money in Big Tech platforms. Most importantly, FinTech credit is more likely to serve as a complement to traditional bank credit on the same Big Tech platform, as these two credit sources cater to different payment amounts. Therefore, the rise of FinTech credit is closely related to consumption downgrading, as FinTech credit is often used to purchase of goods and services with much lower prices than those purchased using traditional financial access. Moreover, the payment convenience of FinTech credit became more obvious after the outbreak of COVID-19, as maintaining access to traditional financial services became more difficult. Our findings thus reveal the niche occupied by FinTech credit and the interaction between consumption and consumer credit in the face of exogeneous, adverse shocks, with policy implications in regard to efforts to enhance the resilience of consumer spending.

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References

[1] Agarwal, S., Qian, W., Tan, R., Agarwal, S., Qian, W., Tan, R., 2020a. Financial inclusion and financial technology. Household finance: A functional approach, 307-346.

[2] Agarwal, S., Qian, W., Ren, Y., Tsai, H. T., Yeung, B. Y., 2020b. The real impact of FinTech: Evidence from mobile payment technology. Available at SSRN 3556340.

[3] Agur, I., Peria, S. M., Rochon, C., 2020. Digital financial services and the pandemic: Opportunities and risks for emerging and developing economies. International Monetary Fund Special Series on COVID-19, Transactions, 1, 2-1.

[4] Allen, L., Shan, Y., Shen, Y., 2022. Do FinTech mortgage lenders fill the credit gap? evidence from natural disasters. Journal of Financial and Quantitative Analysis, 1-42.

[5] Andersen, A. L., Hansen, E. T., Johannesen, N., Sheridan, A., 2022. Consumer responses to the COVID‐19 crisis: Evidence from bank account transaction data. The Scandinavian Journal of Economics, 124(4), 905-929.

[6] Bahmani-Oskooee, M., Xi, D., 2011. Exchange rate volatility and domestic consumption: A multicountry analysis. Journal of Post Keynesian Economics,

34(2), 319-330.
[7] Bahmani-Oskooee, M., Kutan, A. M., Xi, D., 2015. Does exchange rate volatility hurt domestic consumption? Evidence from emerging economies. International economics, 144, 53-65.
[8] Baker, S. R., Farrokhnia, R. A., Meyer, S., Pagel, M., Yannelis, C., 2020. How does household spending respond to an epidemic? Consumption during the 2020 COVID-19 pandemic. The Review of Asset Pricing Studies, 10(4), 834-862.
[9] Bao, Z., Huang, D., 2021. Shadow banking in a crisis: Evidence from FinTech during COVID-19. Journal of Financial and Quantitative Analysis, 56(7), 2320-2355.
[10] Beck, T., Gambacorta, L., Huang, Y., Li, Z., Qiu, H., 2022. Big techs, QR code payments and financial inclusion.
[11] Ben-David, I., Fermand, E., Kuhnen, C. M., Li, G., 2018. Expectations uncertainty and household economic behavior (No. w25336). National Bureau of Economic Research.
[12] Benito, A., 2006. Does job insecurity affect household consumption? Oxford Economic Papers, 58(1), 157-181.
[13] Berg, T., Burg, V., Gombović, A., Puri, M., 2020. On the rise of FinTech: Credit scoring using digital footprints. The Review of Financial Studies, 33(7), 2845-2897.
[14] Bian, W., Cong, L. W., Ji, Y., 2023. The Rise of E-Wallets and Buy-Now-Pay-Later: Payment Competition, Credit Expansion, and Consumer Behavior (No. w31202). National Bureau of Economic Research.
[15] Binder, C., 2017a. Fed speak on main street: Central bank communication and household expectations. Journal of Macroeconomics, 52, 238-251.
[16] Binder, C. C., 2017b. Measuring uncertainty based on rounding: New method and application to inflation expectations. Journal of Monetary Economics, 90, 1-12.
[17] Bloom, N., Bond, S., Van Reenen, J., 2007. Uncertainty and investment dynamics. The review of economic studies, 74(2), 391-415.
[18] Bordo, M. D., Duca, J. V., Koch, C., 2016. Economic policy uncertainty and the credit channel: Aggregate and bank level US evidence over several decades. Journal of Financial stability, 26, 90-106.
[19] Buchak, G., Matvos, G., Piskorski, T., Seru, A., 2018. FinTech, regulatory arbitrage, and the rise of shadow banks. Journal of financial economics, 130(3), 453-483.
[20] Buchak, G., Hu, J., Wei, S. J., 2021. FinTech as a financial liberator (No. w29448). National Bureau of Economic Research.
[21] Byrnes, J. P., Miller, D. C., Schafer, W. D., 1999. Gender differences in risk taking: A meta-analysis. Psychological bulletin, 125(3), 367.
[22] Carlin, B., Olafsson, A., Pagel, M., 2017. FinTech adoption across generations: Financial fitness in the information age (No. w23798). National Bureau of Economic Research.
[23] Carroll, C., Slacalek, J., Tokuoka, K., White, M. N., 2017. The distribution of wealth and the marginal propensity to consume. Quantitative Economics, 8(3), 977-1020.
[24] Chen, H., Qian, W., Wen, Q., 2021. The impact of the COVID-19 pandemic on consumption: Learning from high-frequency transaction data. In AEA Papers and Proceedings, Vol. 111, pp. 307-311.

[25] Chen, S., Doerr, S., Frost, J., Gambacorta, L., Shin, H. S., 2023. The FinTech gender gap. Journal of Financial Intermediation, 54, 101026.
[26] Christelis, D., Georgarakos, D., Jappelli, T., van Rooij, M, 2020. Consumption uncertainty and precautionary saving. Review of Economics and Statistics, 102(1), 148-161.
[27] Chronopoulos, D. K., Lukas, M., Wilson, J. O., 2020. Consumer spending responses to the COVID-19 pandemic: An assessment of Great Britain. Available at SSRN 3586723.
[28] Claessens, S., Frost, J., Turner, G., Zhu, F., 2018. FinTech credit markets around the world: size, drivers and policy issues. BIS Quarterly Review September.
[29] Cong, L. W., Yang, X., Zhang, X., 2021. Smes amidst the pandemic and reopening: Digital edge and transformation. No. 2392-2022-134.
[30] Croson, R., Gneezy, U., 2009. Gender differences in preferences. Journal of Economic literature, 47(2), 448-474.
[31] Crouzet, N., Gupta, A., Mezzanotti, F., 2023. Shocks and technology adoption: Evidence from electronic payment systems. Journal of Political Economy, 131(11), 3003-3065.
[32] De Bruin, W. B., Manski, C. F., Topa, G., Van Der Klaauw, W., 2011. Measuring consumer uncertainty about future inflation. Journal of Applied Econometrics, 26(3), 454-478.
[33] Demirgüç-Kunt, A., Singer, D., 2017. Financial inclusion and inclusive growth: A review of recent empirical evidence. World Bank Policy Research Working Paper, (8040).
[34] Erel, I., Liebersohn, J., 2022. Can FinTech reduce disparities in access to finance? Evidence from the Paycheck Protection Program. Journal of Financial Economics, 146(1), 90-118.
[35] Frost, J., 2020. The economic forces driving FinTech adoption across countries. The technological revolution in financial services: how banks, FinTechs, and customers win together, 838, 70-89.
[36] Frost, J., Gambacorta, L., Huang, Y., Shin, H. S., Zbinden, P., 2019. BigTech and the changing structure of financial intermediation. Economic Policy, 34(100), 761-799.
[37] Fu, J., Mishra, M., 2022. FinTech in the time of COVID− 19: Technological adoption during crises. Journal of Financial Intermediation, 50, 100945.
[38] Fulford, S. L., 2015. How important is variability in consumer credit limits?. Journal of Monetary Economics, 72, 42-63.
[39] Fuster, A., Plosser, M., Schnabl, P., Vickery, J., 2019. The role of technology in mortgage lending. The Review of Financial Studies, 32(5), 1854-1899.
[40] Gambacorta, L., Huang, Y., Li, Z., Qiu, H., Chen, S., 2023. Data versus collateral. Review of Finance, 27(2), 369-398.
[41] Gao, H., Wen, H., Wang, X., 2022. Pandemic effect on corporate financial asset holdings: Precautionary or return-chasing?. Research in International Business and Finance, 62, 101750.
[42] Gertler, P., Higgins, S., Malmendier, U., Ojeda, W., 2022. Why are firms slow to adopt profitable opportunities?. Working Paper.
[43] Grennan, J., Michaely, R., 2021. FinTechs and the Market for Financial Analysis.

Journal of Financial and Quantitative Analysis, 56(6), 1877-1907.
[44] Guiso, L., Zaccaria, L., 2023. From patriarchy to partnership: Gender equality and household finance. Journal of Financial Economics, 147(3), 573-595.
[45] Hau, H., Huang, Y., Shan, H., Sheng, Z., 2019. How FinTech enters China's credit market. In AEA Papers and Proceedings, Vol. 109, pp. 60-64.
[46] Higgins, S., 2019. Financial technology adoption. Northwestern University: Kellogg School of Management.
[47] Hu, X., Huang, Y., Li, B., Lu, T., 2023. Inclusive Decision Making via Contrastive Learning and Domain Adaptation. Available at SSRN 4496106.
[48] Huang, Z., Tan, Y., Yang, Z., Zhang, X., 2023. FinTech adoption and the effects of economic uncertainty on household consumption. China Economic Review, 102011.
[49] Hülsewig, O., Mayer, E., Wollmershäuser, T., 2006. Bank loan supply and monetary policy transmission in Germany: An assessment based on matching impulse responses. Journal of Banking & Finance, 30(10), 2893-2910.
[50] Jack, W., Ray, A., and Suri, T., 2013. Transaction networks: Evidence from mobile money in Kenya. American Economic Review, 103(3), 356-361.
[51] Jagtiani, J., Lemieux, C., 2018. Do FinTech lenders penetrate areas that are underserved by traditional banks?. Journal of Economics and Business, 100, 43-54.
[52] Ji, Y., Wang, X., Huang, Y., Chen, S., Wang, F., 2023. Buy now, pay later as liquidity insurance: Evidence from an early experiment in China. China Economic Review, 80, 101998.
[53] Jiménez, G., Ongena, S., Peydró, J. L., Saurina, J., 2012. Credit supply and monetary policy: Identifying the bank balance-sheet channel with loan applications. American Economic Review, 102(5), 2301-2326.
[54] Liu, Y., Zhang, Y., Zhang, Y., Xiao, H., 2022. Small business owners' FinTech credit in crises: Theory and evidence from farmers under the COVID-19. Pacific-Basin Finance Journal, 71, 101692.
[55] Lyons, A. C., Kass-Hanna, J., Fava, A., 2022. FinTech development and savings, borrowing, and remittances: A comparative study of emerging economies. Emerging Markets Review, 51, 100842.
[56] Parlour, C. A., Rajan, U., Zhu, H., 2022. When FinTech competes for payment flows. The Review of Financial Studies, 35(11), 4985-5024.
[57] Stiglitz, J. E., Weiss, A., 1981. Credit rationing in markets with imperfect information. The American Economic Review, 71(3), 393-410.
[58] Suri, T., Bharadwaj, P., Jack, W., 2021. FinTech and household resilience to shocks: Evidence from digital loans in Kenya. Journal of Development Economics, 153, 102697.
[59] Tang, H., 2019. Peer-to-peer lenders versus banks: Substitutes or complements? Review of Financial Studies, 32(5):1900–1938
[60] Tantri, P., 2021. FinTech for the poor: Financial intermediation without discrimination. Review of Finance, 25(2), 561-593.
[61] Telyukova, I. A., 2013. Household need for liquidity and the credit card debt puzzle. Review of Economic Studies, 80(3), 1148-1177.
[62] Thakor, A. V., 2020. Fintech and banking: What do we know?. Journal of Financial Intermediation, 41, 100833.

[63] Yang, T., Zhang, X., 2022. FinTech adoption and financial inclusion: Evidence from household consumption in China. Journal of Banking and Finance, 145, 106668.

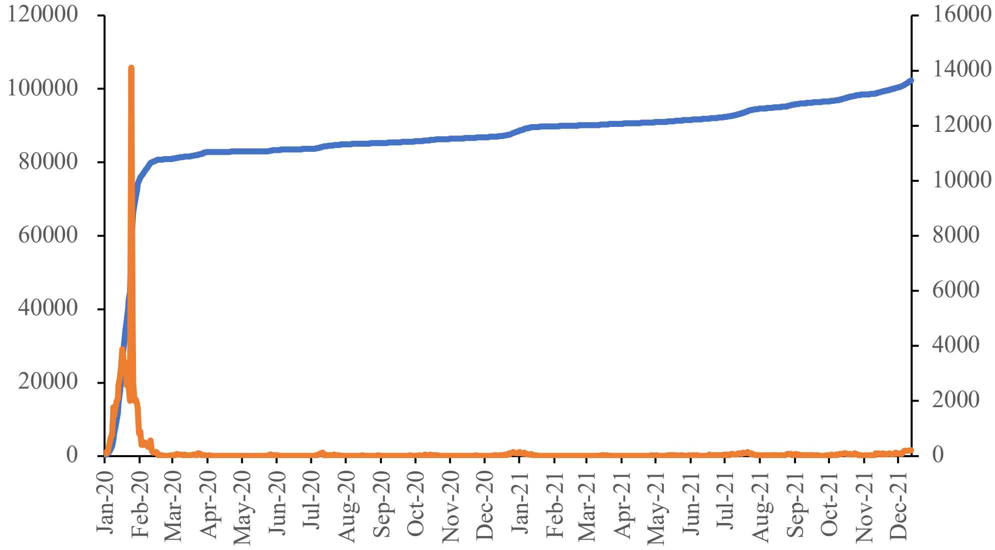

Figure 1. The cumulative and newly confirmed cases of COVID-19. The cumulative confirmed cases (blue solid line, left axis) and newly confirmed cases (orange solid line, right axis) of COVID-19 during the period ranging from January 2020 to December 2021.

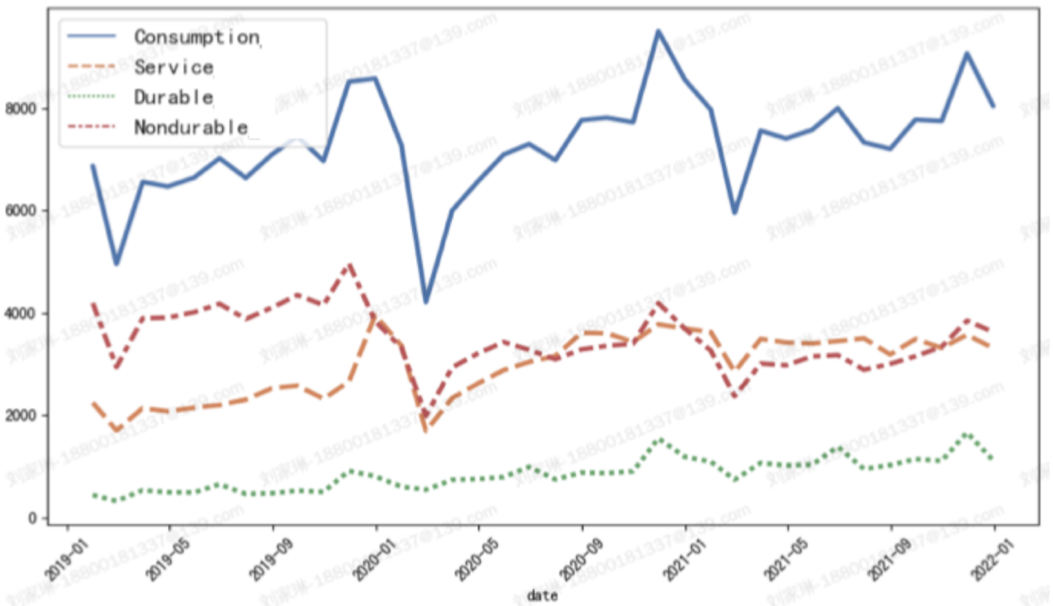

Figure 2. Consumption and its categories. The average amount of consumption (blue solid line) and categories such as service goods consumption (orange dotted line), nondurable goods consumption (red dotted line) and durable goods consumption (green dotted line) over the period of Jan 2019 to Dec 2021 of a random sample of 100,000 Alipay users.

Figure 3. Consumer credit adoption. The upper panel shows the average consumption amount by using credit card payments (blue solid line) and FinTech credit payments (orange dotted line) over the period of Jan 2019 to Dec 2021 of a random sample of 100,000 Alipay users. The lower panel shows the proportion of total consumer credit payments (blue solid line) in total consumption, credit card payments (orange dotted line) in total consumption and FinTech consumer credit payments (green dotted line) in total consumption over the period of Jan 2019 to Dec 2021 of a random sample of 100,000 Alipay users.

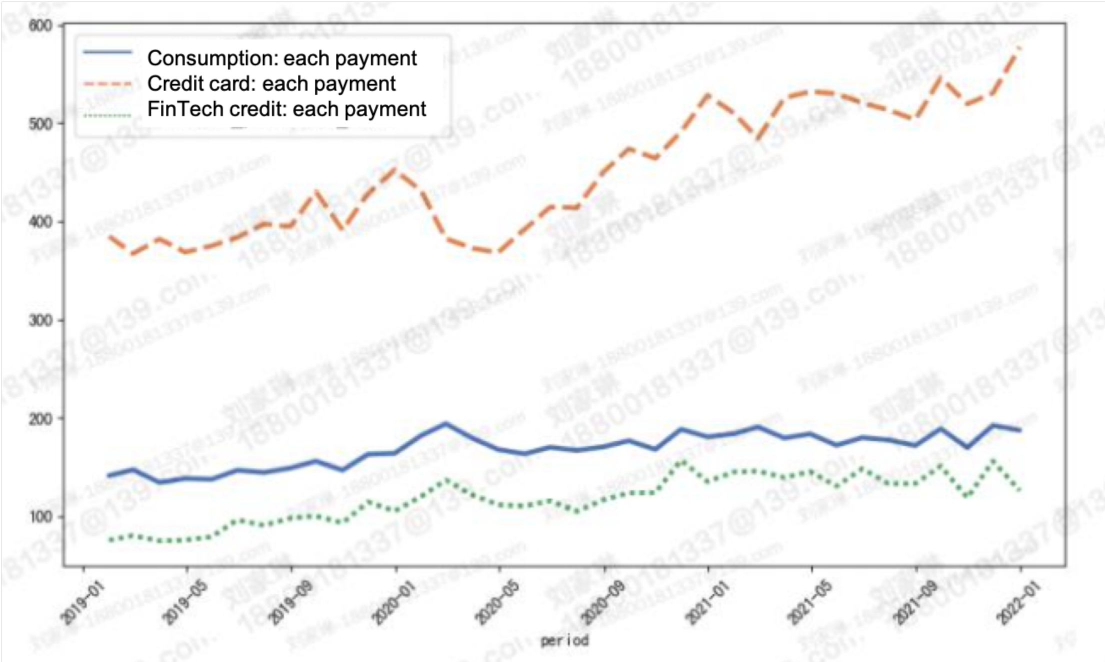

Figure 4. The average transaction amount per payment. Consumption per payment (blue solid line), credit card transaction amount per payment (orange dotted line), and FinTech credit transaction amount per payment (green dotted line) on average over the period of Jan 2019 to Dec 2021 of a random sample of 100,000 Alipay users.

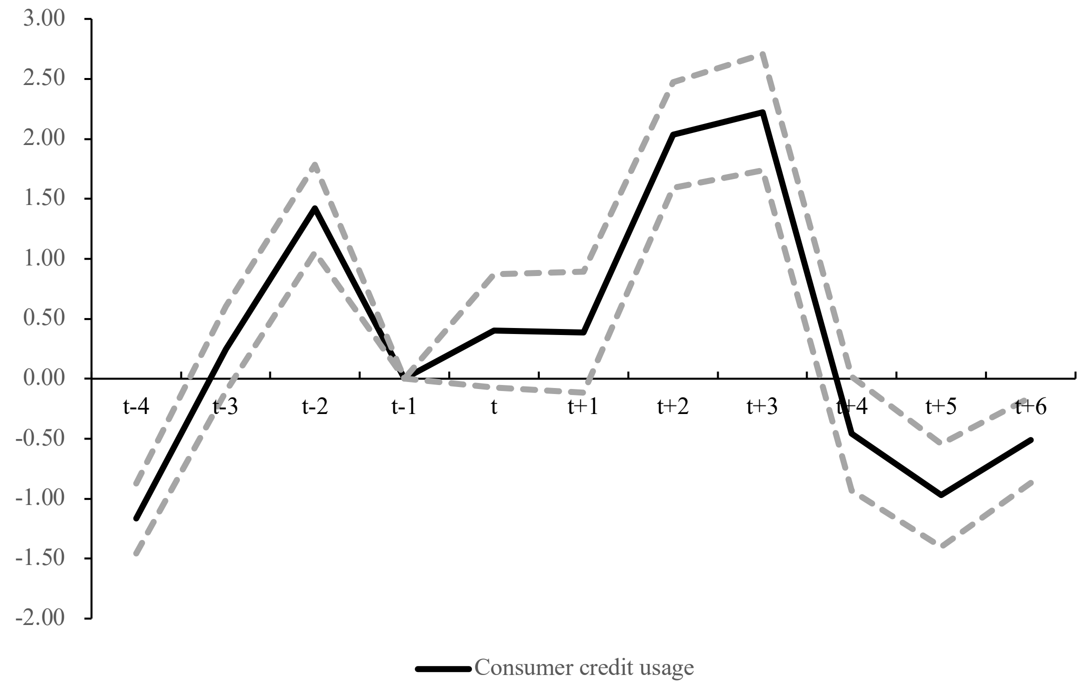

Figure 5. The dynamic change in total consumer credit usage. The black solid line represents total consumer credit usage. The grade dotted lines represent the 95% confidence interval.

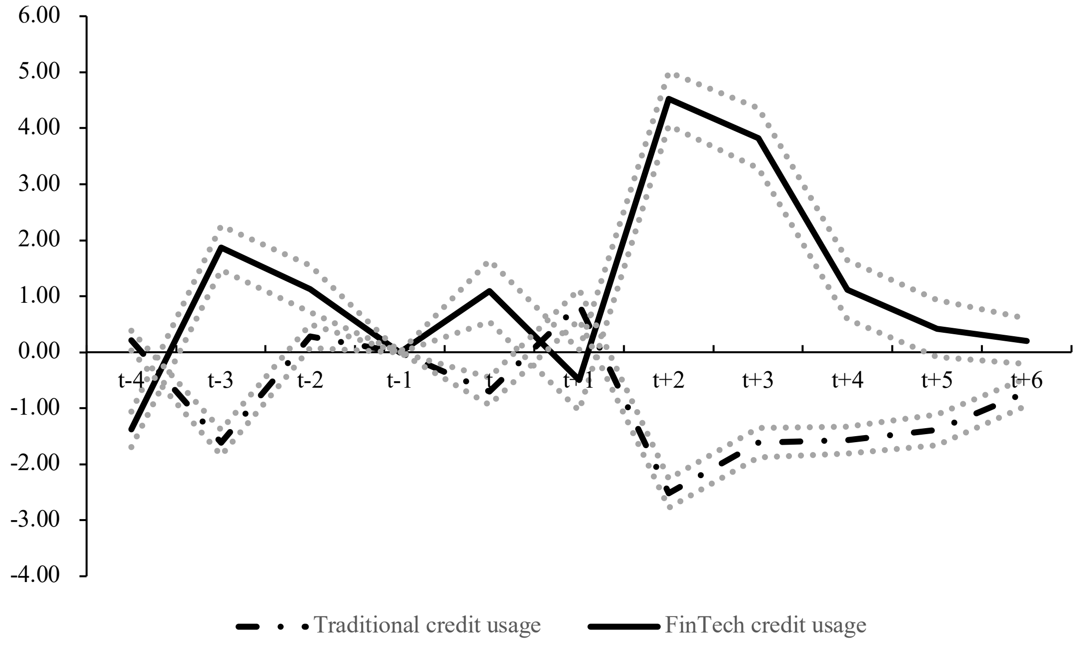

Figure 6. The dynamic change in traditional credit usage and FinTech credit usage. The black solid line represents FinTech credit usage. The black dotted line represents traditional credit usage. The grade dotted lines represent the 95% confidence interval.

Table 1 Summary Statistics

	N	Mean	Sd	Min	P50	Max
Panel A: Dependent variables						
Consumption (log)	3506409	7.8531	1.3966	3.5836	7.8924	11.1821
Service (log)	3506409	6.8266	1.6462	0.0000	6.9734	10.3340
Durable (log)	3506409	2.9668	2.8944	0.0000	3.0345	9.5312
NonDurable (log)	3506409	6.4913	2.0606	0.0000	6.7314	10.6808
ConsumptionNum (log)	3506409	3.5869	0.8970	1.0986	3.6889	5.2575
ServiceNum (log)	3506409	2.9757	1.0168	0.0000	3.0910	4.8903
DurableNum (log)	3506409	0.7431	0.7650	0.0000	0.6931	2.9444
NonDurableNum (log)	3506409	2.5066	0.9952	0.0000	2.6391	4.5326
Consumer credit usage	3506409	64.6008	35.9353	0.0000	79.4948	100.0000
Traditional bank credit usage	3506409	13.2086	26.9558	0.0000	0.0000	100.0000
FinTech credit usage	3506409	51.3915	38.1624	0.0000	54.4572	100.0000
Panel B: Key independent variables						
Covid	3572604	0.0666	0.4714	0.0000	1.0000	1.0000
Confirmed (log)	2990520	4.4717	1.6291	0.6931	4.2905	10.8199
Confirmed (ratio)	2990520	0.0181	0.0905	0.0000	0.0012	0.5458
Panel C: Individual characteristics						
Female	99239	0.3833	0.4862	0.0000	0.0000	1.0000
Age	99239	33.1753	8.1859	21.0000	31.0000	80.0000
Risk1	99239	0.0550	0.2279	0.0000	0.0000	1.0000
Risk2	99239	0.3816	0.4858	0.0000	0.0000	1.0000
Risk3	99239	0.2195	0.4139	0.0000	0.0000	1.0000
Risk4	99239	0.3069	0.4612	0.0000	0.0000	1.0000
Risk5	99239	0.0349	0.1836	0.0000	0.0000	1.0000
Digital_assets (log)(t-1)	3473365	7.3025	3.4614	0.0000	8.0537	12.9153
Panel D: Macor control variables						
GDP (log)(t_{year}-1)	2981424	8.7107	0.9520	6.4983	8.7751	10.2281
Population (log)(t_{year}-1)	1988544	6.3466	0.5162	4.8520	6.4118	7.3139
Second (t_{year}-1)	2981424	40.4422	8.1579	21.4800	40.3600	58.0400
Third (t_{year}-1)	2981424	53.6702	9.0489	35.6200	52.4700	72.5100

Note: This table reports the summary statistics of 99,239 individuals who were randomly selected from Ant Group surveys between January 2019 and December 2021. Female is a binary variable that equals 1 if the individual is a woman and 0 otherwise. Age is a nonnegative variable that represents the age of an individual during the sampling period. Risk1-Risk5 are all binary variables that equal 1 if the individual's risk preference is in the first level, second level, third level, fourth level, or the highest level, respectively, and equal 0 otherwise (a higher level indicates a higher risk preference). Digital_assets is a continuous variable (log value) that represents an individual's total asset holdings on the Big Tech platform. Covid is a dummy variable indicating post-COVID periods that equals 1 for periods in or after January 2020 and 0 otherwise. Confirmed (log) denotes the log value for the confirmed COVID-19 cases in the city where the individual is located during the first quarter of 2020. The confirmed ratio denotes the number of confirmed COVID-19 cases per 100 people in the city where the individual was located during the first quarter of 2020. Consumer credit usage denotes the share of consumer credit payment to the total amount of consumption during the whole year-month. Traditional bank credit usage denotes the share of bank credit card payments in the total amount of consumption during the whole year-month. FinTech credit usage denotes the share of FinTech credit payments in the total amount of consumption during the whole year-month. Variables ending with (log) denote the log value for the total amount of consumption (Consumption (log)), service goods consumption (Service (log)), durable goods consumption (Durable (log)), nondurable goods consumption (NonDurable (log)) during the whole year-month. Variables, including Num, denote the log value for the payment numbers of total consumption (ConsumptionNum (log)), service goods consumption (ServiceNum (log)), durable goods consumption (DurableNum (log)), and nondurable goods consumption (NonDurableNum (log)). GDP (log) denotes the lagged 1-year gross domestic product of the city where the consumer is located. Population (log) denotes the lagged 1-year population (log value) of the city where the consumer is located at the end of the year. Second and Third denote the lagged 1-year share of secondary industry and the share of tertiary industry on gross domestic product, respectively. We excluded individuals with unreported gender or risk preference, and we winsorized all continuous variables at the 1% and 99% levels.

Table 2 Baseline DID: The Effect of the COVID-19 Outbreak Shock on Consumer Credit

	Full sample					
	Y_{it} = *Consumer credit usage* (*share*)		Y_{it} = *Traditional bank credit usage* (*share*)		Y_{it} = *FinTech credit usage* (*share*)	
	(1)	(2)	(3)	(4)	(5)	(6)
Covid*Confirmed	-0.2861 (0.2031)	0.4317** (0.2007)	0.1184 (0.1557)	-0.6431*** (0.1428)	-0.4099* (0.2180)	1.0673*** (0.2337)
Observation	2932136	1876468	2932136	1876468	2932136	1876468
Adj_R^2	0.4654	0.4871	0.5812	0.6073	0.4850	0.5078
Controls	No	Yes	No	Yes	No	Yes
Individual F.E.	Yes	Yes	Yes	Yes	Yes	Yes
Year-Month F.E.	Yes	Yes	Yes	Yes	Yes	Yes

Note: Table 2 reports the response of total consumer credit usage (Columns (1)-(2)), traditional bank credit usage (Columns (3)-(4)) and FinTech credit usage (Columns 5-6)) to the outbreak of COVID-19. Columns (1)-(6) report the results for share based on consumption amount. The variable of consumer credit usage is the share of total consumer credit on aggregate consumption. The variable of traditional bank credit usage is the share of bank credit card payments on consumption. The variable of FinTech credit usage is the share of BNPL payment on consumption. Covid is a dummy variable indicating post-COVID periods that equals 1 for periods in or after January 2020 and 0 otherwise. Confirmed denotes the cumulative confirmed COVID-19 cases per 100 people in the city where an individual is located during the first quarter of 2020. The control variables include lagged time-variant characteristic (Digital_assets) and lagged city-level macroeconomic variables such as GDP (log), population (log), the share of second industry on GDP (Second), and time series. All specifications include individual fixed effects and year-month fixed effects. Standard errors are clustered at the city level and presented in parentheses. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

Table 3 FinTech and Traditional Bank Credit Usage (Conditional on Dual Access)

	Dual-access Subsample (samples used both bank credit card and FinTech credit before the shock)			
	$Y_{it} = Traditional\ bank\ credit\ usage\ (share)$		$Y_{it} = FinTech\ credit\ usage\ (share)$	
	(1)	(2)	(3)	(4)
Covid*Confirmed	-0.3587*	-0.8213***	0.7118**	1.1621***
	(0.2060)	(0.1879)	(0.3004)	(0.3139)
Observation	1039992	625408	1039992	625408
Adj_R^2	0.6015	0.6249	0.5100	0.5289
Controls	No	Yes	No	Yes
Individual F.E.	Yes	Yes	Yes	Yes
Year-Month F.E.	Yes	Yes	Yes	Yes

Note: Table 3 reports the impact of the COVID-19 pandemic on traditional bank credit usage (Columns (1)-(2)) and FinTech credit usage (Columns (3)-(4)) conditional on individuals who were exposed to bank credit and FinTech credit before COVID-19. Specifically, we selected individuals whose average usage of bank credit cards and FinTech credit was above 0 between January 2019 and June 2019, and we estimate Model (1) using a sample covering the period of July 2019 to December 2021. The variables are the same as those used in Table 2. All specifications include individual fixed effects and year-month fixed effects. Standard errors are clustered at the city level and displayed in parentheses. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

Table 4 FinTech and Traditional Bank Credit Usage (Conditional on No-Access FinTech)

	No-Access to FinTech Subsample (no use of FinTech credit before the shock)			
	$\boldsymbol{Y_{it} = Traditional\ bank\ credit\ usage(adoption)}$		$\boldsymbol{Y_{it} = FinTech\ credit\ usage\ (adoption)}$	
	(1)	(2)	(3)	(4)
Covid*Confirmed	1.1142**	-0.3869	-0.4013	2.7275***
	(0.4762)	(0.4218)	(0.6655)	(0.6627)
Observation	165462	99492	165462	99492
Adj_R^2	0.6046	0.6252	0.5091	0.5276
Controls	No	Yes	No	Yes
Individual F.E.	Yes	Yes	Yes	Yes
Year-Month F.E.	Yes	Yes	Yes	Yes

Note: Table 4 reports the impact of the COVID-19 pandemic on traditional bank credit usage (Columns (1)-(2)) and FinTech credit usage (Columns (3)-(4)) conditional on individuals who were not exposed to FinTech credit before COVID-19. Specifically, we select individuals whose average usage of FinTech credit equaled 0 between January 2019 and June 2019, and we estimate Model (1) using a sample from July 2019 to December 2021. The variables are the same as those used in Table 2. All specifications include individual fixed effects and year-month fixed effects. Standard errors are clustered at the city level and displayed in parentheses. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

Table 5 The Effect of the COVID-19 Outbreak Shock on Consumption

	Dual-Access Subsample (samples used both bank credit card and FinTech credit before the shock)				
	Consumption (log)		Service (log)	Durable (log)	Nondurable (log)
	(1)	(2)	(3)	(4)	(5)
Covid*Confirmed	-0.2379***	-0.3822***	-0.5295***	-0.1864***	-0.5522***
	(0.0162)	(0.0175)	(0.0270)	(0.0355)	(0.0374)
Observation	1039992	625408	625408	625408	625408
R^2	0.5058	0.5317	0.4865	0.2941	0.4277
Controls	No	Yes	Yes	Yes	Yes
Individual F.E.	Yes	Yes	Yes	Yes	Yes
Year-Month F.E.	Yes	Yes	Yes	Yes	Yes

Note: Table 5 reports the impact of the COVID-19 pandemic on total consumption (Columns (1)-(2)), service goods consumption (Column (3)), durable goods consumption (Column (4)), and nondurable goods consumption (Column (5)) for individuals who were exposed to bank credit and FinTech credit before the onset of COVID-19. Specifically, we selected individuals whose average usage of bank credit cards and FinTech credit was above 0 between January 2019 and June 2019, and we estimate Model (1) using a sample from July 2019 to December 2021. The dependent variables are all expressed in logarithmic units. Other variables are the same as those used in Table 2. All specifications include individual fixed effects and year-month fixed effects. Standard errors are clustered at the city level and presented in parentheses. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

Table 6 The COVID-19 Outbreak Shock on Consumption: Alternative Measurements

	Dual-Access Subsample (samples used both bank credit card and FinTech credit before the shock)				
	Consumption (log)		Service (log)	Durable (log)	Nondurable (log)
	(1)	(2)	(3)	(4)	(5)
	Panel A: $Y_{it} = Consumption\ (numbers\ log)$				
Covid*Confirmed	-0.2643***	-0.4682***	-0.5494***	-0.0469***	-0.4694***
	(0.0152)	(0.0162)	(0.0169)	(0.0098)	(0.0274)
Observation	1039992	625408	625408	625408	625408
R^2	0.5941	0.6305	0.6164	0.3617	0.5414
	Panel B: $Y_{it} = Consumption\ (\ log)$ **Confirmed (the log value for cumulative confirmed COVID-19 cases during 2020 Q1)**				
Covid*Confirmed	-0.0094*	-0.0226***	-0.0403***	-0.0155***	-0.0229*
	(0.0053)	(0.0059)	(0.0042)	(0.0040)	(0.0124)
Observation	2932136	1876468	1876468	1876468	1876468
R^2	0.4864	0.5130	0.4746	0.2849	0.4086
	Both Panels A and B				
Controls	No	Yes	Yes	Yes	Yes
Individual F.E.	Yes	Yes	Yes	Yes	Yes
Year-Month F.E.	Yes	Yes	Yes	Yes	Yes

Note: Table 6 reports the impact of the COVID-19 pandemic on total consumption (Columns (1)-(2)), service goods consumption (Column (3)), durable goods consumption (Column (4)), and nondurable goods consumption (Column (5)) conditional on individuals who are exposed to bank credit and FinTech credit before COVID-19. Specifically, we selected individuals whose average usage of bank credit cards and FinTech credit was above 0 between January 2019 and June 2019, and we estimate Model (1) using a sample from July 2019 to December 2021. Panel A demonstrates the regression results where consumption is measured as the log value of payment numbers and confirmed consumption is measured as the cumulative number of confirmed COVID-19 cases per 100 people during the first quarter of 2020. Panel B illustrates the regression results where consumption is measured as the log value of consumption amounts and confirmed consumption is measured as the log value for cumulative confirmed COVID-19 cases during the first quarter of 2020. Covid is a dummy variable indicating post-COVID periods that equals 1 for periods in or after January 2020 and 0 otherwise. Other variables are the same as those used in Table 2. All specifications include individual fixed effects and year-month fixed effects. Standard errors are clustered at the city level and presented in parentheses. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

Table 7 FinTech and Traditional Bank Credit Usage for Each Payment (Dual Access)

	Dual-Access Subsample (samples used both bank credit card and FinTech credit before the shock)			
	$\boldsymbol{Y_{it} = Traditional\ bank\ credit(RMB/1000)}$		$\boldsymbol{Y_{it} = FinTech\ credit(RMB/1000)}$	
	(1)	(2)	(3)	(4)
Covid*Confirmed	-0.1814***	-0.1528***	0.0004	0.0014
	(0.0128)	(0.0153)	(0.0021)	(0.0032)
Observation	272141	164885	272141	164885
Adj_R^2	0.3020	0.3087	0.3225	0.3356
Controls	No	Yes	No	Yes
Individual F.E.	Yes	Yes	Yes	Yes
Year-Month F.E.	Yes	Yes	Yes	Yes

Note: Table 7 reports the impact of the COVID-19 pandemic on traditional bank credit payments per transaction (Columns (1)-(2)) and FinTech credit payments per transaction (Columns (3)-(4)) conditional on individuals who were exposed to bank credit and FinTech credit before COVID-19. Specifically, we selected individuals whose average usage of bank credit cards and FinTech credit was above 0 between January 2019 and June 2019, and we estimate Model (1) using a sample from July 2019 to December 2021. Dependent variables are all expressed in thousand RMB units. Other variables are the same as those used in Table 2. All specifications include individual fixed effects and year-month fixed effects. Standard errors are clustered at the city level and presented in parentheses. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

Table 8 FinTech and Traditional Bank Credit Usage (Dual Access): Traditional Financial Service Access

	Dual-Access Subsample			
	(1)	(2)	(3)	(4)
	Traditional		FinTech	
Covid*Confirmed* Traditionalaccess_high	0.9722**	1.6150***	-0.6539	-3.9892***
	(0.4293)	(0.3826)	(0.9060)	(0.8132)
Covid*Confirmed	-0.4482**	-0.9685***	0.7731***	1.5253***
	(0.2104)	(0.1899)	(0.2814)	(0.3073)
Observation	1039992	625408	1039992	625408
Adj_R^2	0.6015	0.6249	0.5100	0.5289
Interaction terms	Yes	Yes	Yes	Yes
Controls	No	Yes	No	Yes
Individual F.E.	Yes	Yes	Yes	Yes
Year-Month F.E.	Yes	Yes	Yes	Yes

Note: Table 8 reports the heterogeneity results among consumers living in cities with different levels of traditional financial service access. We re-estimate the model by focusing on individuals who were exposed to credit before COVID-19. Specifically, we selected individuals whose average usage of bank credit cards and FinTech credit was above 0 between January 2019 and June 2019, and we estimate the model using a sample from July 2019 to December 2021. We construct variables based on consumption amount. Columns (1) to (2) report the results for traditional bank credit usage, and Columns (3) to (4) report the results for FinTech credit usage. We use the number of bank branches per square kilometer of a county in 2019 to represent traditional finance access. *Traditionalaccess_high* is a binary variable that equals 1 if the county has more bank branches per kilometer square (higher than the median of sample) and 0 otherwise. Variables are the same as those used in Table 2. All specifications include individual fixed effects and year-month fixed effects. Standard errors are clustered at the city level and presented in parentheses. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

Table 9 Heterogeneity Analysis: Age

	Dual-access Subsample			
	(1)	(2)	(3)	(4)
	Traditional		FinTech	
Covid*Confirmed*Age>=31	3.1711***	1.1443***	-7.8329***	-6.9008***
	(0.2921)	(0.2613)	(0.5398)	(0.4837)
Covid*Confirmed	-2.1404***	-1.4409***	5.1006***	5.0027***
	(0.2135)	(0.1998)	(0.3487)	(0.3902)
Observation	1039992	625408	1039992	625408
Adj_R^2	0.6015	0.6249	0.5101	0.5290
Interaction terms	Yes	Yes	Yes	Yes
Controls	No	Yes	No	Yes
Individual F.E.	Yes	Yes	Yes	Yes
Year-Month F.E.	Yes	Yes	Yes	Yes

Note: Table 9 reports the heterogeneity analysis among consumers of different ages. We re-estimate the model by focusing on individuals who were exposed to credit before COVID-19. Specifically, we selected individuals whose average usage of bank credit cards and FinTech credit was above 0 between January 2019 and June 2019, and we estimate the model using a sample from July 2019 to December 2021. We constructed dependent variables based on consumption amount. Columns (1) to (2) report the results for traditional bank credit usage, and Columns (3) to (4) report the results for FinTech credit usage. *Age>=31* is a binary variable that equals 1 if the consumer is older than 31 years old and 0 otherwise. Variables are the same as those used in Table 2. All specifications include individual fixed effects and year-month fixed effects. Standard errors are clustered at the city level and presented in parentheses. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

Table 10 Heterogeneity Analysis: Gender

	Dual-access Subsample			
	(1)	(2)	(3)	(4)
	Traditional		FinTech	
Covid*Confirmed*Female	-1.0987***	-1.5460***	1.3887***	1.3198***
	(0.3205)	(0.2600)	(0.5920)	(0.4749)
Covid*Confirmed	0.0376	-0.2642	0.2007	0.6921*
	(0.2565)	(0.2168)	(0.4242)	(0.3660)
Observation	1039992	625408	1039992	625408
Adj_R^2	0.6015	0.6249	0.5100	0.5290
Interaction terms	Yes	Yes	Yes	Yes
Controls	No	Yes	No	Yes
Individual F.E.	Yes	Yes	Yes	Yes
Year-Month F.E.	Yes	Yes	Yes	Yes

Note: Table 8 reports the heterogeneity analysis across consumer gender. We re-estimate the model by focusing on individuals who were exposed to credit before COVID-19. Specifically, we selected individuals whose average usage of bank credit cards and FinTech credit was above 0 between January 2019 and June 2019, and we estimate the model using a sample from July 2019 to December 2021. We constructed variables based on consumption amount. Columns (1) to (2) report the results for traditional bank credit usage, and Columns (3) to (4) report the results for FinTech credit usage. *Female* is a binary variable that equals 1 if the individual is female and 0 otherwise. Other variables and samples are the same as those used in Table 2. All specifications include individual fixed effects and year-month fixed effects. Standard errors are clustered at the city level and presented in parentheses. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

Table 11 Heterogeneity Analysis: Administrative Region

	Dual-access Subsample			
	(1)	(2)	(3)	(4)
	Traditional		FinTech	
Covid*Confirmed*Central	-67.8436**	-47.8400	-79.0910*	19.6952
	(29.6509)	(34.0834)	(46.5803)	(68.1239)
Covid*Confirmed*Western	283.6651	31.5423	-1343.8398**	-949.7470
	(315.8244)	(339.9518)	(674.9385)	(692.4641)
Covid*Confirmed	67.6602**	47.0944	79.4893*	-18.7105
	(29.6487)	(34.1156)	(46.5778)	(68.1896)
Observation	1039992	625408	1039992	625408
Adj_R^2	0.6015	0.6249	0.5100	0.5289
Interaction terms	Yes	Yes	Yes	Yes
Controls	No	Yes	No	Yes
Individual F.E.	Yes	Yes	Yes	Yes
Year-Month F.E.	Yes	Yes	Yes	Yes

Note: Table 11 reports the heterogeneity analysis among consumers located in different regions. We re-estimate the model by focusing on individuals who were exposed to credit before COVID-19. Specifically, we selected individuals whose average usage of bank credit cards and FinTech credit was above 0 between January 2019 and June 2019, and we estimate the model using a sample from July 2019 to December 2021. We constructed variables based on consumption amounts. Columns (1) to (2) report the results for traditional bank credit usage, and Columns (3) to (4) report the results for FinTech credit usage. Here, we divided regions according to administrative region in China and compared the response of consumer credit usage of people living in the central regions and western regions with people living in the eastern regions. Central is a binary variable that equals 1 if the consumer lives in the central region and 0 otherwise. Western is a binary variable that equals 1 if the consumer lives in the western region and 0 otherwise. We merge the dummy variable of city-level to individual-level data according to an individual's location. Other variables are the same as those used in Table 2. All specifications include individual fixed effects and year-month fixed effects. Standard errors are clustered at the city level and presented in parentheses. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

Table 12 Heterogeneity Analysis: Trust in the Big Tech Platform

	Dual-access Subsample			
	(1)	(2)	(3)	(4)
	Traditional		FinTech	
Covid*Confirmed*High_trust	-0.3334	-0.0420	5.0219***	2.4326**
	(0.3267)	(0.3074)	(0.5266)	(0.4852)
Covid*Confirmed	-0.2771	-0.8069***	-0.4391	0.6089*
	(0.2276)	(0.2125)	(0.3275)	(0.3463)
Observation	1039992	625408	1039992	625408
Adj_R^2	0.6015	0.6249	0.5100	0.5289
Interaction terms	Yes	Yes	Yes	Yes
Controls	No	Yes	No	Yes
Individual F.E.	Yes	Yes	Yes	Yes
Year-Month F.E.	Yes	Yes	Yes	Yes

Note: Table 12 reports the heterogeneity analysis among consumers with different levels of trust in the Big Tech platform. We re-estimate the model by focusing on individuals who were exposed to credit before COVID-19. Specifically, we selected individuals whose average usage of bank credit cards and FinTech credit was above 0 between January 2019 and June 2019, and we estimate the model using a sample from July 2019 to December 2021. We constructed variables based on consumption amount. Columns (1) to (2) report the results for traditional bank credit usage, and Columns (3) to (4) report the results for FinTech credit usage. Here, we use consumers' monthly holdings of online financial assets to reflect people's trust in the Big Tech platform to some extent. *High_trust* is a binary variable constructed based on the average of (log) total assets during the first half of 2019. It equals 1 if it is above the full sample's top 25% quantiles and 0 otherwise. Other variables are the same as those used in Table 2. All specifications include fixed effects and year-month fixed effects. Standard errors are clustered at the city level and presented in parentheses. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

Table 13 Heterogeneity Analysis: Wealth

	Dual-access Subsample			
	(1)	(2)	(3)	(4)
	Traditional		FinTech	
Covid*Confirmed*High_wealth	0.1653	0.6570**	-0.2716	-2.2351***
	(0.2901)	(0.2736)	(0.4789)	(0.4363)
Covid*Confirmed	-0.4321*	-1.1078***	0.8261**	2.1236***
	(0.2451)	(0.2379)	(0.3298)	(0.3611)
Observation	1039992	625408	1039992	625408
Adj_R^2	0.6015	0.6429	0.5100	0.5289
Interaction terms	Yes	Yes	Yes	Yes
Controls	No	Yes	No	Yes
Individual F.E.	Yes	Yes	Yes	Yes
Year-Month F.E.	Yes	Yes	Yes	Yes

Note: Table 13 reports the heterogeneity analysis among consumers with different wealth levels. We re-estimate the model by focusing on individuals who were exposed to credit before COVID-19. Specifically, we selected individuals whose average usage of bank credit cards and FinTech credit was above 0 between January 2019 and June 2019, and we estimate the model using a sample from July 2019 to December 2021. We constructed variables based on consumption amount. Columns (1) to (2) report the results for traditional bank credit usage, and Columns (3) to (4) report the results for FinTech credit usage. Here, we obtain the (log) amount of total deposits of the household sector in a city during the first half of 2019 and assume it reflects consumer wealth to some extent. High_wealth is a binary variable that equals 1 if the total wealth of the city is higher than the full sample's median and 0 otherwise. We merge the dummy variable of city-level to individual-level data according to an individual's location. Other variables are the same as those used in Table 2. All specifications include fixed effects and year-month fixed effects. Standard errors are clustered at the city level and presented in parentheses. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.