An Anatomy of FinTech Lending in China During COVID-19*

Zhengyang Bao and Difang Huang

Abstract

We evaluate the performance of Chinese FinTech credit providers during COVID-19. Comparing samples of FinTech and bank loan records across the outbreak, we find that FinTech companies have the advantage of expanding credit access to new and financially constrained borrowers after the shock. However, this increased credit provision may not be sustainable. The delinquency rate of FinTech loans triples after the outbreak, but there is no significant change in the rate of bank loans. Borrowers holding both loan types prioritize the payment of bank loans. These results indicate the merits and disadvantages of the FinTech credit providers during the epidemic.

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I. Introduction

The Chinese FinTech lending industry is a vital component of the shadow banking system in the country. It provides accessible and personalized credit services to people who cannot satisfy their credit demands from banks. In 2020, the industry housed more than 1,000 FinTech lending companies, providing RMB 24.2 trillion in credit to about 75 million users. Despite its sheer size, there is little empirical research that evaluates the performance of this industry. We fill this gap by providing the first examination of FinTech loan outcomes before and after the COVID-19 pandemic.

The pandemic hits the economy by surprise, allowing us to study how the FinTech industry copes with unexpected adverse shocks. We collect random samples of loan records from three large Chinese FinTech companies spanning the outbreak of the pandemic.[1] To benchmark the performance of the FinTech companies, we also obtain an analogous sample from a leading commercial bank in China for the same period. We include in our data only the loans that require no collateral and with monthly pledge payments to capture the most popular form of FinTech loans and monitor their performance at a relatively high frequency.[2]

[1]The sample period ends prior to changes in the regulation of the FinTech industry in China to avoid potential complications. For example, it rattled the credit and asset markets that the Chinese authority suddenly suspended the listing of its largest FinTech company, the Ant Technology Group, on November 3rd, 2020, a few days before the scheduled initial public offering to accommodate the policy amendments. We elaborate on the evolution of FinTech regulations in China in Appendix C.

[2]We exclude secured loans for a number of reasons. First, credit loans comprise more than 70% of the total credit issued by the FinTech companies we study. Second, the purpose of borrowing can be different between collateralized loans and credit loans: the collateral requirement may create extra incentives for pledge payments (Berger et al., 2011a,b; Bester, 1985; Cason et al., 2012). Third, most FinTech companies in China only provide credit loans. Thus, including collateral loans in the FinTech sample may not reflect the actual performance of the industry. Fourth, there are various collateral categories and distinct practices in dealing with the collateral upon default. These differences may make the comparison between FinTech and bank loans less meaningful.

In concrete, we identify 217,842 and 158,879 active FinTech and bank borrowers during the observation period (i.e., 2019:07-2020:06) and analyze their borrowing and repayment behaviors.

We examine the performance of these financial intermediaries in two aspects: the quantity and quality of loans. An ex-ante prediction of their relative performance after the adverse shock is difficult. For loan quantity, the FinTech industry offers better accessibility and flexibility for individuals but may lack the reserve to expand credit access. For loan quality, while FinTech companies may attract borrowers who are more vulnerable to income shocks (i.e., not eligible for bank loans), they can adjust their ex-post repayment enforcement mechanisms quickly and effectively (see Du et al., 2020; Liao et al., 2020; Huang and Bao, 2020).

We first investigate the quantity of loans using the full borrower-by-month panel data. We observe the size of new credit granted by the FinTech companies and the bank surges after the start of the pandemic, noting the increment is sharper for FinTech loans. The beneficiaries of the extra credit access vary between the FinTech companies and the bank. The expansion in the bank credit is largely enjoyed by pre-existing borrowers, while the increase in the FinTech credit is shared between both new and pre-existing borrowers. Furthermore, the percentage of new users rises for the FinTech companies but declines for the bank after the pandemic outbreak. We also partition the new users according to their income level and find that the fraction of low-income users elevates in the FinTech sample, which is opposite to the bank. We further discover that FinTech companies have the advantage of providing credit to borrowers who are financially constrained and those who reside in places with higher infection rates during the pandemic. These results indicate that the FinTech industry outperforms banks in providing credit to those who need it most during the unexpected health crisis.

We then evaluate the quality of loans using the delinquency rate following the standard practice in the literature.[3] We exclude loan records that stop before and start after the

[3]The loan delinquency rate commonly serves as the key indicator of the performance of financial inter-

outbreak of the pandemic to avoid the potential selection biases from the exit and entry decisions. In total, there left 98,127 borrowers from the FinTech companies and 74,591 borrowers from the bank who have loans satisfying these sampling criteria.

Our data reveal that FinTech and bank loans have similar delinquency rates before the pandemic, but there is a dramatic increase in the rate for the FinTech companies but not for the bank during the periods of instability caused by the COVID-19 disease. This finding is robust to the propensity score matching and entropy balancing matching methods when we address the ex-ante heterogeneity between FinTech and bank borrowers. We then implement seemingly unrelated regressions for the propensity score matched sample to tackle the potential correlated error terms across regressions for FinTech and bank loans. Interestingly, the sharp increase in FinTech loan delinquency rates cannot be fully explained by the presence of first-time borrowers (as opposed to those who had credit records before the observation window) nor the severity of the pandemic in borrowers' residential cities. To explore potential interpretations, we match the FinTech and bank samples using the unique national ID number for each borrower and identify 627 borrowers holding both FinTech and bank loans before and after the pandemic outbreak. Fixing observed and unobserved borrower characteristics, we find borrowers have the pecking order to default on their FinTech loans first. Additionally, we note that the interest rate is a good predictor of the delinquency probability for both loan types before the outbreak, but such predictability perishes for FinTech loans after the outbreak. This set of results reveal the potential challenge of maintaining a sustainable delinquency rate for the FinTech industry during the pandemic.

This paper adds to the fast-growing literature on financial intermediaries, especially on FinTech companies. To the best of our knowledge, we are the first to study the performance of the Chinese FinTech industry during the COVID-19 pandemic. Despite its wide popularity globally (see Braggion et al., 2018; de Roure et al., 2019; Di Maggio and Yao, 2020, for

mediaries, including banks (see Cerqueiro et al., 2016; Jiménez et al., 2014; Fisman et al., 2017) and FinTech companies (see Chava et al., 2017; Di Maggio and Yao, 2020).

example), studying the FinTech industry in a Chinese context is meaningful for several reasons. First, the financial system in China is dominated by commercial banks (Song and Xiong, 2018); this is different from many western lending markets, which are diversified, consisting of commercial banks, FinTech companies, title lenders, payday lenders, etc. Our data allow us to compare the repayment behavior between FinTech and bank loans in an environment where commercial banks dominate the consumer credit market. Second, the FinTech companies in the US apply FICO scores to screen borrowers while there are no such restrictions in China. Therefore, FinTech companies in China provide credit to a population of borrowers with more heterogeneity, including those who are less credit-worthy. Third, our data contains comprehensive information about the borrowers, allowing us to study the underlying channels that drive the distinct outcomes between FinTech and bank loans.

Our results complement the existing FinTech literature in several dimensions. First, this paper is linked to the literature studying the behavioral features of FinTech lending. For example, Butler et al. (2017) discover that a higher accessibility to bank financing leads to a cut in the interest rates charged by FinTech credit providers, Vallée and Zeng (2019) suggest that a reduction in the amount of borrower information provided to FinTech investors weakens their ability to screen out borrowers with higher delinquency risks, Iyer et al. (2016) demonstrate that eliciting soft information about borrowers can help enforce the repayments of FinTech loans, Chava et al. (2017) show that those borrowers who are less likely to be eligible for FinTech loans are more likely to misrepresent the purpose of borrowing when making loan applications, and Hertzberg et al. (2018) suggest that the choice of loan terms is related to the delinquency probability. We study the behavioral changes in loan origination and repayment caused by the pandemic. Second, we add to the literature on the relationship between FinTech companies and banks. For instance, Buchak et al. (2018) document that the loan rates determined by FinTech companies are more informative of borrowers' delinquency than those set by banks. Fuster et al. (2019), Tang (2019), and de Roure et al. (2019) confirm that there exists a substitution relationship between FinTech lending and traditional banks in the US mortgage market and consumer credit markets. Di Maggio and Yao (2020) find evidence that most FinTech borrowers are credit-worthy while present-biased using unique data with detailed information on borrower credit histories. We contribute to this strand of literature by comparing borrowing and repayment behaviors of FinTech and bank borrowers over a period of instability. The results indicate that FinTech companies were more friendly to the new borrowers during the pandemic, but they experience a larger jump in the delinquency rate compared with the bank. Third, we contribute to the literature on the regulation of financial innovation (Brunnermeier et al., 2017; Hachem and Song, 2016; Song and Xiong, 2018). Despite the radical changes in the regulatory regime for the FinTech industry in China, there is little empirical evidence informing this change. We first document the strengths and weaknesses of the Chinese FinTech industry to advise policymakers.

Our paper also extends the literature on the impact of the epidemic. Fan et al. (2018), for instance, estimate the expected death and national income losses from pandemic-related risks using an expected-loss framework. There are also studies documenting the impact of the pandemic on economic growth (Acemoglu and Johnson, 2007; Bloom and Mahal, 1997; McDonald and Roberts, 2006), human capital investment (Bleakley, 2007; Fortson, 2011; Young, 2005), and real estate value (Ambrus et al., 2020; Glaeser and Gyourko, 2005; Guerrieri et al., 2013). Besides, the COVID-19 disease triggers a fast-growing literature that focuses specifically on the identification and estimation of the economic consequences caused by the pandemic. For instance, Fang et al. (2020) and Huang (2020) find that the social distancing and city lockdown is effective in reducing the spread of virus and mortality rate in both China and the US. Atkeson (2020) build a Susceptible-Infectious-Removed (SIR) model to study the relationship between the severity of the pandemic and economic growth. Baker et al. (2020) empirically estimate the impact of the COVID-19 on consumption using the transaction-level financial data in the United States. Similarly, Chen et al. (2020) investigate how the pandemic alters households' grocery shopping patterns using the transaction data in China. Our paper adds to this literature by studying a unique Chinese context and quantify the impact of COVID-19 on different types of financial intermediaries across borrowers with different social-economic statuses.

The rest of this paper is organized as follows. Section II provides details about the institutional background. Section III describes the data and sample design. Section IV studies the characteristics of borrowers and loans. Section V presents the empirical methodology. Section VI discusses the impact of the pandemic on credit provision and the delinquency rate for the FinTech and banking industries. Section VII summarizes the findings and concludes the whole paper.

II. Background

A. The Chinese FinTech Lending Industry

In this paper, we focus on Chinese FinTech companies whose primary business is to provide credit to individual borrowers.[4] The emergence of the FinTech lending industry in China is partly due to the high barriers some low-income households face when accessing the formal banking sector. Compared with traditional banks, FinTech companies operate digitally, process loan applications faster, and provide more flexible and personalized options to borrowers (such as loan conditions and collateral requirements). In 2020, there were more than 1,000 FinTech lending companies operating in China with approximately 75 million users and RMB 24.2 trillion total loan size. They provide several broadly defined loan types, including credit loans and asset-based loans.

The three FinTech companies where we collect data from attract borrowers nationwide and provide credit services including credit loans, consumption loans, asset-backed loans, and small and medium-sized enterprise loans. We focus on the credit loans with pre-specified minimum monthly repayment requirements for individuals. These loans require each borrower

[4]Many FinTech enterprises provide other financial services such as insurance, asset management, third-party payment, investment and wealth management, and robo-advisor.

to pay a minimal proportion of the loan balance at the end of each month, and comprise 73% of the total value of outstanding loans in December 2019. We choose this loan type because of its popularity, and the monthly repayment scheme enables us to monitor the changes in the loan outcomes at a relatively high frequency.

To apply for a credit loan from a FinTech company, a potential borrower needs to submit a loan application. A typical FinTech company collects information about the borrower's identification (including the unique national ID number, gender, age, and birthplace), residential address, current employment status, and monthly income before any transactions take place. The borrower also needs to submit the requested loan amount to the company. The FinTech company evaluates the borrower based on the information provided and rejects the application if the borrower fails to meet the company's criteria. Each successful borrower may have multiple origination (i.e., access to credit) as long as the total loan amount does not exceed the pre-specified credit upper bound determined by the FinTech company. Each successful borrower must make each monthly repayment before the corresponding deadline; otherwise, s/he is subject to a penalty for delinquency.

B. Credit Card Borrowing in China

Banks dominate the credit market in China.[5] The bank where we collect data from is one of the leading state-owned commercial banks. It has a network of branches covering all provinces and municipalities in China and is among the top ten in the Chinese banking industry based on the annual profitability and operation scale.[6] The main business for these commercial banks is to take deposits and to make loans. Bank loans are classified into several broadly defined types such as credit cards, leases, mortgages, term loans, and other asset-

[5] Song and Xiong (2018) provide details on the bank-based financial institutions in China. The commercial banks in China consists of the Big-Four state-owned banks and those with diversified ownerships.

[6] See https://www.china-cba.net/Index/show/catid/14/id/31202.html for the full ranking of banks in China at the end of 2019 by the China Banking Association.

based loans. We focus on credit card borrowings in this paper as it is the most comparable with the FinTech credit loans.

Credit cards allow the holders to make unsecured loans with pre-specified monthly payment schedules. The Bank of China issued the first credit card in China in 1985. Soon after, all commercial banks started to participate in the credit card lending market, making it a key source of credit provision for Chinese citizens. According to the official statistics published by the People's Bank of China (PBOC), the total number of active credit cards exceeded 778 million, and the entire outstanding credit was RMB 7.91 trillion in 2020.

Credit cards are classified into two types according to whether customers deposit reserve funds: the quasi-credit card and the standard credit card. The quasi-credit card has the functions of both a credit card and debit card. The cardholder must first deposit a certain amount of reserve fund as required by the issuing bank; when the reserve fund is insufficient to pay, the card can be overdrawn within the credit limit specified by the issuing bank. The standard credit card can be classified into two types according to the issuance objects: the general-purpose credit card (issued to the general public) and the private label credit card (issued to personnel associated with partnering enterprises). The private label credit card is a business-branded credit card signifying the partnership between the issuing bank and a corporation. This type of credit card has more lenient terms and conditions and offers loyalty rewards when the cardholder uses the card at designated places. We use the data based only on the general-purpose credit card because this type of card is the most comparable with credit loans offered by FinTech companies. For example, unlike private label credit cards, a general-purpose credit card does not require the holder to associate with specific (usually profitable and famous) companies and has pre-specified monthly repayment requirements (Keys and Wang, 2019).

To apply for a general-purpose credit card (credit card hereafter) from the bank we study, an applicant must submit an application form with detailed personal information and supplementary documents, including a photocopy of national identification, employment certificate, and proof of income. The bank uses these pieces of information to determine whether to approve the application and the interest rate together with the maximum loan amount for the credit line upon the approval. The interest rate may differ across cardholders. During the review process, the bank may contact the applicant and his/her employer either by phone or in-person to confirm the authenticity of the application materials. The approved applicant receives the credit card by mail and has to activate the card following the instructions before accessing any credit. After these steps, the borrower can have multiple originations as long as the total credit amount does not exceed pre-specified credit line that determined by the bank.

C. More Details on the FinTech and Bank Loans

There is no information sharing among banks or FinTech companies during our sample period (see Jiang et al., 2021, for more details). For a customer who applies for a FinTech loan (credit card), the only source of information available to the FinTech company (bank) is the customer's borrowing and repayment records within this financial intermediary.

Each of the FinTech and bank loans studied in this paper requires the borrower to repay a minimum proportion of the loan balance monthly. The minimum proportion varies from 5% to 15% of the total balance across FinTech companies and banks.[7] If a borrower fails to pay the minimum amount by the monthly deadline, s/he receives a delinquent record. The borrower cannot borrow further from the financial intermediary unless s/he reinstates the loan account to normal status by paying the corresponding interest and extra penalties for the violation. If the borrower does not reinstate the account within a certain period, the corresponding credit provider may either lower the internal credit rating or pursue the repayment through legal processes. It is worth noting that the borrower receives a delinquency record for each month before reinstating the loan account.

[7] A revolver has to make the corresponding minimum monthly repayment first to originate new credits in that month.

In each month, each active loan (i.e., a loan with a non-zero outstanding balance) receives at least one record from the following category: origination, repayment, and delinquency. It is, however, possible for a borrower to originate new credit and make repayments multiple times. As a result, we may have several origination and repayment records in each month for each account (borrower). For the purpose of analyses, we compile all origination records that occur each month into one aggregated origination record at the borrower-month level and all repayment records into an aggregated delinquency record at the loan-month level. We discuss the construction of the datasets in more detail in Section III.

D. COVID-19 in China

COVID-19 is an infectious disease that caused a global pandemic starting in January 2020. As of October 2020, more than 40 million cases had been reported worldwide resulting in more than one million deaths. The pandemic has taken a tremendous toll on the economy due to disease prevention measures including social distancing and city lockdown (see Anderson et al., 2020; Chen et al., 2020; Clay and Parker, 2020; Cutler, 2020; Eichenbaum et al., 2020; Fang et al., 2020).

COVID-19 was first identified in the city of Wuhan in China as an unknown viral pneumonia. Chinese officials first reported the possibility of a new viral disease to the World Health Organization (WHO) on December 31, 2019. On the next day, Chinese social media was flooded with different messages about a possible outbreak of an unknown disease in Wuhan. On January 20, 2020, Chinese authorities confirmed the virus could spread from person to person as it spread across more cities in China and around the world. On January 23, 2020, the whole of Wuhan city went into strict lockdown, and all major Chinese cities were closed soon after.

The pandemic severely hit the Chinese economy. The annualized GDP growth rate of the first quarter of 2020 was -6.8% (the rate of the last quarter of 2019 was 6%), the first time the growth rate had fallen below zero in decades. The unemployment rate also surged by 20% from January to February.

We use January 2020 as the cutoff for the starting of the pandemic period for China for several reasons. First, the disease was initially recognized by medical scientists in January 2020. Second, social media in China first reported accurate information about the disease in that month. Third, the government took radical measures including the lockdown of cities, mandating the wearing of face masks, and halting non-essential industries in January as well.

III. Data

A. Data Sources

The first data source is the credit loan records from three of the largest FinTech companies in China. We collect loan records of 217,842 FinTech borrowers at a monthly frequency from 2019:07 to 2020:06. Each entry is either a new borrowing, a repayment, or a delinquent record for insufficient repayment. The dataset also includes borrower's demographic information, including age, employment, education, gender, marriage status, residential address, as well as their credit attributes, including assets (car, real estate), debts (car loan, mortgage), credit history with the credit provider (account type, loan type, loan payment), and the current loan information (outstanding balance, interest rate).

Our second data source comes from one of the leading state-owned commercial banks in China. We collect a random sample of the bank's credit records (i.e., details on the credit access, balance, repayments, and delinquency at the account level) of general-purpose credit card borrowers at a monthly frequency between 2019:07 and 2020:06. For each borrower, we observe detailed information about his/her demographics, including age, gender, marital status, education, employment, income, and place of residence. The data also includes her credit history with the bank and the current credit information, including the total amount of credit granted, credit balance, and monthly repayment status. As described earlier, we use credit card borrowing because it is the most comparable form of credit to the FinTech loans in terms of loan contract characteristics.[8] For example, FinTech and credit card loans have no collateral requirement, and each borrower must pay a fraction of the outstanding balance each month.

B. Sample Construction

There are two issues preventing us from analyzing the raw data directly. First, all four financial intermediaries allow multiple borrowing and repayments within a month; therefore, it is possible for some borrowers to have more than one credit record in a month. Second, these credit providers use different measurements to collect some variables, creating a comparability problem.

To capture each borrower's aggregated borrowing and repayment in each month, we combine all the borrowing/repayment records for each account in each month and leave only one borrowing/repayment observation for each loan-month.

To make different sources of information comparable, we combine variables from the two data sources and convert a few variables with different measures to the same standard to make them comparable across these data sources (detailed variable definitions are introduced in Table A in Appendix I). We drop the variables that are not comparable across financial intermediaries. For example, some FinTech companies collect borrowers' social media information such as their activities on WeChat (Chinese equivalent of WhatsApp) and Weibo (Chinese version of Twitter).

We transform the raw data regarding employment, income, and education into indicator variables. The employment indicator equals one if the borrower is employed at the time of the loan application; the high-income indicator equals one if the borrower has a monthly income greater than RMB 10,000; and the high education indicator equals one if the borrower's

[8] Interested readers may refer to Chava et al. (2017) and Di Maggio and Yao (2020) that compare the credit card and FinTech borrowings in the United States.

highest education level is equal to or above a bachelor's degree and zero otherwise.[9]

For the borrowers' credit attributes, the financial intermediaries collect information about borrowers' asset condition (ownership of car and real estate) and other outstanding loans (car loan and mortgage) at the origination of the loan contracts. We, again, convert these variables to indicators for the analysis. For credit history, the history delinquency indicator equals one if the borrower has defaulted at least once with the financial intermediary in the past. We also collect the number of borrower's past delinquencies, the amount borrowed before 2019:07, the number of credit accesses, and the average duration of cycles before 2019:07.[10]

For the loan information during the sample period, we calculate the total amount of loan originated, number of credit accesses and the duration of the cycle across the sample period. We also calculate the annualized interest rate for each loan using the internal rate of return method.

After these steps, we combine observations from the two sources and create a FinTech indicator variable to distinguish the loan source. Our combined dataset contains 217,842 FinTech borrowers and 158,879 bank borrowers with at least one credit record during the sample period. We create two samples to analyze the quantity and quality of loans.

To investigate the impact of the pandemic on the quantity of loans provided, we focus on the borrowing records (in contrast to repayment records) and create a balanced borrower by year-month panel data with all 217,842 FinTech borrowers and 158,879 bank borrowers across 12 months. We impute the missing observation (i.e., no active loans) with zero value (i.e., no origination and zero balance) and use these borrower-month observations to study loan quantity.

[9]We use monthly income of RMB 10,000 as the cut-off for the income level because the bank collects the exact income amount for each individual while FinTech companies store this information using income ranges. RMB 10,000 is a common cut-off used by all FinTech firms.

[10]We define a cycle as the process that starts from the origination of a balance and ends when the balance is fully repaid.

To explore changes in loan quality and to avoid the selection of borrowers before and after the pandemic outbreak, we restrict the sample to loan records that originating before 2019:12 (inclusive) and ending after 2020:02 (inclusive). In this loan-level sample, there are 721,233 repayment records (i.e., each contains a dummy variable for the loan-month delinquency behavior) for 98,127 FinTech borrowers, and 581,810 repayment records for 74,591 bank borrowers. We also identify 627 borrowers with 7,371 repayment records from both bank and FinTech loans using the unique national identification information collected by both bank and FinTech companies.[11] We use this loan-level data for the analysis of borrower characteristics and loan quality.

IV. Borrower and Loan Characteristics

In this section, we summarize the key borrower and loan characteristics and explore the pre-existing heterogeneities among individuals borrowing from different financial intermediaries using our loan-level data. We then investigate the differences in loan characteristics between FinTech and bank. A detailed description of the variables is reported in Table A in Appendix I.

A. Borrowers' Characteristics

We outline the descriptive statistics for each variable over the sample period in Table 1 for all borrowers and subsets of borrowers: (1) who borrow from the FinTech companies ($N = 98,127$), (2) who borrow from the bank ($N = 74,591$), and (3) who borrow from both the FinTech companies and the bank ($N = 627$). We analyze three sets of variables

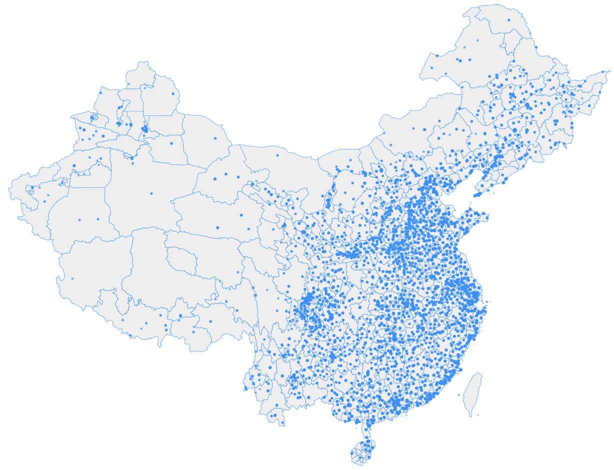
[11]It is possible that an individual borrows money from multiple FinTech companies, but we do not observe this in our sample. One potential caveat is that we do not have data from all FinTech companies and banks in China for the sample period. However, such a lack of observability happens at random and can weaken our results. Therefore, our approach is conservative; the real difference is likely to be greater than reported in the paper.

related to borrower demographics, credit characteristics, and the current loan contract. We also show the residence address of borrowers in our sample across cities in Figure 1. The geographic location of borrowers covers almost all cities in China, indicating that our sample is representative.

Table 1: Summary Statistics.
This table summarizes the key variables from the loan-level sample containing 173,345 FinTech and bank loan borrowers, the sample containing 98,127 FinTech borrowers, the sample containing 74,591 bank borrowers, and sample of 627 borrowers with both FinTech and bank loans. Our sample period begins from 2019:07 to 2020:06 (inclusive). We report the mean and standard deviation for each variable. The detailed variable definitions are presented in Appendix I.

	Full Sample		FinTech Sample		Bank Sample		Both Sample	
Variable	Mean	SD	Mean	SD	Mean	SD	Mean	SD
Panel A: Demographic Variable								
Borrower Age	33.08	7.31	29.99	6.71	37.15	5.93	29.96	6.77
Employment Indicator	0.59	0.49	0.49	0.50	0.73	0.44	0.49	0.50
High Income Indicator	0.16	0.37	0.10	0.30	0.25	0.43	0.11	0.31
Higher Education Indicator	0.69	0.46	0.63	0.48	0.77	0.42	0.62	0.49
Male Indicator	0.51	0.50	0.53	0.50	0.48	0.50	0.51	0.50
Married Indicator	0.49	0.50	0.49	0.50	0.50	0.50	0.47	0.50
Panel B: Credit Variable								
Car Indicator	0.43	0.50	0.39	0.49	0.49	0.50	0.38	0.49
Car Loan Indicator	0.04	0.20	0.07	0.25	0.01	0.05	0.06	0.24
House Indicator	0.60	0.49	0.55	0.50	0.66	0.47	0.54	0.50
Mortgage Indicator	0.18	0.39	0.19	0.39	0.17	0.38	0.20	0.40
Hist. DLQ Indicator	0.14	0.35	0.20	0.40	0.06	0.24	0.22	0.41
Hist. No. of DLQ	0.39	1.58	0.59	1.96	0.13	0.77	0.57	1.58
Hist. Balance	6414	10029	8099	12319	4182	4909	8031	11988
Hist. No of Credit Access	9.06	13.95	10.04	15.04	7.77	12.24	9.85	15.83
Hist. Average Cycle Duration	13.67	2.96	11.82	1.15	16.10	2.86	11.70	1.40
Panel C: Current Loan Information								
Loan Amount	4078	4056	4918	4759	2966	2465	5033	6124
No. of Credit Access	8.41	7.42	8.79	10.61	7.89	9.47	8.52	11.23
Average Cycle Duration	13.02	2.73	10.97	1.21	15.62	2.74	11.24	1.35
Interest Rate	16.18	2.00	17.16	1.60	14.87	1.71	17.13	1.51

(a) FinTech Borrowers



(b) Bank Borrowers

(c) Both FinTech and Bank Borrowers

Figure 1: Location of all borrowers. This figure plots the geographic distribution of individuals who borrow from FinTech companies (Panel A), who borrow from the bank (Panel B), and who borrow from both FinTech companies and the bank (Panel C) at the city level. Each dot on the map represents the residential address of a borrower.

A.1. Demographic Characteristics

First, we analyze borrowers' demographic variables, including age, gender, marital status, employment, income, and education (Table 1 Panel A). On average, borrowers are 33 years old, 59% of them are employed, 16% of them belong to the high-income group, 69% have a bachelor's degree or higher, 51% of them are male, and 49% are married.

A.2. Credit Characteristics

The second set of variables, Table 1 Panel B, contains borrowers' credit characteristics recorded by the FinTech companies and the bank. On average, about 14% of borrowers in our sample have a delinquency history, 4% have car loans, 18% have mortgages, 43% have cars, and 60% own a piece of real estate. The historical average cycle duration is 13.67 months, the average historical loan balance is RMB 6,414, and the average historical number of credit access and delinquencies are 9.06 and 0.39, respectively.

A.3. Current Loan Information

The third set of variables, Table 1 Panel C, characterizes the current loan contracts. We analyze the loan amount, the number of times credit is accessed, the average cycle duration, and the interest rate. The average number of credit accesses for a typical borrower is 8.41 times during the sample period. Additionally, the average balance is RMB 4,078, with 13.02 months duration, and a 16.18% annualized interest rate.

B. Borrowers' Heterogeneity

We compare the characteristics of FinTech and bank borrowers. As shown in Table 1, there are significant differences between borrowers in most variables we examined. For example, FinTech borrowers are younger, less likely to be employed, have fewer assets, and borrow a larger amount, consistent with the results in recent studies on the Chinese FinTech industry (see Liao et al., 2020, for example).

We examine this ex-ante heterogeneity among individuals in more detail by regressing the FinTech indicator on borrower demographic and credit characteristic variables. First, we exploit the relationship between the FinTech indicator and demographic characteristics. In

Table 2a, we show that borrowers with FinTech loans are more likely to be younger (Column 1), less likely to be employed (Column 2), less likely to earn a high income (Column 3), less likely to have a college degree or higher (Column 4), more likely to be male (Column 5), and less likely to be married (Column 6).

Second, we investigate whether FinTech borrowers have different credit characteristics. We regress the FinTech indicator on borrowers' credit variables and report the results in Table 2b. Columns (1) and (2) suggest that FinTech borrowers are more likely to have default histories and more likely to default on the current loan. In Columns (3) and (4), we show that FinTech borrowers are also more likely to have car loans and mortgages, suggesting that these borrowers are more likely to be constrained by poor financial circumstances. Columns (5) and (6) indicate that FinTech borrowers are less likely to own a car or a piece of real estate than bank borrowers. Column (7) shows that, on average, the FinTech borrowers have had more access to credit in the past.

We further explore the differences in loan features between FinTech and bank borrowers. We regress the loan amount, average cycle duration, and the loan interest rate on the FinTech borrower indicator and show the results in Table 3a. We control for the borrower's observed characteristics and the city-month fixed effects and city fixed effects. Column (1) points out that the FinTech companies grant more credit to each borrower on average: a typical FinTech loan is RMB 2,132 more than a Bank loan. In Column (2), we discover that the FinTech loan cycle duration is about four months shorter than that of bank loans. In Column (3), we find, after controlling for the credit amount and cycle duration, the interest rate for FinTech on average is about 2.64% higher than bank loan interest rates.

We also investigate the heterogeneities in the FinTech and bank loans among borrowers who hold both loan types. We present the results for the differences in loan features in Columns (1) to (3) of Table 3b, after controlling for borrower fixed effects. The size of an average FinTech loan is RMB 2,556 more than a bank loan, the average cycle duration is about 4.4 months shorter, and the interest rate charged by FinTech companies is 2.20

Table 2: Comparison of Borrower's Characteristics for FinTech and Bank Loans. **This table reports the estimation results for regressions that explore the link between borrower's characteristics and the likelihood of borrowing from FinTech companies rather than banks. Table 2a investigates how borrower's demographics correlate to the tendency to borrow from FinTech companies, and Table 2b connects the borrower's credit characteristics to the likelihood of having a FinTech loan. The *p*-values are reported in parentheses below each coefficient. *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively. Standard errors are clustered at the city and time level.**

(a) Borrower's demographics and FinTech indicator

	FinTech Indicator					
	(1)	(2)	(3)	(4)	(5)	(6)
Borrower Age	-0.033***					
	(0.000)					
Employment Indicator		-0.250***				
		(0.000)				
High Income Indicator			-0.268***			
			(0.000)			
Higher Education Indicator				-0.155***		
				(0.000)		
Male Indicator					0.043***	
					(0.000)	
Married Indicator						-0.014***
						(0.000)
City FEs	Yes	Yes	Yes	Yes	Yes	Yes
City*Time FEs	Yes	Yes	Yes	Yes	Yes	Yes
Adjusted R^2	0.237	0.063	0.042	0.022	0.003	0.002
Observations	1,303,043	1,303,043	1,303,043	1,303,043	1,303,043	1,303,043

(b) Credit characteristics and FinTech indicator

	FinTech Indicator						
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Hist. DLQ Indicator	0.286***						
	(0.000)						
Hist. No. of DLQ		0.046***					
		(0.000)					
Car Loan Indicator			0.425***				
			(0.000)				
Mortgage Indicator				0.040***			
				(0.000)			
Car Indicator					-0.100***		
					(0.000)		
House Indicator						-0.116***	
						(0.000)	
Hist. No. of Credit Access							0.003***
							(0.000)
City FEs	Yes	Yes	Yes	Yes	Yes	Yes	Yes
City*Time FEs	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Adjusted R^2	0.041	0.023	0.030	0.002	0.011	0.015	0.008
Observations	1,303,043	1,303,043	1,303,043	1,303,043	1,303,043	1,303,043	1,303,043

Table 3: Borrower's Characteristics and the Loan Amount, Cycle Duration, and the Interest Rate.

This table reports the estimation results for regressions that use borrower's characteristics to explain three key loan characteristics (amount, duration, and interest rate). Table 3a investigates the sample for borrowers with either FinTech or Bank loans, and Table 3b restricts the sample to borrowers with both FinTech and Bank loans. Column (1) shows the results for loan amount, Column (2) displays the results for cycle duration and Column (3) presents the results for loan interest rate. The *p*-values are reported in parentheses below each coefficient. *, **, and * indicate significance at the 10%, 5%, and 1% levels, respectively. Standard errors are clustered at the city and time level.**

(a) Borrower with either FinTech or Bank loans

	Loan Amount	Cycle Duration	Interest Rate
	(1)	(2)	(3)
Fintech Indicator	2132.480***	-4.269***	2.642***
	(0.000)	(0.000)	(0.000)
Demographic Controls	Yes	Yes	Yes
Credit Controls	Yes	Yes	Yes
Loan Amount	No	No	Yes
Cycle Duration	No	No	Yes
Borrower FEs	No	No	No
City FEs	Yes	Yes	Yes
City*Time FEs	Yes	Yes	Yes
Adjusted R^2	0.112	0.512	0.400
Observations	1,303,043	1,303,043	1,303,043

(b) Borrower with both FinTech and Bank loans

	Loan Amount	Cycle Duration	Interest Rate
	(1)	(2)	(3)
Fintech Indicator	2556.255***	-4.409***	2.203***
	(0.000)	(0.000)	(0.000)
Demographic Controls	Yes	Yes	Yes
Credit Controls	Yes	Yes	Yes
Loan Amount	No	No	Yes
Cycle Duration	No	No	Yes
Borrower FEs	Yes	Yes	Yes
City FEs	Yes	Yes	Yes
City*Time FEs	Yes	Yes	Yes
Adjusted R^2	0.459	0.724	0.639
Observations	7,371	7,371	7,371

percentage points higher than the bank. Consistent with the summary statistics in Table 1, our results show that the differences between FinTech and bank loans characteristics are robust.

V. Empirical Methodology

Our baseline empirical model identifies the impact of the pandemic from the time-series change in loan outcomes for individuals borrowing from a particular type of financial intermediary.[12] The specification takes the following form:

$$Y_{i,t} = \alpha + \beta \text{FinTech}_i \times \text{After}_t + \gamma X_{i,t} + \delta_c + \xi_{c,t} + \tau_i + \varepsilon_{i,t} \tag{1}$$

The left-hand side variable $Y_{i,t}$ in most specifications is the loan outcome of a borrower i, living in the city c, at month t. For example, when we explore the effect of the pandemic on the access to credit, the dependent variable is the amount of money that borrower i borrows (from either a FinTech or a bank lender) at month t; when we investigate the impact of the pandemic on loan quality, the dependent variable is the delinquency indicator that equals one if the required repayment for borrower i at month t is not fulfilled on time and zero otherwise.[13] After_t is an indicator variable that equals one if the time t is after January 2020 and zero otherwise. FinTech_i is an indicator variable that equals one if the loan of borrower i is granted by a FinTech company and zero otherwise. The independent variables $X_{i,t}$ are

[12]We also consider other econometric specifications including before-after models and seemingly unrelated regressions in our paper. We present the details about these supplementary models in Appendix II and III.

[13]As the dependent variable (the loan delinquency indicator) is binary, it is desirable to fit a probability model (i.e., Logit and Probit models) to estimate the equations. However, estimating non-linear models may yield unstable estimates given our large sample size (Fraser et al., 2005). Despite this, our linear econometric specification still provides highly accurate estimates for the marginal effects. As a robustness check, we run Logit and Probit models for FinTech and bank loans separately, and all marginal effects are similar to those estimated linearly.

the borrower's observed characteristics, including the demographic covariates, credit history, and loan characteristics.

For most of our analyses, we show empirical results that include the city fixed effects (δ_c), city-time fixed effects ($\xi_{c,t}$), and borrower fixed effects (τ_i). This specification allows us to rule out a series of identification concerns. For instance, the city fixed effects capture the time-invariant city-level attributes such as trends and cycles associated with the credit conditions for each city. They also absorb potential changes in the economic policies, including government subsidies targeting citizens living in certain cities (see Chen et al., 2020, for example). The city-time fixed effects absorb any time-varying changes at the city level, including the shocks in credit demand and changes in labor market conditions. Additionally, the borrower fixed effects account for the time-invariant determinants of each borrower. The error term $\varepsilon_{i,t}$ is clustered at the city and time levels, accounting for the serial correlation in the loan outcome and the possible correlation of borrower's behavior in the same city. The coefficient β on the interaction term $\text{FinTech}_i \times \text{After}_t$ is the difference-in-differences estimate. It measures how the two types of loan outcomes respond to the pandemic differently when controlling for all time-varying, observed and unobserved, borrower and financial intermediary heterogeneities. While our main results show the average effect across all borrowers, we also allow the effect to be heterogeneous across the borrowers' characteristics. As robustness checks, we further estimate the difference-in-differences specification on matched samples using different matching methods to control for the ex-ante differences between FinTech and bank borrowers.

VI. Empirical Results

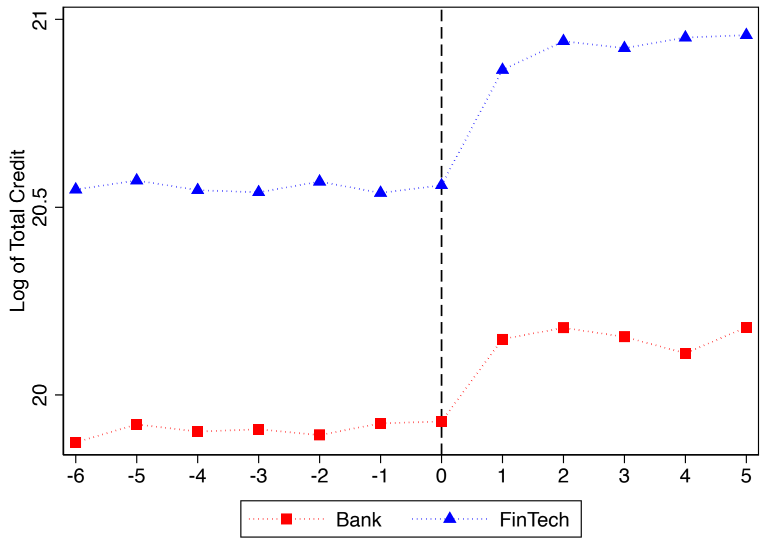
A. Loan Quantity

In this section, we compare the differentials in the changes of the loan quantity between the FinTech and bank borrowers before and after the pandemic by applying the difference-in-differences approach on the borrower-by-month panel data. As described earlier, we identify 217,842 FinTech borrowers and 158,879 bank borrowers during the observation period, so we have 4,520,652 credit origination observations.

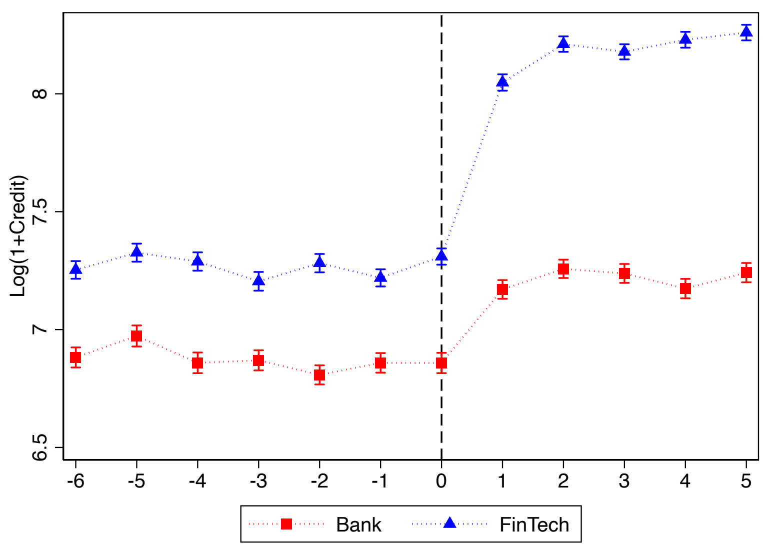
A.1. Loan Quantity for FinTech and Bank Borrowers

We begin the analysis by showing the (unconditional) new credit access before and after the pandemic outbreak for FinTech and bank loans. The horizontal axis of Figure 2 measures time (in month) relative to the outbreak of COVID-19 in China in January 2020. The event time $t = 0$ represents the month when COVID-19 was first identified in the country, and the negative and positive numbers represent the months before and after the outbreak, respectively. We plot the (log) total new credit issued by the FinTech companies and the bank in Figure 2a. We also depict the average of (log) new credit received by each borrower and the corresponding 95 percent confidence interval in Figure 2b. As shown in both figures, the demand for FinTech and bank loans increases at the aggregate and individual levels after the start of the pandemic. Interestingly, the increment in the amount of credit issued by FinTech companies is higher than that of the bank.

Following Fisman et al. (2017) and Di Maggio and Yao (2020), we further investigate the extensive and intensive margins of credit provision for both types of financial intermediaries before and after the start of the pandemic. In other words, we examine how the pandemic affects the probability a borrower receives new credit from either the FinTech companies or the bank, and conditional on the borrower receiving new credit, how the pandemic affects the loan quantity. We estimate the baseline equation (i.e., Equation (1) in Section V) and control for borrower attributes (demographic, credit, and loan contract) and city and city-by-time fixed effects. In Table 4, we report the coefficient for FinTech $\times$ After using our baseline specification for each of the four dependent variables: a dummy equal to one if the borrower receives any new credit (Columns 1 and 2), the number of new credit originations



(a) Log of total credit issued by FinTech and bank



(b) Log of total credit received by borrowers

Figure 2: Credit access for FinTech and bank borrowers before and after COVID-19. Figure 2a shows the (log) total new credit issued by FinTech and bank before and after COVID-19. Figure 2b plots the average values of (log) new credit received by FinTech and bank borrowers before and after COVID-19 with the 95% confidence interval. The sample period is 2019:07 to 2020:06. The horizontal axis displays event time (in months), where $t = 0$ corresponds to 2020:01.

(Columns 3 and 4), and (log) total new credit (Columns 5 and 6).[14] The estimates indicate that all measures of credit access increase more for FinTech borrowers compared with bank borrowers after the pandemic, and the effect is both economically and statistically significant.

Table 4: The Pandemic and Borrower's Credit Access.
This table shows the estimation results for the difference-in-differences regressions that explore the impact of the pandemic on the probability that a borrower receives new credit (Column 1–2), on the number of new credits originated (Column 3–4), and on the (log) total new credit (Columns 5–6) after controlling a set of borrower and loan characteristics. The p-values are reported in parentheses below coefficients. *, **, and * indicate significance at the 10%, 5%, and 1% levels, respectively. Standard errors are clustered at the city and time level.**

	Dummy = 1 if credit >0		Number of new credit		Log of (1+credit)	
	(1)	(2)	(3)	(4)	(5)	(6)
FinTech*After	0.036***	0.031***	0.592***	0.524**	0.804***	0.725***
	(0.000)	(0.003)	(0.001)	(0.023)	(0.000)	(0.001)
Demographic Controls	Yes	Yes	Yes	Yes	Yes	Yes
Credit Controls	Yes	Yes	Yes	Yes	Yes	Yes
Loan Controls	Yes	Yes	Yes	Yes	Yes	Yes
City FEs	No	Yes	No	Yes	No	Yes
City*Time FEs	No	Yes	No	Yes	No	Yes
Adjusted R^2	0.006	0.382	0.042	0.188	0.366	0.727
Observations	4,520,652	4,520,652	4,520,652	4,520,652	4,520,652	4,520,652

A.2. Loan Quantity and the Severity of Pandemic

We now turn to evaluate the potential heterogeneous impact of the pandemic on the FinTech-bank gap in credit provision across cities. Using borrowers' residential address information collected by the bank and FinTech companies, we interact our baseline regression with the indicator for the city of Wuhan (Table 4, Column 1), for cities in Hubei Province (Column 2), for cities with top 10 Wuhan population inflow in January 2020 based on Tencent mobility (Column 3), and for cities with top 10 COVID infection cases until April 30th, 2020 (Column 4). We show the estimation results in Table 5.

[14]As we use the log(1+x) transformation on the loan amount x, the zero value is defined. Moreover, the results are robust to the ArcSinh transformation on the loan amount.

In Table 5a, we include the interaction terms generated by city indicators and the difference in differences term for the extensive margins. In Column (1), the estimated coefficient of the interactive term is 0.2% and significant at the 1% level, implying the gap between the FinTech companies and the bank in the likelihood of providing new credit is 0.2 percentage point wider for borrowers in Wuhan than the non-Wuhan cities. The results are similar when we consider analogous regressions for borrowers who reside in Hubei Province in Column (2), and the top 10 cities with most migrants from Wuhan in Column (3). More generally, in Column (4), we find that FinTech borrowers in cities with the top 10 COVID-19 cases experienced a 0.4 percentage point increase in the FinTech-bank gap in the extensive margin of credit provision after controlling for borrower characteristics and city and city-time fixed effects.

In Table 5b, we present the estimates for intensive margins. The results are similar to those of extensive margins. The FinTech companies have the advantage in providing credit to borrowers in more infected cities during the pandemic. The FinTech-bank gap in the total credit originated is 0.04% larger for borrowers in Wuhan, 0.03% larger for borrowers in Hubei Province, 0.01% larger for borrowers in the cities with top 10 Wuhan population inflow, and 0.02% larger for borrowers in the 10 cities with the most COVID-19 infection cases. To conclude, the severity of the pandemic appears to correlate with the FinTech-bank gap in terms of credit access, but it does not rationalize the entire gap as the term FinTech*After remains positive and significant after controlling for the severity of the pandemic.

A.3. Loan Provision and Borrowers' Financial Statuses

Whether financially constrained individuals can access credit, especially during the health crisis, is another policy-related question. We address this question using income (i.e., the high-income indicator) and employment (i.e., the employment indicator) information we collect. To compare each type of financial intermediary, we consider a before and after econometrics specification for the FinTech and bank sub-samples separately. The detailed

Table 5: Severity of the Pandemic and Borrower's Credit Access

This table presents the estimation results for regressions studying how the severity of the pandemic in the borrower's city of residency affects credit access for FinTech and bank loans. Table 5a reports the results for extensive margins of credit access, and the Table 5b displays the results for intensive margins. The p-values are reported in parentheses below each coefficient. *, **, and * indicate significance at the 10%, 5%, and 1% levels, respectively. Standard errors are clustered at the city and time level.**

(a) Extensive margins of credit access

	Dummy = 1 if credit > 0			
	(1)	(2)	(3)	(4)
FinTech*After	0.031***	0.031***	0.032***	0.031***
	(0.004)	(0.004)	(0.003)	(0.004)
FinTech*After*$D_{\text{Wuhan City}}$	0.002***			
	(0.000)			
FinTech*After*$D_{\text{Hubei Province}}$		0.001***		
		(0.002)		
FinTech*After*$D_{\text{Top10 Wuhan inflow cities}}$			0.001*	
			(0.087)	
FinTech*After*$D_{\text{Top10 COVID infected cities}}$				0.004***
				(0.000)
Demographic Controls	Yes	Yes	Yes	Yes
Credit Controls	Yes	Yes	Yes	Yes
Loan Controls	Yes	Yes	Yes	Yes
City FEs	Yes	Yes	Yes	Yes
City*Time FEs	Yes	Yes	Yes	Yes
Adjusted R^2	0.382	0.382	0.382	0.382
Observations	4,520,652	4,520,652	4,520,652	4,520,652

(b) Intensive margins of credit access

	Log of (1+credit)			
	(1)	(2)	(3)	(4)
FinTech*After	0.725***	0.720***	0.724***	0.723***
	(0.001)	(0.001)	(0.000)	(0.001)
FinTech*After*$D_{\text{Wuhan City}}$	0.041**			
	(0.010)			
FinTech*After*$D_{\text{Hubei Province}}$		0.027***		
		(0.000)		
FinTech*After*$D_{\text{Top10 Wuhan inflow cities}}$			0.005*	
			(0.099)	
FinTech*After*$D_{\text{Top10 COVID infected cities}}$				0.016**
				(0.041)
Demographic Controls	Yes	Yes	Yes	Yes
Credit Controls	Yes	Yes	Yes	Yes
Loan Controls	Yes	Yes	Yes	Yes
City FEs	Yes	Yes	Yes	Yes
City*Time FEs	Yes	Yes	Yes	Yes
Adjusted R^2	0.727	0.727	0.727	0.727
Observations	4,520,652	4,520,652	4,520,652	4,520,652

regression model can be found in Appendix II. This specification enables us to study the changes in the extensive and intensive margins of credit access for borrowers with different income and employment status before and after the pandemic.

In Table 6, we present the results for the changes in the extensive margin in Panel (A) and the changes in the intensive margin on Panel (B). For each panel, we report results for FinTech borrowers (i.e., the FinTech sub-sample) in Columns (1) and (2) and the results for bank borrowers (i.e., the bank sub-sample) in Columns (3) and (4). We include the controls for demographics, credit and loan characteristics, as well as city fixed effects, and city-by-time fixed effects to alleviate the endogeneity concern in all specifications. Overall, we find FinTech lenders are more likely to grant credit for both financially constrained (i.e., low-income or unemployed) and financially unconstrained (i.e., high-income or employed) borrowers after the pandemic, while the bank provides more credit mainly for high income borrowers and employed borrowers after the shock.

A.4. Loan Access to New Borrowers

As FinTech companies operate digitally and have no physical entities, FinTech lending can be more accessible to new customers than bank lending, which may require face-to-face verifications (Agarwal et al., 2020a,b). Therefore, we expect FinTech companies to provide more convenience to new borrowers, especially during the pandemic lockdown period from January 23, 2020 to April 8th 2020.

We present our analysis by showing the ratio of new borrowers before and after the start of the pandemic for both FinTech companies and the bank. The horizontal axis of Figure 3 measures time (in months) relative to the outbreak of COVID-19 in China from January 2020. The event time $t = 0$ represents the month when COVID-19 was officially reported in China, and the negative and positive numbers represent the months before and after the outbreak, respectively. The vertical axis measures the ratio of new borrowers relative to the total borrowers for both FinTech companies and the bank in 2019:07. As shown in Figure 3a,

Table 6: Financially Constrained Borrowers and Credit Access.

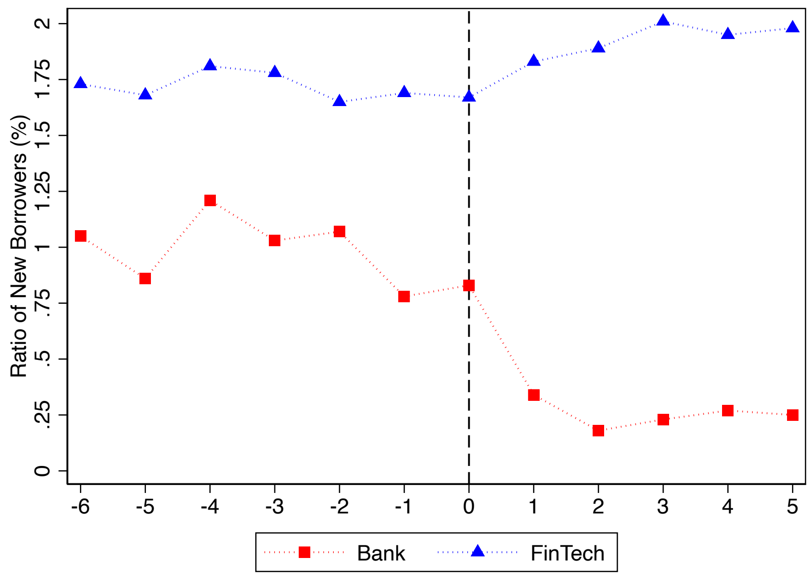
This table presents the estimation results for regressions studying the correlation between financially constrained borrowers and the credit access for FinTech and bank loans. Table 6a reports the results for extensive margins of credit access, and Table 6b displays the results for intensive margins. The p-values are reported in parentheses below coefficients. *, **, and * indicate significance at the 10%, 5%, and 1% levels, respectively. Standard errors are clustered at the city and time level. Standard errors are clustered at the city-month level.**

(a) Extensive margins of credit access

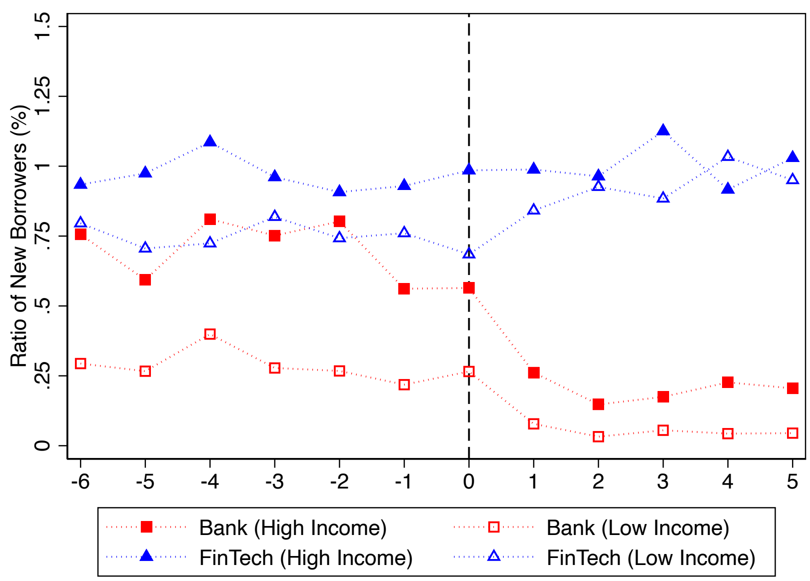
	Dummy = 1 if credit >0			
	FinTech Borrowers		Bank Borrowers	
	(1)	(2)	(3)	(4)
After*High Income	0.061***		0.046**	
	(0.000)		(0.011)	
After*Low Income	0.058***		0.007	
	(0.000)		(0.191)	
After*Employed		0.063***		0.039**
		(0.000)		(0.024)
After*Unemployed		0.056***		0.017
		(0.000)		(0.112)
Demographics Controls	Yes	Yes	Yes	Yes
Credit Controls	Yes	Yes	Yes	Yes
Loan Controls	Yes	Yes	Yes	Yes
City FEs	Yes	Yes	Yes	Yes
City*Time FEs	Yes	Yes	Yes	Yes
Adjusted R^2	0.366	0.366	0.415	0.415
Observations	2,614,104	2,614,104	1,906,548	1,906,548

(b) Intensive margins of credit access

	Log(1+credit)			
	FinTech Borrowers		Bank Borrowers	
	(1)	(2)	(3)	(4)
After*High Income	0.889***		0.201***	
	(0.000)		(0.002)	
After*Low Income	0.871***		0.081*	
	(0.000)		(0.093)	
After*Employed		0.891***		0.192***
		(0.000)		(0.002)
After*Unemployed		0.884***		0.087
		(0.000)		(0.108)
Demographics Controls	Yes	Yes	Yes	Yes
Credit Controls	Yes	Yes	Yes	Yes
Loan Controls	Yes	Yes	Yes	Yes
City FEs	Yes	Yes	Yes	Yes
City*Time FEs	Yes	Yes	Yes	Yes
Adjusted R^2	0.685	0.685	0.747	0.747
Observations	2,614,104	2,614,104	1,906,548	1,906,548



(a) Ratio of new borrowers



(b) Ratio of new borrowers by income level

Figure 3: The ratio of new borrowers before and after COVID-19. This figure plots the ratio of new borrowers for FinTech and bank lenders before and after the outbreak of COVID-19. The sample period is 2019:07 to 2020:06. The horizontal axis displays event time (in months), where $t = 0$ corresponds to 2020:01 (the start of the pandemic).

the rate of new borrowers for FinTech companies (the bank) increases (decreases) after the outbreak. We then further decompose all new borrowers according their income level. We present the results in Figure 3b. For FinTech lenders, the ratio of either low-income or high-income new borrowers increases; for bank lenders, the ratio declines regardless of the income levels. Compared with the bank, the FinTech companies have the advantages of providing credit access for new (low-income) customers after the pandemic. These results are robust when we estimate the before-after regression model on the FinTech and bank sub-samples.

B. Loan Quality

After analyzing the changes in loan quantities, we expand the focus to the quality of the loans granted by these two types of financial intermediaries before and after the crisis. To avoid selection bias caused by the entry and exit decisions, we only use the loan records that start before 2019:12 (before) and end after 2020:02 (after). This provides a sample of 721,233 repayment records for 98,127 FinTech borrowers, 581,810 records for 74,591 bank borrowers, and 7,371 records for 627 borrowers with both FinTech and bank loans. We scrutinize the changes in the loan delinquency rate and compare the differentials between FinTech and bank loans by regressing the difference-in-differences specification on this loan-level data.

B.1. Loan Quality for FinTech and Bank Loans

We begin the analysis by plotting the (unconditional) delinquency rate before and after the pandemic outbreak for both FinTech and bank loans. The horizontal axis of Figure 4 measures time (in months) relative to the outbreak of COVID-19 in China in January 2020. The event time $t = 0$ represents the month when the COVID-19 disease first hit China, and the negative and positive numbers represent the months before and after the start of the outbreak, respectively. The vertical axis measures the average delinquency rate for both FinTech and bank loans. We plot the mean delinquency rate together with the corresponding 95 percent confidence interval around it. As the sample only includes records that span the pandemic outbreak, there are fewer observations in months further before $t = -1$ and further after $t = 1$.

As shown in Figure 4, prior to the pandemic, both FinTech and bank loans have a similar delinquency rate between 2%-5%, and there is no statistical difference for each monthly pairwise comparison ($p > 0.1$).[15] After the outbreak, the rate for bank loans stays at the same level, while the rate for FinTech loans jumps up sharply and becomes significantly higher than the rate for bank loans ($p < 0.001$ for each monthly pairwise comparison). Remarkably, five months after the outbreak, the delinquency rate for FinTech loans exceeds 20%, but the rate remains at 4% for bank loans, such a difference is significant in both statistical ($p < 0.001$) and economic sense.

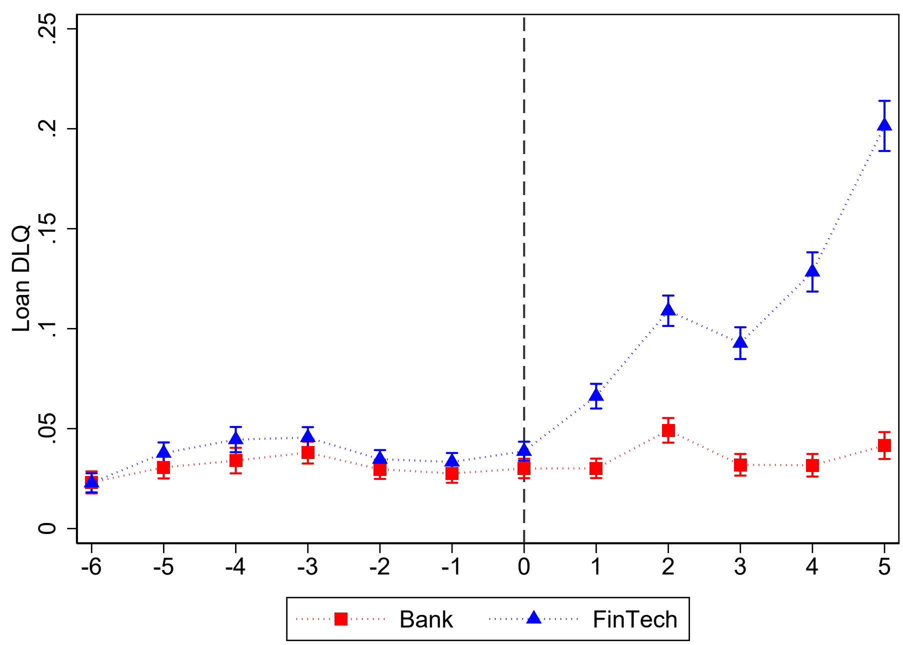


Figure 4: Delinquency rate for bank and FinTech loans before and after COVID-19. This figure plots average values of the delinquency rate for both bank and FinTech loans before and after COVID-19 with the 95% confidence interval. The sample period is 2019:07 to 2020:06. The horizontal axis displays event time (in months), where $t = 0$ corresponds to 2020:01 (the start of the pandemic).

[15]Without further specification, the p-values reported in this paper are from two-tailed t-tests.

Table 7: The Pandemic and Loan Delinquency Rates.
This table shows the estimation results for the difference-in-differences regressions that compare the delinquency behavior before and after the pandemic outbreak after controlling a set of borrower and loan characteristics for both bank and FinTech loans. The p-values are reported in parentheses below each coefficient. *, **, and * indicate significance at the 10%, 5%, and 1% levels, respectively. Standard errors are clustered at the city and time level.**

	Loan Delinquency Indicator			
	(1)	(2)	(3)	(4)
FinTech*After	0.082***	0.081***	0.075***	0.074***
	(0.002)	(0.001)	(0.001)	(0.001)
Demographic Controls	No	Yes	Yes	Yes
Credit Controls	No	Yes	Yes	Yes
Loan Controls	No	Yes	Yes	Yes
City FEs	No	No	Yes	Yes
City*Time FEs	No	No	Yes	Yes
Loan Amount Bin FEs	No	No	No	Yes
Cycle Duration Bin FEs	No	No	No	Yes
Adjusted R^2	0.024	0.056	0.166	0.168
Observations	1,303,043	1,303,043	1,303,043	1,303,043

To compare changes in delinquency rates, we estimate the effect of the pandemic on the loan quality using the difference-in-difference econometric specification. Table 7 displays the estimation results. Column (1) reports that FinTech borrowers are 8.2 percentage points more likely to be delinquent than bank borrowers after the pandemic. Columns (2)-(3) present similar results when we include a battery of controls such as the borrowers' demographic attributes, credit characteristics, loan information, as well as city fixed effects and city-by-time fixed effects. These results indicates that our results are robust to the city-level attributes and the time-varying heterogeneities. Following Di Maggio and Yao (2020), we further control the potential non-linear effect of loan amount and cycle duration on the loan performance by controlling the fixed effects on the bins[16] of these two variables and report the results in Column (4). Overall, all specifications reveal that the quality of FinTech loans

[16]We divide the range of observed values for each variable into five bins with equal width and create a dummy variable for each bin to capture fixed effects for the bin.

deteriorates more than bank loans after the pandemic.

Given the ex-ante differences in borrowers' attributes and characteristics of the FinTech and bank loan contracts, one concern is that such heterogeneity may confound our previous analysis. We apply matching methods to address this. In Table 8a, we use the propensity score matching method (Abadie and Imbens, 2016) based on borrowers' demographics and credit information to find the closest match for each FinTech loan among all bank loans.[17] In this matched sample, we find borrowers with similar characteristics are still significantly more likely to default FinTech loans than bank loans.

We then apply the entropy balancing method (Hainmueller, 2012) to check if the main results are robust to different matching methods. Table 8b suggests that the results based on the entropy-matched sample are very similar.[18] These results confirm that FinTech borrowers are significantly more likely to be delinquent than comparable bank borrowers.

Another concern with the previous analyses is that we do not observe all FinTech and bank accounts for each borrower in our sample. For example, a borrower may have accounts in other FinTech companies and banks. This may obscure the shocks common to both loan types, causing the error terms to be correlated. We address this concern by applying the seemingly unrelated regression (SUR) and explain this specification in detail in Appendix III. This specification generalizes our baseline regression (1) for both FinTech and bank borrowers and takes the unobserved characteristics of the borrower and potential correlated error terms across both FinTech and bank borrowers into account (Zellner, 1962; Zellner and Ando, 2010). We apply the SUR method on the propensity score matched sample and present the

[17]We perform the propensity score matching method on our loan-level sample. We estimate a probit regression using the FinTech loan indicator as the dependent variable and all demographic and credit variables as independent variables for borrowers in each city. We use the nearest neighbor criteria to select the matched sample between FinTech and bank loans.

[18]The entropy balancing method generalizes the propensity score method and re-weights the loan-level sample such that the pre-specified moment conditions are satisfied (we consider the first and second moments for the analyses).

Table 8: Loan Delinquency Rate Based on Matched Sample.

This table presents the estimation results for the difference-in-differences regressions in two matched samples that compare the delinquency behavior before and after the outbreak of the pandemic after controlling a set of borrower and loan characteristics for both FinTech and bank loans. Table 8a reports results using the matched sample based on propensity score methods. Table 8b shows results using the matched sample based on the entropy balancing method. The *p*-values are reported in parentheses below each coefficient. *, **, and * indicate significance at the 10%, 5%, and 1% levels, respectively. Standard errors are clustered at the city and time level.**

(a) Propensity score matched sample

	Loan Delinquency Indicator			
	(1)	(2)	(3)	(4)
FinTech*After	0.069***	0.067***	0.065***	0.064***
	(0.002)	(0.001)	(0.001)	(0.001)
Demographic Controls	No	Yes	Yes	Yes
Credit Controls	No	Yes	Yes	Yes
Loan Controls	No	Yes	Yes	Yes
City FEs	No	No	Yes	Yes
City*Time FEs	No	No	Yes	Yes
Loan Amount Bin FEs	No	No	No	Yes
Cycle Duration Bin FEs	No	No	No	Yes
Adjusted R^2	0.028	0.035	0.273	0.275
Observations	195,456	195,456	195,456	195,456

(b) Entropy balancing matched sample

	Loan Delinquency Indicator			
	(1)	(2)	(3)	(4)
FinTech*After	0.073***	0.071***	0.070***	0.070***
	(0.001)	(0.003)	(0.002)	(0.001)
Demographic Controls	No	Yes	Yes	Yes
Credit Controls	No	Yes	Yes	Yes
Loan Controls	No	Yes	Yes	Yes
City FEs	No	No	Yes	Yes
City*Time FEs	No	No	Yes	Yes
Loan Amount Bin FEs	No	No	No	Yes
Cycle Duration Bin FEs	No	No	No	Yes
Adjusted R^2	0.014	0.043	0.196	0.201
Observations	977,282	977,282	977,282	977,282

Table 9: Loan Delinquency Rate Based on Matched Sample with Seemingly Unrelated Regression.

This table presents the estimation results for the seemingly unrelated regressions that compare the delinquency behavior before and after the outbreak of the pandemic after controlling a set of borrower and loan characteristics for both FinTech and bank loans using the propensity score matched sample. The p-values are reported in parentheses below each coefficient. *, **, and * indicate significance at the 10%, 5%, and 1% levels, respectively.**

	Loan Delinquency Indicator			
	(1)	(2)	(3)	(4)
FinTech*After	0.068***	0.066***	0.065***	0.064***
	(0.004)	(0.002)	(0.001)	(0.002)
Demographics Controls	No	Yes	Yes	Yes
Credit Controls	No	Yes	Yes	Yes
Loan Controls	No	Yes	Yes	Yes
City FEs	No	No	Yes	Yes
City*Time FEs	No	No	Yes	Yes
Loan Amount Bin FEs	No	No	No	Yes
Cycle Duration Bin FEs	No	No	No	Yes
Adjusted R^2	0.028	0.035	0.272	0.275
Observations	195,456	195,456	195,456	195,456

estimate for the difference-in-differences coefficient for the delinquency rate in Table 9. In general, borrowers are still significantly more likely to default FinTech loans than bank loans after taking the potential correlations between these two types of loans into account.

B.2. Loan Quality and the Severity of the Pandemic

We then explore the potential heterogeneous effect of the epidemic on loan quality across borrowers' geographic locations. We interact our baseline regression (1) with the indicator for the city of Wuhan (Column 1), for cities in Hubei Province (Column 2), for cities with the top 10 Wuhan population inflow in January 2020 based on Tencent mobility (Column 3), and for cities with the top 10 COVID-19 infection cases until April 30th, 2020 (Column 4).

In Table 10, we show the estimates of the specification that includes the interaction terms with city indicators. In Column (1), the estimated coefficient of the interactive term is 0.4%

Table 10: Severity of the Pandemic and Loan Delinquency Rate.

This table presents the estimation results for regressions studying how the severity of the pandemic in the borrower's city of residency affects the delinquency rate for FinTech and bank loans. The p-values are reported in parentheses below coefficients. *, **, and * indicate significance at the 10%, 5%, and 1% levels, respectively. Standard errors are clustered at the city and time level.**

	Loan Delinquency Indicator			
	(1)	(2)	(3)	(4)
FinTech*After	0.075***	0.075***	0.075***	0.075***
	(0.001)	(0.001)	(0.001)	(0.001)
FinTech*After*$D_{\text{Wuhan City}}$	0.004**			
	(0.010)			
FinTech*After*$D_{\text{Hubei Province}}$		0.001*		
		(0.085)		
FinTech*After*$D_{\text{Top10 Wuhan inflow cities}}$			0.001**	
			(0.027)	
FinTech*After*$D_{\text{Top10 COVID infected cities}}$				0.002**
				(0.036)
Demographic Controls	Yes	Yes	Yes	Yes
Credit Controls	Yes	Yes	Yes	Yes
Loan Controls	Yes	Yes	Yes	Yes
City FEs	Yes	Yes	Yes	Yes
City*Time FEs	Yes	Yes	Yes	Yes
Adjusted R^2	0.166	0.166	0.166	0.166
Observations	1,303,043	1,303,043	1,303,043	1,303,043

and statistically significant, implying borrowers living in Wuhan contribute to an additional 0.4 percentage point increase in the FinTech-bank delinquency rate gap compared to those living in other cities. In Columns (2) and (3), we report the result for cities in Hubei province and the 10 cities with most population inflow from Wuhan, respectively. The estimated coefficients of the interactive term are all positive and significant as in Column (1). More generally, in Column (4), we find the severity of the pandemic expands the FinTech-bank delinquency gap. However, the severity of the pandemic alone cannot fully explain the gap as the coefficient attached to the variable $\text{FinTech}_i \times \text{After}_t$ is still positive and significant in all four regressions.

B.3. Loan Quality and First-time Borrowers

This subsection explores how much of the FinTech-bank delinquency gap can be explained by the existence of first-time borrowers.[19] We categorize each individual into either the first-time borrower group or the pre-existing borrower group depending on whether the borrower has a loan record with the corresponding financial intermediary before the observation period. We then interact the baseline regression with the indicators specifying the two groups and explore the potential heterogeneous effect of the pandemic on the loan delinquency for first-time and pre-existing borrowers. We present the results in Table 11. In all four specifications, the estimates for first-time and pre-existing borrowers are similar: the delinquency rate for FinTech loans increases 7.5-8.2 percentage points more than that of the bank for pre-existing borrowers, and 7.1-7.9 percentage points for first-time borrowers. In sum, our results indicate that the differentials in the quality of FinTech and bank loans are unlikely to be driven by the first-time borrowers.

B.4. What Drives the Differences in the Loan Performance?

Our previous results confirm that FinTech borrowers are significantly more likely to be delinquent than bank borrowers after the pandemic. We also show that neither the presence of first-time borrowers nor the severity of the pandemic in borrowers's residential cities can fully explain the difference. What might be the reason for this FinTech-bank gap in the delinquency probability? One possibility is borrowers prioritize the repayment of certain loan types. To shed light on this conjecture, we focus on the 627 borrowers with both FinTech and bank loans to explore their behaviors before and after the pandemic.

Figure 5 sketches the (unconditional) loan performance for these borrowers. We find borrowers have similar delinquency rates of between 2% - 6% before the pandemic for both

[19]The sample restricts the observations to start before and end after the outbreak, therefore, we mechanically exclude the arriving of new borrowers after the outbreak. First-time borrowers refer to those who start their first loan after the beginning of the observation window and before the pandemic outbreak.

Table 11: First-time Borrowers and Loan Delinquency Rate.
This table presents the estimation results for regressions studying how the pandemic affected the delinquency rate for first-time and pre-existing FinTech and bank borrowers. The p-values are reported in parentheses below coefficients. *, **, and * indicate significance at the 10%, 5%, and 1% levels, respectively. Standard errors are clustered at the city and time level.**

	Loan Delinquency Indicator			
	(1)	(2)	(3)	(4)
FinTech*After*Pre-existing	0.082***	0.081***	0.076***	0.075***
	(0.001)	(0.002)	(0.001)	(0.001)
FinTech*After*First-time	0.079**	0.075**	0.073***	0.071***
	(0.023)	(0.011)	(0.006)	(0.004)
Demographic Controls	No	Yes	Yes	Yes
Credit Controls	No	Yes	Yes	Yes
Loan Controls	No	Yes	Yes	Yes
City FEs	No	No	Yes	Yes
City*Time FEs	No	No	Yes	Yes
Loan Amount Bin FEs	No	No	No	Yes
Cycle Duration Bin FEs	No	No	No	Yes
Adjusted R^2	0.024	0.056	0.166	0.168
Observations	1,303,043	1,303,043	1,303,043	1,303,043

FinTech and bank loans, and there is no statistically significant difference for each monthly pairwise comparison. After the start of the pandemic, the delinquency rate for bank loans remains similar as before, while the rate for FinTech loans increases sharply and becomes significantly higher than the rate for bank loans ($p < 0.005$ for each monthly pairwise comparison).

We further investigate this sub-sample of borrowers, examining their behavior before and after the start of the pandemic using the difference-in-differences specification, controlling for borrowers' fixed effects, city fixed effects, and city-by-month fixed effects. We also add all observable characteristics to control for potential time-varying attributes that may obscure our results. In Table 12, we find evidence that borrowers tend to prioritize the payment of bank loans during the pandemic. Holding all observed and unobserved borrower characteristics, we find that borrowers are 4 percentage points more likely to default FinTech loans

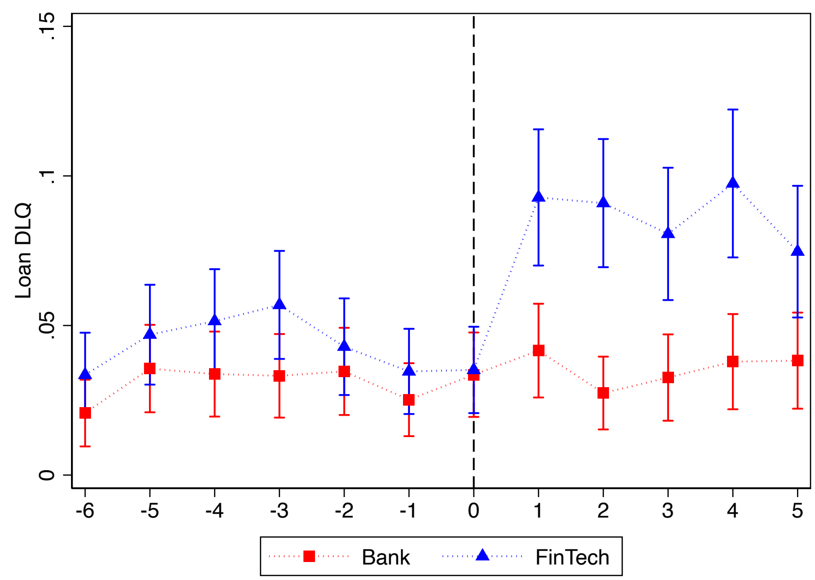


Figure 5: Loan outcomes for borrowers holding both FinTech and bank loans before and after the outbreak. This figure plots average values of the delinquency rate before and after the start of the pandemic, with 95% confidence intervals. The sample period is 2019:07 to 2020:06. The horizontal axis displays event time (in months), where $t = 0$ corresponds to 2020:01 (the start of the pandemic).

than bank loans after the pandemic, and this result is highly significant ($p = 0.001$).

B.5. Loan Quality and Pricing

Our findings show that FinTech companies provide more credit access to borrowers after the start of the pandemic, while FinTech borrowers have a higher probability of delinquency than bank borrowers with comparable characteristics. However, such a leap in access to credit may not be sustainable if the interest rates of FinTech loans do not compensate for the probability of delinquency. We explore this issue by investigating whether the loan interest rates can predict the loan quality before and after the pandemic.

Following Rajan et al. (2015), we study the correlation between interest rates and loan performance and test whether the FinTech companies have better algorithms for the pricing

Table 12: Differentials in the Changes in Delinquency Rates of FinTech and Bank Loans for Borrowers Holding Both Loan Types.

This table shows the estimation results for the difference-in-differences regressions comparing the delinquency behavior before and after the outbreak of the pandemic after controlling a set of borrower and loan characteristics for both FinTech and bank loans. The p-values are reported in parentheses below each coefficient. *, **, and * indicate significance at the 10%, 5%, and 1% levels, respectively. Standard errors are clustered at the city and time level.**

	Loan Delinquency Indicator			
	(1)	(2)	(3)	(4)
FinTech*After	0.047***	0.045***	0.042***	0.040***
	(0.002)	(0.001)	(0.001)	(0.001)
Demographic Controls	No	Yes	Yes	Yes
Credit Controls	No	Yes	Yes	Yes
Loan Controls	No	Yes	Yes	Yes
Borrower FEs	No	No	Yes	Yes
City FEs	No	No	No	Yes
City*Time FEs	No	No	No	Yes
Adjusted R^2	0.049	0.078	0.254	0.273
Observations	7,371	7,371	7,371	7,371

of loans. We consider the following econometric specification:

$$Y_{i,t} = \alpha + \beta \text{Rate}_{i,t} + \gamma X_{i,t} + \delta_c + \xi_{c,t} + \varepsilon_{i,t},$$

where the dependent variable $Y_{i,t}$ is the loan delinquency indicator. The coefficient β captures the correlation between interest rate and loan default probability. As the correlation might be driven by potential adverse selection and moral hazard (Di Maggio and Yao, 2020), we add a full vector of controls to mitigate this concern. In Column (1) of Table 13a, we show the interest rate of FinTech loans is positively correlated with the default probability in the absence of any controls before the pandemic. When we add other attributes and fixed effects in Column (2), the adjusted R^2 increases from 0.004 to 0.217, while the coefficient is still positive and significant. However, after the start of the pandemic, the coefficients of interest rate in Columns (3) and (4) decline and become statistically insignificant, suggesting that FinTech interest rates may not respond to changes in the delinquency risks of FinTech borrowers.

Table 13: Loan Pricing for FinTech and Bank Loans.
This table presents the estimation results for the difference in the relationship between loan performance and interest rate between FinTech and bank loans in our sample. Table 13a reports the results for FinTech loans, and Table 13b displays the results for bank loans. The *p*-values are reported in parentheses below each coefficient. *, **, and * indicate significance at the 10%, 5%, and 1% levels, respectively. Standard errors are clustered at the city and time level.**

(a) FinTech loans

	Loan Delinquency Indicator			
	Before		After	
	(1)	(2)	(3)	(4)
Interest Rate	0.342***	0.316***	0.206	0.169
	(0.000)	(0.004)	(0.190)	(0.103)
Demographics Controls	No	Yes	No	Yes
Credit Controls	No	Yes	No	Yes
Loan Controls	No	Yes	No	Yes
City FEs	No	Yes	No	Yes
City*Time FEs	No	Yes	No	Yes
Adjusted R^2	0.004	0.217	0.000	0.128
Observations	432,740	432,740	288,493	288,493

(b) Bank loans

	Loan Delinquency Indicator			
	Before		After	
	(1)	(2)	(3)	(4)
Interest Rate	0.314***	0.299**	0.302**	0.286**
	(0.001)	(0.034)	(0.030)	(0.019)
Demographics Controls	No	Yes	No	Yes
Credit Controls	No	Yes	No	Yes
Loan Controls	No	Yes	No	Yes
City FEs	No	Yes	No	Yes
City*Time FEs	No	Yes	No	Yes
Adjusted R^2	0.005	0.175	0.003	0.164
Observations	349,086	349,086	232,724	232,724

We turn to the analogous analyses for bank loans in Table 13b. In Columns (1) and (2), the coefficients of interest rate are economically and statistically significant. Moreover, as shown in Columns (3) and (4), the relation doesn't change much after the pandemic. Overall, these results show the interest rates for FinTech loans are correlated with the delinquency probability before the pandemic while the correlation declines after the pandemic. While for bank loans, the relation is robust throughout. Our results suggest the higher delinquency rate after the pandemic are likely to lower the profits for the FinTech companies.

VII. Discussion and Conclusion

This paper takes a first glimpse into the performance of the FinTech industry in China. Using the outbreak of the COVID-19 pandemic as an exogenous shock, we compare the changes in credit access and delinquency rates between FinTech and bank borrowers. We find the FinTech industry has the superiority in granting credit to low-income and unemployed borrowers, as well as those who reside in areas with more COVID cases during the pandemic. However, the data also suggest the quality of FinTech loans is more susceptible to adverse shocks. We witness the FinTech companies have a similar delinquency rate as the bank before the pandemic, but the rate of the FinTech industry skyrockets after the outbreak while banks are unaffected. To control for observed and unobserved borrower characteristics, we also identify borrowers who have outstanding FinTech and bank loans at the same time. By focusing on these borrowers, we find borrowers are more likely to default their FinTech loans rather than their bank loans. These findings highlight the strengths and weaknesses of the FinTech industry before and after the start of the pandemic.

However, as a limitation of our data, we are unable to explain why the FinTech industry is influenced by the pandemic in such ways. We have several conjectures. First, the enforcement mechanisms used by FinTech companies may fail to provide enough incentives for the borrowers to repay the money during the pandemic. For example, some FinTech companies send personnel to interact with potential defaulters personally to persuade them to make the repayments. Interacting with potential defaulters is, however, impossible during strict lockdowns. Second, borrowers may choose to default FinTech loans rather than bank loans for strategic reasons. In general, it is very likely for borrowers to interact with a bank again over their life course, but they can easily switch to other FinTech companies who has no access to their history of delinquency. We encourage future researchers to tease these channels apart.

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Appendix

I. Variable Definition

The key variables are defined in Table A.

Table A: Variable Definitions.

Variable	Definition
	Panel A: Demographic variable
Borrower Age	Age of the borrower.
Employment Indicator	Indicator that equals one if the borrower is full-time employed and zero otherwise.
High Income Indicator	Indicator that equals one if the borrower's monthly income is higher than RMB 10,000 and zero otherwise.
Higher Education Indicator	Indicator that equals one if the borrower has a bachelor's degree or above and zero otherwise.
Male Indicator	Indicator that equals to one if the borrower is male and zero otherwise.
Married Indicator	Indicator that equals one if the borrower is married and zero otherwise.
	Panel B: Credit variable
Car Indicator	Indicator that equals one if the borrower owns a car and zero otherwis
Car Loan Indicator	Indicator that equals one if the borrower has an unpaid car loan and zero otherwise.
House Indicator	Indicator that equals one if the borrower owns a piece of real-estate and zero otherwise.
Mortgage Indicator	Indicator that equals one if the borrower has an unpaid mortgage and zero otherwise.
Hist. DLQ Indicator	Indicator that equals one if the borrower has at least one delinquency record at this financial institution before 2019:07.
Hist. No of DLQ	Total number of delinquency records for each borrower before 2019:07
Hist. Balance	Total loan balance before 2019:07 for each borrower.
Hist. No. Credit Access	Number of credit access before 2019:07 for each borrower.
Hist. Average Cycle Duration	The average duration of cycles before 2019:07 for each borrower.
	Panel C: Loan Information
Loan Amount	Total credit amount originated in RMB during 2019:07-2020:06.
No. of Credit Access	Number of credit access during 2019:07-2020:06 for each borrower.
Average Cycle Duration	The duration of loan cycles during 2019:07-2020:06 for each borrower.
Interest Rate	Total loan annualized interest rate (%).

II. Details of Before and After Specification

In addition to the difference-in-difference regression, we estimate the before and after econometric specification for FinTech and bank loan subsamples as shown below:

$$Y_{i,t} = \alpha + \beta \text{After}_t + \gamma X_{i,t} + \delta_c + \xi_{c,t} + \tau_i + \varepsilon_{i,t},\ i \in \{\text{FinTech}, \text{Bank}\}, \tag{2}$$

where the dependent variable $Y_{i,t}$ is the loan outcome. The coefficient β captures the effect of pandemic on the loan outcome for FinTech and bank loan subsamples, respectively. As the relationship might be driven by adverse selection and moral hazard (Di Maggio and Yao, 2020), we add a full vector of controls for borrower characteristics $X_{i,t}$, the city fixed effects δ_c, and city-by-month fixed effects $\xi_{c,t}$ to mitigate this concern.

III. Details in Seemingly Unrelated Regression

We estimate the impact of pandemic on loan delinquency rates using seemingly unrelated regressions (SUR) as a robustness check. SUR generalizes our baseline specification for both FinTech and bank borrowers and takes the potential correlated error terms across both FinTech and bank borrowers into account (Zellner, 1962; Zellner and Ando, 2010). It also enables the direct comparison of coefficients from the FinTech equation with those from the bank equation. The specification is as follows:

$$\begin{pmatrix} Y_{i,t} \\ Y_{j,t} \end{pmatrix} = \begin{pmatrix} \alpha_{\text{FinTech}} + \beta_{\text{FinTech}} \text{After}_t + \gamma_{\text{Fintech}} X_{i,t} + \delta_c + \xi_{c,t} + \tau_i \\ \alpha_{\text{Bank}} + \beta_{\text{Bank}} \text{After}_t + \gamma_{\text{Bank}} X_{i,t} + \delta_c + \xi_{c,t} + \tau_j \end{pmatrix} + \begin{pmatrix} \varepsilon_{i,t} \\ \varepsilon_{j,t} \end{pmatrix} \tag{3}$$
$$i \in \{\text{FinTech}\}, j \in \{\text{Bank}\}$$

The coefficients β_{Fintech} and β_{Bank} on After_t are the estimates of the effect of the pandemic on the delinquency rate of FinTech and bank loans, respectively. The difference between these two coefficients (i.e., the difference-in-differences estimator) illustrates how the two types of financial intermediaries respond to the pandemic differently when controlling for all time-varying, observed and unobserved, borrower and financial intermediary heterogeneities.

IV. The Regulations for FinTech Lenders in China

In July 2015, the Peoples Bank of China (PBOC) and ten Ministries and Commissions released Guidance on Promoting the Healthy Development of FinTech to the public, along with a series of policies and measures designed to encourage financial innovations and to broaden financing channels for individuals. The Guidance aims to simplify and decentralize financial governance, improve fiscal and taxation policies, and promote credit infrastructure and services. In August 2017, the China Banking and Insurance Regulatory Commission (CBIRC) issued Guidelines for the Depository of On-line Lending Funds and Guidelines for the Disclosure of Information on Business Activities of On-line Lending Intermediaries, standardizing the practices for the FinTech lending industry. With these supportive policies and mild supervisions from the government, the Chinese FinTech lending industry enters a fast and stable development stage. This stage was terminated by the outbreak of the COVID-19 pandemic and the subsequent policy amendments.

In July 2020, CBIRC released the Interim Measures for the Administration of Internet Loans. This sets the credit upper limit for personal credit loans from on-line providers to be RMB 200,000. It also specifies that the loan term shall not exceed one year if the principal is repaid in one lump sum at maturity. In addition, each on-line credit provider must collect borrowers name, ID number, contact telephone number, and other essential information for risk assessment, pre-lending investigation, and post-lending management.

In August 2020, the Supreme People's Court released the "Decision on Amending Laws for Chinese FinTech Credit Providers after Public Hearings". The decision sets the upper limit for the legal interest rate that FinTech companies can charge, which is four times the Loan Prime Rate (IPR) for one-year loans.

In September 2020, CBIRC issued a notice on "Strengthening Supervision and Management of Internet Micro-finance Companies". The notice restricts the business scope for on-line micro-finance companies (including FinTech lenders). To promote healthy development of these companies, the notice further standardizes their practices regarding capital management, collection management, information disclosure, custody of customer information, and active cooperation with the government.

In November 2020, PBOC released additional regulations for on-line micro-finance businesses.[20] One key amendment in the regulation specifies that each on-line credit company must not expand business beyond the province where it is registered. This leads to the suspension of the listing of the largest FinTech credit provider, the Ant Technology Group.

[20]Interested readers may find some debates on the regulatory changes from the following websites https://www.ftchinese.com/story/001090247?archive and https://asia.nikkei.com/Opinion/Why-Beijing-was-right-to-rein-in-Jack-Ma-s-rogue-Ant-Group-IPO.