How does the COVID-19 pandemic reshape the lending behavior of financial institutions?

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A Thesis
in
The Department
of
Finance

Presented in Partial Fulfillment of the Requirements
for the Degree of Master of Science (Finance) at Concordia University
Montreal, Quebec, Canada

April 2022

CONCORDIA UNIVERSITY
School of Graduate Studies

This is to certify that the thesis prepared

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Entitled: How does the COVID-19 pandemic reshape the lending beha

and submitted in partial fulfillment of the requirements for the degree of

Master of Science (Finance)

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How does the COVID-19 pandemic reshape the lending behavior of financial institutions?

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Abstract

In this study, I explore the impact of COVID-19 on the lending behavior of traditional and FinTech banks. I use difference-in-difference and triple-diff-in-diff approach with 2019-2020 HMDA loan application data and the Covid Community Vulnerability Index (CVI) to study 1) borrower profiles and loan application demand, 2) lender scrutiny stringency i.e. application approval rates, 3) loan interest rates, and 4) securitization of loans in counties with different level of epidemic vulnerability before and after the epidemic. I find that borrowers in regions with high vulnerability are able to embrace FinTech more quickly. At the same time, FinTech has expanded its previous target demographic to older, non-white, and ethnic minority borrowers. However, the supply side has not softened its application review criteria in response to the surge in demand. Lenders have been more cautious, and while minorities are more willing to apply for FinTech loans, it is worth noting that traditional banks have taken on a social responsibility at this time to increase their lending approval rates for such community. FinTech banks, on the other hand, have expanded the sale of loans, shifting the uncertainty risk to the broad investors.

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1 Introduction

In 2020, the sudden onset of COVID-19 fundamentally changed the world. Not only did the epidemic cause economic recession and financial volatility, but more importantly, it changed human behavior. On March 13, 2020, President Trump officially declared a national emergency and implemented draconian measures to prevent the epidemic spread. From the initial travel ban to the successive stay-at-home orders, workplace closures, public event cancellations, party bans, and public transportation shutdowns issued by each state, it was not until the widespread introduction of the vaccine in 2021 that people gradually returned to their old lifestyles, but the aftermath of the pandemic continued to affect and even essentially alter people's routine. According to a survey[1] conducted by the National Retail Federation last May, up to 19% of people started using mobile payments or proximity credit cards in order to reduce physical contact, and more than half of them said they would continue to use this contactless payment method. And during this particular period, people are also transitioning from offline to online spending. Robinhood, a provider of stock investment services, and Coinbase, a provider of cryptocurrency trading, have successfully attracted many consumers by eliminating the monetary thresholds and cumbersome applications that traditional investment institutions are accustomed to, and have indirectly driven a boom in investment among young Americans.

As stated in the loan market trends report by the Home Mortgage Disclosure Act (HMDA) that Quicken Loans is riding high with 1,141,000 loans originated in 2020, more than twice the number of loans originated in second place. Eleven out of the top 25 closed-end respondents by total loan originations listed are FinTech companies. Does this mean that the

[1] Press releases available at: https://nrf.com/media-center/press-releases/coronavirus-leads-more-use-contactless-credit-cards-and-mobile-payments

COVID-19 has highlighted the advantages of FinTech in terms of speed, convenience, and no-touch, accelerating its growth? Did banks extend different types of loans and credit criteria than usual during this epidemic?

Using HMDA 2019-2020 loan application information, I employ the classification method of Buchak et al. (2018) to divide loan originators into FinTech and non-FinTech banks and apply the difference-in-differences (DID) method to observe the variation in public demand for borrowing from the two types of banks before and after the epidemic, and their respective adjustment in supply. The results are consistent with pioneering findings that FinTech banks did not constantly accommodate the high demand for loans due to concerns during the crisis, but instead restricted their lending to older people, those with smaller loans and refinancing types of loans that require fewer resources to process (Choi et al., 2019; Fuster et al., 2017; Sharpe & Sherlund, 2016). Meanwhile, in times of COVID-19, FinTech has become the first choice for ethnic minorities and non-white lenders, but non-FinTech banks have reversed their criticism of discrimination and been more supportive of these vulnerable groups.

I employ the Covid Community Vulnerability Index scores to define the vulnerability of the epidemic in each county as high and low risk and use the triple-difference-in-differences method to demonstrate explicitly the impact of the pandemic on the behavior of both lenders and borrowers. The results validate that FinTech banks are more popular with lenders in high-risk areas and that lending policies are laxer there correspondingly. Furthermore, I study how banks' financing decisions shifted under the pressure of the epidemic, i.e., how they finance themselves to support the surging demand. It turns out that both before and after the epidemic, FinTech banks always sell more loans than non-FinTech banks in high- and low-risk areas, transferring risk to investors through securitization. Traditional banks, on the other hand, are more cautious in their securitization decisions in high-risk areas.

In what follows, this paper summarizes the literature review on how FinTech has substituted traditional banks in general and introduces new research trends since COVID-19. Section 3 presents data and empirical methods and models. Section 4 displays empirical results and analysis. Section 5 further discusses the results and concludes the paper.

2 Literature Review and Hypotheses Development

This research focuses on comparing the changes in mortgage lenders and borrowers between FinTech and traditional financial institutions after experiencing the shock that is COVID-19. The contrast with traditional financial institutions has been there since the beginning with the new entry of FinTech banks, reshaping financial services with lower barriers and greater accessibility to serve the masses (Philippon, 2016). The extensive literature begins by detailing the advantages of FinTech banks, which are faster and more efficient in loan processing, credit analysis, and financing capabilities, supported by big data and technological algorithms, as compared to traditional banks with alternative advantages (Fuster et al., 2019). Berg et al. (2020) analyze the use of digital footprints for predicting consumer credit scores, affirming that information gathered by big data such as time spent shopping, frequently used email addresses, and type of devices used is no less important than consumer credit scores assessed by credit bureaus. Iyer et al. (2016) even find in an earlier study that compare to precise credit scores, peer borrower predictions of borrower creditworthiness applied by FinTech companies are more accurate and enhanced lending efficiency. Another controversial drawback of traditional banks compared to FinTech banks is lending discrimination. Bartlett et al. (2021) analyze HMDA application information and find that while FinTech algorithms also more or less favor whites, face-to-face origination of loans by non-FinTech lenders to minorities charge 40% higher interest rates than FinTech banks. This paper examines the unique advantages of FinTech highlighted during COVID-19 and provides empirical evidence for the above advantages.

Clearly, the response from this notable competitive advantage of FinTech has been beneficial for the specific populations served. Some scholars therefore study FinTech's substitutive relationship with traditional banks. Tang (2019) finds by analyzing Lending Club's loan information that P2P lending platforms have captured banks' market share among low-quality borrowers after the supply side of banks tightened while complementing banks in the business of providing smaller loans. Cornaggia et al. (2018)'s findings are also consistent with the former, that FinTech lending being a substitute relationship with banks in serving a high-risk customer segment. FinTech banks are gaining more market share from some economically underdeveloped and poorly credited regions that are underserved by traditional banks (De Roure et al., 2021; Jagtiani et al., 2021; Jagtiani & Lemieux, 2018). Competitive pressures from FinTech have also forced banks in transit-friendly areas to offer lower interest rates to borrowers (Butler et al., 2017). In this study, I employ COVID-19 as an exogenous shock to compare the supply and demand of FinTech and traditional bank loans by classifying counties into high and low risk areas and enrich the literature on the study of substitution of FinTech for traditional banks in terms of regional distribution and borrower characteristics.

As the pandemic unfolded, a large literature on FinTech development in the context of COVID-19 emerged. After the pandemic, spending habits shifted toward credit card payments (Baker et al., 2020), the spread of mobile payments reduced the number of ATMs, increased credit card use and higher credit limits (Agarwal et al., 2020), and there was a 24%-32% increase in daily downloads of financial mobile clients (Fu & Mishra, 2020). One of the reasons for the elevated interest in FinTech is that in times of crisis, investors are more concerned with the advice itself rather than the form of the advice (David & Sade, 2019). FinTech itself is an evolution that makes people's lives easier by simplifying all the cumbersome offline processes to their fingertips, arguably a solution tailored to one day respond to a crisis like the COVID-19 pandemic. Najaf et al. (2021) study transaction data from Lending Club and conclude that after the pandemic, P2P lending attracts borrowers who have little access to credit institutions. The fully online operation gives them an absolute advantage over banks and, combined with the fact that FinTech banks would relax their underwriting standards to gain a competitive advantage over traditional banks in the wake of the natural disaster (Allen et al., 2020), become the most viable option for marginal borrowers during the epidemic. This paper reflects the value of FinTech at the demand level by comparing the borrowers' demographic characteristics approved by FinTech and non-FinTech before and after the pandemic.

Indeed, Erel & Liebersohn (2020) demonstrate by introducing payroll protection plans (PPPs) during COVID-19 that FinTechs expand the supply of financial service providers with their penetration at the margins. Not only is the degree of convenience FinTech banks superior, but Fuster et al. (2021) present evidence that harder recruitment and greater operational frictions during the pandemic lead to a lack of elasticity in the supply of credit, at a time when technology-based lenders, i.e. FinTech, may have been less constrained by these frictions and gained market share. They also report a tightening of credit standards by industry practitioners in response to higher forbearance and default risks. Similar to my approach is the study by Bao & Huang (2021), except that they use transaction data from a Chinese FinTech company and a bank and find that during the epidemic, the FinTech-served population has higher credit risk and higher delinquency rates. I contribute to the literature on the impact of natural disasters such as

COVID-19 on FinTech and non-FinTech loan originations, specifically the shift of supply and demand of credits, and changes in demographic characteristics.

This paper differs from the preceding studies in that, first, I analyze the impact of the COVID-19 epidemic on the lending market from two broad perspectives: loan supply and demand, observing not only shifts in consumer behavior but also providing insight into the social role lenders played during the crisis. Second, I use a difference-in-differences approach to explain behavioral differences between FinTech and non-FinTech banks, pre- and post-epidemic, in high- and low-risk areas. I also document changes in banks' financing decisions in the face of the epidemic, providing investors and policymakers with a new perspective on assessing FinTech banks' market risk under stress.

Therefore, I develop the following hypotheses:

H1.A: Borrowers' demand for FinTech loans increased after the epidemic.

The U.S. Federal Reserve lowered the target range for the federal funds rate by 1 percentage point to between 0% and 0.25% and launched a $700 billion quantitative easing program to address the negative impact of the COVID-19 outbreak on the U.S. economy. Interest rate cuts can reduce the cost of credit, increase spending, and create jobs, helping to inject market dynamism, stimulate the economy and hence increase demand for loans.

H1.B: The population served by FinTech is older than other lenders after the epidemic, more likely to be ethnic minorities and non-white, and more likely to be lending for refinancing purposes.

Based on the study of FinTech consumer groups by Bartlett et al., (2021); Cornaggia et al. (2018); Tang (2019), I hypothesize that the COVID-19 pandemic prompted e-commerce to reach a wider range of people, especially those who were underserved by non-FinTech banks.

H1.C: The more severe the epidemic, the greater the demand for FinTech loans.

The government has imposed stricter travel restrictions in areas with severe epidemics, and people would choose FinTech banks that do not require face-to-face meetings out of concern for safety and convenience.

H2.A: The supply of FinTech lenders shrinks after the epidemic.

Excessive demand for loans triggered by falling interest rates makes FinTech more cautious in granting loans to hedge risk.

H2.B: FinTech banks prefer to lend to older, better-credit applicants during an epidemic, and the type of loan is more likely to be refinancing.

While the more receptive to online lending and progressively more financially empowered millennials will be a major source of demand growth for FinTech banks, older borrowers with solid incomes and mature behavior can mitigate the uncertainty caused by the epidemic as financial institutions that originate loans. By the same token, refinancing involves less manpower and fewer resources needed to assess than issuing new loans and is a more rational choice given the risk.

H2.C: The more severe the epidemic, the tighter the supply of FinTech loans.

Admittedly, as the core principle on which the above assumptions are based, eliminating the uncertainty created by the epidemic should be the primary criterion for financial institutions to grant loans. Counties with more vulnerable infrastructure are subject to higher risk, thus influencing the evaluation decisions of financial institutions. While these areas may also be the target population that is underserved by traditional banks and substituted by FinTech banks, I suspect that the uncertainty created by the epidemic will be an important condition for FinTech banks to assess viability.

H2.D: Both banks offer lower rates in the post-epidemic period, with FinTech banks cutting their rates even more.

In the wake of the global outbreak of COVID-19 in March, the Federal Reserve cut interest rates sharply, lowering the target range for the federal funds rate to near zero, and initiated unlimited quantitative easing to relieve financial market pressure and minimize the impact of the pandemic on the U.S. economy. As a result, mortgage rates will certainly be reduced across the board as a matter of monetary policy. Moreover, FinTech banks use the Internet to leverage big data and computer models and technology to eliminate the need for intermediaries and human resources to complete high-value financial activities. During the period of the epidemic when close contact is avoided as much as possible, they take advantage of their strengths to reduce lending costs and thus offer preferable loan rates.

H3.A: FinTech banks relied more on securitized financing than traditional banks before the epidemic.

Credit asset securitization is an important way for banking financial institutions to revitalize their stock of credit assets, selling interest and principal to investors in the form of transactions, and playing an active role in enhancing the quality and efficiency of the banking industry in serving the real economy. Since there is no need to take deposits like traditional banks, loan securitization is the main financing method for financial institutions like LendingClub.

H3.B: FinTech banks are selling loans to finance themselves more dramatically than traditional banks in the wake of the epidemic.

When banks don't own the loans, they don't need to take the risk, which reduces the possibility of a recurrence of the savings and loan crisis under the pressure of the epidemic.

However, during the epidemic, financial institutions need to expand the scale of financing to cater to the climbing demand of investors. In this process of loan securitization, P2P platforms not only act as a class special purpose vehicle (SPV), but also assume the role of underwriters, so the asset securitization business carried out by Internet financial platforms with the background of e-commerce has considerable market potential compared to traditional banks. In addition, Greenbaum & Thakor (1987) find that banks tend to use securitization funding channels for high-quality assets and deposits to fund low-quality assets. If the epidemic is seen as a factor that increases risk, then high risk implies low quality, and traditional banks should use more deposits and have fewer loans to sell relative to FinTech banks.

3 Empirical Strategy

3.1 Data and variable

3.1.1 HMDA loan data

The Home Mortgage Disclosure Act (HMDA) requires all financial institutions to maintain and disclose loan-level information. From the U.S. Consumer Financial Protection Bureau, I obtained the Loan Application Registry (LAR) for all financial institutions for 2019 through 2020. Using 2019 and 2020 as a proxy for pre- and post-epidemic, respectively, is a compromise. Because at the time of writing, the epidemic is still ongoing and only time will tell how it will end. But 2020 is indeed the immediate reaction to the market blow, with four unprecedented meltdowns in U.S. stocks and negative oil prices, hence it is by far the most appropriate year to represent post-epidemic market stress. I screen a sample of all applications for loans that are conventional in loan type and are secured by a first lien. Based on Buchak et al. (2018)'s classification of financial institutions, I match the institution name and classify loan originators to FinTech traditional banks, FinTech shadow banks, non-FinTech traditional banks, and non-FinTech shadow banks. Partial bank classification list is presented in Internet Appendix (Table IA1). Each registration contains information about the applicant's demographics, the applicant's financial status, and loan characteristics. I record for each application the applicant's age group, gender, race, ethnicity, annual income, and debt-to-income ratio; loan information includes the mortgage originator's Legal Entity Identifier (LEI), year of application, loan amount, loan purpose (home purchase/improvement or refinance), type of residence (primary/secondary residence or investment property), conforming loan limit (conforming or nonconforming), loan interest rate, and interest rate spread. All variables are defined in Appendix (Table A1). I then match the bank names to the HMDA database and classify lenders into FinTech and non-FinTech categories, both of which include shadow and traditional banks.[2] The valid full sample contains a total of over 14 million applications, of which FinTech and non-FinTech banks each account for about 5 million and 9 million entries, respectively.

Table 1 inserts about here

Table 1 presents a summary of the applicant demographic characteristics and loan information data for loan applications received by the four types of banks. In terms of the applicant demographic profile, traditional banks have an older user base than shadow banks in their respective categories, with the average age of applicants for FinTech and non-FinTech traditional banks being 49.65 and 48.69 years old, categorically, compared to 48.39 and 45.59 years old for the corresponding shadow banks. All four types of banks have more male applicants than females (with an average likelihood of 0.66). Applicants are more likely to be minorities (0.1), applicants are more likely to be white than non-white (0.84), and FinTech banks are somewhat less likely to have white applicants than non-FinTech (0.82 and 0.8 vs. 0.87 and

[2] The sample include 66 FinTech lenders (37 FinTech shadow banks and 29 FinTech traditional banks), and 410 non-FinTech lenders (134 non-FinTech shadow banks and 276 non-FinTech traditional banks).

0.86). The average annual income for all applicants is $142,660, with FinTech bank applicants earning more on average than non-FinTech bank applicants. The DTI ratio is higher for shadow bank applicants than for traditional banks (35.66% and 35.54% vs. 31.9% and 34.68%). The loan information shows that shadow banks generally have higher loan amounts than traditional banks. For the full sample (FinTech shadow banks), 42% (29%) of loans were for home purchase. 94% of loans were for owner-occupation, and the share is similar across lender types. The interest rates on loans from FinTech lenders are on average lower than those from non-FinTech lenders (3.53% and 3.55% vs. 3.67% and 3.98%).

Table 2 inserts about here

Table 2 presents summary statistics on loan information for FinTech and non-FinTech banks before and after the epidemic. Total loan applications grew by 3.8 million (9,082,591-5,294,529) in 2020, with FinTech banks growing by 1.4 million (3,261,783-1,844,266) and non-FinTech by 2.4 million (3,450,263-3,261,783). Looking at the full sample of applications, the age of applicants decreased from 47.71 before the epidemic to 47.46, with non-FinTech banks showing a greater decrease than FinTech. The gender of applicants changed little overall, remaining predominantly male (0.66). The epidemic reduced ethnic minorities' applications at non-FinTech banks (from 0.1 to 0.09), while applications from whites increased (0.86 to 0.87). Applicants' incomes generally increased by $2,510, with FinTech applicants increasing by an average of $2,190 and non-FinTech applicants by a more significant $2,640. The increase in income eased debt ratios by an average of 1.84% (36.51%-34.67%), which contributed to an increase in applications of approximately 71% (9,082,591/5,294,529-1). Application approval rates also improved from 80% before the epidemic to 83%, with a 3.67% increase for non-FinTech (82.37% to 86.04%). and a slightly lower 2.28% increase for FinTech banks (75.26% to 77.54%). Improved income and better DTI ratios allowed non-FinTech lenders to increase loan amounts by nearly $4,800, but loan amounts in all applications from FinTech banks decreased by the same magnitude, reflecting the divergence of needs between the customer segments served by FinTech banks and traditional banks. Borrowers shift their primary purpose from home purchase to refinance after the epidemic (0.54 to 0.35), a shift that is more pronounced among non-FinTech banks (0.58 to 0.39). Home loans for owner-occupation have become more frequent than for investment (0.92 to 0.94). Another factor fueling loan applications is the general narrowing of interest rates (4.34% to 3.35%) and interest rate spreads (0.52% to 0.27%), with FinTech banks offering lower interest rates than non-FinTech.

3.1.2 COVID vulnerability data

Considering that the vulnerability of the impact of the epidemic and the differences in infrastructure and response initiatives across counties may cause behavioral bias among applicants and FinTech banks, I include the Covid Community Vulnerability Index (CVI) to observe the impact of the vulnerability of the epidemic on loan supply and applicant demand across types of banks. This dataset scores the vulnerability of the COVID-19 pandemic at the county level, assessing the vulnerability of each county in eight dimensions: number of severe cases, economic damage, mobile health resource needs, food access complexity, community connection needs, mental health resources, health system collapse risk, and ease of access to reliable information. The heat maps of the vulnerability index are displayed in Figure IA1.

3.2 Methodology

The analysis of the impact of the epidemic on bank lending is demonstrated through four main stages: the demand of borrowers under the epidemic, the supply of loans by originators, the selection criteria of banks for borrowers, and the financing approaches of banks. First, to explore the impact of the epidemic on the demand for loans originated by FinTech and non-FinTech banks, I use the number of loan applications to express demand and apply a difference-in-difference analysis to visually compare the shift in lender behavior between the two types of banks under the epidemic. The OLS regression equation is as follows:

Equation 1

$$\begin{aligned}\ln\,(Applications_{c,t}) &= \beta_1 Severity_c \times FinTech_{i,t} \times Post_t + \beta_2 Severity_c \times FinTech_{i,t} \\ &+ \beta_3 Severity_c \times Post_t + \beta_4 FinTech_{i,t} \times Post_t + \beta_5 Severity_c + \beta_6 FinTech_{i,t} \\ &+ \beta_7 Post_t + \gamma_c + \varepsilon_{c,t}\end{aligned}$$

Where $ln(Applications)$ represents the logarithmically transformed number of loan applications in county c, year t. When the county's vulnerability score exceeds the median, Severity is 1, otherwise it is zero. FinTech is a dummy that equals one, indicating that the originator is classified as a FinTech traditional or FinTech shadow bank, and zero for non-FinTech traditional or non-FinTech shadow bank. If this application occurs after the outbreak i.e., 2020, dummy Post is equal to 1, and vice versa occurs in 2019 as 0. I use county fixed effects to rule out any effects caused by categories not included in the same independent variable. The coefficient β, which is an estimate of the triple-difference-in-differences variable, represents the difference in loan outcomes across loan originators due to the epidemic when controlling for applicant demographic characteristics, loan information, and county-level epidemic vulnerability.

The second section that examines the supply of banks again uses the OLS equation, where the nominal variable of banks approving or not approving loan applications is used as the dependent variable, with the following regression equations:

Equation 2

$$Approval_{i,t} = \beta_1 FinTech_{i,t} \times Post_t + \beta_2 FinTech_{i,t} + \beta_3 Post_t + Controls_{i,t} + \gamma_c + \varepsilon_{i,t}$$

Equation 2 captures the shifts in FinTech and traditional bank application approvals before and after the epidemic in counties with different levels of risk, where Approval represents the approval status of application i in year t. I set other variables such as demographic characteristics and loan information other than the independent variable as control variables because there are differences in the populations served by loans with various characteristics. I include county and time interaction fixed effects in the supply analysis.

Equation 3

$$FinTech_{i,t} = \beta_1 Characteristics_{i,t} \times Post_t + \beta_2 Characteristics_{i,t} + Controls_{i,t} + \gamma_{c,t} + \varepsilon_{i,t}$$

Equation 4

$$Approval_{i,t} = \beta_1 Characteristics_i \times Post_t + \beta_2 Characteristics_i + \beta_3 Post_t + Controls_{i,t} + \gamma_c + \varepsilon_{i,t}$$

Equation 3 and 4 describe the changes in demographic characteristics and borrowing information for FinTech and non-FinTech loans before and after the epidemic, with dependent variable being FinTech bank, and approved application indicator respectively.

Equation 5

$$Sell_{i,t} = \beta_1 FinTech_i \times Post_t + \beta_2 FinTech_i + \beta_3 Post_t + Controls_{i,t} + \gamma_c + \varepsilon_{i,t}$$

Finally, I examine how FinTech and traditional banks in different risk regions compare in terms of selling their loans out before and after the epidemic. Sell is a dummy variable that is 1 for loans that were sold out by the lender in the same calendar year of origination, and 0 otherwise. Demographic characteristics variables such as age, gender, race, ethnicity, income, and DTI ratio, and loan application information such as loan amount, conforming indicator, residence, home purchase indicator, interest rate, and interest rate spread are added as control variables. This regression also incorporates county fixed effects.

4 Empirical Results

4.1 Loan Demand

4.1.1 Application Quantity

First, I use the triple-difference-in-differences method to explore the demand for loans from FinTech compared to non-FinTech in post-epidemic areas with severe outbreaks (Table 3). Columns (1) to (8) show eight different criteria to determine whether a county is severely affected by the epidemic. During the epidemic, there is a significant boost in loan demand from traditional banks in non-vulnerable areas (row 5), while demand in vulnerable areas is not as strong relative to the former, as shown in row 2. However, FinTech banks have a clear advantage over non-FinTech banks in terms of loan demand in high-risk areas (row 1). Since high-risk areas are defined by the strength of resistance to epidemic strikes, i.e., those counties with scarce food resources, community facilities, poor medical care, and a weak economic base are more vulnerable to destruction. These areas are largely likely to have relatively few traditional bank branches accessible during the city lockdown, and as De Roure et al. (2021), Jagtiani et al. (2021), and Jagtiani and Lemieux (2018)'s findings point out, FinTech are substitutes for traditional banks in less developed areas in terms of the population they serve.

Table 3 inserts about here

I address the concern about the possibility of the results being dominated by one type of the banks by splitting the banks into subsamples of shadow and traditional banks, the results of which are shown in IA2 in the Internet Appendix. Regardless of whether it is shadow or traditional banks, we are able to see that both shocks, FinTech and pandemic, have the accordant impact on the demand side. However the interaction of these two (row 4) has a contrasting effect on the two subsamples: FinTech produces a positive incremental change in demand for the shadow bank group in the low-risk areas after the epidemic, while it is relatively reduced for the traditional bank group. In the pre-epidemic shadow bank group, FinTechs receive greater demand for loans in high-vulnerability areas (row 3) and relatively diminished after the epidemic (row 1); while the opposite is true for the traditional bank subsample. The results in Table 3 are to some extent dominated by traditional banks.

4.1.2 Application Characteristics

Table 4 inserts about here

Table 4 explores the impact of the epidemic on the FinTech applicant profile and loan characteristics using a DID approach. The results suggest that during the epidemic, people with less access to financial services were more likely to borrow from FinTech. The demographic characteristics of pre-epidemic applicants are largely consistent with the results in Table IA3 and IA4 presented in the Internet Appendix, with younger individuals normally more likely to borrow from FinTech banks, but the growing importance of online activities during the epidemic and the significant increase in demand for online services such as online shopping, online education, webcasting, and Internet finance have led to a broader age group being reached by FinTech businesses, which, combined with the stronger financial capability of elder people, who are exposed to online lending (column 1). Consistent with Bartlett et al. 's (2021) finding that non-FinTech banks discriminately charge Latinx/African Americans higher interest rates and turn them to FinTech, and the epidemic reinforces this willingness (column 3). At the same time, minorities also shifted from traditional banks to FinTech, increasing their applications during the epidemic (column 4). The income of FinTech loan applicants at the time of the epidemic was slightly lower than that of non-FinTech (column 5). And the debt ratios of FinTech borrowers changed from significantly higher before the epidemic to not noticeably different from the credit profiles of non-FinTech borrowers (column 6), the loan amount applied to FinTech banks is also comparable to traditional banks since the outbreak (column 7). The epidemic reinforced the convenience of FinTech, with people in need of refinance seeking more help from FinTech and still preferring to apply for newly issued home purchase loans from non-FinTech banks (column 8). This phenomenon confirms Fuster et al. (2019)'s study that FinTech's target customers are concentrated in the smaller loan and refinancing business and benefit from a more convenient and faster loan application and approval process.

4.2 Loan Supply

4.2.1 Likelihood of Application Approval

After observing the changes in consumer behavior due to the epidemic, I pivot my attention to the dependent variable that can represent the supply of loan distributors – the application approval indicator. Tables 5 and 6 document the variation in application approvals for FinTech banks in high-risk and low-risk regions before and after the epidemic, respectively, using a DID approach. Before the epidemic FinTech banks treated applications more stringently than non-FinTech banks in both highly vulnerable (Table 5) and less vulnerable areas (Table 6), with significantly negative coefficients for high-risk areas by almost all measures. The predictive coefficients of the DID method for FinTech and Post are also consistent with this result when regional risk is not considered (Table IA5 in Internet Appendix). After the outbreak, FinTech's loan approvals remained strict and selective across most dimensions in low-risk areas (Table 6). Compared to the pre-outbreak period, there is only a slight blurring of supply intentions in high-risk areas (Table 5), especially in areas with more severe cases and a more overwhelmed healthcare system, other than that a reduced supply dominates. This suggests that FinTech banks' lending requirements have become stricter overall in the face of the epidemic, and only slightly more benign in more vulnerable areas. The results remain robust when a triple difference-in-differences approach is performed and tabulated in Internet Appendix (Table IA4). I use the alternative 25% and 75% quantile cut-off values and the results still support this conclusion.

Table 5 and 6 insert about here

FinTech banks had lower loan approval rates than non-FinTech banks before the epidemic which is robust even when splitting the sample into shadow and traditional banks, as demonstrated in tables IA6 and IA7 in the Internet Appendix. The only thing that shows a difference from the total sample is that in high-vulnerability areas, the approval rates of traditional FinTech banks are more deterministically lower in the post-epidemic period, while the results are ambiguous among shadow banks.

There are several possible factors for the lower lending supply of FinTech banks. While very accommodative monetary policies played a crucial role in sustaining economic growth during the epidemic, thus supporting bank profits, very low interest rates also compressed banks' net interest margin, prompting both borrowers and lenders to take on greater risk. FinTech banks therefore avoid the risk of default by strict lending conditions. Secondly, large Internet technology companies entering the financial sector and taking advantage of data monopoly can not only consolidate the market dominance of their original business, but also bring their original customers into the scope of financial services, and do not rule out the possibility of them riding roughshod over the customers in an environment lacking competition. Third, some studies have shown that after a natural disaster, when interest rates fall and loan demand is above average, both FinTech and non-FinTech banks have capacity constraints that transfer the pressure to borrowers. Either select those applicants with better credit profiles or choose to approve those applications that can draw on fewer resources and issue more refinanced loans than home purchase loans (Choi et al., 2019; Fuster et al., 2017; Sharpe & Sherlund, 2016). That said, the COVID-19 pandemic is, after all, an unprecedented crisis with far-reaching effects that have even spread to the present, and we are still in the midst of it who can't predict where the future will take us, and FinTech banks are no exception.

4.2.2 Approved Application Characteristics

Table 7 and 8 insert about here

Following the study of the demand-side applicant characteristics, I again use the DID method to represent the borrower profiles and loan types preferred by supply-side lenders. Tables 7 and 8 show what kind of loans both FinTech and non-FinTech bank lenders prefer to grant to whom before and after the epidemic, respectively. Overall the profiles of FinTech borrowers have more significant adjustments than that of traditional banks, reflecting the latter's lower sensitivity in the face of the COVID-19. Both FinTech and non-FinTech banks are more likely to grant loans to younger white or non-minority males before the epidemic (columns 1-4), but after the epidemic, the population with access to loans is older than before, with an increase in female FinTech loan approval and an increase in non-white and ethnic minority non-FinTech approval. One reason for such a shift in non-FinTech banks may be influenced by the provisions of the 1977 community reinvestment act (CRA), where regulators encouraged banks to accommodate low- and moderate-income and ethnic minority borrowers, especially in times of crisis, and after natural disasters (Cortts & Strahan, 2014). FinTech banks, on the other hand, are not restricted by this law. In addition, FinTech banks have relaxed their standards in treating lenders' debt ratios compared to the pre-epidemic period (column 6). All banks are more inclined to approve applications with higher loan amounts before the epidemic, while non-FinTech banks did not become stricter on loan amounts after the epidemic (column 7), but rather FinTech banks may be mitigating risk by controlling loan amounts. For both types of banks, the approval rate for home purchase loans before the epidemic was higher than for refinancing, but after the epidemic, as the number of applications increased dramatically and the uncertainty caused by the crisis increased, banks are more cautious in reviewing new loans, resulting in a significantly higher success rate for refinancing applications.

Table 9 and 10 insert about here

Tables 9 and 10 show the profile of the interest rates of the loans granted. Before the epidemic, the difference in interest rates of FinTech banks compared to traditional banks was ambiguous (row 2), especially in high-risk areas where there was almost no significant variation (Table 6). But as the epidemic began, both FinTech and non-FinTech banks lowered their rates out of the federal reserve quantitative easing policy response (rows 1 and 3), and FinTech banks cut their rates even more (row 1). This result reflects the automation advantage of FinTech banks, that compared to traditional banks, they eliminate the friction of face-to-face consultations and the various costs it incurs and plays a positive role in lowering interest rates. FinTech banks exploit this business-friendly environment to accelerate their expansion and increase their market share.

4.3 Sell of Loans

Knowing that demand for home loans rose sharply after the outbreak, while the supply of FinTech loans contracted to varied degrees in high- and low-risk areas, and that the demographic characteristics of the originated loans differed from those before the outbreak, I speculate that banks become more cautious after the outbreak. To confirm this suspicion, I examine whether the sources of financing for FinTech and non-FinTech banks had changed. The HMDA database contains information that banks are selling loans originated to government-backed institutions such as Freddie Mac and Fannie Mae, or other purchasers of securitizations, which is an important form of financing for both traditional and FinTech banks that can reflect the financing decisions and growth orientation of banks under the pressure of the epidemic. Tables 11 and 12 describe how banks sell loans in high- and low-risk counties before and after the epidemic, respectively. During the sample period, FinTech banks always sell more loans than traditional banks (rows 1 and 2) because traditional banks have a large portion of funding from deposits, while strictly FinTech banks do not, but only borrow money from banks. Under the pressure of the COVID-19, FinTechs still choose to increase the selling of loans, while traditional banks show more caution in high-risk counties (row 3). Whereas non-FinTech banks in high-risk areas have mostly negative significant DID coefficients after the epidemic, the results for low-risk areas are more inconclusive, with unclear positive and negative results. The expansion of securitization by FinTech banks during the epidemic increases the systemic risk to some extent by transmitting risk uncertainty to investors.

Table 11 and 12 insert about here

5 Conclusion

FinTech banks, with their knowledge of the financial industry and the superiority of digital technology, are majoring in segments that have been left out by traditional financial institutions to meet the vast needs that have long been neglected through easier and more efficient services and have grown rapidly in recent years. FinTech is replacing traditional banks or filling the overlooked market gap has long been the center of academic conversation. The Black Swan event COVID-19 that occurred in 2020 is the catalyst for accelerating the popularity of online finance. Through the demand shock of this external crisis on the loan market, I find that borrowers in regions with high vulnerability are able to embrace FinTech more quickly. At the same time, FinTech has expanded its previous target demographic to older, non-white and minority borrower penetration. However, the supply side has not softened its application review criteria in response to the surge in demand. While FinTech approval rates movement is ambiguous in higher-risk counties compared to safer places, the scrutiny is stricter on a broad scale. Interest rates on loans are also generally lower, and FinTech's technological advantages allow them to reduce costs during the epidemic and offer even lower rates than traditional banks. All banks tend to lend to older borrowers, and it's worth noting that while ethnic minorities are more willing to apply for loans from FinTech, which is more prudent at this point, instead it's the non-FinTech banks that are carrying on the social responsibility and taking better care of such communities. It’s evident that lending institutions are more sensitive during the pandemic and are more willing to accept refinancing rather than home purchase loans which require the use of a considerable amount of examination resources.

Where is the money coming from for the increased number of loans originated? By examining changes in the volume of loans sold by banks for securitization, I find that FinTech banks, which had always been interested in securitization as a primary method of financing, increased their efforts to pass on risk during the epidemic. Traditional banks, while also trending this way, were more cautious in securitizing in high-risk areas, mostly due to concerns about loan quality and overall financial system risk.

The above findings enlighten us that FinTech loans are in greater demand in areas that are more vulnerable during the COVID-19, such as counties that have more severe cases, have overwhelmed health systems, and need more food and mental health resources. Accordingly, FinTech banks eased supply to these vulnerable areas at the expense of passing the risk on to investors at large. I conjecture that the key to the pandemic’s drive for FinTech is that borrowers are having to adopt the contactless process, i.e., online lending, whether out of active avoidance or bound by strict policies. This burst of demand may be accidental, but the demand itself is inevitable. To verify this, one would wait until the end of COVID-19 to determine if this trend continues, which can be placed on a list of future studies.

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Table 1. Summary Statistics for 4 Types of Financial Institutions (all applications pre and post COVID-19, N=14,377,120)

	Full Sample		FinTech Shadow Banks		FinTech Traditional Banks		Non-FinTech Shadow Banks		Non-FinTech Traditional Banks	
Variable	Mean	SD	Mean	SD	Mean	SD	Mean	SD	Mean	SD
Panel A: Demographic Variable										
Borrower Age	47.55	13.64	48.39	13.51	49.65	13.64	45.59	13.24	48.69	13.97
Male	0.66	0.47	0.66	0.47	0.65	0.48	0.66	0.47	0.67	0.47
Hispanic or Latino	0.10	0.30	0.11	0.31	0.10	0.31	0.11	0.32	0.07	0.26
White	0.85	0.36	0.82	0.39	0.80	0.40	0.87	0.34	0.86	0.34
Income ($000)	134.55	875.47	120.03	805.39	177.99	835.16	118.73	882.75	154.58	941.67
Panel B: Credit Variable										
DTI Ratio	35.32	10.14	35.66	10.23	31.90	12.63	35.54	9.66	34.68	10.69
Panel C: Current Loan Information										
Loan Amount ($)	318973.7	1121072	279390.3	295790.4	401727.1	1802280	300473.6	1164688	349773.6	1202630
Home Purchase	0.42	0.49	0.29	0.46	0.44	0.50	0.48	0.50	0.43	0.50
Residence	0.94	0.24	0.95	0.22	0.94	0.23	0.94	0.24	0.92	0.27
Conforming	0.95	0.21	0.99	0.12	0.86	0.35	0.98	0.13	0.91	0.28
Interest Rate (%)	3.71	228.61	3.53	1.02	3.55	0.80	3.67	1.07	3.98	440.26
Rate Spread (%)	0.36	13.39	0.43	26.86	0.17	2.61	0.42	0.86	0.27	0.64

Table 2. Summary Statistics (all applications pre and post COVID-19, N=14,377,120)

	Full Sample				FinTech Banks				Non-FinTech Banks			
	Pre		Post		Pre		Post		Pre		Post	
Variable	Mean	SD	Mean	SD	Mean	SD	Mean	SD	Mean	SD	Mean	SD
Panel A: Demographic Variable												
Borrower Age	47.71	13.95	47.46	13.45	48.84	13.85	48.70	13.39	47.10	13.97	46.75	13.43
Male	0.66	0.47	0.66	0.47	0.65	0.48	0.66	0.47	0.66	0.47	0.66	0.47
Hispanic or Latino	0.11	0.31	0.10	0.30	0.11	0.31	0.11	0.31	0.10	0.30	0.09	0.29
White	0.85	0.36	0.85	0.36	0.81	0.39	0.81	0.39	0.86	0.35	0.87	0.34
Income ($000)	132.96	1,263.06	135.47	534.60	135.08	990.16	137.27	696.29	131.82	1,387.98	134.46	416.38
Panel B: Credit Variable												
DTI Ratio	36.51	10.21	34.67	10.05	37.01	10.07	35.02	10.24	36.33	10.25	34.51	9.96
Panel C: Current Loan Information												
Loan Amount	318,126.1	1,234,941	319,467.9	1,049,007	317,902.8	1,356,459	313,075.4	730,964.9	318,245.4	1,164,798	323,050	1,190,632
Home Purchase (Or refinance)	0.54	0.50	0.35	0.48	0.46	0.50	0.26	0.44	0.58	0.49	0.39	0.48
Residence (Or investment property)	0.92	0.26	0.94	0.23	0.94	0.24	0.95	0.21	0.92	0.27	0.94	0.24
Conforming	0.94	0.24	0.96	0.20	0.93	0.26	0.96	0.19	0.94	0.23	0.96	0.20
Interest Rate (%)	4.34	16.62	3.35	285.45	4.17	0.97	3.19	0.78	4.42	20.27	3.43	350.77
Rate Spread (%)	0.52	22.45	0.27	0.87	0.50	38.83	0.28	1.11	0.53	0.87	0.27	0.71
Panel D: Loan Origination Information												
	Number	/Total	Number	/Total	Number	/Total	Number	/Total	Number	/Total	Number	/Total
No. of approval	4,230,142	0.7990	7,537,344	0.8299	1,388,010	0.7526	2,529,169	0.7754	2,842,132	0.8237	5,008,175	0.8604
$ amount of approval	1.42e+12		2.48e+12		4.75e+11		8.23e+11		9.50e+11		1.66e+12	
No. of application	5,294,529		9,082,591		1,844,266		3,261,783		3,450,263		5,820,808	
$ amount of application	1.68e+12		2.90e+12		5.86e+11		1.02e+12		1.10e+12		1.88e+12	
No. of sell	3,101,612	0.7332	6,082,553	0.8070	1,015,747	0.7318	2,065,629	0.8167	2,085,865	0.7339	4,016,924	0.8021
No. of nonsell	1,128,530	0.2668	1,454,791	0.1930	372,263	0.2682	463,540	0.1833	756,267	0.2661	991,251	0.1979

Table 3. County pandemic vulnerability-year-level loan application

	$ln(Applications)$							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Severe Cases	Food Services	Economic	Community	Mental Health	Mobile Health	Overwhelm	Info Access
(1) Vulnerability*FinTech*Post	.0704***	.0552***	.0068	.0372*	.0665***	.0216	.0739***	.042
	4.48	4.05	.49	2.36	4.56	1.48	4.57	1.18
(2) Vulnerability*Post	-.1584***	-.1113***	-.0184	-.0149	-.0509***	-.0631***	-.1312***	-.0024
	(12.1)	(10.74)	(1.75)	(1.22)	(4.49)	(5.75)	(10.09)	(.1)
(3) Vulnerability*FinTech	-.1123***	.0717**	.002	.0747*	-.138***	.1407***	-.0299	.1833***
	(3.54)	2.77	.08	2.5	(5.27)	5.45	(.97)	3.7
(4) FinTech*Post	-.0542***	-.0268**	.0045	-.0012	-.0328**	-.0015	-.0536***	.005
	(3.95)	(2.71)	.47	(.16)	(2.74)	(.18)	(3.78)	.71
(5) Post	.5237***	.4532***	.3931***	.3883***	.4157***	.41***	.493***	.3848***
	44.43	58.83	52.26	63.63	43.41	63.66	42.41	71.45
(6) FinTech	-.0167	-.1582***	-.1159***	-.1329***	-.0319	-.1696***	-.0903***	-.1274***
	(.59)	(8)	(6.51)	(9.04)	(1.55)	(10.2)	(3.32)	(9.63)
County FEs	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Adjusted R^2	.952	.952	.951	.951	.952	.952	.951	.952
Observations	12628	12628	12628	12628	12628	12628	12628	12628

This table reports estimation results of the triple diff-in-diff regressions that show the demand of the FinTech and Non-FinTech bank loans using the following regression equation, which is estimated at the county level for the period 2019-2020:

$$\ln(Applications_{c,t}) = \beta_1 Severity_c \times FinTech_{i,t} \times Post_t + \beta_2 Severity_c \times FinTech_{i,t} + \beta_3 Severity_c \times Post_t + \beta_4 FinTech_{i,t} \times Post_t + \beta_5 Severity_c + \beta_6 FinTech_{i,t} + \beta_7 Post_t + \gamma_c + \varepsilon_{c,t}$$

The dependent variable is the logarithmically transformed number of applications. Columns (1) - (8) are the different criteria for determining a county as a serious area of the outbreak. When the vulnerability score exceeds the median, the vulnerability indicator is 1, otherwise it is zero. The FinTech Indicator is equal to 1 if the mortgage originator is a FinTech entity, otherwise zero. Post is a dummy variable that takes the value of 1 for an entry recorded in 2020. The t-statistics are reported below coefficients. *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively. Standard errors are clustered at the county level.

Table 4. The pandemic and FinTech bank loan characteristics

	FinTech Indicator							
	Borrower Demographic Characteristics					Credit	Current Loan Information	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Age>65	Male	White	Hispanic or Latino	Income ($million)	DTI ratio	Loan Amount ($million)	Refinance
Characteristic*Post	.0287***	.0037*	-.0328***	.0163**	-.0089*	.0002	.0094	.0331***
	9.79	1.96	(4.5)	2.66	(2.07)	1.12	0.3	7.64
Characteristic	-.0157***	-.0076***	-.035***	-.0236***	-.0009	.0012***	-.1075***	.0961***
	(7.09)	(4.5)	(7.81)	(4.51)	(.73)	11.41	(11.99)	34.63
Demographic Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Loan Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
County*Time FEs	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Adjusted R^2	.0553	.0699	.07	.0699	.0699	.0699	.0699	.0701
Observations	7842767	7302765	7302765	7302765	7302765	7302765	7302765	7302765

This table reports estimation results of the difference-in-differences regressions that show the probability of loans with various borrower demographic characteristics (columns 1-5), borrower's credit information (column 6) and loan information (columns 7-8) originated from FinTech rather than non-FinTech banks using the following regression equation, which is estimated at the loan level for the period 2019-2020:

$$FinTech_{i,t} = \beta_1 Characteristics_{i,t} \times Post_t + \beta_2 Characteristics_{i,t} + Controls_{i,t} + \gamma_{c,t} + \varepsilon_{i,t}$$

The FinTech Indicator is equal to 1 if the mortgage originator is a FinTech entity, otherwise zero. Post is a dummy variable that takes the value of 1 for an entry recorded in 2020. All other independent variables are defined in Appendix (Table A1). The t-statistics are reported below coefficients. *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively. Standard errors are clustered at the county-time interaction level.

Table 5. Loan approval in high vulnerability areas (>median)

	Application Approval							
	(1) Severe Cases	(2) Food Services	(3) Economic	(4) Community	(5) Mental Health	(6) Mobile Health	(7) Overwhelm	(8) Info Access
FinTech*Post	.0212***	-.0058*	-.0085***	-.0083***	-.0095***	-.0002	.0125***	-.0102***
	7.74	(2.24)	(4.23)	(5.28)	(4.87)	(.08)	3.82	(7.1)
FinTech	-.0858***	-.0627***	-.0558***	-.0529***	-.0514***	-.0701***	-.0815***	-.0503***
	(20.7)	(12.98)	(14.56)	(19.31)	(15.3)	(22.5)	(17.99)	(20.41)
Post	-.0117***	.0039*	.0057***	.0056***	.0069***	.0045*	-.0096***	.0073***
	(5.93)	2.46	4.13	5.31	5.39	2.2	(4.29)	7.52
Demographic Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Loan Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
County FEs	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Adjusted R^2	.177	.121	.108	.103	.11	.123	.176	.0898
Observations	1618924	3829120	5009258	7744554	5675545	3749994	1696223	8719317

This table reports estimation results of the difference-in-differences regressions that show the probability of FinTech rather than non-FinTech loan applications being approved in high vulnerability counties (vulnerability scores > median) after the pandemic using the following regression equation, which is estimated at the loan level for the period 2019-2020:

$$Approval_{i,t} = \beta_1 FinTech_{i,t} \times Post_t + \beta_2 FinTech_{i,t} + \beta_3 Post_t + Controls_{i,t} + \gamma_c + \varepsilon_{i,t}$$

The dependent variable is the application approval indicator, which is equal to 1 if the loan is originated, otherwise 0. FinTech Indicator is equal to 1 if the mortgage originator is a FinTech entity, otherwise 0. Columns (1) - (8) are the different criteria for determining a county as a serious area of the outbreak. When the vulnerability score exceeds the median, the vulnerability indicator is 1, otherwise it is zero. Post is a dummy variable that takes the value of 1 for an entry recorded in 2020. All other independent variables are defined in Appendix (Table A1). The t-statistics are reported below coefficients. *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively. Standard errors are clustered at the county-time interaction level.

Table 6. Loan approval in low vulnerability areas (<median)

	Application Approval							
	(1) Severe Cases	(2) Food Services	(3) Economic	(4) Community	(5) Mental Health	(6) Mobile Health	(7) Overwhelm	(8) Info Access
FinTech*Post	-.0135***	-.0086***	-.0053**	.0006	-.0029	-.0122***	-.0122***	.027***
	(9.58)	(5.79)	(2.85)	.18	(1.63)	(7.47)	(8.55)	8.46
FinTech	-.0465***	-.0481***	-.0536***	-.0634***	-.0597***	-.0439***	-.0469***	-.0936***
	(18.38)	(19.3)	(18.95)	(14.72)	(19.71)	(14.17)	(18.6)	(21.7)
Post	.0086***	.0066***	.0048***	.0033	.0025*	.0067***	.0083***	-.0144***
	9.08	7.12	4.94	1.93	2.44	8.18	9.01	(5.94)
Demographic Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Loan Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
County FEs	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Adjusted R^2	.0838	.086	.1	.12	.098	.0883	.0815	.217
Observations	7759191	5548995	4368857	1633561	3702570	5628121	7681892	658798

This table reports estimation results of the difference-in-differences regressions that show the probability of FinTech rather than non-FinTech loan applications being approved in low vulnerability counties (vulnerability scores < median) after the pandemic using the following regression equation, which is estimated at the loan level for the period 2019-2020:

$$Approval_{i,t} = \beta_1 FinTech_{i,t} \times Post_t + \beta_2 FinTech_{i,t} + \beta_3 Post_t + Controls_{i,t} + \gamma_c + \varepsilon_{i,t}$$

The dependent variable is the application approval indicator, which is equal to 1 if the loan is originated, otherwise 0. FinTech Indicator is equal to 1 if the mortgage originator is a FinTech entity, otherwise 0. Columns (1) - (8) are the different criteria for determining a county as a serious area of the outbreak. When the vulnerability score exceeds the median, the vulnerability indicator is 1, otherwise it is zero. Post is a dummy variable that takes the value of 1 for an entry recorded in 2020. All other independent variables are defined in Appendix (Table A1). The t-statistics are reported below coefficients. *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively. Standard errors are clustered at the county-time interaction level.

Table 7. Loan approval of FinTech borrowers

	Application Approval								
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
	Age>65	Male	White	Hispanic or Latino	Income ($million)	DTI ratio	Loan Amount ($million)	Conforming	Home Purchase
Characteristic*Post	.0175***	-.0115***	.002	.0037	-.0699**	.0009***	-.1255***	.0718***	-.0405***
	9.33	(10)	.99	1.25	(2.77)	11.42	(15.58)	10.52	(19.83)
Characteristic	-.0233***	.0045**	.0622***	-.0566***	-.0009***	-.0095***	.4033***	.2559***	.0603***
	(8.88)	3.98	16.36	(12.07)	(4.75)	(73.69)	17.51	19.2	18.62
Post	-.0098***	-.0002	-.0093***	-.008***	.0003	-.041***	.0263***	-.0783***	.0078***
	(9.84)	(.16)	(5.08)	(7.4)	.1	(12.96)	12.39	(11.51)	4.6
Demographic Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Loan Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
County FEs	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Adjusted R^2	.117	.117	.117	.117	.117	.117	.117	.117	.117
Observations	2365971	2365931	2365931	2365931	2365931	2365931	2365931	2365931	2365931

This table reports estimation results of the difference-in-differences regressions that show the probability of applications with various borrower demographic characteristics (columns 1-5), borrower's credit information (column 6) and loan information (columns 7-9) being approved in FinTech banks using the following regression equation, which is estimated at the loan level for the period 2019-2020:

$$Approval_{i,t} = \alpha + \beta_1 Characteristics_{i,t} \times Post_t + \beta_2 Characteristics_{i,t} + \beta_3 Post_t + Controls_{i,t} + \gamma_c + \varepsilon_{i,t}$$

The dependent variable is the application approval indicator, which is equal to 1 if the loan is originated, otherwise 0. Post is a dummy variable that takes the value of 1 for an entry recorded in 2020. All other independent variables are defined in Appendix (Table A1). The t-statistics are reported below coefficients. *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively. Standard errors are clustered at the county-time interaction level.

Table 8. Loan approval of non-FinTech borrowers

	Application Approval								
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
	Age>65	Male	White	Hispanic or Latino	Income ($million)	DTI ratio	Loan Amount ($million)	Conforming	Home Purchase
Characteristic*Post	.0164***	.0006	-.0056**	.0088***	-.0041	-.00002	-.0329	.0128***	-.0334***
	12.9	.71	(2.88)	4.46	(1.03)	(.22)	(1.95)	5.41	(18.05)
Characteristic	-.0252***	.0029**	.0808***	-.0404***	-.0052*	-.0078***	.0947***	.1082***	.0538***
	(11.57)	2.69	22.27	(15.79)	(2.17)	(58.7)	5.23	8.1	32.24
Post	.0057***	.0066***	.0118***	.0062***	.0075***	.0076**	.0164**	-.0052*	.024***
	5.8	5.55	5.19	7.05	7.21	2.63	3.17	(2.03)	17.78
Demographic Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

	Application Approval								
Loan Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
County FEs	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Adjusted R^2	.0964	.0974	. 0974	. 0974	. 0974	. 0974	.0975	.0974	.0979
Observations	7012410	7012147	7012147	7012147	7012147	7012147	7012147	7012147	7012147

This table reports estimation results of the difference-in-differences regressions that show the probability of applications with various borrower demographic characteristics (columns 1-5), borrower's credit information (column 6) and loan information (columns 7-9) being approved in non-FinTech banks using the following regression equation, which is estimated at the loan level for the period 2019-2020:

$$Approval_{i,t} = \alpha + \beta_1 Characteristics_{i,t} \times Post_t + \beta_2 Characteristics_{i,t} + \beta_3 Post_t + Controls_{i,t} + \gamma_c + \varepsilon_{i,t}$$

The dependent variable is the application approval indicator, which is equal to 1 if the loan is originated, otherwise 0. Post is a dummy variable that takes the value of 1 for an entry recorded in 2020. All other independent variables are defined in Appendix (Table A1). The t-statistics are reported below coefficients. *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively. Standard errors are clustered at the county-time interaction level.

Table 9. Interest rate in low vulnerability counties

	Interest Rate							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Severe Cases	Food Services	Economic	Community	Mental Health	Mobile Health	Overwhelm	Info Access
(1) FinTech*Post	-.0101***	-.0103***	-.0097***	-.0095***	-.01***	-.0096***	-.0101***	-.0071***
	(171.33)	(38.84)	(133.09)	(83.91)	(130.62)	(119.31)	(172.91)	(29.89)
(2) FinTech	-.0004***	-.0004	.00005	.0005**	-.0002*	.0002*	-.0004***	.0035***
	(4.47)	(1.95)	.434	3.23	(2.03)	2.08	(4.44)	11.52
(3) Post	-.0096***	-.0097***	-.0094***	-.0093***	-.0094***	-.0094***	-.0096***	-.0089***
	(228.18)	(33.65)	(235)	(169.2)	(188.44)	(219.54)	(228.07)	(115.44)
Demographic Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Loan Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
County FEs	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Adjusted R^2	.378	.00137	.338	.377	.36	.319	.377	.394
Observations	6653047	4789337	3763162	1387875	4809071	3194326	6594941	499793

This table reports estimation results of the difference-in-differences regressions that show the relationship between interest rate and loan originators in low vulnerability counties (vulnerability scores < median) after the pandemic using the following regression equation, which is estimated at the loan level for the period 2019-2020:

$$Rate_{i,t} = \beta_1 FinTech_{i,t} \times Post_t + \beta_2 FinTech_{i,t} + \beta_3 Post_t + \gamma_c + \varepsilon_{i,t}$$

The dependent variable is the recorded interest rate for the originated loans. FinTech Indicator is equal to 1 if the mortgage originator is a FinTech entity, otherwise 0. Post is a dummy variable that takes the value of 1 for an entry recorded in 2020. All other independent variables are defined in Appendix (Table A1). Columns (1) - (8) are the different criteria for determining a county as a serious area of the outbreak. When the vulnerability score exceeds the median, the vulnerability indicator is 1, otherwise it is zero. The t-statistics are reported below coefficients. *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively. Standard errors are clustered at the county level.

Table 10. Interest rate in high vulnerability counties

	Interest Rate							
	(1) Severe Cases	(2) Food Services	(3) Economic	(4) Community	(5) Mental Health	(6) Mobile Health	(7) Overwhelm	(8) Info Access
(1) FinTech*Post	-.0092***	-.0096***	-.0102***	-.0101***	-.01***	.0103***	-.0092***	-.0102***
	(10.85)	(64.06)	(34.57)	(51.47)	(26.34)	(39.02)	(11.17)	(59.21)
(2) FinTech	.0013	.0003	-.0002	-.0002	.0001	-.0003	.0011	-.0004*
	1.95	1.48	(0.98)	(1.42)	.41	(1.55)	1.73	(2.51)
(3) Post	-.0103***	-.0097***	-.01***	-.0098***	-.0101***	-.0099***	-.0103***	-.0098***
	(10.89)	(186.03)	(30.94)	(46.23)	(24.36)	(34.64)	(11.19)	(52.46)
Demographic Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Loan Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
County FEs	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Adjusted R^2	-.0003	.395	.00148	.0024	.0011	.00171	-.0002	.0025
Observations	1295822	3159532	4185707	6560994	3139798	4754543	1353928	7449076

This table reports estimation results of the difference-in-differences regressions that show the relationship between interest rate and loan originators in high vulnerability counties (vulnerability scores > median) after the pandemic using the following regression equation, which is estimated at the loan level for the period 2019-2020:

$$Rate_{i,t} = \alpha + \beta_1 FinTech_{i,t} \times Post_t + \beta_2 FinTech_{i,t} + \beta_3 Post_t + \gamma_c + \varepsilon_{i,t}$$

The dependent variable is the recorded interest rate for the originated loans. FinTech Indicator is equal to 1 if the mortgage originator is a FinTech entity, otherwise 0. Post is a dummy variable that takes the value of 1 for an entry recorded in 2020. All other independent variables are defined in Appendix (Table A1). Columns (1) - (8) are the different criteria for determining a county as a serious area of the outbreak. When the vulnerability score exceeds the median, the vulnerability indicator is 1, otherwise it is zero. The t-statistics are reported below coefficients. *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively. Standard errors are clustered at the county level.

Table 5. Sell of FinTech loans in high vulnerability areas (>median)

	Sell							
	(1) Severe Cases	(2) Food Services	(3) Economic	(4) Community	(5) Mental Health	(6) Mobile Health	(7) Overwhelm	(8) Info Access
(1) FinTech*Post	.0281**	.0072	.0289***	.0463***	.0209**	.0472***	.017	.058***
	2.84	.94	4.11	7.62	3.04	6.79	1.74	10.2
(2) FinTech	.1413***	.0972***	.1048***	.1067***	.1125***	.115***	.1266***	.1111***
	16.92	12.87	15.98	21.39	17.67	17.33	15.17	23.69
(3) Post	-.0758***	-.0437***	-.0291***	-.0144***	-.0546***	-.0196***	-.0783***	-.0072
	(20.09)	(6.37)	(4.87)	(3.17)	(16.06)	(3.49)	(19.9)	(1.72)
Demographic Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Loan Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
County FEs	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Adjusted R^2	.221	.134	.134	.1	.165	.123	.217	.0956
Observations	1201052	2899805	3862849	6084008	2907004	4392728	1251572	6913221

This table reports estimation results of the difference-in-differences regressions that show the probability of FinTech rather than non-FinTech loan being purchased in high vulnerability counties (vulnerability scores > median) after the pandemic using the following regression equation, which is estimated at the loan level for the period 2019-2020:

$$Sell_{i,t} = \alpha + \beta_1 FinTech_{i,t} \times Post_t + \beta_2 FinTech_{i,t} + \beta_3 Post_t + Controls_{i,t} + \gamma_c + \varepsilon_{i,t}$$

The dependent variable is the selling indicator, which is equal to 1 if the loan is sold, otherwise 0. FinTech Indicator is equal to 1 if the mortgage originator is a FinTech entity, otherwise 0. Columns (1) - (8) are the different criteria for determining a county as a serious area of the outbreak. When the vulnerability score exceeds the median, the vulnerability indicator is 1, otherwise it is zero. Post is a dummy

	Sell							
	(1) Severe Cases	(2) Food Services	(3) Economic	(4) Community	(5) Mental Health	(6) Mobile Health	(7) Overwhelm	(8) Info Access

variable that takes the value of 1 for an entry recorded in 2020. All other independent variables are defined in Appendix (Table A1). The t-statistics are reported below coefficients. *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively. Standard errors are clustered at the county level.

Table 6. Sell of FinTech loans in low vulnerability areas (<median)

	Sell							
	(1) Severe Cases	(2) Food Services	(3) Economic	(4) Communit y	(5) Mental Health	(6) Mobile Health	(7) Overwhelm	(8) Info Access
(1) FinTech*Post	.0696***	.0756***	.0626***	.0601***	.0728***	.0527***	.0716***	.0312***
	11.36	10.88	8.22	6.05	9.51	5.79	11.77	3.99
(2) FinTech	.1095***	.1232***	-.1201***	.1449***	.1135***	.1095***	.112***	.1559***
	22.38	24.45	21.41	17.47	18.44	20.36	22.61	20.7
(3) Post	.0072	-.0015	-.013*	-.0386***	.0105	-.0143*	.0081	-.0798***
	1.63	(.31)	(2.57)	(6.45)	1.86	(2.14)	1.84	(24.58)
Demographic Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Loan Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
County FEs	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Adjusted R^2	.0787	.111	.102	.173	.0794	.112	.0838	.291
Observations	6177889	4479136	3516092	1294933	4471937	2986213	6127369	465720

This table reports estimation results of the difference-in-differences regressions that show the probability of FinTech rather than non-FinTech loan being purchased in low vulnerability counties (vulnerability scores < median) after the pandemic using the following regression equation, which is estimated at the loan level for the period 2019-2020:

$$Sell_{i,t} = \beta_1 FinTech_{i,t} \times Post_t + \beta_2 FinTech_{i,t} + \beta_3 Post_t + Controls_{i,t} + \gamma_c + \varepsilon_{i,t}$$

The dependent variable is the selling indicator, which is equal to 1 if the loan is sold, otherwise 0. FinTech Indicator is equal to 1 if the mortgage originator is a FinTech entity, otherwise 0. Columns (1) - (8) are the different criteria for determining a county as a serious area of the outbreak. When the vulnerability score exceeds the median, the vulnerability indicator is 1, otherwise it is zero. Post is a dummy variable that takes the value of 1 for an entry recorded in 2020. All other independent variables are defined in Appendix (Table A1). The t-statistics are reported below coefficients. *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively. Standard errors are clustered at the county level.

Appendix

Table A1. Variable Definitions

Variable	Description	Source
FinTech Indicator	Indicator that equals one if the classification of the financial institution is a FinTech shadow or traditional bank, equals zero if the institution is a non-FinTech shadow or traditional bank.	Buchak et al., (2018)
Post	Indicator that equals one if the activity year is in 2021, and zero if the loan is generated in 2020.	HMDA
Approval	Indicator that equals one if the action taken is loan originated or application approved but not accepted, equals zero if the application is denied.	HMDA
Demographic variable		
Borrower Age	The average of each age group is taken as the borrower age.	HMDA
Male	Indicator that equals one if the borrower is male, and zero if the borrower is female.	HMDA
Hispanic or Latino	Indicator that equals one if the ethnicity of applicant is Hispanic or Latino, Mexican, Puerto Rican, Cuban, and Other Hispanic or Latino, and zero if the ethnicity is Not Hispanic or Latino.	HMDA
White	Indicator that equals one if the race of applicant is White, and zero if the race is American Indian or Alaska Native, Asian, Asian Indian, Chinese, Filipino, Japanese, Korean, Vietnamese, Other Asian, Black, or African American, Native Hawaiian or Other Pacific Islander, Native Hawaiian, Guamanian, Samoan, and Other Pacific Islander.	HMDA
Income	The gross annual income in dollars. If credit decision is made, gross annual income relied on in making the credit decision; Or, if a credit decision was not made, the gross annual income relied on in processing the application.	HMDA
Credit variable		
DTI Ratio	Ratio of the applicant’s or borrower’s total monthly debt to total monthly income relied on.	HMDA
Loan variable		
Loan Amount	Amount of the loan or the amount applied for.	HMDA
Home Purchase	Indicator that equals one if the loan purpose is home purchase or home improvement, and zero if the purpose is refinancing or cash-out refinancing.	HMDA
Residence	Indicator that equals one if the occupancy type is principle/second residence, and zero if it’s an investment property.	HMDA
Conforming	Indicator that equals one if the conforming loan limit is conforming, and zero if nonconforming.	HMDA
Interest Rate	Interest rate on the approved application or loan.	HMDA
Rate Spread	Difference between the annual percentage rate and average prime offer rate for a comparable transaction.	HMDA
Pandemic vulnerability variable		

Variable	Description	Source
Severe Cases	Describes likelihood that constituents within a community will develop severe complications following covid-19 infection	GitHub, The COVID Community Vulnerability Index[3]
Food Services	Describes existing need for food-based community efforts, services, and non-profits	GitHub, The COVID Community Vulnerability Index
Economic	Describes the likelihood that a community will experience severe economic hardship due to COVID-19 complications	GitHub, The COVID Community Vulnerability Index
Community	Describes the likelihood that an area could benefit from community connecting services (in other words, which communities most lack community and social connectedness)	GitHub, The COVID Community Vulnerability Index
Mental Health	Describes existing need for additional mental health support and resources	GitHub, The COVID Community Vulnerability Index
Mobile Health	Describes the likelihood that a community could benefit from mobile health services	GitHub, The COVID Community Vulnerability Index
Overwhelm	Describes the likelihood that the existing health infrastructure will be overwhelmed by a covid outbreak	GitHub, The COVID Community Vulnerability Index
Info Access	Describes the likelihood that constituents have difficulty accessing reliable covid-19 data	GitHub, The COVID Community Vulnerability Index

[3] Data available at: https://github.com/community-insight-impact/covid_community_vulnerability#the-covid-community-vulnerability-index

Internet Appendix

Table IA1. Top 50 Loan Originators in 2019-2020

Rank	Institution Name	Number of loans originated Total	2020	2019	Lender Classification
1	Quicken Loans	1,340,869	944,698	396,171	FinTech Shadow
2	Fairway Independent Mort Corp	773,865	499,254	274,611	Non-FinTech Shadow
3	Wells Fargo Bank NA	525,607	287,879	237,728	FinTech Traditional
4	Caliber Home Loans, Inc.	485,968	317,354	168,614	Non-FinTech Shadow
5	JPMorgan Chase Bank, NA	399,105	220,523	178,582	Non-FinTech Traditional
6	loanDepot.com LLC	334,077	231,989	102,088	FinTech Shadow
7	Bank of America NA	312,080	153,134	158,946	FinTech Traditional
8	Nationstar Mortgage	220,406	154,820	65,586	Non-FinTech Shadow
9	PrimeLending	202,846	123,980	78,866	Non-FinTech Shadow
10	New American Funding (dba for Broker Solutions Inc)	200,666	137,404	63,262	Non-FinTech Shadow
11	Guaranteed Rate, Inc	173,650	107,129	66,521	FinTech Shadow
12	Flagstar Bank	160,970	107,265	53,705	Non-FinTech Traditional
13	Freedom Mortgage Corporation	144,346	95,092	49,254	Non-FinTech Shadow
14	HomeBridge Financial Services, Inc.	140,204	94,558	45,646	Non-FinTech Shadow
15	Guild Mortgage Company	135,889	87,218	48,671	FinTech Shadow
16	CMG Mortgage Inc.	129,282	82,944	46,338	Non-FinTech Shadow
17	Academy Mortgage Corporation	124,918	79,676	45,242	Non-FinTech Shadow
18	Supreme Lending/ Everett Financial Inc.	123,230	84,694	38,536	Non-FinTech Shadow
19	PNC Bank N.A.	119,560	64,585	54,975	Non-FinTech Traditional
20	Movement Mortgage, LLC	115,480	75,269	40,211	FinTech Shadow
21	American Pacific Mortgage Corporation	113,314	82,704	30,610	Non-FinTech Shadow
22	Huntington National Bank	99,392	59,791	39,601	Non-FinTech Traditional
23	AmeriSave Mortgage Corporation	93,946	77,801	16,145	FinTech Shadow
24	Cardinal Financial Company LP	91,215	69,398	21,817	FinTech Shadow
25	PennyMac Loan Services LLC	88,446	65,465	22,981	FinTech Shadow
26	Paramount Residential Mortgage Group Inc.	87,256	61,284	25,972	Non-FinTech Shadow
27	Primary Residential Mortgage Inc.	84,598	57,446	27,152	Non-FinTech Shadow
28	Stearns Lending, LLC	83,458	52,708	30,750	Non-FinTech Shadow
29	Provident Funding Associates	82,098	45,269	36,829	FinTech Shadow
30	Fifth Third Bank, National Association	79,470	44,685	34,785	Non-FinTech Traditional
31	Regions Bank	79,336	49,176	30,160	Non-FinTech Traditional
32	Navy Federal Credit Union	77,156	47,506	29,650	Non-FinTech Traditional
33	Sierra Pacific Mortgage	75,470	47,834	27,636	Non-FinTech Shadow
34	Vanderbilt Mortgage and Finance, Inc	73,210	42,222	30,988	Non-FinTech Shadow
35	Residential Mortgage Services	71,148	46,476	24,672	Non-FinTech Shadow
36	Bay Equity Home Loans	70,228	48,282	21,946	Non-FinTech Shadow
37	American Financial Network Inc.	67,394	47,664	19,730	Non-FinTech Shadow
38	Citibank, N.A.	59,536	31,913	27,623	Non-FinTech Traditional
39	KeyBank National Association	58,193	34,277	23,916	Non-FinTech Traditional
40	Atlantic Bay Mortgage Group LLC	57,048	37,062	19,986	Non-FinTech Shadow
41	Summit Funding Inc.	56,226	37,094	19,132	Non-FinTech Shadow
42	21st Mortgage	56,118	30,914	25,204	FinTech Shadow
43	Mortgage Investors Group	54,150	36,021	18,129	FinTech Shadow
44	Ark-La-Tex Financial Services LLC	53,254	35,616	17,638	Non-FinTech Shadow
45	Pulte Mortgage LLC	53,178	28,230	24,948	Non-FinTech Shadow
46	Prosperity Home Mortgage LLC	51,955	35,809	16,146	Non-FinTech Traditional
47	Lennar Mortgage, LLC	48,556	26,873	21,683	FinTech Shadow
48	TD Bank	46,971	26,710	20,261	Non-FinTech Traditional
49	NVR Mortgage Finance Inc	41,368	21,148	20,220	Non-FinTech Shadow
50	First Republic Bank	41,171	24,057	17,114	Non-FinTech Traditional

Table IA2. County pandemic vulnerability-year-level loan application by subsamples

	$ln(Applications)$							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Severe Cases	Food Services	Economic	Community	Mental Health	Mobile Health	Overwhelm	Info Access
	Panel A: Shadow banks subsample							
(1) Vulnerability*FinTech*Post	-.0351*	-.0281	-.0225	-.0188	-.0486**	.0235	-.022	-.0351*
	(2.04)	(1.63)	(1.3)	(1.09)	(2.81)	1.37	(1.28)	(2.04)
(2) Vulnerability*Post	-.0665***	-.0765***	.0085	.0499***	.0123	-.0492**	-.0713***	-.0665***
	(4.44)	(5.11)	.56	3.3	.81	(3.28)	(4.75)	(4.44)
(3) Vulnerability*FinTech	.1922***	.24***	.0982***	-.0564*	.0974***	.1323***	.2167***	.1922***
	7.23	9.07	3.66	(2.1)	3.63	4.95	8.16	7.23
(4) FinTech*Post	.0695***	.0659***	.0638***	.0619***	.0773***	.04**	.0631***	.0695***
	5.75	5.5	4.87	4.46	5.72	3.21	5.09	5.75
(5) Post	.5685***	.5733***	.5301***	.5093***	.528***	.5597***	.5709***	.5685***
	54.21	54.61	46.16	41.49	44.21	52.18	52.69	54.21
(6) FinTech	-.2892***	-.3127***	-.2418***	-.1637***	-.2419***	-.2582***	-.3017***	-.2892***
	(15.42)	(16.77)	(11.92)	(7.92)	(12.02)	(13.32)	(15.97)	(15.42)
County FEs	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Adjusted R^2	.946	.946	.945	.945	.945	.945	.945	.946
Observations	12327	12327	12327	12327	12327	12327	12327	12327
	Panel B: Traditional banks subsample							
(1) Vulnerability*FinTech*Post	.0643**	.0124	-.0231	-.0147	.0021	.0419*	.0165	-.006
	3.29	.63	(1.17)	(.74)	.11	2.13	.84	(.3)
(2) Vulnerability*Post	-.1234***	-.1116***	-.0168	-.0119	-.0763***	-.0859***	-.105***	.0811***
	(10.42)	(9.37)	(1.38)	(.98)	(6.33)	(7.15)	(8.81)	6.69
(3) Vulnerability*FinTech	-.5202***	-.1426	-.1366***	-.083*	-.4921***	.0852*	-.3494***	.274***
	(14.7)	(3.9)	(3.73)	(2.27)	(13.85)	2.33	(9.69)	7.54
(4) FinTech*Post	-.2581***	-.2322***	-.2124***	-.2173***	-.2263***	-.2462***	-.2343***	-.2212***
	(20.3)	(18.2)	(14.44)	(14.42)	(15.89)	(17.96)	(18.31)	(13.34)
(5) Post	.3547***	.3484***	.2997***	.2971***	.3312***	.335***	.3456***	.2491***
	41.59	43.5	32.61	31.69	35.64	39.63	41.43	26.73
(6) FinTech	-.9497***	-1.1407***	-1.1438***	-1.1712***	-.9603***	-1.2561***	-1.0354***	-1.3521***
	(40.08)	(44.1)	(41.69)	(43.21)	(38.12)	(45.99)	(40.7)	(49.58)
County FEs	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Adjusted R^2	.913	.908	.908	.908	.913	.908	.91	.909
Observations	12337	12337	12337	12337	12337	12337	12337	12337

This table reports estimation results of the triple diff-in-diff regressions that show the demand of the FinTech and Non-FinTech bank loans in shadow bank subsample (Panel A) and traditional bank subsample (Panel B), using the following regression equation, which is estimated at the county level for the period 2019-2020:

$$\ln\left(Applications_{c,t}\right) = \beta_1 Severity_c \times FinTech_{i,t} \times Post_t + \beta_2 Severity_c \times FinTech_{i,t} + \beta_3 Severity_c \times Post_t + \beta_4 FinTech_{i,t} \times Post_t + \beta_5 Severity_c + \beta_6 FinTech_{i,t} + \beta_7 Post_t + \gamma_c + \varepsilon_{c,t}$$

The dependent variable is the logarithmically transformed number of applications. Columns (1) - (8) are the different criteria for determining a county as a serious area of the outbreak. When the vulnerability score exceeds the median, the vulnerability indicator is 1, otherwise it is zero. The FinTech Indicator is equal to 1 if the mortgage originator is a FinTech entity, otherwise zero. Post is a dummy variable that takes the value of 1 for an entry recorded in 2020. The t-statistics are reported below coefficients. *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively. Standard errors are clustered at the county level.

Table IA3. Comparison of borrower's characteristics for FinTech and bank loans

	FinTech Indicator					
	(1)	(2)	(3)	(4)	(5)	(6)
Borrower Age	.00196***					.00179***
	24.4					20.6
Male		-.00989***				-.00899***
		(8.54)				(7.63)
White			-.0598***			-.0628***
			(16.7)			(16.5)
Hispanic or Latino				.0104***		-.00392
				3.51		(1.17)
Income ($million)					-.0014***	-.0001
					(3.04)	(.21)
County*Time FEs	Yes	Yes	Yes	Yes	Yes	Yes
Adjusted R^2	.0582	. 0589	. 0629	.0622	.0552	.0664
Observations	13039223	11901051	10614105	10656290	12796244	9827383

This table reports estimation results of testing the likelihood of borrowers with various demographic characteristics borrowing from FinTech rather than non-FinTech banks using the following regression equation, which is estimated at the loan level for the period 2019-2020:

$$FinTech_{i,t} = \beta Demographic\_Characteristics_{i,t} + \gamma_{c,t} + \varepsilon_{i,t}$$

The FinTech Indicator is equal to 1 if the mortgage originator is a FinTech entity, otherwise zero. All other independent variables are defined in Appendix (Table A1). Columns (1)-(5) present the results for a single demographic characteristic, while column (6) shows a multivariate regression. The t-statistics are reported below coefficients. *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively. Standard errors are clustered at the county-time interaction level.

Table IA4. Comparison of loan characteristics of FinTech and bank loans

	FinTech Indicator							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
DTI ratio	.00102***							.0017***
	13.9							19.47
Loan Amount ($million)		-.00531**						-.1344***
		(4.94)						(17.45)
Home Purchase (or refinance)			-.101***					-.1527***
			(37.4)					(57.99)
Residence (Or investment property)				.0441***				Omitted
				15.2				
Conforming Loan					.00798			Omitted
					1.74			
Interest Rate (absolute)						-.0001		-.00004***
						(1.93)		(7.04)
Rate Spread (absolute)							.00184**	.0097
							2.53	1.23
County*Time FEs	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Adjusted R^2	.0497	.0554	.0625	.0665	.0557	.0571	.0585	.0784
Observations	9944858	13138746	12752214	7441062	13093557	10820690	10329463	8007560

This table reports estimation results of testing the likelihood of loans with various characteristics originated from FinTech rather than non-FinTech banks using the following regression equation, which is estimated at the loan level for the period 2019-2020:

$$FinTech_{i,t} = \beta Loan\_Characteristics_{i,t} + \gamma_{c,t} + \varepsilon_{i,t}$$

The FinTech Indicator is equal to 1 if the mortgage originator is a FinTech entity, otherwise zero. All other independent variables are defined in Appendix (Table A1). Columns (1)-(7) present the results for a single demographic characteristic, while column (8) shows a multivariate regression. The t-statistics are reported below coefficients. *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively. Standard errors are clustered at the county-time interaction level.

Table IA5. Loan approval and county-level pandemic vulnerability

	Application Approval							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Severe Cases	Food Services	Economic	Community	Mental Health	Mobile Health	Overwhelm	Info Access
(1) Vulnerability*FinTech*Post	.0392***	.0026	-.0032	-.0092	.0131*	-.0073	.0281***	-.0459***
	5.75	.39	(.54)	(1.49)	2.4	(1.27)	3.91	(6.15)
(2) FinTech*Post	-.0129***	-.0075*	-.0044	.0017	-.0116**	-.0016	-.0115***	.0365***
	(4.07)	(2.37)	(1.25)	.33	(3.1)	(.41)	(3.64)	5.36
(3) Vulnerability*FinTech	-.0439***	-.0137*	-.0025	.0103*	-.0263***	.0065	-.0387***	.0516***
	(7.93)	(2.49)	(.53)	2.04	(6.08)	1.41	(6.47)	9.01
(4) FinTech	-.0475***	-.0491***	-.0538***	-.0638***	-.046***	-.0591***	-.0479***	-.103***
	(18.88)	(19.44)	(19.01)	(14.87)	(14.53)	(19.09)	(19.02)	(19.92)
Demographic Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Loan Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
County*Time FEs	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Adjusted R^2	.106	.106	.106	.106	.106	.106	.106	.106
Observations	9378065	9378065	9378065	9378065	9378065	9378065	9378065	9378065

This table reports estimation results of the difference-in-differences-in-differences regressions that show the probability of FinTech rather than non-FinTech loan applications being approved in high vulnerability counties after the pandemic using the following regression equation, which is estimated at the loan level for the period 2019-2020:

$$Approval_{c,t} = \beta_1 Severity_c \times FinTech_{i,t} \times Post_t + \beta_2 Severity_c \times FinTech_{i,t} + \beta_3 Severity_c \times Post_t + \beta_4 FinTech_{i,t} \times Post_t + \beta_5 Severity_c + \beta_6 FinTech_{i,t} + \beta_7 Post_t + \gamma_c + \varepsilon_{c,t}$$

The dependent variable is the application approval indicator, which is equal to 1 if the loan is originated, otherwise 0. The FinTech Indicator is equal to 1 if the mortgage originator is a FinTech entity, otherwise zero. Columns (1)-(8) are the different criteria for determining a county as a serious area of the outbreak. When the vulnerability score exceeds the median, the vulnerability indicator is 1, otherwise it is zero. Post is a dummy variable that takes the value of 1 for an entry recorded in 2020. All other independent variables are defined in Appendix (Table A1). The t-statistics are reported below coefficients. *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively. Standard errors are clustered at the county-time interaction level.

Table IA6. Loan approval in high vulnerability areas by subsamples (>median)

	Application Approval							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Severe Cases	Food Services	Economic	Community	Mental Health	Mobile Health	Overwhelm	Info Access
	Panel A: Shadow banks subsample							
FinTech*Post	.0287***	.0001	-.0039	-.0676***	.0036	-.0041*	.0196***	-.0069***
	10.09	.02	(1.86)	(23.96)	1.63	(2.01)	6.36	(4.86)
FinTech	-.0949***	-.0746***	-.0692***	-.0054***	-.0837***	-.0673***	-.0917***	-.0666***
	(23.88)	(15.89)	(17.88)	(3.47)	(31.14)	(19.12)	(23.35)	(25.73)
Post	-.0266***	-.0064**	-.0023	.0002	-.0062***	-.0008	-.0232***	.0023*
	(10.55)	(3.19)	(1.57)	0.2	(3.56)	(.61)	(9.18)	2.51
Demographic Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Loan Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
County FEs	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Adjusted R^2	.199	.121	.1	.092	.129	.098	.195	.071
Observations	971967	2667067	3449147	5394738	2515159	3878683	1084301	5995338
	Panel B: Traditional banks subsample							
FinTech*Post	-.0135***	.002***	-.0224***	-.0203***	-.0196***	-.0215***	-.0185***	-.0209***
	(4.31)	(10.99)	(12.38)	(13.19)	(8.48)	(12.83)	(5.87)	(13.88)
FinTech	-.1003***	-.0885***	-.0788***	-.0723***	-.0907***	-.0754***	-.0947***	-.0699***
	(21.23)	(19.81)	(22.73)	(22.77)	(18.64)	(21.5)	(17.55)	(24.48)
Post	.0129***	.0166***	.0136***	.01***	.0156***	.0138***	.0148***	.0106***
	6.88	8.86	8.75	8.05	8.78	9.42	7.38	8.9
Demographic Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Loan Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
County FEs	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Adjusted R^2	.114	.107	.105	.104	.107	.11	.117	.103
Observations	715521	1443149	1951149	3014472	1449907	2298128	694437	3495313

This table reports estimation results of the difference-in-differences regressions that show the probability of FinTech rather than non-FinTech loan applications being approved in high vulnerability counties (vulnerability scores > median) after the pandemic using the following regression equation, which is estimated at the loan level for the period 2019-2020:

$$Approval_{i,t} = \beta_1 FinTech_{i,t} \times Post_t + \beta_2 FinTech_{i,t} + \beta_3 Post_t + Controls_{i,t} + \gamma_c + \varepsilon_{i,t}$$

The dependent variable is the application approval indicator, which is equal to 1 if the loan is originated, otherwise 0. FinTech Indicator is equal to 1 if the mortgage originator is a FinTech entity, otherwise 0. Columns (1) - (8) are the different criteria for determining a county as a serious area of the outbreak. When the vulnerability score exceeds the median, the vulnerability indicator is 1, otherwise it is zero. Post is a dummy variable that takes the value of 1 for an entry recorded in 2020. All other independent variables are defined in Appendix (Table A1). The t-statistics are reported below coefficients. *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively. Standard errors are clustered at the county-time interaction level.

Table IA7. Loan approval in low vulnerability areas by subsamples (<median)

	Application Approval							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Severe Cases	Food Services	Economic	Community	Mental Health	Mobile Health	Overwhelm	Info Access
	Panel A: Shadow banks subsample							
FinTech*Post	-.0108***	-.0068***	-.0034	.0053	-.0092***	-.0031	-.0097***	.0353***
	(7.83)	(4.58)	(1.83)	1.56	(5.34)	(1.7)	(6.76)	9.28
FinTech	-.0624***	-.0636***	-.0676***	-.0728***	-.058***	-.07***	-.0622***	-.0828***
	(23.58)	(23.35)	(23.13)	(17.87)	(18.04)	(22.85)	(23.23)	(17.67)
Post	.0051***	.0039***	.0013	-.0053*	.0035***	-.0004	.0051***	-.0316***
	5.91	3.59	1.1	(2.2)	3.38	(.35)	5.81	(9.49)
Demographic Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Loan Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
County FEs	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Adjusted R^2	.062	.066	.088	.117	.068	.091	.058	.249
Observations	5410801	3715701	2933621	988030	3867609	2504085	5298467	387430
	Panel B: Traditional banks subsample							
FinTech*Post	-.0209***	-.021***	-.0199***	-.0226***	-.0213***	-.0212***	-.0203***	-.0149***
	(13.43)	(10.93)	(8.8)	(6.27)	(12.02)	(8.39)	(13.18)	(3.66)
FinTech	-.0666***	-.0589***	-.0616***	-.0634***	-.061***	-.0618***	-.0667***	-.0847***
	(22.24)	(20.33)	(16.02)	(14.66)	(19.2)	(15.36)	(22.14)	(8.64)
Post	.0093***	.0083***	.0091***	.0159***	.0089***	.0079***	.0088***	.0162***
	7.31	6.08	5.76	7.41	6.48	4.67	7.34	7.46
Demographic Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Loan Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
County FEs	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Adjusted R^2	.103	.096	.097	.099	.098	.087	.101	.112
Observations	3084798	2357170	1849170	785847	2350412	1502191	3105882	305006

This table reports estimation results of the difference-in-differences regressions that show the probability of FinTech rather than non-FinTech loan applications being approved in low vulnerability counties (vulnerability scores < median) after the pandemic using the following regression equation, which is estimated at the loan level for the period 2019-2020:

$$Approval_{i,t} = \beta_1 FinTech_{i,t} \times Post_t + \beta_2 FinTech_{i,t} + \beta_3 Post_t + Controls_{i,t} + \gamma_c + \varepsilon_{i,t}$$

The dependent variable is the application approval indicator, which is equal to 1 if the loan is originated, otherwise 0. FinTech Indicator is equal to 1 if the mortgage originator is a FinTech entity, otherwise 0. Columns (1) - (8) are the different criteria for determining a county as a serious area of the outbreak. When the vulnerability score exceeds the median, the vulnerability indicator is 1, otherwise it is zero. Post is a dummy variable that takes the value of 1 for an entry recorded in 2020. All other independent variables are defined in Appendix (Table A1). The t-statistics are reported below coefficients. *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively. Standard errors are clustered at the county-time interaction level.

Table IA8. Loan Approval and FinTech Bank Indicator

	Application Approval
FinTech*Post	-.0616***
	(29.13)
FinTech	-.0805***
	(31.74)
Post	.0211***
	27.69
County FEs	Yes
Adjusted R^2	.043
Observations	14316804

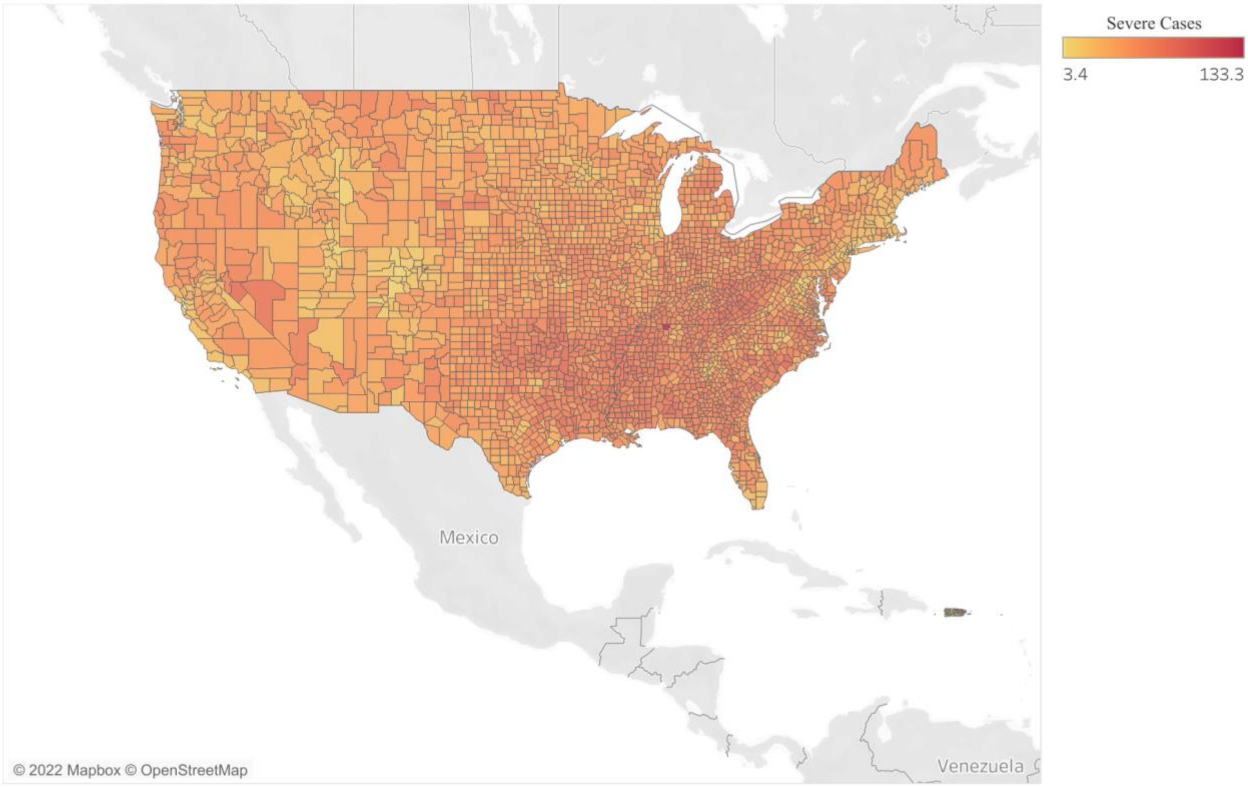
This table reports estimation results of the difference-in-differences regressions that show the probability of FinTech rather than non-FinTech loan applications being approved after the pandemic using the following regression equation, which is estimated at the loan level for the period 2019-2020:

$$Approval_{i,t} = \beta_1 FinTech_{i,t} \times Post_t + \beta_2 FinTech_{i,t} + \beta_3 Post_t + Controls_{i,t} + \gamma_c + \varepsilon_{i,t}$$

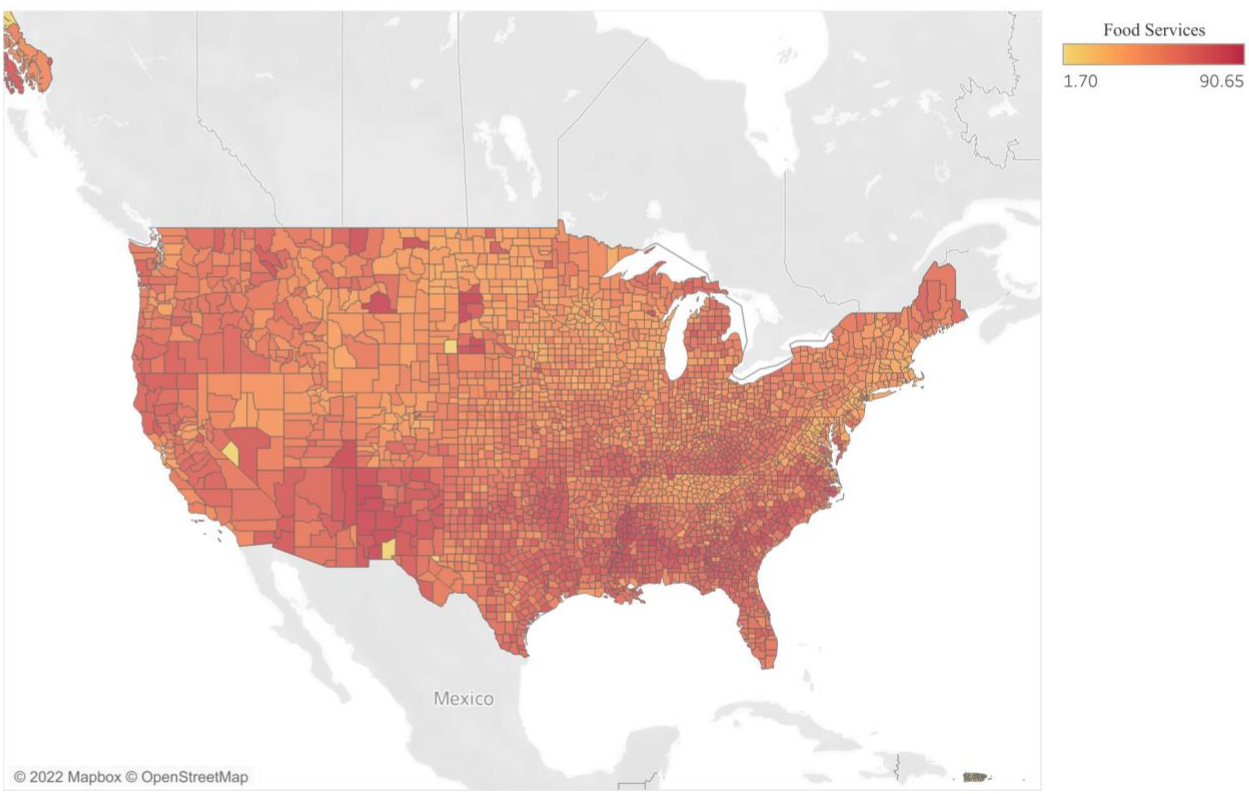
The dependent variable is the application approval indicator, which is equal to 1 if the loan is originated, otherwise 0. FinTech Indicator is equal to 1 if the mortgage originator is a FinTech entity, otherwise 0. Post is a dummy variable that takes the value of 1 for an entry recorded in 2020. The t-statistics are reported below coefficients. *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively. Standard errors are clustered at the county level.

Figure IA1. Covid Community Vulnerability Index Heat Map

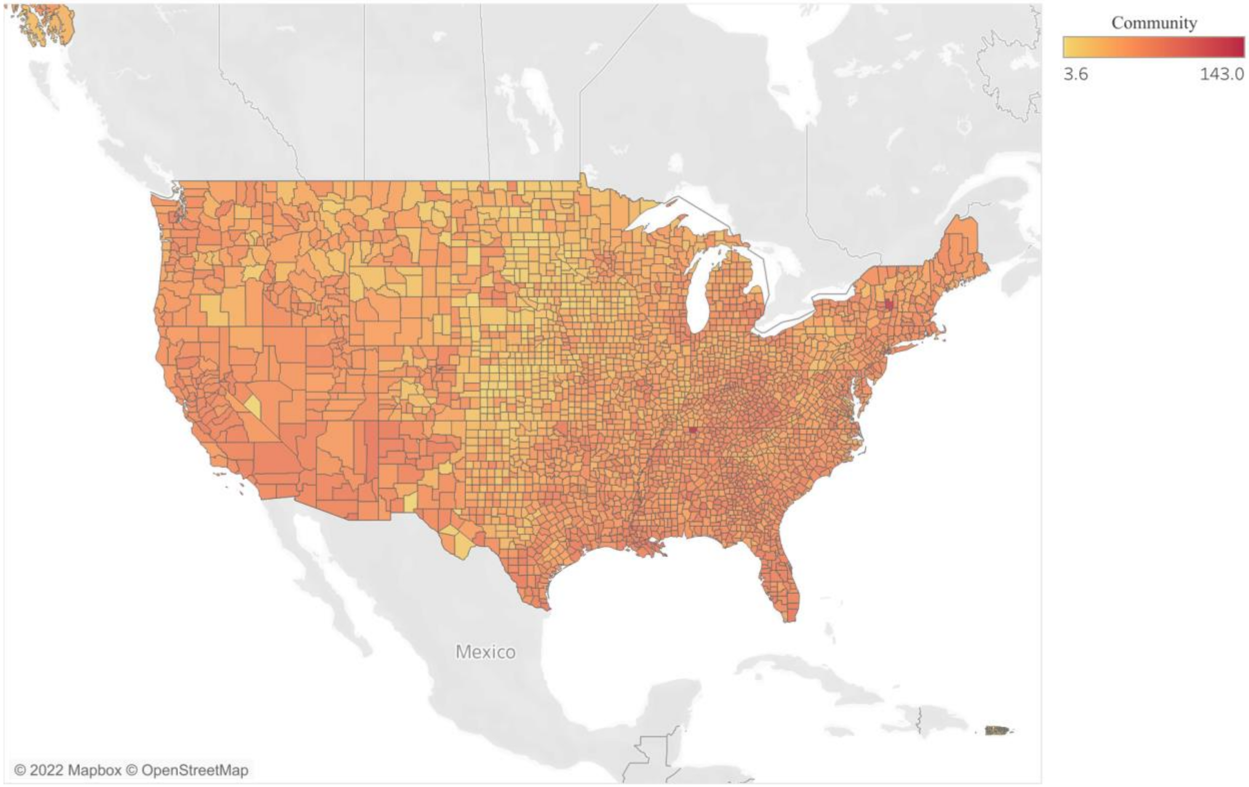
<CCVI> Severe COVID Case Complications



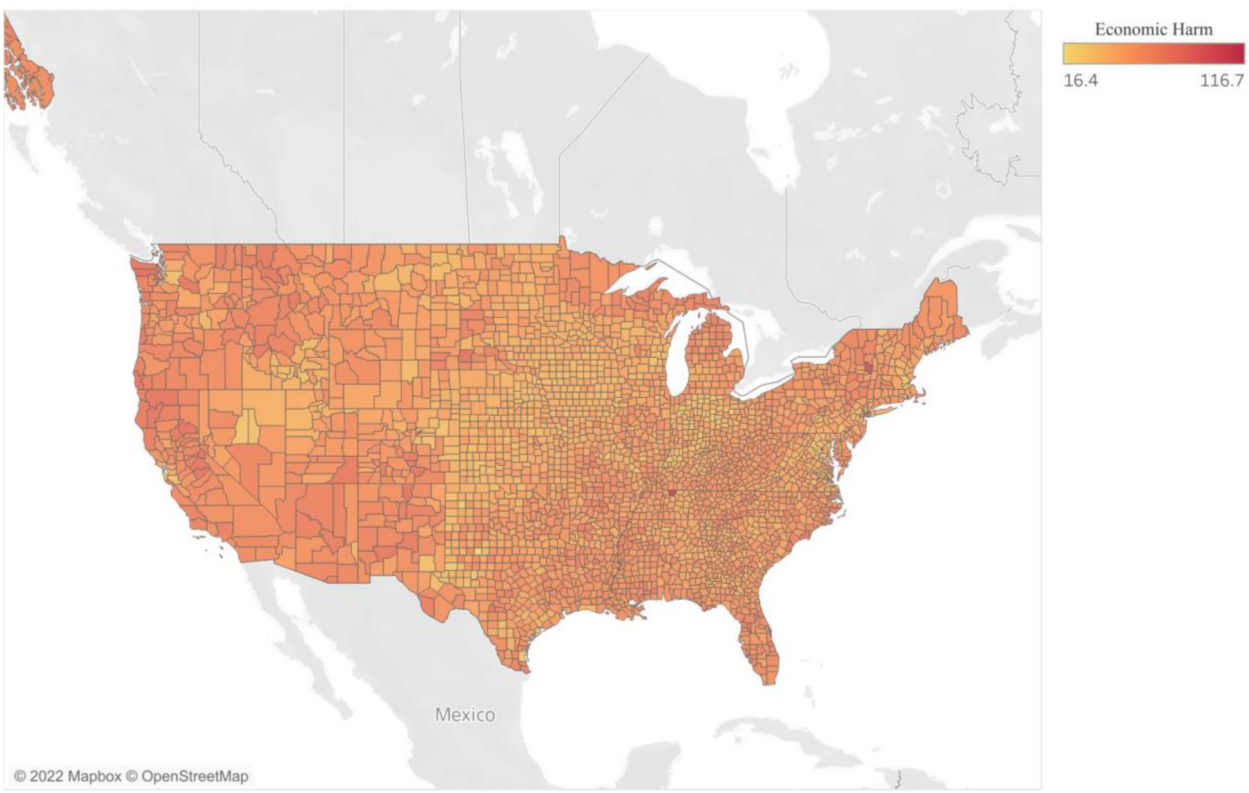
<CCVI> Food Access Complications



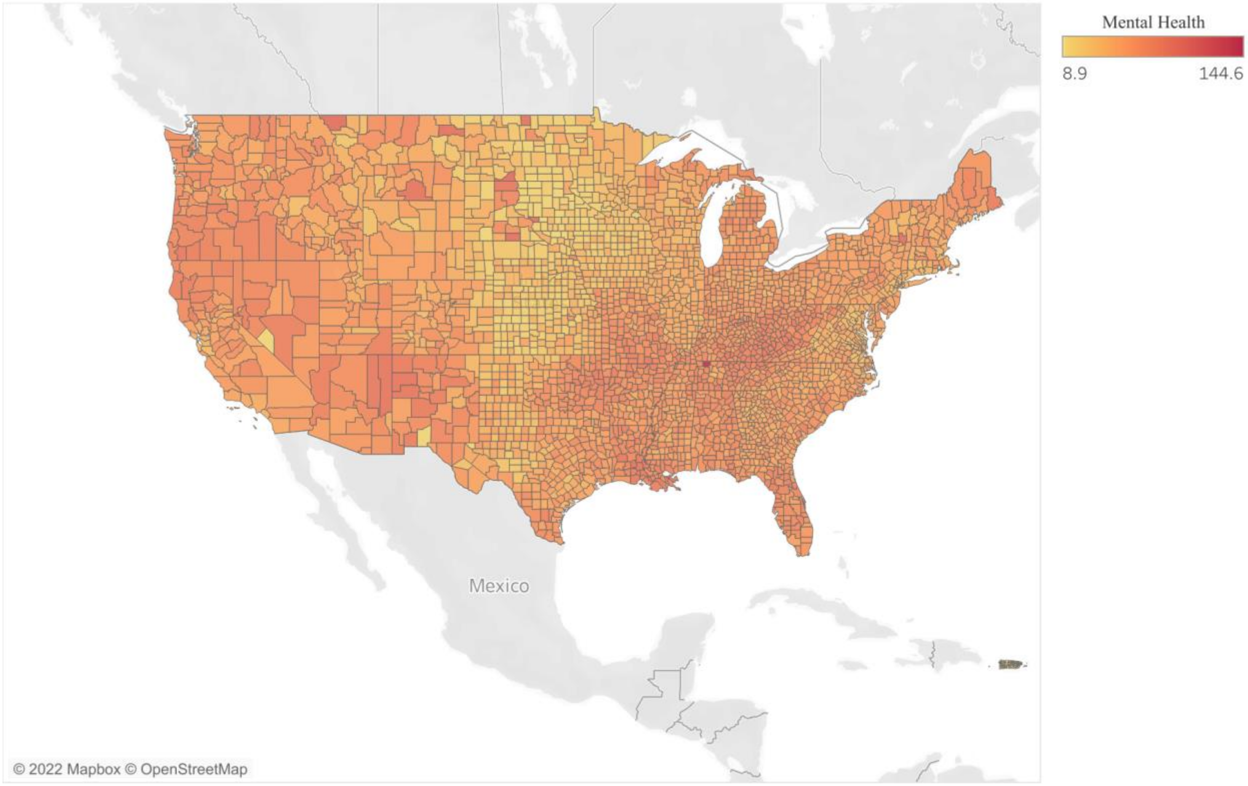
<CCVI> Need for Community Connection



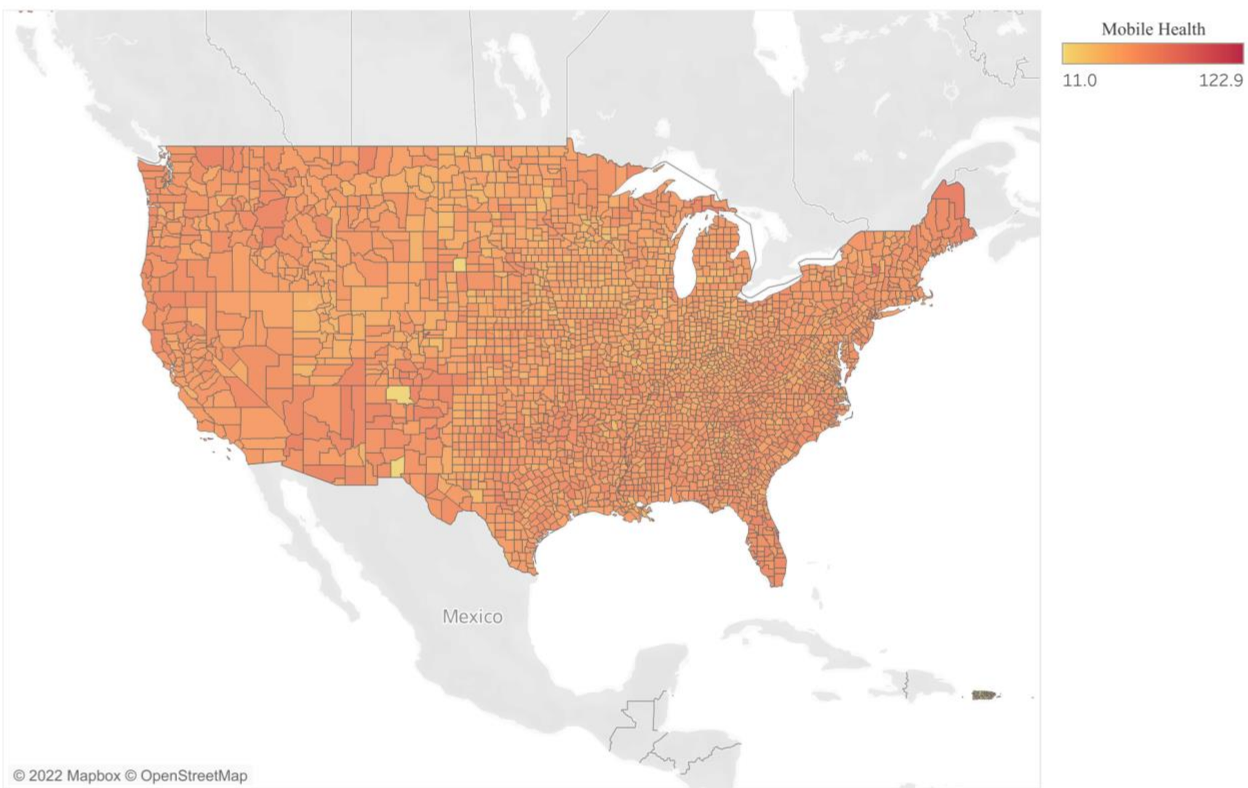
<CCVI> Risk of Severe Economic Harm



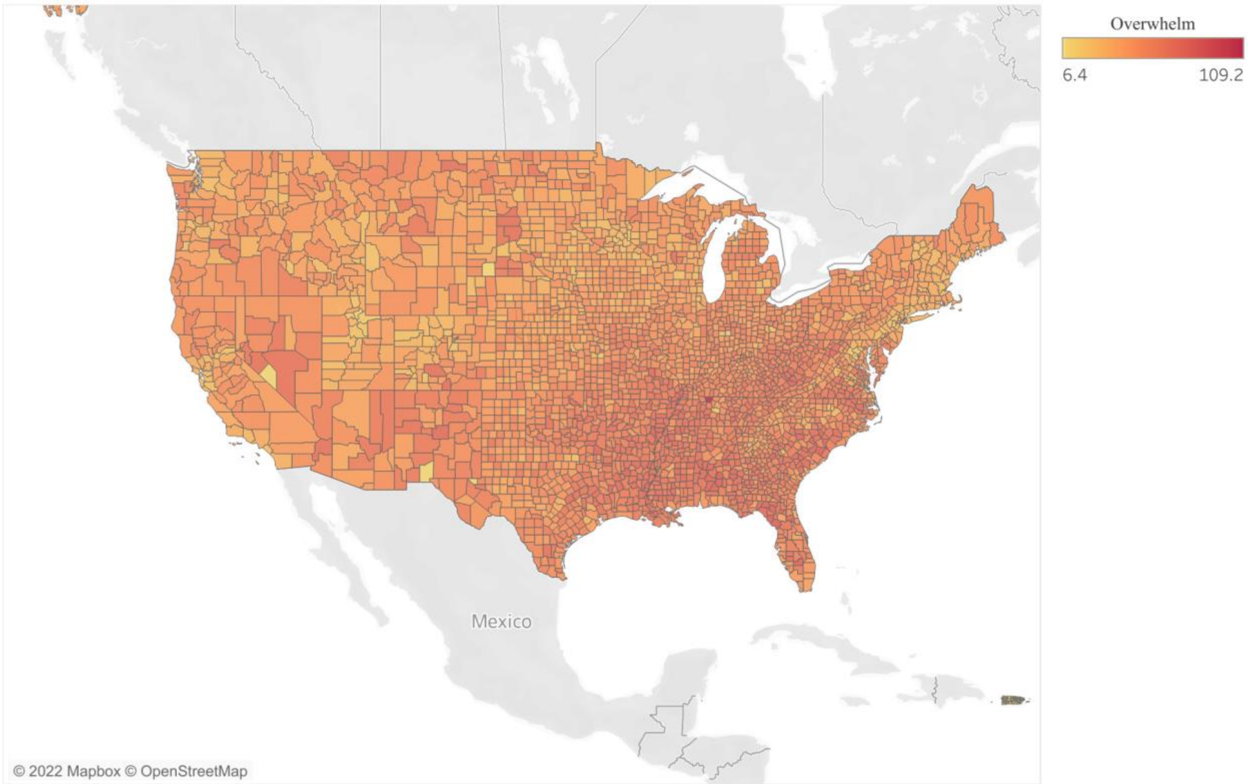
<CCVI> Need for Mental Health Resources



<CCVI> Need for Mobile Health Resources



<CCVI> Risk of Overwhelming Healthcare System



<CCVI> Lack of Information Access