The Real Effects of Fintech Credit: Evidence from Peer-to-Peer Lending Availability[*]

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Abstract

We examine the real economic effects of fintech credit availability, characterized by the presence of peer-to-peer (P2P) lenders, and explore possible channels through which these effects might operate. To isolate the treatment effect of fintech credit availability, the empirical design exploits local variation in regulatory restrictions on P2P lending and natural disasters affecting local economic conditions. We find that the structural changes in local credit markets, associated with the advent of P2P lenders, mitigates the adverse effects of natural disasters on local GDPs, incomes, business establishments, and employment. These effects primarily arise from banks responding to increased credit demands in the aftermath of natural disasters, potentially influenced by competitive pressure from emerging fintech lenders in local credit markets.

Keywords: Fintech, P2P lending, Natural disasters, Credit markets, Competition

JEL: G21, G23, G28

1. Introduction

The structural changes in local credit markets have long been believed to have a significant impact on the real economy. For instance, Jayaratne and Strahan (1996) document that the relaxation of bank branch restrictions in the U.S. states had substantial positive effects on per capita growth in income and output in the regions. Even in recent decades, credit market structures have continued to undergo reforms. One of the primary drivers of the recent structural shifts in local credit markets is the rise of fintech credits, particularly the advent of peer-to-peer (P2P) lending platforms.

The P2P online lending platforms facilitate the funding of unsecured personal loans by matching individuals with lenders. P2P lending has become increasingly popular globally including the U.S, Europe and China (see, for example, Milne and Partboteeah 2016; Braggion, Manconi and Zhu 2018; De Roure, Pelizzon, and Thakor 2022). P2P lenders pioneered online and automated borrower screening as well as crowdfunding that have since been adopted by a larger set of fintech firms. According to Experian, a consumer credit reporting company, P2P lending's total share of the unsecured personal loan space, specifically for loans under $50,000, had climbed to a record-high 57% as of July of 2021.[1]

The growth in P2P lending worldwide has not escaped the eyes of academic researchers. Existing studies focus primarily on the determinants of P2P loan provision, including borrowers' characteristics such as appearance and social ties (for example, Duarte, Siegel, and Young 2012; Freedman and Jin 2017), and information production and sharing (for example, Michels 2012; Franks, Serrano-Velarde, and Sussman 2016; Vallee and Zeng 2019). The economic consequences of availability of P2P lending and its rise, however, remain largely underexplored.[2] The objective

[1] See the details of P2P loan market shares from here: https://www.nasdaq.com/articles/upstart-sofi-lendingclub%3A-which-fintech-has-leading-market-share.

[2] Cumming, Farag, Johan, and McGowan (2022) document the direct effect of P2P lending on one particular aspect of real outcomes (entrepreneurship). Our paper examines the real effects of P2P lending availability comprehensively

of this paper is to provide evidence on these consequences, focusing on the real economic effects of structural changes in local credit market characterized by the advent of P2P lenders across local economies in the U.S.

Despite the potential importance of these effects, evidence on the role of fintech credit in economic outcomes is difficult to obtain. Fintech credit and economic outcomes are determined jointly and reflect an equilibrium outcome of credit supply and demand. It is therefore empirically challenging to separate between the treatment effects of fintech credit and confounding economic factors. To address the identification challenges, we exploit exogenous variation in fintech credit availability stemming from state-level changes in regulatory hurdles for P2P lending. Our measure of P2P lending availability follows the methodology outlined by Cornaggia, Wolfe, and Yoo (2018) and Cumming et al. (2022). In order for individual borrowers to obtain credit through P2P lenders, online platforms must meet state-level banking and consumer financing standards, in the form of licenses for lending, loan brokering, money transfer, and collection. We exploit the variation of such entry barriers across states and time. Specifically, we consider P2P lending more readily available in a given state if borrowers are able to access a new loan through either of the two leading P2P platforms, Lending Club and Prosper, in that state for more than six months during the year.[3] Otherwise, we consider P2P lending less easily available in the state. It is important to note that we limit samples to 2008-2012 and eight U.S. states with time-varying regulatory availability of P2P lending during the period.[4] [5] For those eight states, we confirm that the lack of

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by covering its impacts on local gross domestic products (GDPs), personal incomes, median household incomes, business establishments, and employment and identifying their possible underlying channels.

[3] Lending Club and Prosper have approximately 45% and 30% shares in the U.S. P2P lending markets, respectively (Cumming et al., 2022).

[4] The eight U.S. states are Idaho, Indiana, Nebraska, North Carolina, Tennessee, Idaho, Indiana, Nebraska, North Carolina, and Tennessee. After 2012, most U.S. states did not make any further changes to entry barriers for P2P lenders.

[5] In untabulated results, we confirm that our estimation results are robust to including all U.S. states in our sample.

P2P loan originations is largely due to the regulatory restrictions for the P2P lending in the states rather than due to the lack of local credit demands in the regions, through Lending Club's 10-K filings and SEC's cease-and-desist order for Prosper.[6] [7]

We first examine the relationship between P2P lending availability and both local fintech lending and credit market structures. The estimation results show that fintech lending, including P2P loans and fintech mortgages, experiences a more significant increase in counties where P2P lending is readily available compared to those with limited accessibility. Conversely, the number of banks and branches, as well as their mortgage and small business loan originations, tend to decline more rapidly in counties where P2P lending is available. Based on these findings, we conclude that in areas where P2P loans are easily available, local credit markets exhibit a structural shift towards fintech credits encroaching upon traditional bank lending.[8]

Next, to identify the real economic effects of fintech credit availability, alongside structural shifts in local credit markets, we employ region-specific natural disasters as a source of exogenous shocks on the local economy. We identify region-specific natural disasters, such as hurricanes, severe storms, and floods, using data from Federal Emergency Management Agency (FEMA).[9] FEMA disaster declarations are made in response to natural disasters that cause severe damages to a region such that the Federal Government's assistance is requested. The joint shocks to economic conditions and P2P lending allow us to study the real economic effects of fintech credit

[6] Lending Club discloses the list of U.S. states in which its P2P lending services are not available by its 10-K filing.
[7] In November 2008, the SEC issued a cease-and-desist order for Prosper, shutting Prosper down until April 2009. See details from here: https://finovate.com/peer-to-peer_lender_prosper_reopens_today_at_finovatestartup.
[8] We contribuite to Cornaggia et al. (2018) and Cumming et al. (2022) by showing that the regulatory availability of P2P lending correlates structural changes in local credit markets, extending beyond the mere presence of P2P lenders in those markets.
[9] Studies using natural disasters as exogenous shocks include Baker and Bloom (2013) for changes in economic uncertainty, Cortés (2014) for local firms' rebuilding after disasters, Barrot and Sauvagnat (2016) for supplier-customer networks, Cortés and Strahan (2017) for multi-market banks' capital reallocation in mortgage lending, Dlugosz, Gam, Gopalan, and Skrastins (2023) for bank branches' ability to set deposit rates locally, and Gallagher, Billings, and Ricketts (2023) for human capital investment.

availability.[10] In particular, we hypothesize that natural disasters will increase local credit demand and that the presence of P2P lenders might incite traditional banks to aggressively supply credit in response to the heightened demand, spurred by competitive pressures from the emerging fintech lenders. This structural change in local credit markets possibly contributes to faster recovery of local economy following natural disasters.[11] We compare economic outcomes in disaster regions in states with readily available P2P lending to disaster regions in states without such available P2P lending, thus avoiding endogeneity concerns related to the actual P2P lending volume.

For this analysis, we perform estimations using difference-in-differences regressions. The first difference compares periods before and after natural disasters in the regions, while the second difference compares regions where P2P lending was available for more than six months during the year to those where it was available for at most six months during the year. The estimates suggest that the adverse economic effects of natural disasters are less severe in regions where P2P lending is more easily accessible upon natural disasters compared to regions where it is less available. We find that in counties where P2P lending is easily available, the post-disaster declines in local GDPs, median household incomes, the number of establishments, and personal incomes are significantly mitigated by 1.0-6.2% compared to those lacking access to P2P lending. These estimates suggest that structural changes in local credit markets associated with the presence of P2P lenders helps alleviate the adverse effects of natural disasters, leading, for example, to a median annual household income that is $435 higher than in disaster-hit counties without P2P lending available.

[10] The real effects of the P2P lending availability might be subject to an endogeneity concern that the state government's P2P lending authorization could be associated with unobservable economic or credit market conditions of the regions. For this reason, we focus on interaction effects of P2P lending availability and natural disasters on economic outcomes after controlling for any potential endogenous relationship between the P2P lending availability and real economic outcomes of the regions.

[11] Tang (2019) and Cornaggia et al. (2018) empirically document that the P2P lenders serve as substitutes for traditional banks. Their findings are in line with our prediction that traditional banks aggressively increase their credit supply in response to the advent of P2P lenders due to increased competition with them in local credit markets, which ultimately make positive real economic effects in the aftermath of natural disasters.

These findings remain robust with the inclusion of county and time-by-shock fixed effects, which account for time-invariant county characteristics and time-varying socioeconomic conditions of disaster-affected regions that might affect their real outcomes and credit market status. Taken together, the estimates suggest that the availability of P2P loans, coupled with structural changes in local credit markets, mitigates the real effects of adverse economic shocks.

While fintech lenders might be particularly well equipped to respond to a large and rapid increase in loan demand following natural disasters, the observed effect size appear large given the nascent nature and relatively small size of P2P lending during our sample period of 2008 to 2012.[12] [13] To delve deeper into the mechanisms driving the real economic effects, we investigate the relation between P2P loan availability and banks' lending activities in regions hit by natural disasters. We find that following natural disasters, there is a notable increase in banks' mortgage origination and approval rates. Specifically, in counties where P2P lending is readily available, these rates increase significantly by 15% and 2.7 percentage points, respectively, compared to counties without P2P lenders, following disasters. Banks' origination of small business loans also experiences a significant rise in disaster-affected counties when P2P lenders are present, particularly for loans targeting low-revenue borrowers and those with smaller loan amounts. In disaster-hit counties where P2P lending is accessible, these loan volumes increase by 13.1% and 5.3%, respectively, compared to those lacking P2P availability. Collectively, our findings indicate that the positive real effects of fintech credit availability, characterized by the presence of P2P lenders, primarily results from the proactive response of traditional banks to the surge in credit

[12] Lending Club and Prosper started their P2P lending services from 2007 and 2006, respectively.
[13] As of 2013, only 5% of personal loans were generated by fintech lenders. See details from the report published by Federal Reserve Bank of St. Louis (2019):
https://www.stlouisfed.org/publications/regional-economist/second-quarter-2019/unsecured-personal-loans-fintech#:~:text=A%20record%2Dbreaking%20number%20of,consumers%20when%20compared%20to%202017.

demand following natural disasters in regions where P2P loan is available, potentially influenced by heightened competition from fintech lenders.

Our study contributes to the growing literature on fintech and P2P lending (e.g., Buchak et al. 2018). One strand of the literature focuses on the relation between bank and P2P credit provision. Prior studies, including Tang (2019), Butler, Cornaggia, and Gurun (2018), and Cornaggia et al. (2018), find that P2P lenders substitute for bank lending by serving infra-marginal bank borrowers. Other studies, such as De Roure, Pelizzon, and Thakor (2022), find that P2P lenders complement bank lending by originating riskier loans and serving underserved borrowers. Our paper adds to this literature by providing new evidence on how the interplay between traditional banks and fintech lenders in local credit markets, in response to increased loan demand, help mitigate adverse economic shocks.[14]

Another strand of literature studies the real effects of lending. Morse (2011) finds that payday lenders mitigate the effects of individual financial distress. Danisewicz and Elard (2023) document a persistent rise in personal bankruptcies following a decline in marketplace lending in Connecticut and New York. Our paper is closely related to Cumming et al. (2022), who document that P2P lending provokes an increase in the quantity of entrepreneurship, especially in more regionally disadvantaged areas. While they focus on one particular outcome (entrepreneurship), our study address overall real economic effects, including those on local GDPs, incomes, business establishments, and employment, with further exploration of the indirect channels facilitated by banks. Overall, our paper contributes to this literature by showing that the availability of P2P lending, coupled with local credit market restructuring, mitigates the adverse effects of natural

[14] Our paper is also closely related to Allen, Shan, and Shen (2023), Bradley, Hnriksson, and Valsala (2024), and Qi, Li, and Sun (2021). Similar to our setting, these studies employ natural disasters as credit demand shock to examine fintech lenders' responsiveness to such events.

disasters on the local economy. This is primarily achieved through traditional banks responding to the heightened post-disaster credit demand and the competitive pressures exerted by P2P lenders in local credit markets.

2. Institutional background and data

2.1. Availability of peer-to-peer lending

Peer-to-peer lending platforms provide unsecured consumer or small business loans by matching individual borrowers with retail and institutional investors, thereby providing access to credit as well as investment opportunities. Borrowers typically list loan requests on the platform and investors commit funds to a given listing. Interest rates are either determined through a reverse auction or assigned by the platform based on borrowers' credit risk. A listing becomes a loan once it receives sufficient funds from investors. The loan is then repaid typically in the form of fixed sized installment payments over three to five years.

The global P2P lending market was valued at around $80 billion in 2021 and is expected to grow to approximately $700 billion by 2030 at an annual rate of about 30% based on several different sources.[15] In the U.S., the P2P lending market is dominated by Lending Club and Prosper, the two largest and best-known P2P lending platforms in the U.S.[16] Lending Club and Prosper started operations in 2007 and 2006, respectively, with a focus on connecting retail borrowers to retail investors. While either of the two platforms provides loans to borrowers across all U.S. states except for Iowa at the end of 2022,[17] the initial roll-out of their lending services, in terms of access

[15] For more details about the statistics see: https://www.globenewswire.com/news-release/2023/01/11/2586809/0/en/P2P-Lending-Market-Size-to-Touch-USD-804-2-Billion-by-2030-Says-Acumen-Research-and-Consulting.html and https://www.precedenceresearch.com/peer-to-peer-lending-market.

[16] The combined market shares of Lending Club and Prosper are approximately 75% in the U.S. P2P lending markets (Cumming et al., 2022).

[17] As of the end of 2022, P2P lending is unavailable in Iowa for both platforms and in West Virginia for Prosper. See details from here: LendingClub Personal Loans Review 2021 | US News and Legal Compliance | Prosper

for borrowers, was uneven across states and time, due to federal as well as state-level regulatory hurdles. For example, as Cornaggia et al. (2018) document, the state government of Mississippi issued a cease-and-desist order to Lending Club in 2009 following the expiration of its loan broker license. Also, for three quarters of 2010, Lending Club ceased lending activities in Kansas state during its negotiations with the state government. As another example, SEC issued a cease-and-desist order for Prosper from November 2008 until April 2009. Following Cornaggia et al. (2018), who documented the variation in access to P2P lending across states and times, we construct a measure of the availability of P2P lending to distinguish between regions in which borrowers have better accessibility to P2P lending and regions where borrowers do not have such accessibility to P2P lending.

To measure the availability of P2P lending for borrowers, we first determine the availability of P2P lending for each state and month between 2008 and 2012, the time, over which both platforms gradually expanded across the U.S.[18] We define P2P lending as available when either Lending Club or Prosper originate loans in a given month and state, and as unavailable when neither platform originates any loans during a given month. That is, we assume that the lack of any loans originating in a state reflects the presence of regulatory hurdles or barriers. We then convert the monthly indicator of the availability of P2P lending into an annual state-level measure of P2P availability that takes on the value of one when P2P lending is available for more than six months during the year and zero otherwise. In other words, if borrowers in a state can apply and obtain P2P loans for more than half of the year through either Lending Club or Prosper, P2P lending is readily available in the state in the given year, otherwise it is not. We limit our samples to eight states (Idaho, Indiana, Nebraska, North Carolina, Tennessee, Idaho, Indiana, Nebraska, North

[18] After 2012, most U.S. states did not make any further changes to P2P lending licenses in the states.

Carolina, and Tennessee) in which the state-year level P2P lending availability has time-varying changes during our sample period of 2008 to 2012 in each state. We confirm that our constructed P2P availability measures are consistent with the P2P regulatory barriers identified by Lending Club's 10-K filings and SEC's cease-and-desist order for Prosper in 2008 to 2009. This means that the lack of P2P lending is indeed due to the regulatory restriction against the P2P businesses in the state rather than by the insufficient local credit demands in the areas.

Figure 1 provides a map of the availability of P2P lending over our sample period (2008-2012) for the eight U.S. states included in our samples. While P2P lending is more readily available in five states (Idaho, Indiana, Nebraska, North Carolina, and Tennessee), it is less available to borrowers in other states (Iowa, Maine, and North Dakota) during our sample period.

[Insert Figure 1 about here]

2.2. Natural disasters

While variation of access to P2P lending due to differences in regulation and regulatory costs counters concerns about the endogeneity of P2P lending activity, the P2P loan availability itself might be subject to another endogeneity concern that the state government's P2P lending policies can be associated with unobservable local economic and credit market conditions. For this reason, our analysis rests on a second source of exogenous variation in loan demand due to natural disasters and focuses on the interaction effects of the P2P loan availability and natural disasters on real economic outcomes. We use data from Federal Emergency Management Agency (FEMA) to identify counties that are affected by natural disasters that are sufficiently severe to trigger an emergency declaration by the U.S. President. Specifically, FEMA natural disasters are declared at the request of state governors if the resources of local governments are deemed to be insufficient to help the local areas to recover from the natural disaster. Types of FEMA natural disasters include severe storms, floods, hurricanes, wildfires, snowstorms, and tornados. Using the FEMA data, we identify counties affected by natural disasters and the year of the FEMA declaration for each natural disaster. Over our sample period from 2008 to 2012, 34% of counties in our dataset experienced at least one FEMA-declared natural disaster in a given year. Figure 2 shows disaster counties in our sample (eight states) from 2008 to 2012. In our empirical analysis, we compare real economic outcomes between disaster and non-disaster counties and between states with more readily available P2P lending and those without such P2P lending.

[Insert Figure 2 about here]

2.3. Outcomes

In this section, we discuss the related data sources and provide summary statistics for all outcome variables as well as control variables. All variables are defined in Appendix A.

2.3.1. Real economic outcomes

To measure the effect of the availability of P2P lending on real outcomes, such as GDPs, incomes and employment, we rely on county-level data from several sources. We use the data for county-level GDPs provided by the Bureau of Economic Analysis (BEA). Median household income for each year is available from the U.S. Census Bureau. We obtain the number of establishments in each county and year from the County Business Pattern dataset provided by the U.S. Census Bureau. We rely on data from BEA for the annual county-aggregate personal income as well as its components, i.e., wages and salaries; dividends, interest, and rent; proprietors' income; as well as government transfers. The number of employed workers in each county is available from the Quarterly Workforce Indicators provided by the U.S. Census Bureau. We convert the original quarterly data into an annual average.

In Table 1, we present the corresponding summary statistics. For real outcome variables, we first report statistics for the raw annual county-level variable, followed by statistics for the natural log, which we use in our analyses, and which is again calculated as the log of one plus the raw values. On average, a county's GDPs and median annual household incomes are $2.3 billion and $43,511, respectively. The mean value for the number of establishments in each county is 1,251. The average amount of annual county-aggregate personal income is around $2.0 billion, which consists of wage and salaries ($1.0 billion), dividends, interest, and rent ($0.3 billion), proprietors' income ($0.2 billion), and government transfers (0.4 billion). The average number of employed workers is 22,364. Table 1 also reports summary statistics for *Shock* and *P2P Loan Available,* which are indicator variables that identify the occurrence of natural disasters at county-year level and P2P lending availability at state-year level, respectively. Around 34% of counties experience a natural disaster, while P2P lending is available in 63% of counties in our sample.

[Insert Table 1 about here]

2.3.2. P2P lending data

To examine the relationship between P2P lending availability and the activities of P2P lenders in local markets, we once again rely on loan level data from Lending Club and Prosper. We obtain detailed information on all loan applications and originations between 2008 and 2012 from Lending Club and Prosper, including the loan amount and the city in which the borrower resides.[19] After assigning cities to counties, we count the number of P2P loan applications and originations for each year and county and aggregate the corresponding loan amounts. Panel A of Table B.1 in the Appendix presents the corresponding summary statistics in levels (numbers and amounts), scaled by county population (thousands of people), for annual P2P loan application and origination.

[19] For loan applications and originations from 2008 to 2012, both Lending Club and Prosper provide information on a borrower's city of residence. Our construction of the micro-level sample of P2P loan applications and originations follows Tang (2019).

As noted, our sample is limited to the eight states in which regulatory P2P availability is time-varying during our sample period of 2008 to 2012. The average numbers of annual loan application and origination per thousand people in P2P available counties are 0.038 and 0.003, respectively, and the average annual dollar amounts of applied and originated loans per thousand people for each county are $448 and $37, respectively.

2.3.3. Fintech mortgage data

To identify the relationship between P2P lending availability and other fintech credits, we employ fintech mortgage loan application and origination in our analyses. To obtain the fintech mortgage data, we rely on data provided by regulators (FFIEC) under the Home Mortgage Disclosure Act (HMDA), from which we identify each fintech mortgage originator's aggregate annual mortgage application and origination in each county. For the classification of mortgage originators as fintech or non-fintech lenders, we follow the method suggested by Buchak et al. (2018). In Panel B of Table B.1 in the Appendix, we report the summary statistics for county-aggregate fintech mortgage application and origination (numbers and amounts), scaled by county population (thousands of people), in our sample from 2008 to 2012. The average number of annual fintech mortgage application and origination per thousand people in each county are 0.994 and 0.472, respectively, and the average annual dollar amount of applied and originated fintech mortgages per thousand people for each county are $142,403 and $71,472, respectively.

2.3.4. Bank and branch growth rate data

To understand how the P2P lending availability is related to the structural changes in traditional banking sectors, we explore the annual growth rate of the number of banks and branches in each county. To measure the growth rate, we rely on Summary of Deposits (SOD) data from the FDIC. Because the number of banks and branches in each county is available as of June 30th each year from the SOD, we measure the annual growth rate over the past year, up to June 30th. In Panel C of Table B.1 in the Appendix, we report the average annual growth rate of the number of banks and branches in each county, which are 2.2% and 1.3% in our sample, respectively.

2.3.5. Bank mortgage and small business lending data

For the tests on bank mortgage origination and approval rates, we rely on the data under HMDA, which allows us to identify banks' aggregate annual mortgage origination in each county (by each type of mortgages). Banks' average mortgage approval rates in a county (aggregate mortgage origination divided by its application in the county during a year) are also available from the same data source. In Panel D of Table B.1 in the Appendix, we find that on average the county-level aggregate of banks' mortgage origination volumes during a year is $125 million, among which loan volumes to low-income borrowers are $19 million and the loan amount for conforming loans are $113 million in our sample.[20] Average mortgage approval rate is around 65.5% in our sample period of 2008 to 2012.

Finally, we explore the changes made to banks' small business loan originations in the P2P loan available counties following natural disasters. We obtain banks' small business loan data from FFIEC. According to Panel E of Table B.1 in the Appendix, the average volume of small business loans originated by banks is $36 million, among which $16 million is supplied to low-revenue borrowers.

3. Empirical results

Our empirical analysis focuses on how structural changes in local credit markets characterized by the advent of P2P lenders affects real economic activities in the areas hit by natural disasters. Before addressing the real effects, we first examine how the P2P lending availability is associated

[20] Definition of conforming mortgages is explained in the section 3.3.

with the structural changes in local credit markets with a focus on fintech loan volume, growth rates of the number of banks and branches, and the sizes of banks' mortgage and small business loan originations in the counties.

3.1. Structural changes in local credit markets

We first investigate how local credit markets is affected by fintech lending availability. We expect that the P2P loan availability is not merely associated with increased P2P loan supply in the regions. The presence of P2P lenders in the local markets might be correlated with overall credit market conditions in the regions. If borrowers are more easily accessible to new financial technology, i.e., P2P lending, other types of fintech lending might be more easily available to the borrowers in the regions. Such readily accessible fintech credits can be associated with local banking market structures as well. More competition from fintech lending in local credit markets can lead to a decline of banks' credit supply in the regions. Alternatively, limited banks' credit supply in local markets may facilitate more fintech lending in the regions. To test the relationship between the presence of P2P lenders and local credit market structure, we design the regression models as follows.

$$Y_{i,t} = \beta_0 + \beta_1\, P2P\ Loan\ Available_{i,t} + \delta_i + \delta_t + \epsilon_{i,t} \tag{1}$$

The subscripts i and t refer to the county and year, respectively. Y represents a set of outcome variables related to local credit market structures. First, we use loan application and origination amounts (thousand \$) from P2P lenders (Lending Club and Prosper) and fintech mortgage lenders, scaled by county population (thousands of people), as the outcome variable. *P2P Loan Available* is a dummy variable that is equal to one if the P2P loan is available for more than 6 months during the year, zero otherwise. We add county (δ_i) and year (δ_t) fixed effects in the regressions. Panel A of Table 2 reports the regression results. The coefficient estimates for *P2P*

Loan Available are all statistically significantly positive. The results suggest that annual Lending Club and Prosper loan application and origination amounts are higher by $940 and $77 per thousand people, respectively, in the P2P loan available counties. The fintech mortgage application and origination amounts are even higher by $13,739 and $14,446, respectively, in the P2P available regions. These results indicate that the P2P lending availability is closely associated with overall fintech lending application and origination, extending beyond merely those of P2P loans.

[Insert Table 2 about here]

Next, we move on to the association between the P2P lending availability and structural changes in banking markets. In Equation (1), we use annual growth rates of the number of banks and branches in the county as the outcome variable. Because we can identify the number of banks and branches as of June 30th each year, we measure annual growth rates of them over the past year, up to June 30th. Correspondingly, we identify the P2P loan availability based on the past year, up to June 30th. Panel B of Table 2 reports the regression results. We find that if P2P lending is more readily available during the past 12 months in the counties, the number of banks and branches are more likely to decrease in the regions. The estimation results show that the growth rates are - 1.9% and -1.6% for the number of banks and branches, respectively, in the P2P available regions.

The reduction of the number of banks and branches might lead to a decline in their credit supply to local markets. To test this prediction, we employ banks' aggregate mortgage origination volume and small business loan origination amounts (with a natural log) as the outcome variables in Equation (1). As reported in Panel C of Table 2, banks' aggregate mortgage and small business loan origination is declining by -24.0% and -9.6 respectively in the counties where P2P lending is readily available compared to those lacking P2P lending accessibility. Taken together, we conclude that the P2P lending availability is highly associated with overall structural changes in local credit markets, marked by a shift towards fintech credits from traditional bank lending.

3.2. Real economic effects given natural disasters

Next, we examine the effects of structural changes in local credit markets, marked by the advent of fintech lenders, on real economic outcomes following the occurrence of a natural disaster in the area. Specifically, we hypothesize that natural disasters have negative consequences for the real economy, but that structural changes in local credit markets, characterized by the presence of fintech lenders, might amplify or ameliorate these effects. To test these predictions, we estimate the following regression model:

$$\begin{aligned} Y_{i,t} &= \beta_0 + \beta_1 P2P\ Loan\ Available_{i,t} + \beta_2\ Shock_{i,t} \times P2P\ Loan\ Available_{i,t} \\ &\quad + \beta_3\ Ln(Population)_{i,t} + \delta_i + \delta_t \times Shock_{i,t} + \epsilon_{i,t} \end{aligned} \tag{2}$$

The subscripts *i* and *t* refer to the county and year, respectively. For our baseline tests, we consider four outcome variables: *Ln(GDP)*, *Ln(Median income)*, *Ln(Number of establishments)*, and *Ln(Personal income)*. *Ln(GDP)* is the natural log of one plus a county's GDP during the year. *Ln(Median Income)* is the natural log of one plus a county's median household income in the year. *Ln(Number of establishments)* is the natural log of one plus a county's number of establishments in the year. *Ln(Personal income)* is the natural log of one plus a county's aggregate personal income in the year. *P2P Loan Available* is an indicator variable that equals one if P2P lending is available in the state for more than six months of the year and zero otherwise, showing the relationship between the presence of P2P lenders and the real outcomes absent natural disasters in the regions. *Shock* is an indicator variable that takes a value of one if the county experienced a natural disaster during that year and zero otherwise. The interaction term of *Shock* and *P2P Loan Available*, which is the main coefficient of our interest, identifies the incremental effects of P2P lending availability, combined with the structural changes in local credit markets, on real economic outcomes given natural disasters in the regions. *Ln(Population)* is included as a control variable to capture the effects of population size on economic variables in the county. Finally, all regressions include *County* (δ_i) and *Year-by-Shock* ($\delta_t \times Shock$) fixed effects in the regressions to control for time-invariant county characteristics as well as time-varying unobservable socioeconomic conditions of disaster-hit regions that could potentially affect real economic outcomes as well as credit market conditions in the regions. All standard errors are clustered at the county level.

The regression results are reported in Table 3. The coefficients for the interaction term *Shock* × *P2P Loan Available* are all positive and statistically significant at 1-5% level, implying that the structural changes in local credit markets, characterized by the emergence of P2P lenders, might mitigate the adverse real effects of natural disasters on the local economy.[21] The effects also appear to be sizeable, with an approximate increase in GDPs by $142 million, in median household income by $435, in the number of establishments by 16 units, and in personal incomes by $72 million.[22] Interestingly, the coefficient of *P2P Loan Available* are all negative and statistically significant, which indicates the negative relationship between real economic outcomes and P2P loan availability absent natural disasters in the regions. These results might be driven by structural changes in local credit markets, highlighted by a decline in traditional bank lending, as evidenced by the regression results in Panels B and C of Table 2.

[Insert Table 3 about here]

[21] In Table B.2 in the Appendix, we relate *Shock* and real economic values. We find significantly negative effects of natural disasters on local GDP, the number of business establishment, and personal incomes, confirming the adverse effects of natural disasters on real economic outcomes.

[22] We estimate the sizes of economic effects by multiplying mean values and coefficients of interaction terms. For GDP, $2,290 million × 0.062 = $142 million. For median household income, $43,511 × 0.010 = $435. For the number of establishments, 1251 units × 0.013 = 16 units. For personal incomes, $1,960 million × 0.037 = $72 million.

Next, we further examine the real effects of P2P lending accessibility by focusing on four major components of personal incomes at the county level (wages and salaries; dividends, interest, and rent; proprietors' income; government transfers) following a natural disaster. For this test, we use the same regression setting as in Equation (2) and use components of personal incomes as outcome variables: *Ln(Wages and salaries)*, *Ln(Dividends, interest, and rent)*, *Ln(Proprietor income)*, and *Ln(Government transfers)*. Table 4 reports the regression results. Similar to other economic outcomes, the presence of P2P lenders mitigates the negative effects of a natural disaster. There is one exception: total government transfers are significantly lower when P2P lending is available. In other words, fintech loans might serve as a substitute for government transfers in counties affected by a natural disaster.

[Insert Table 4 about here]

In the final step of our analysis of the real effects of P2P lending availability, coupled with structural shifts in local credit markets, we examine the effects on employment by decomposing the effects by firm size, in particular in terms of number of employees. For this test, we classify firms into two different groups: firms with 0-249 employees and those with more than 250 employees, respectively. We sum up the number of employees for each group in the county during the year and use the natural log of the number plus one as our outcome variable. The coefficient of the interaction term is positive and statistically significant for smaller firms (with the employment size of 0-249) but insignificant for larger firms (with the employment size of at least 250). The results imply that the availability of P2P lending in the regions might mitigate the negative effects of natural disasters on small firms' employments, which is possibly due to their reduced borrowing constraints given the disasters.

[Insert Table 5 about here]

In summary, in Tables 3 through 5, we find consistent results across different real economic outcome variables in regard to the positive effects of the structural changes of local credit markets, characterized by P2P lending availability, on real economic activities.[23]

3.3. Effects on bank lending given natural disasters

In this section, we explore the channels behind the real economic effects of local credit market restructuring. In the previous section, while the sizes of the real effect are moderate in absolute terms, they appear relatively large given the limited role of fintech lending during our sample period.[24] Hence, we examine whether the availability of fintech lending has an effect on the lending activity of traditional bank lenders in disaster-hit areas.

For this test, we first employ the growth rates of the number of banks and branches in each county as dependent variables in Equation (1). We measure annual growth rates of them over the past year, up to the end of June of the current year for each county level. We report the regression results in Table 6. First, we find the inverse relationship between the availability of P2P loans and growth rates of the number of banks and branches in the regions absent the natural disasters, as noted by the negative coefficients of *P2P Loan Available (Jul-Jun)*. In contrast, the positive coefficients for the interaction terms indicate that with natural disasters, such negative relationship between P2P loan availability and growth rates of bank and branch numbers in the counties is significantly mitigated. These results imply that banks are less likely to close their branches in the

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[23] As a robustness check, we add a more stringent fixed effect (Year-by-Region-by-P2P Loan Available-by-County Size) in the regressions. *Region* represents eight U.S. regions into which all U.S. states are categorized by the Bureau of Economic Analysis, as illustrated in Figure B.1 of the Appendix. *County Size* represents quartiles into which all counties in our sample are sorted based on lagged county GDP size each year, with 1 indicating the smallest and 4 indicating the largest. We find consistent results even with the addition of this stringent fixed effect. The results are reported in Tables B.3 to B.5 in the Appendix.

[24] As of 2013, the shares of personal loans generated by banks, credit unions, and fintech lenders are 40%, 31%, and 5%, respectively (Federal Reserve Bank of St. Louis, 2019). See details from here: https://www.stlouisfed.org/publications/regional-economist/second-quarter-2019/unsecured-personal-loans-fintech#:~:text=A%20record%2Dbreaking%20number%20of,consumers%20when%20compared%20to%202017.

regions in response to heightened credit demands following natural disasters in the P2P loan available regions than in the areas lacking P2P loan accessibility.[25]

[Insert Table 6 about here]

Next, we proceed to examine the effects on bank lending activities. We observe county-level origination and application for each bank annually, which we aggregate across all banks within each county. This allows us to use county-aggregate mortgage origination and the county-average mortgage approval rates (county-aggregate mortgage origination divided by its application volume) as the outcome variables in the regressions. Table 7 reports the regression results for the effects of P2P lending availability on banks' mortgage origination and approval rates in counties affected by natural disasters. In Column 1, we use aggregate mortgage origination as the outcome variable and find that the interaction term, *Shock × P2P Loan Available,* is significantly positive. This suggests that banks tend to originate more lending following natural disasters if P2P lending is more readily available in the local markets. Next, we explore further into the effects on other mortgage-related variables, such as average mortgage approval rates, aggregate mortgage amounts originated for low-income borrowers, and mortgage origination volumes for conforming loans.[26] Columns 2-4 in Table 7 report the results. We find significantly positive coefficients of interaction terms, *Shock × P2P Loan Available*. Those results clearly highlight that banks are more inclined to expand their lending in counties where P2P lending is more easily accessible following natural disasters compared to in other counties. We can conclude that increased competitive pressures

[25] As a robustness check, we examine the likelihood of a bank branch opening and closing in the regions where P2P lending is available, with or without natural disasters, using branch-level data. As indicated in Table B.6 of the Appendix, a new bank branch is less likely to open, and an existing branch is more likely to close in counties where P2P lending is readily available in the absence of natural disasters. However, if natural disasters affect the regions, the likelihood of branch closures in P2P loan available regions decreases, consistent with our finding in Table 6.

[26] Conforming mortgages are the mortgages eligible to be purchased by the government-sponsored enterprises (GSEs) such as Fannie Mae and Freddie Mac for securitization. To be eligible to be sold to the GSEs, the mortgage loan size should be below a specified threshold set by the Federal Housing Finance Agency.

stemming from structural changes in local credit markets, exemplified by the emergence of P2P lending platforms, may prompt traditional banks to approve mortgage loans more aggressively in those local markets compared to others not undergoing such local credit market restructuring. The effects on banks' mortgage originations are more pronounced for loans targeting low-income borrowers or those with smaller sizes, which are the primary targets of P2P lending, as supported by Tang (2019) and De Roure, Pelizzon, and Thakor (2022).

[Insert Table 7 about here]

As the next step, we proceed to explore the effects of P2P lending accessibility on banks' small business lending in the event of natural disasters in local markets. The results are reported in Table 8. Similar to the findings in Table 7, the interaction terms, *Shock* × *P2P Loan Available* are positive in all columns. While the results of the interaction term are statistically weaker in Column 1, where the total small business lending origination volume (with a natural log) is used as the outcome variable, they are much stronger statistically in Columns 2 and 3, where we focus on loan originated to low revenue borrowers and loan with small size. These results once again substantiate the mechanism that banks' responsiveness to increased loan demand following natural disasters is more significant in local credit markets experiencing structural changes, represented by the emergence of the P2P lending platform. This could be the primary driver of the positive real effects of the structural changes in local credit markets following natural disasters in the regions.

[Insert Table 8 about here]

3.4. Effects on fintech lending given natural disasters

Finally, we investigate how fintech lending availability affects the activities of fintech lenders in the aftermath of natural disasters. In the previous section, we find that banks are more responsive to increased loan demands following natural disasters when they face greater competitive pressures amidst structural changes in local credit markets. Similarly, we can anticipate that fintech lenders will also increase their loan origination in response to natural disasters. On the other hand, the behavioral changes of banks in response to natural disasters in P2P-available regions may lead to banks absorbing more credit market shares, potentially weakening fintech lending activities in the same regions.

To examine the above predictions, we employ P2P loan applications and originations as the outcome variables in Equation (2). Specifically, we use four outcome variables: P2P application number, P2P application amount, P2P origination number, and P2P origination amount. The regression results are reported in Table 9. The P2P lending availability is positively associated with the P2P application and origination in the absence of natural disasters. However, both P2P loan application and origination decrease in P2P-available regions affected by natural disasters. This result may be attributed to banks absorbing more credit market shares in response to increased loan demands following natural disasters in P2P-available areas. This also confirms that the positive real effects of P2P lending availability are mainly driven by banks' responsiveness rather than the direct effect of P2P lenders' credit provision in the regions.

[Insert Table 9 about here]

In Table 10, we employ fintech mortgage application and origination as the outcome variable in Equation (2). We find consistent results with those for P2P loans. Both fintech mortgage application and origination decrease in P2P-available regions affected by natural disasters. Once again, we conclude that the primary driver of the positive real economic effects of P2P loan availability is the aggressive bank lending activities in response to increased loan demands following natural disasters in P2P available counties rather than the direct effect of the fintech lending.

[Insert Table 10 about here]

4. Conclusion

Economists have long argued that financial innovation spurs growth and economic development, while public perception has remained more skeptical. In this study, we provide empirical evidence on the impacts of the presence of P2P lenders in local credit markets on real economic outcomes in the regions. We find that financial innovation in form of P2P lending, combined with structural changes in local credit markets, appears to produce positive real economic effects in terms of local GDP, income, business establishment, and employment in response to adverse economic shocks. These effects primarily manifest indirectly through the credit expansion by existing banks in response to increased credit demands following negative economic shocks, potentially attributable to heightened competition pressures resulting from the presence of fintech lenders in local markets.

From a welfare perspective, we note that while the immediate real effects of P2P lending availability seem positive, it is possible that longer-term effects are less positive and include increased delinquencies, defaults, and possible bankruptcies, which could cloud the positive assessment of financial innovation suggested by the results of our study.

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Figure 1: Map of states with different levels of P2P loan availability

This figure illustrates the map of the states with different level of the availability of P2P loans during the period from 2008 to 2012 in the U.S. In this study, we limit samples to Iowa, Maine, North Dakota, Idaho, Indiana, Nebraska, North Carolina, and Tennessee (shaded states) where the regulatory availability of P2P loans changes over time from 2008 to 2012. Depending on the number of years P2P lending is available in the state within the 2008-2012 period, states are painted with different colors.

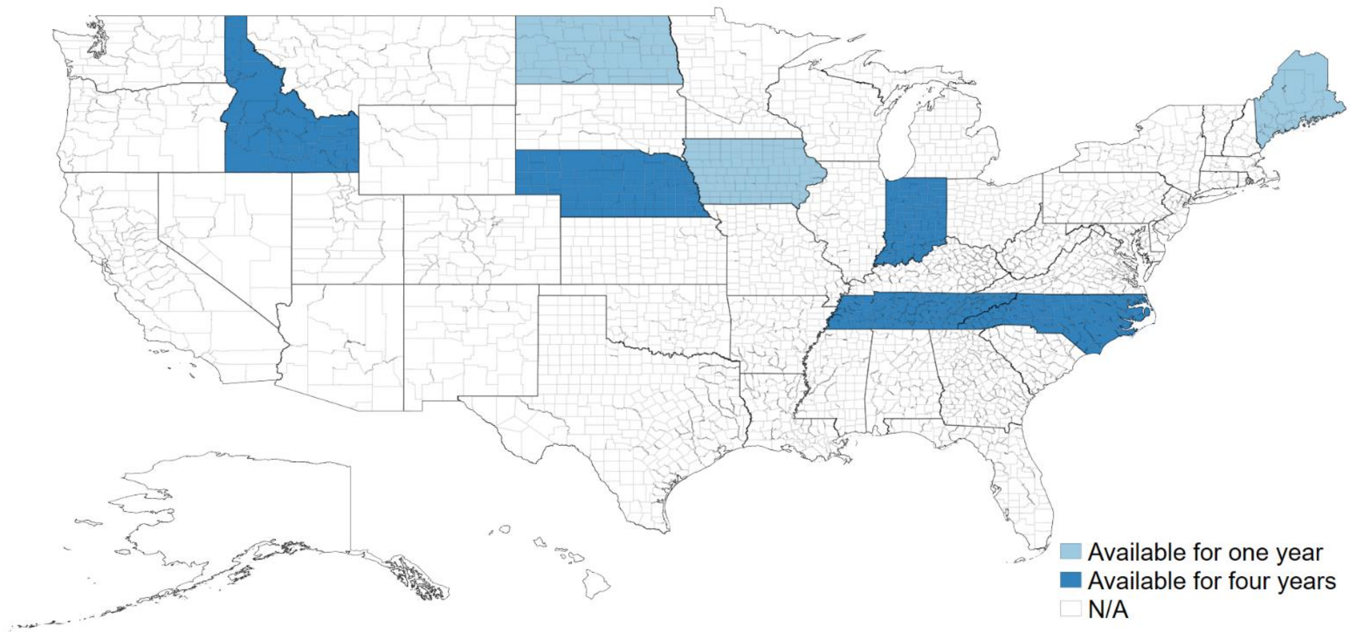

Figure 2: Map of natural disaster counties

This figure shows counties with FEMA-declared natural disasters for five years from 2008 to 2012 in the U.S. In this study, we limit samples to the counties that belong to Iowa, Maine, North Dakota, Idaho, Indiana, Nebraska, North Carolina, and Tennessee (shaded areas) where the regulatory availability of P2P loans changes over time from 2008 to 2012. Depending on the number of years in which a county faces FEMA-declared natural disasters from 2008 to 2012, counties are painted with different colors.

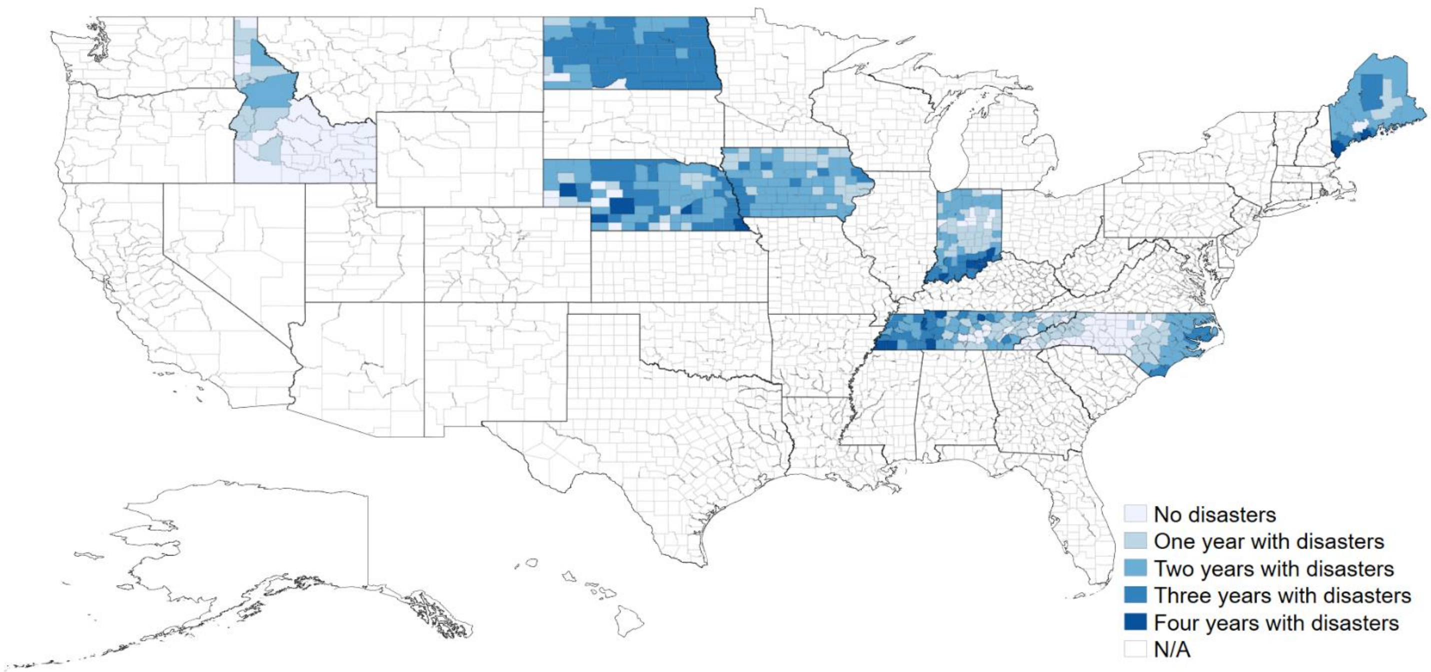

Table 1: Summary statistics

This table presents the summary statistics for the key regression variables. The sample period runs from 2008 to 2012. Appendix A provides a description of all variables.

	N	Mean	S.D.	Min	Max
Gross domestic products (million $)	2,935	2,290	6,653	10	85,730
Median income ($)	2,935	43,511	7,884	23,526	93,166
Number of establishments (#)	2,935	1,251	2,704	6	28,518
Personal income (million $)	2,935	1,960	4,504	11	56,308
Wages and salaries (million $)	2,935	968	2,878	3	36,230
Dividends, interest, and rent (million $)	2,935	325	742	3	8,523
Proprietors' income (million $)	2,935	202	770	0	19,863
Government transfers (million $)	2,935	375	670	3	7,182
Number of employed workers (#)	2,935	22,364	59,469	26	645,596
Ln(GDP)	2,935	13.516	1.365	9.208	18.267
Ln(Median income)	2,935	10.665	0.176	10.066	11.442
Ln(Number of establishments)	2,935	6.219	1.294	1.946	10.258
Ln(Personal income)	2,935	13.533	1.317	9.351	17.846
Ln(Wages and salaries)	2,935	12.459	1.531	8.105	17.405
Ln(Dividends, interest, and rent)	2,935	11.730	1.296	7.936	15.958
Ln(Proprietors' income)	2,935	11.265	1.277	0.000	16.804
Ln(Government transfers)	2,935	12.012	1.316	7.939	15.787
Ln(Number of employed workers)	2,935	8.749	1.580	3.314	13.378
Shock	2,935	0.338	0.473	0.000	1.000
P2P Loan Available	2,935	0.630	0.483	0.000	1.000
Ln(Population)	2,935	3.165	1.219	0.366	6.852

Table 2: Regulatory availability of P2P lending and local credit markets

This table presents the relationship between the regulatory availability of P2P loan in a county and local credit market structures from 2008 to 2012. We investigate county-level P2P loan and fintech mortgage volume, bank/branch growth rates, and banks' mortgage and small business lending origination volume. *P2P Loan Available* is a dummy variable that takes a value of one if a borrowing from the P2P lending platform is legally available in the county for more than six months in the year, zero otherwise. *P2P Loan Available (Jul-Jun)* is a dummy variable that takes a value of one if a borrowing from the P2P lending platform is legally available in the county for more than six months over the past year, up to June 30th of the current year, zero otherwise. In Panel A, the amounts of P2P loan application (Column 1) and origination (Column 2), and those of fintech mortgage application (Column 3) and origination (Column 4), scaled by county population (thousands of people), are used as the dependent variables. In Panel B, *Bank growth rate* is the growth rate of the number of banks within the county over the past one year, up to June 30th of the current year. *Branch growth rate* is the growth rate of the number of bank branches within the county over the past one year, up to June 30th of the current year. In Panel C, *Ln(Mortgages)* is the natural log of a county's aggregate amount of banks' mortgage origination during the year. *Ln(SBLs)* is the natural log of a county's aggregate amount of banks' small business lending origination during the year. In Panels B and C, the regressions include *Ln(Population)*, which is the natural log of a county's total population (thousands of people) in the previous year, as a control variable. In this table, we include *County* and *Year* fixed effects in the regressions. Standard errors are clustered at the county level; *t*-statistics are in parentheses. Statistical significance at the 10%, 5%, and 1% levels is denoted by *, **, and ***, respectively.

Panel A: P2P loan and fintech mortgage	P2P loan		Fintech mortgage	
	P2P loan application amount	P2P loan origination amount	Fintech mortgage application amount	Fintech mortgage origination amount
	(1)	(2)	(3)	(4)
P2P Loan Available	0.940***	0.077***	13.739**	14.446***
	(10.59)	(7.48)	(2.20)	(3.52)
Observations	2,960	2,960	2,960	2,960
Adjusted R^2	0.348	0.189	0.730	0.650
County FE	Y	Y	Y	Y
Year FE	Y	Y	Y	Y

Table 2: continued

Panel B: Bank and branch growth rate	Bank growth rate	Branch growth rate
	(1)	(2)
P2P Loan Available (Jul-Jun)	-0.019***	-0.016***
	(-3.11)	(-2.84)
Ln(Population)	-0.195*	-0.179**
	(-1.74)	(-2.10)
Observations	2,935	2,935
Adjusted R^2	0.055	0.032
County FE	Y	Y
Year FE	Y	Y

Panel C: Bank mortgage and SBL origination	Ln(Mortgages)	Ln(SBLs)
	(1)	(2)
P2P Loan Available	-0.240***	-0.096**
	(-7.79)	(-2.41)
Ln(Population)	1.139*	2.303***
	(1.78)	(3.58)
Observations	2,934	2,935
Adjusted R^2	0.976	0.968
County FE	Y	Y
Year FE	Y	Y

Table 3: Regulatory availability of P2P lending and real economic effects given natural disasters

This table presents the relationship between the regulatory availability of P2P loan in a county and its real economic values from 2008 to 2012, given natural disasters in the county. *Ln(GDP)* is the natural log of a county's gross domestic products in the year. *Ln(Median income)* is the natural log of a county's median household income in the year. *Ln(Number of establishments)* is the natural log of a county's total number of establishments in the year. *Ln(Personal income)* is the natural log of a county's aggregate personal income in the year. *P2P Loan Available* is a dummy variable that takes a value of one if a borrowing from the P2P lending platform is legally available in the county for more than six months in the year, zero otherwise. *Shock* is a dummy variable that takes a value of one if the county experiences at least one natural disaster declared by the FEMA in the year, zero otherwise. This regression includes *Ln(Population)*, which is the natural log of a county's total population (thousands of people) in the previous year, as a control variable. We include *County* and *Year-by-Shock* fixed effects in the regressions. Standard errors are clustered at the county level; *t*-statistics are in parentheses. Statistical significance at the 10%, 5%, and 1% levels is denoted by *, **, and ***, respectively.

	Ln(GDP)	Ln(Median income)	Ln(Number of establishments)	Ln(Personal income)
	(1)	(2)	(3)	(4)
P2P Loan Available	-0.071***	-0.045***	-0.045***	-0.062***
	(-3.66)	(-6.85)	(-6.02)	(-5.15)
Shock × P2P Loan Available	0.062***	0.010**	0.013***	0.037***
	(5.49)	(2.11)	(3.63)	(5.03)
Ln(Population)	0.499	-0.175	0.728***	0.623**
	(0.95)	(-1.12)	(3.38)	(2.32)
Observations	2,935	2,935	2,935	2,935
Adjusted R^2	0.995	0.939	0.999	0.998
County FE	Y	Y	Y	Y
Year-by-Shock FE	Y	Y	Y	Y

Table 4: Regulatory availability of P2P lending and personal income components given natural disasters

This table presents the relationship between the regulatory availability of P2P loan in a county and the value of each component of the county's aggregate personal incomes from 2008 to 2012, given natural disasters in the county. *Ln(Wages and salaries)* is the natural log of a county's income from wages and salaries in the year. *Ln(Dividends, interest, and rent)* is the natural log of a county' income from dividends, interest, and rent in the year. *Ln(Proprietors' income)* is the natural log of a county's current-production income of sole proprietorships, partnerships, and tax-exempt cooperatives in the year. *Ln(Govt. transfers)* is the natural log of a county's income from personal current transfer receipts in the year. All other regression specifications are the same as in Table 3. Standard errors are clustered at the county level; *t*-statistics are in parentheses. Statistical significance at the 10%, 5%, and 1% levels is denoted by *, **, and ***, respectively.

	Ln(Wages and salaries)	Ln(Dividends, interest, and rent)	Ln(Proprietors' income)	Ln(Govt. transfers)
	(1)	(2)	(3)	(4)
P2P Loan Available	-0.086***	-0.100***	-0.034	0.026***
	(-5.18)	(-10.13)	(-1.13)	(8.44)
Shock × P2P Loan Available	0.023***	0.038***	0.120***	-0.015***
	(3.85)	(5.54)	(4.61)	(-5.85)
Ln(Population)	1.408***	0.638***	-0.976**	0.901***
	(2.88)	(3.12)	(-2.12)	(15.67)
Observations	2,935	2,935	2,935	2,935
Adjusted R^2	0.998	0.998	0.955	1.000
County FE	Y	Y	Y	Y
Year-by-Shock FE	Y	Y	Y	Y

Table 5: Regulatory availability of P2P lending and employment given natural disasters

This table presents the relationship between the regulatory availability of P2P loan in a county and its total number of the employed for each of two sub-groups sorted by firm sizes from 2008 to 2012, given natural disasters in the county. *Ln(Total number of employed workers)* is the natural log of an annual average of a county's total number of the employed each quarter. All other regression specifications are the same as in Table 3. Standard errors are clustered at the county level; *t*-statistics are in parentheses. Statistical significance at the 10%, 5%, and 1% levels is denoted by *, **, and ***, respectively.

	Ln(Number of employed workers)	
Firm Size (# of employees)	0-249	250+
	(1)	(2)
P2P Loan Available	-0.064***	-0.047
	(-3.64)	(-1.42)
Shock × P2P Loan Available	0.029***	-0.018
	(3.58)	(-0.47)
Ln(Population)	1.013**	1.627**
	(2.26)	(2.31)
Observations	2,906	2,799
Adjusted R^2	0.996	0.986
County FE	Y	Y
Year-by-Shock FE	Y	Y

Table 6: Regulatory availability of P2P lending and the growth rates of the number of banks and branches given natural disasters

This table presents the relationship between the regulatory availability of P2P loan in a county and the annual growth rates of the number of banks and branches within the county, given natural disasters in the county. *Bank growth rate* is the growth rate of the number of banks within the county over the past one year, up to June 30th of the current year. *Branch growth rate* is the growth rate of the number of bank branches within the county over the past one year, up to June 30th of the current year. *P2P Loan Available (Jul-Jun)* is a dummy variable that takes a value of one if a borrowing from the P2P lending platform is legally available in the county for more than six months over the past year, up to June 30th of the current year, zero otherwise. *Shock (Jul-Jun)* is a dummy variable that takes a value of one if the county experiences at least one natural disaster declared by the FEMA over the past year, up to June 30th of the current year, zero otherwise. We include *County* and *Year-by-Shock (Jul-Jun)* fixed effects in the regressions. Standard errors are clustered at the county level; *t*-statistics are in parentheses. Statistical significance at the 10%, 5%, and 1% levels is denoted by *, **, and ***, respectively.

	Bank growth rate	Branch growth rate
	(1)	(2)
P2P Loan Available (Jul-Jun)	-0.026***	-0.028***
	(-3.53)	(-3.81)
Shock (Jul-Jun) × P2P Loan Available (Jul-Jun)	0.024*	0.035***
	(1.91)	(2.96)
Ln(Population)	-0.168	-0.161*
	(-1.50)	(-1.80)
Observations	2,935	2,935
Adjusted R^2	0.062	0.041
County FE	Y	Y
Year-by-Shock (Jul-Jun) FE	Y	Y

Table 7: Regulatory availability of P2P lending and bank mortgages given natural disasters

This table presents the relationship between the regulatory availability of P2P loan in a county and its aggregate amounts of banks' mortgage origination and the average mortgage approval rates during the year from 2008 to 2012, given natural disasters in the county. *Ln(Mortgages)* is the natural log of a county's aggregate amount of mortgage origination by banks during the year. *Mortgage approval rate* is a county's aggregate amount of mortgage origination by banks divided by that of mortgage application during the year. *Ln(Low income mortgages)* is the natural log of a county's aggregate amount of mortgages originated by banks to borrowers with annual gross incomes below $50,000. *Ln(Conforming mortgages)* is the natural log of a county's aggregate amount of banks' mortgages issued by banks that meet the criteria for purchase by government-sponsored enterprises (GSEs) such as Fannie Mae and Freddie Mac for securitization. To meet the criteria, the mortgage loan size should be below a specified threshold set by the Federal Housing Finance Agency. All other regression specifications are the same as in Table 3. Standard errors are clustered at the county level; *t*-statistics are in parentheses. Statistical significance at the 10%, 5%, and 1% levels is denoted by *, **, and ***, respectively.

	Ln(Mortgages)	Mortgage approval rate	Ln(Low income mortgages)	Ln(Conforming mortgages)
	(1)	(2)	(3)	(4)
P2P Loan Available	-0.280***	-0.029***	-0.165***	-0.262***
	(-7.57)	(-3.76)	(-3.30)	(-7.52)
Shock × P2P Loan Available	0.154***	0.027***	0.238***	0.133***
	(4.00)	(3.08)	(3.80)	(3.93)
Ln(Population)	1.573**	-0.133	0.473	1.523***
	(2.55)	(-1.12)	(0.71)	(2.84)
Observations	2,934	2,934	2,934	2,934
Adjusted R^2	0.977	0.488	0.933	0.982
County FE	Y	Y	Y	Y
Year-by-Shock FE	Y	Y	Y	Y

Table 8: Regulatory availability of P2P lending and small business lending given natural disasters

This table presents the relationship between the regulatory availability of P2P loan in a county and its aggregate amount of bank's small business lending origination during the year from 2008 to 2012, given natural disasters in the county. *Ln(SBLs)* is the natural log of a county's aggregate amount of banks' small business lending origination during the year. *Ln(Low-revenue SBLs)* is the natural log of a county's aggregate amount of banks' small business lending originated to borrowers with gross annual revenues below $1 million. *Ln(Small-sized SBLs)* is the natural log of a county's aggregate amount of small business lending by banks, specifically loans ranging from $100,000 and $250,000. All other regression specifications are the same as in Table 3. Standard errors are clustered at the county level; *t*-statistics are in parentheses. Statistical significance at the 10%, 5%, and 1% levels is denoted by *, **, and ***, respectively.

	Ln(SBLs)	Ln(Low-revenue SBLs)	Ln(Small-sized SBLs)
	(1)	(2)	(3)
P2P Loan Available	-0.115***	-0.110**	-0.085***
	(-2.66)	(-2.21)	(-3.12)
Shock × P2P Loan Available	0.054	0.131**	0.053**
	(1.31)	(2.44)	(1.98)
Ln(Population)	2.483***	1.970***	1.799***
	(3.91)	(2.64)	(3.82)
Observations	2,935	2,935	2,935
Adjusted R^2	0.969	0.953	0.978
County FE	Y	Y	Y
Year-by-Shock FE	Y	Y	Y

Table 9: Regulatory availability of P2P lending and P2P loan applications and originations given natural disasters

This table presents the relationship between the regulatory availability of P2P loan in a county and county-aggregate application and origination of P2P loans, given natural disasters in the county. The number and the amount of P2P loan application (Columns 1-2) and those of P2P loan origination (Columns 3-4), scaled by county population (thousands of people), are used as the dependent variables. *P2P Loan Available* is a dummy variable that takes a value of one if a borrowing from the P2P lending platform is legally available in the county for more than six months in the year, zero otherwise. *Shock* is a dummy variable that takes a value of one if the county experiences at least one natural disaster declared by the FEMA during the year, zero otherwise. We include two sets of fixed effects in the regressions: *County* and *Year* fixed effects and *County* and *Year-by-Shock* fixed effects. Standard errors are clustered at the county level; *t*-statistics are in parentheses. Statistical significance at the 10%, 5%, and 1% levels is denoted by *, **, and ***, respectively.

	P2P application number	P2P application amount	P2P origination number	P2P origination amount
	(1)	(2)	(3)	(4)
P2P Loan Available	0.090***	1.141***	0.008***	0.103***
	(10.88)	(10.76)	(8.00)	(7.41)
Shock × P2P Loan Available	-0.052***	-0.652***	-0.006***	-0.078***
	(-7.08)	(-6.97)	(-5.53)	(-5.54)
Observations	2,960	2,960	2,960	2,960
Adjusted R^2	0.376	0.369	0.193	0.200
County FE	Y	Y	Y	Y
Year-by-Shock FE	Y	Y	Y	Y

Table 10: Regulatory availability of P2P lending and fintech mortgage applications and originations given natural disasters

This table presents the relationship between the regulatory availability of P2P loan in a county and county-aggregate application and origination of fintech mortgage, given natural disasters in the county. The number and the amount of fintech mortgage application (Columns 1-2) and those of fintech mortgage origination (Columns 3-4), scaled by county population (thousands of people), are used as the dependent variables. *P2P Loan Available* is a dummy variable that takes a value of one if a borrowing from the P2P lending platform is legally available in the county for more than six months in the year, zero otherwise. *Shock* is a dummy variable that takes a value of one if the county experiences at least one natural disaster declared by the FEMA during the year, zero otherwise. We include two sets of fixed effects in the regressions: *County* and *Year* fixed effects and *County* and *Year-by-Shock* fixed effects. Standard errors are clustered at the county level; *t*-statistics are in parentheses. Statistical significance at the 10%, 5%, and 1% levels is denoted by *, **, and ***, respectively.

	Fintech mortgage application number	Fintech mortgage application amount	Fintech mortgage origination number	Fintech mortgage origination amount
	(1)	(2)	(3)	(4)
P2P Loan Available	0.097**	21.741***	0.114***	21.721***
	(2.03)	(3.12)	(3.95)	(4.34)
Shock × P2P Loan Available	-0.104**	-31.129***	-0.123***	-24.706***
	(-2.03)	(-4.69)	(-3.95)	(-5.44)
Observations	2,960	2,960	2,960	2,960
Adjusted R^2	0.632	0.735	0.589	0.654
County FE	Y	Y	Y	Y
Year-by-Shock FE	Y	Y	Y	Y

Appendix A. Definition of Variables

Variable	Definition	Level
P2P loan application number	Aggregate number of P2P loan application (scaled by county population) through *Lending Club* or *Prosper* in the county during the year	County-Year
P2P loan application amount	Aggregate amount (thousand $) of P2P loan application (scaled by thousands of people) through *Lending Club* or *Prosper* in the county during the year	County-Year
P2P loan origination number	Aggregate number of P2P loan origination (scaled by county population) through *Lending Club* or *Prosper* in the county during the year	County-Year
P2P loan origination amount	Aggregate amount (thousand $) of P2P loan origination (scaled by thousands of people) through *Lending Club* or *Prosper* in the county during the year	County-Year
Fintech mortgage application number	Aggregate number of fintech mortgage application (scaled by county population) in the county during the year	County-Year
Fintech mortgage application amount	Aggregate amount (thousand $) of fintech mortgage application (scaled by thousands of people) in the county during the year	County-Year
Fintech mortgage origination number	Aggregate number of fintech mortgage origination (scaled by county population) in the county during the year	County-Year
Fintech mortgage origination amount	Aggregate amount (thousand $) of fintech mortgage origination (scaled by thousands of people) in the county during the year	County-Year
Bank growth rate	Growth rate of the number of banks within the county over the past one year, up to June 30th of the current year	County-Year
Branch growth rate	Growth rate of the number of bank branches within the county over the past one year, up to June 30th of the current year	County-Year
Ln(GDP)	Natural log of one plus a county's gross domestic products (thousand $) in the year	County-Year
Ln(Median income)	Natural log of one plus a county's median household income ($) in the year	County-Year
Ln(Number of establishments)	Natural log of one plus a county's total number of establishments in the year	County-Year
Ln(Personal income)	Natural log of one plus a county's aggregate personal income (thousand $) in the year	County-Year
Ln(Wages and salaries)	Natural log of one plus a county's total income (thousand $) from wages and salaries in the year	County-Year
Ln(Dividends, interest, and rent)	Natural log of one plus a county' total income (thousand $) from dividends, interest, and rent in the year	County-Year
Ln(Proprietors' income)	Natural log of one plus a county's total current-production income (thousand $) of sole proprietorships, partnerships, and tax-exempt cooperatives in the year.	County-Year
Ln(Government transfers)	Natural log of one plus a county's total income (thousand $) from personal current transfer receipts in the year	County-Year
Ln(Number of employed workers)	Natural log of one plus an annual average of a county's total number of employed workers each quarter	County-Year
Ln(Mortgages)	Natural log of one plus a county's aggregate amount (thousands $) of banks' mortgage origination during the year	County-Year

Variable	Definition	Level
Mortgage approval rate	The ratio of a county's aggregate amount of banks' mortgage origination over that of mortgage application in the year (winsorize at top and bottom 1 percent).	County-Year
Ln(Low income mortgages)	Natural log of one plus a county's aggregate amount (thousands $) of banks' mortgages originated to borrowers with annual gross income below $50,000 during the year	County-Year
Ln(Conforming mortgages)	Natural log of one plus a county's aggregate amount (thousands $) of banks' mortgages that are eligible to be purchased by the government-sponsored enterprises (GSEs) such as Fannie Mae and Freddie Mac for securitization during the year. To be eligible to be sold to such GSEs, the mortgage loan size should be below a specified threshold set by the Federal Housing Finance Agency	County-Year
Ln(SBLs)	Natural log of one plus a county's aggregate amount of banks' small business lending origination during the year.	County-Year
Ln(Low-revenue SBLs)	*n*atural log of one plus a county's aggregate amount of banks' small business lending originated to borrowers with gross annual revenues below $1 million.	County-Year
Ln(Small-sized SBLs)	Natural log of one plus a county's aggregate amount of banks' small business lending with loan among between $100,000 and $250,000.	County-Year
Shock	Dummy variable that takes a value of one if the county experiences at least one natural disaster declared by the FEMA in the year, zero otherwise	County-Year
Shock (Jul-Jun)	Dummy variable that takes a value of one if the county experiences at least one natural disaster declared by the FEMA over the past year up to June 30th of the current year, zero otherwise	County-Year
P2P Loan Available	A dummy variable that takes a value of one if a borrowing from the P2P lending platform is legally available in the county for more than six months in the year, zero otherwise.	State-Year
P2P Loan Available (Jul-Jun)	A dummy variable that takes a value of one if a borrowing from the P2P lending platform is legally available in the county for more than six months over the past year, up to June 30th of the current year, zero otherwise.	State-Year
Ln(Population)	Natural log of one plus a county's total population (thousands of people) at the previous year	County-Year

Appendix B: Additional Figures and Tables

Figure B.1: Map of BEA regions

This figure illustrates the map of the eight regions – New England, Midwest, Southeast, Great Lakes, Plains, Southwest, Rocky Mountains, and Far West – as defined by the Bureau of Economic Analysis (BEA) in the U.S. All U.S. states are categorized into one of these eight BEA regions.

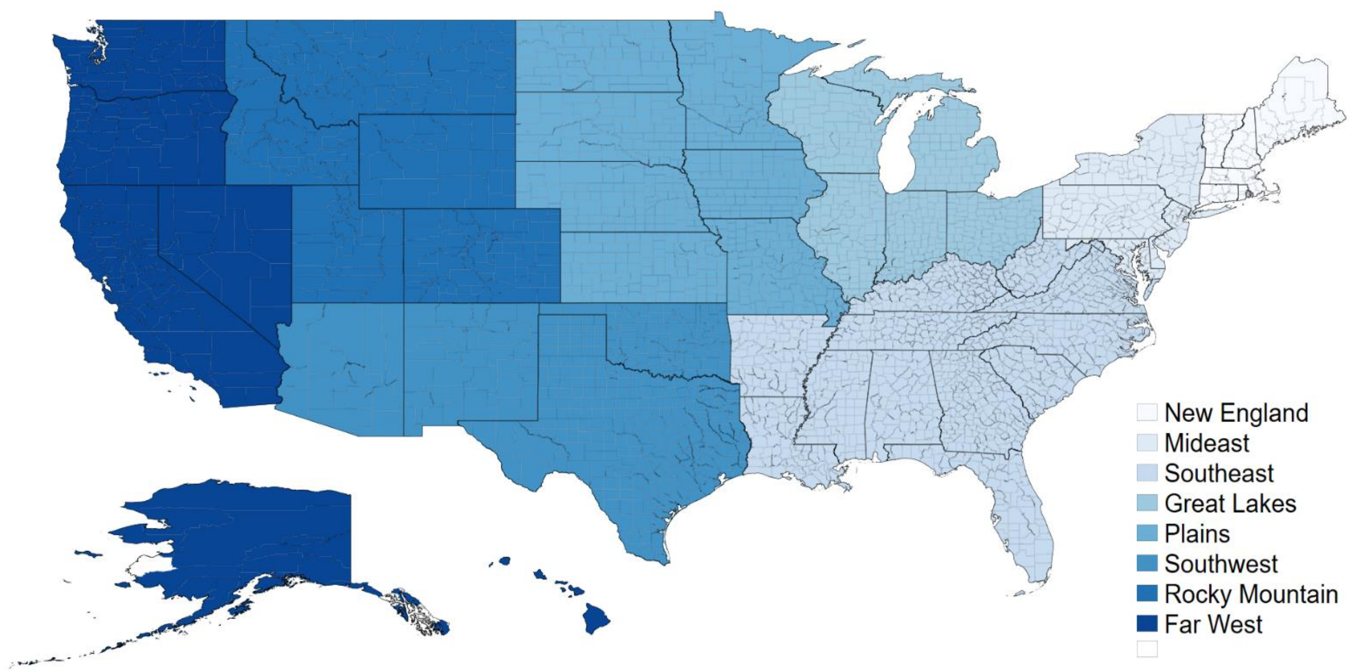

Table B.1: Additional summary statistics

This table presents additional summary statistics for the key regression variables. The sample period runs from 2008 to 2012. Appendix A provides a description of all variables.

Panel A: P2P Lending (scaled by county population, thousands of people)	N	Mean	S.D.	Min	Max
P2P application number (#)	2,960	0.038	0.119	0.000	1.076
P2P application amount (thousand $)	2,960	0.448	1.540	0.000	14.675
P2P origination number (#)	2,960	0.003	0.015	0.000	0.253
P2P origination amount (thousand $)	2,960	0.037	0.200	0.000	5.170
Shock	2,960	0.338	0.473	0.000	1.000
P2P Loan Available	2,960	0.630	0.483	0.000	1.000

Panel B: Fintech Mortgage (scaled by county population, thousands of people)	N	Mean	S.D.	Min	Max
Fintech mortgage application number (#)	2,960	0.994	0.706	0.000	6.951
Fintech mortgage application amount (thousand $)	2,960	142.403	136.458	0.000	1624.330
Fintech mortgage origination number (#)	2,960	0.472	0.410	0.000	3.714
Fintech mortgage origination amount (thousand $)	2,960	71.472	82.186	0.000	1011.762
Shock	2,960	0.338	0.473	0.000	1.000
P2P Loan Available	2,960	0.630	0.483	0.000	1.000

Panel C: Growth rates of the number of banks and branches	N	Mean	S.D.	Min	Max
Bank growth rate	2,935	0.022	0.093	-0.500	1.000
Branch growth rate	2,935	0.013	0.086	-0.800	0.833
Shock (Jul-Jun)	2,935	0.362	0.481	0.000	1.000
P2P Loan Available (Jul-Jun)	2,935	0.630	0.483	0.000	1.000

Table B.1: continued

Panel D: Bank lending (mortgage)	N	Mean	S.D.	Min	Max
Mortgages (million $)	2,934	125	328	0.000	4,970
Low-income mortgages (million $)	2,934	19	39	0.000	393
Conforming mortgages (million $)	2,934	113	292	0.000	4,346
Ln(Mortgages)	2,934	10.213	1.874	0.000	15.419
Ln(Low income mortgages)	2,934	8.598	1.881	0.000	12.883
Ln(Conforming mortgages)	2,934	10.135	1.881	0.000	15.285
Mortgage approval rates	2,934	0.655	0.098	0.000	1.000
Shock	2,934	0.338	0.473	0.000	1.000
P2P Loan Available	2,934	0.630	0.483	0.000	1.000
Ln(Population)	2,934	3.166	1.218	0.366	6.852

Panel E: Bank lending (small business lending)	N	Mean	S.D.	Min	Max
Small business lending (million $)	2,935	36	93	0.018	1,157
Low-revenue small business lending (million $)	2,935	16	38	0.000	513
Small-sized small business lending mortgages (million $)	2,935	10	22	0.018	266
Ln(SBLs)	2,935	9.020	1.782	2.944	13.156
Ln(Low-revenue SBLs)	2,935	8.209	1.845	0.000	12.158
Ln(Small-sized SBLs)	2,935	8.084	1.487	2.944	11.638
Shock	2,935	0.338	0.473	0.000	1.000
P2P Loan Available	2,935	0.630	0.483	0.000	1.000
Ln(Population)	2,935	3.165	1.219	0.366	6.852

Table B.2: Real economic effects of natural disasters

This table presents the effects of natural disasters on real economic outcomes from 2008 to 2012. *Shock* is a dummy variable that takes a value of one if the county experiences at least one natural disaster declared by the FEMA in the year, zero otherwise All other regression specifications are the same as in Table 3. Standard errors are clustered at the county level; *t*-statistics are in parentheses. Statistical significance at the 10%, 5%, and 1% levels is denoted by *, **, and ***, respectively.

	Ln(GDP)	Ln(Median income)	Ln(Number of establishments)	Ln(Personal income)
	(1)	(2)	(3)	(4)
Shock	-0.026***	0.003	-0.005***	-0.016***
	(-5.70)	(1.37)	(-3.21)	(-5.36)
Ln(Population)	0.385	-0.303*	0.588***	0.524*
	(0.75)	(-1.83)	(2.68)	(1.91)
Observations	2,935	2,935	2,935	2,935
Adjusted R^2	0.995	0.935	0.999	0.998
County FE	Y	Y	Y	Y
Year FE	Y	Y	Y	Y

Table B.3: Regulatory availability of P2P lending and real economic effects given natural disasters

This table presents the relationship between the regulatory availability of P2P loan in a county and its real economic values from 2008 to 2012, given natural disasters in the county. In these regressions, we include *County* and *Year-by-Region-by-P2P Loan Available-by-County Size* fixed effects. *Region* represents eight U.S. regions into which all U.S. states are categorized by the Bureau of Economic Analysis, as illustrated in Figure B.1 of the Appendix. *County Size* represents quartiles into which all counties in our sample are sorted based on lagged county GDP size each year, with 1 indicating the smallest and 4 indicating the largest. All other regression specifications are the same as in Table 3. Standard errors are clustered at the county level; *t*-statistics are in parentheses. Statistical significance at the 10%, 5%, and 1% levels is denoted by *, **, and ***, respectively.

	Ln(GDP)	Ln(Median income)	Ln(Number of establishments)	Ln(Personal income)
	(1)	(2)	(3)	(4)
Shock	-0.027***	0.002	-0.003	-0.025***
	(-3.12)	(0.47)	(-1.10)	(-4.93)
Shock × P2P Loan Available	0.032***	0.011***	0.008**	0.035***
	(3.05)	(2.64)	(2.33)	(5.56)
Ln(Population)	1.277**	0.402***	1.002***	1.269***
	(2.41)	(2.84)	(4.69)	(4.90)
Observations	2,935	2,935	2,935	2,935
Adjusted R^2	0.996	0.953	0.999	0.998
County FE	Y	Y	Y	Y
Year-by-Region-by-P2P Loan Available-by-County Size FE	Y	Y	Y	Y

Table B.4: Regulatory availability of P2P lending and personal income components given natural disasters

This table presents the relationship between the regulatory availability of P2P loan in a county and the value of each component of the county's aggregate personal incomes from 2008 to 2012, given natural disasters in the county. In these regressions, we include *County* and *Year-by-Region-by-P2P Loan Available-by-County Size* fixed effects. *Region* represents eight U.S. regions into which all U.S. states are categorized by the Bureau of Economic Analysis, as illustrated in Figure B.1 of the Appendix. *County Size* represents quartiles into which all counties in our sample are sorted based on lagged county GDP size each year, with 1 indicating the smallest and 4 indicating the largest. All other regression specifications are the same as in Table 4. Standard errors are clustered at the county level; *t*-statistics are in parentheses. Statistical significance at the 10%, 5%, and 1% levels is denoted by *, **, and ***, respectively.

	Ln(Wages and salaries)	Ln(Dividends, interest, and rent)	Ln(Proprietors' income)	Ln(Govt. transfers)
	(1)	(2)	(3)	(4)
Shock	-0.002	-0.013***	-0.103***	-0.001
	(-0.40)	(-2.75)	(-4.57)	(-0.65)
Shock × P2P Loan Available	0.015**	0.030***	0.115***	0.003
	(2.08)	(4.75)	(4.20)	(1.22)
Ln(Population)	2.096***	1.051***	0.156	0.708***
	(4.08)	(5.42)	(0.33)	(11.66)
Observations	2,935	2,935	2,935	2,935
Adjusted R^2	0.998	0.998	0.963	1.000
County FE	Y	Y	Y	Y
Year-by-Region-by-P2P Loan Available-by-County Size FE	Y	Y	Y	Y

Table B.5: Regulatory availability of P2P lending and employment given natural disasters

This table presents the relationship between the regulatory availability of P2P loan in a county and its total number of the employed for each of two sub-groups sorted by firm sizes from 2008 to 2012, given natural disasters in the county. In these regressions, we include *County* and *Year-by-Region-by-P2P Loan Available-by-County Size* fixed effects. *Region* represents eight U.S. regions into which all U.S. states are categorized by the Bureau of Economic Analysis, as illustrated in Figure B.1 of the Appendix. *County Size* represents quartiles into which all counties in our sample are sorted based on lagged county GDP size each year, with 1 indicating the smallest and 4 indicating the largest. All other regression specifications are the same as in Table 5. Standard errors are clustered at the county level; *t*-statistics are in parentheses. Statistical significance at the 10%, 5%, and 1% levels is denoted by *, **, and ***, respectively.

	Ln(Number of employed workers)	
Firm Size (# of employees)	0-249	250+
	(1)	(2)
Shock	-0.008	-0.005
	(-1.11)	(-0.28)
Shock × P2P Loan Available	0.026***	0.002
	(2.93)	(0.10)
Ln(Population)	1.920***	2.241***
	(4.17)	(2.89)
Observations	2,906	2,799
Adjusted R^2	0.997	0.986
County FE	Y	Y
Year-by-Region-by-P2P Loan Available-by-County Size FE	Y	Y

Table B.6: Regulatory availability of P2P lending and bank branch opening and closing likelihood

This table presents the relationship between the regulatory availability of P2P loan in a state and the likelihood of bank branch opening and closing in the state. *OpenBranch* is a dummy variable that is equal to one if the branch has opened over the past year, up to June 30th of the current year, and zero otherwise. *CloseBranch* is a dummy variable that is equal to one if the branch closes over the next year, starting from July 1st of the current year, and zero otherwise. *P2P Loan Available (Jul-Jun)* is a dummy variable that takes a value of one if a borrowing from the P2P lending platform is legally available in the county for more than six months over the past year, up to June 30th of the current year, zero otherwise. *P2P Loan Available (Jul-Jun forward)* is a dummy variable that takes a value of one if a borrowing from the P2P lending platform is legally available in the county for more than six months over the next year, starting from July 1st of the current year, zero otherwise. *Shock (Jul-Jun)* is a dummy variable that takes a value of one if the county experiences at least one natural disaster declared by the FEMA over the past year, up to June 30th of the current year, zero otherwise. *Shock (Jul-Jun forward)* is a dummy variable that takes a value of one if the county experiences at least one natural disaster declared by the FEMA over the next year, starting from July 1st of the current year, zero otherwise. This regression includes *Ln(Population)*, which is the natural log of a county's total population (thousands of people) in the previous year, as a control variable. *Branch* and *Year-by-Shock (Jul-Jun or Jul-Jun forward)* fixed effects are included in the regressions. Standard errors are clustered at the county level; *t*-statistics are in parentheses. Statistical significance at the 10%, 5%, and 1% levels is denoted by *, **, and ***, respectively.

	OpenBranch	CloseBranch
	(1)	(2)
P2P Loan Available (Jul-Jun)	-0.022***	
	(-3.57)	
Shock (Jul-Jun) × P2P Loan Available (Jul-Jun)	-0.002	
	(-0.23)	
P2P Loan Available (Jul-Jun forward)		0.016***
		(4.11)
Shock (Jul-Jun forward) × P2P Loan Available (Jul-Jun forward)		-0.007*
		(-1.66)
Ln(Population)	-0.021	0.001
	(-1.22)	(0.18)
Observations	56,055	56,057
Adjusted R^2	0.264	0.297
Branch FE	Y	Y
Year-by-Shock (Jul-Jun) FE	Y	N
Year-by-Shock (Jul-Jun forward) FE	N	Y