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Marketplace Lending: A Resilient Alternative in the Face of Natural Disasters?

By *Pejman Abedifar, Hossein Doustali and Steven Ongena*

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ABSTRACT

What is the role played by marketplace lending after natural disasters? Analyzing a sample of more than one and a half million observations from LendingClub around the 33 worst natural disasters that occurred between 2013 and 2017, we find that there is an increase in the demand for marketplace loans by almost 10%. Yet, the platform does not restrict lending to individuals in the affected areas, nor do we observe an increase in interest rates. Interestingly, the performance of borrowers who receive loans after a natural disaster is not significantly different from the borrowers during normal times, indicating that the platform is competent at efficiently meeting the extra loan demand.

Keywords: Marketplace Lending, FinTech, Natural Disasters, Access to Finance, Credit Risk Assessment

JEL Classifications: D14, E51, G2, Q54

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Climate change has increased the frequency and severity of natural disasters.[1] Households in the affected areas are in need of immediate access to credit to defray the damages and to meet their living expenses. Local bank branches may accommodate the credit demand of affected households based on relationship banking technology (Abedifar et al. (2022)); however, technological advancements encourage banks to shrink their branch networks (Agarwal and Zhang (2020)). Figure (1) illustrates that the number of US bank branches has been declining since 2011, and that the decline has become steeper since 2019 with a 7.9% reduction over the 2019-2022 timespan. This trend is also observed in Europe, the UK, and China.[2]

The pruning of branches is expected to be even stronger in the areas that are more exposed to climate risk. Banks located in affected regions face destabilization (Noth and Schüwer (2018)) and an elevated likelihood of default (Klomp (2014)). With the increasing closure of branches and the frequency of natural disasters, the concern arises as to whether marketplace lenders can serve as reliable alternative providers of credit to households.

[Insert figure 1 here]

Marketplace lending began in the early 2000s, and it has been grown at a faster pace since 2009 (Vallee and Zeng (2019)). In 2021, the global marketplace lending market size was US$ 83.79 billion, and it is projected to grow to around US$ 705.81 billion by 2030.[3] This growth is fueled

[1] See Intergovernmental Panel on Climate Change (2012) for more information.

[2] The number of bank branches continued to decline in most EU member states by 8.6% on average in 2020. In the UK, between 2012 and 2020, the total number of bank branches decreased by 40%, and Chinese banks closed 1,300 branches merely in 2020.

[3] According to the report by Precedence Research.

by the increasing use of digitization in the banking sector, the growth of small and medium-sized businesses, and the adoption of innovative technology.[4]

In marketplace lending, borrowers directly connect with lenders through these online platforms. The process begins with borrowers submitting loan applications on the platforms, providing relevant information about their financial profile, the purpose of the loan, and the desired loan amount. The platforms assess the borrowers' creditworthiness using various data points, including credit scores, income verification, and alternative data sources. Based on the available information, the platforms assign a grade to each borrower's profile, which indicates her creditworthiness. Investors/lenders on the platforms review the loan listing and decide which loans they want to fund based on their risk preferences and investment strategies. They can invest in a whole or a portion of a loan.

The replacement of brick-and-mortar branch banking with marketplace lending poses crucial questions for policymakers: 1) Whether there is an increase in demand for marketplace loans after natural disasters; 2) Whether and to what extent marketplace lending meets the credit needs of the affected households; 3) Whether marketplace lending changes the terms of their credit aftermath of a natural disaster; 4) Whether the performance of the credits granted to the affected households is weaker than the performance of the loans in the normal time. This study attempts to address these questions, which - to the best of our knowledge - are overlooked in the literature.

Marketplace lending differs from traditional banking in several key aspects, including its evaluation processes, financing mechanisms, online accessibility, and risk assessment methodologies. These differences have notable implications, particularly in natural disasters.

[4] According to the report by Precedence Research.

Marketplace lending is immune against direct physical damage caused by natural disasters and is expected to continue its operation without disruption. Additionally, the distinctive evaluation process of marketplace lending, which requires no interaction between loan officers and borrowers, makes it ideal for addressing the immediate credit needs of affected households in the aftermath of natural disasters.

Local factors influence the penetration of marketplace lending activities. For instance, the extant research shows that the demand for marketplace loans is higher in areas that may be underserved by traditional banks (Jagtiani and Lemieux (2018)). Hence, to address the potential increase in demand for marketplace loans after natural disasters, we consider the banking market concentration, which represents the regions that may be underserved by traditional banking. In addition, small banks and local branches can provide credit to households affected by natural disasters based on relationship banking (Abedifar et al. (2022)). Therefore, we consider the share of small banks, which shows the areas with more relationship banking presence, in our analysis.

Additionally, it is essential to investigate how marketplace lending assesses the additional risk posed by natural disasters to borrowers and whether such additional risk is priced. Furthermore, examining the performance of borrowers is crucial as it sheds light on the effectiveness of marketplace lending in managing and mitigating risks associated with lending in natural disasters.

We investigate 33 major natural disasters - hurricanes, severe storms, tornadoes, floods, etc. - from 2013 to 2017. We use more than one and a half million loan applications from LendingClub over this period. We also use the FEMA dataset to determine the affected zip codes.[5] Our analysis

[5] In the rest of the paper, the term "zip code" or "three digits zip code" refers to the first three digits of the zip code.

is based on a panel dataset of loan originations at the three-digit zip code-month level and panel regression techniques with lead and lag.

Our findings indicate that the loan volume demanded per thousand inhabitants decreases by approximately $250 (about 8% of the average loan volume request in our sample) in the month that natural disasters occur.[6] However, on average, within three months thereafter, we observe a more than $300 (almost 10% of the average) increase in demand. The presence of small banks in a given zip code is associated with a smaller increase in demand for marketplace loans, potentially because small banks partly accommodate the credit needs of the affected households, which implies that marketplace lending may play a substitution role for traditional small banks. However, the degree of market concentration in the banking industry does not show a significant difference in marketplace loan demand.

The quality of marketplace applicants does not change after catastrophic events. The approval rate, as a proxy for access to finance, also remains unchanged after natural disasters, whereas in traditional financing, some studies show a decrease in the probability of loan approval as the demand for loans increases due to natural disasters (Berg and Schrader (2012), Collier and Babich (2019)). This result shows that marketplace lending provides better financial access than traditional institutions during natural disasters. In addition, the subgrades and the interest rates that marketplace lending assigns to each profile do not change significantly, which contrasts with the traditional bank's response. For instance, Huang et al. (2020) and Correa et al. (2020) find that banks increase loan spreads when exposed to natural disasters.

[6] Throughout this paper, any references to "demand" should be understood as referring to the volume of loans demanded or the number of loan applications, normalized by population per thousand inhabitants.

The consistent response of the marketplace lending during natural disasters, as observed in the unchanged approval rate, can be attributed to its elasticity, which helps to absorb demand shocks (Berg et al. (2022)). This elasticity is based on the FinTech lending process, which can lower processing times, lower operational costs, and improve the user experience (Berg et al. (2022)). Furthermore, the supply-side elasticity minimizes significant fluctuations in interest rates or modifications to subgrades. This is a result of a scenario where an increase in demand causes the demand curve to shift upwards while the elastic supply curve remains more horizontal, ensuring that the point of equilibrium, where supply meets demand, experiences minimal change. This reinforces the stability of the marketplace lending's behavior even in the face of natural disasters.

More importantly, borrowers who obtain loans during these challenging times perform similarly to those who receive loans during normal periods. This consistent performance can be attributed to the advanced technologies employed by marketplace lending platforms. These technologies leverage non-traditional data sources, such as digital footprints (Berg et al. (2019)), borrowers' online behavior, and social networks (Gambacorta et al. (2019)), and employ machine learning algorithms to enhance the informational value of available data (Fuster et al. (2022)). The integration of such innovative tools contributes to the reduction of default and the improvement in recovery rates (Berg et al. (2022)).

Climate change has intensified catastrophic events all over the world, and a growing body of literature examines access to finance in the aftermath of such events. Previous studies have explored the role of various sources of finance, including banks, insurance, Government aid, and credit cards (Koetter et al. (2020), Roth and Kunreuther (1998), Gallagher et al. (2020), and Gallagher and Hartley (2017)). Our research contributes to this strand of literature by focusing on the role of marketplace lending and its complementary position in relation to traditional small banks. To the best of our knowledge, we are the first to investigate the unique position of marketplace lending in natural disasters.

We also contribute to the emerging literature on FinTech lending. The existing studies have shed light on the responses of marketplace lending to shocks like the COVID-19 pandemic (Najaf et al. (2021)), regulatory changes affecting traditional banks (Tang (2019)), and financial crises (Havrylchyk et al. (2016)), our study pioneers in highlighting the efficacy of marketplace lending in assisting households aftermath of natural disasters. It complements the study by Najaf et al. (2021), which shows that the demand for marketplace loans increased during the COVID-19 pandemic when people were advised to stay at home and avoid direct interactions with others. In a similar vein, we show that in the aftermath of a natural disaster that disrupts normal activities in a society, marketplace lending can provide immediate access to credit.

The rest of the paper is organized as follows. The following section provides a comprehensive review of the existing literature. Section II presents information about the dataset used in the study, while Section III outlines the methodology employed in the analysis. In Section IV, the results of the research are discussed and examined. Finally, Section V presents the concluding remarks and summarizes the paper's key findings.

I. Literature Review

Natural disasters have far-reaching economic, environmental, financial, and social consequences. These abrupt and extreme events can hinder economic growth (Cavallo et al. (2010)), destroy household assets (Botzen et al. (2019)), and worsen household credit constraints (Sawada and Shimizutani (2008)). For those who have been affected by natural disasters, access to credit becomes essential.

The economic damages caused by natural catastrophes often lead to a temporary increase in deposit withdrawals and even loan requests to cover their living expenses and replace or repair damaged assets (Brei et al. (2019)). This issue has been addressed in the extant literature as several studies have explored the role of traditional sources of finance in natural disasters. Cortés and Strahan (2017) find that banks, in response to natural disasters, increase lending to affected individuals by reallocating funds from unaffected individuals to those impacted. Roth and Kunreuther (1998) examine the role of insurance in natural disasters and conclude that insurance coverage for natural disasters effectively mitigates financial losses. Gallagher et al. (2020) discuss the role of cash grants on household finance and business survival after a natural disaster. They find that individuals in severely damaged areas with access to cash grants experienced 30% less credit card debt than those without such assistance. Gallagher and Hartley (2017) explore the role of credit card borrowing following natural disasters. They find that while there are spikes in credit card borrowing, overall delinquency rates for heavily affected residents are modest and short-lived.

According to a growing body of research, it is unclear whether bank lending increases or decreases following a natural disaster. Banks may reduce credit to affected areas (Choudhary and Jain (2017), Nguyen and Wilson (2020), Schüwer et al. (2018)). This decline in lending can be attributed to a decrease in collateral value and the weakened economic prospects of borrowers in the affected regions (Baltas et al. (2022)). Moreover, banks may experience a reduction in capital and deposits, which limits their lending capacity (Brei et al. (2019)). According to Cortés and Strahan (2017), banks respond to natural disasters by increasing lending if they have branches in the affected areas. However, this may come at the cost of reducing lending in areas with minimal comparative advantage or without branch presence. Therefore, borrowers in regions unaffected by natural disasters experience a decline in credit supply (Rehbein and Ongena (2022), Ivanov et al. (2020)).

Berg and Schrader (2012) explore the effect of volcanic eruptions on loan demand and credit access using data from an Ecuadorian microfinance institution. They find that volcanic activity increases credit demand; however, access to credit becomes limited. It is also observed that traditional banks tend to increase the loan spread when exposed to natural disasters, as indicated by research conducted by Huang et al. (2020) and Correa et al. (2020).

The literature on relationship banking suggests that specific borrowers may have easier access to bank loans than others. Banks can mitigate the problem of asymmetric information between themselves and borrowers by developing close relationships and obtaining inside information. DeYoung et al. (2004) show that small banks rely more on the relationship in their lending decisions, and several studies show that in the case of natural disasters, borrowers with a stronger relationship are more likely to receive a recovery loan (Abedifar et al. (2022), Koetter et al. (2020)).

With the emergence of disruptive innovation in lending, and the rise of FinTech lending, a growing body of literature examines the position of this phenomenon vis-à-vis traditional banking. Tang (2019) shows that, following the regulatory change that induces banks to tighten their lending criteria, the demand for marketplace loans increased. Najaf et al. (2021) find that marketplace loan volume increased during the COVID-19 pandemic when households are advised to observe social/physical distancing. Havrylchyk et al. (2016) examine the drivers of the increase in consumer demand for marketplace credit. They claim that marketplace lending platforms have filled the gap left by banks in counties more affected by the financial crisis of 2007-08, where banks reduced their lending activities due to deleveraging. The study by Jagtiani and Lemieux (2018) has specifically explored the relationship between the banking market concentration, as measured by the Herfindahl-Hirschman Index (HHI), and the extent of marketplace lending penetration. Their findings indicate that areas with a higher concentration, which traditional banks may underserve, tend to exhibit higher demand for marketplace loans. As banks are shrinking their branch network, the importance of this body of literature is elevated. Yet, there is no study, to the best of our knowledge, that investigates whether marketplace lending can accommodate the financial needs of households in the aftermath of natural disasters, which is the key objective of this study.

II. Sample and Descriptive Statistics

In this study, we collect data from LendingClub, one of the prominent marketplace lending platforms in the United States. We retrieve the data for the 2013- 2017 timespan. The LendingClub dataset is divided into two parts: accepted applications and rejected applications. For loan applications rejected by LendingClub during its initial screening process, the available information includes the requested loan amount, the date of request, the borrower's FICO score, debt-to-income ratio, length of employment, and the first three digits of the zip code of the borrower's location. Additional information on the borrower's credit history and loan performance information is available for the accepted/funded loan applications. The definitions of the variables used in this paper can be found in Table I.

[Insert table I here]

We obtain data on the time and location of natural disasters from the Federal Emergency Management Agency (FEMA). FEMA is an agency of the United States Department of Homeland

Security (DHS), whose primary purpose is to coordinate the response to a disaster. The FEMA's Housing Assistance Program dataset provides information on the type of natural disasters and the total amount of approved aid under the FEMA Individuals and Households Program (IHP), which is used to identify the affected zip codes. The date of each incident is not provided in this dataset. Using Disaster Declarations Summaries from the FEMA dataset, we can find the date of a natural disaster.

The Summary of Deposits data is used to create variables that capture the characteristics of the banking market structure at the three-digit zip-code level. These variables include the share of small banks, banking market concentration, the share of national banks, the share of systematically important banks, the geographical diversity of local banks, the dollar amount of deposits per thousand zip code inhabitants, and the number of branches per capita (100,000 people). We collect demographic data from the Census Bureau, specifically the population, unemployment, and average income at the three-digit zip code level. We also use the house price index (HPI) dataset obtained from the Federal Housing Finance Agency.

We treat our marketplace lending dataset as follows. Due to the presence of outliers, we excluded applicants in the top 1% of income values from the accepted profiles dataset. We limit the dataset to applications with debt-to-income ratios between 0% and 100% and revolving utilization rates below 100%. As for the rejected applications, we eliminate rows containing missing values and restrict the data to applications with credit scores ranging from 300 to 850 and debt-to-income ratios between 0% and 100%. Additionally, we filter the dataset to include loan amount requests between $1,000 and $40,000, as this represents the interval within which LendingClub loans are available. Finally, we limit the rejected applications dataset to credit scores falling within the range observed in the accepted applications dataset. Our approach is based on the assumption that borrowers with credit scores lower than those observed in accepted applications are unlikely to have a viable opportunity to obtain a loan. It is important to note that this restriction does not apply to the analysis of changes in the average FICO scores of all applicants.

Next, we merge the accepted and rejected datasets, aggregate data based on the zip code. This process results in three distinct datasets: one for accepted applications, one for rejected applications, and one for the merged dataset. Accepted and rejected application data are at the individual-month level, and the merged dataset is at the zip code-month level.

In addition to the marketplace lending data, we obtain the FEMA datasets, specifically the Individuals and Households Program (IHP) dataset, for homeowners and renters. We merge these datasets with the Disaster Declarations Summaries data, as described earlier, aggregate them on the three-digit zip codes, and restrict it to the 2013–2017 period.

We select the top 20% of the IHP dataset to identify significant shocks based on the magnitude of assistance provided. This approach is motivated by several factors. First, given that our loan-level data was available at the three-digit zip code level, which may encompass larger areas, we study the most significant catastrophic events to capture meaningful impacts (Atanasov and Black (2019)). Second, we address concerns related to the possibility of affected individuals anticipating shocks by concentrating on the most severely affected zip codes. This acknowledges that while some affected individuals might anticipate such events, the extent of the damage is unexpected. Lastly, our econometric model assumes a consistent effect of each disaster across all affected zip codes. By selecting the most damaging events and assuming reduced heterogeneity in high-damage shocks, we aim to enhance the accuracy of our results and the reliability of our conclusions.

Afterward, we limit the marketplace lending dataset to zip codes that overlap with the affected zip codes identified in the FEMA dataset. These datasets are merged, and indicators related to each natural disaster and zip code are defined. We establish a time window of nine months. In line with previous studies, we adopt a three-month window to capture the post-disaster effect, as suggested by Garmaise and Moskowitz (2009), Runyan (2006), Baltas et al. (2022). In the other six months, we separate the month in which the natural disaster occurred from the remaining months to examine potential differences. The remaining time period is used to establish a pre-parallel trend for comparison. We also exclude zip codes that had no demand for marketplace loans for more than two consecutive months from our analysis. Finally, we merge the finalized datasets with zip code control variables.

We incorporate a range of banking sector control variables derived from the Federal Deposit Insurance Corporation's (FDIC) Summary of Deposits (SOD) database. These control variables encompass various dimensions, for example, the Herfindahl-Hirschman Index (HHI), which measures the concentration of banks in each zip code. Additionally, we consider variables including the dollar amount of deposits per thousand zip code inhabitants, the share of small banks and national banks and systematically important banks in total deposits of each zip code area, the median number of states in which local banks operated, and the number of bank branches per 100,000 persons. The inclusion of these variables enables us to account for the banking landscape's characteristics within the studied areas.

To ensure the exclusion of potential overlaps, we exclude the zip codes with an overlap between the indicators five months before a natural disaster and twelve months after. Figure (2) presents a geographical visualization that illustrates the distribution of zip codes affected by natural disasters.

[Insert figure 2 here]

A. Summary Statistics

The sample consists of 84 unique zip codes with 1,563,703 applications, out of which 261,352 are accepted. Table II exhibits the summary statistics of the various zip code level variables, providing valuable insights into the characteristics of the geographical areas included in the dataset. The average loan volume demanded is around $3,100, with values ranging from a minimum of about $0 to a maximum of $17,630. The Herfindahl-Hirschman Index (HHI) for the zip codes in our sample has an average value of 413, with a minimum of 47 and a maximum of 3,466. The proportion of small banks in a given zip code varies from 0.5% to 87%, with an average of approximately 23%. The population of a zip code is, on average, around 625,000 residents, with a minimum of about 49,000 and a maximum of approximately 2.7 million individuals.

[Insert table II here]

Table III presents loan application characteristics. Panel A includes summary statistics for all loan applications, while Panel B focuses on the accepted profiles. The average loan amount for all applications is approximately $13,000, whereas for the accepted loans sample, it is around $15,000. The minimum credit score for accepted applications is 660, while for all applications, the minimum credit score is merely 300. The average credit score of accepted applications is 695, compared to an average of 643 for all applications. The debt-to-income ratio for the accepted loans averages 18.5%, whereas, for all applications, it is around 23%. On average, borrowers who obtain loans have 12 open accounts and pay approximately 13% interest on their loans.

[Insert table III here]

Lastly, Table IV provides an overview of the frequency of different types of disasters in our datasets. In total, we have 33 events in our sample. The most common types of disasters observed are floods and severe storms, with a frequency of twelve and eight occurrences, respectively.

[Insert table IV here]

III. Methodology and Econometric Specification

A. The Demand for Marketplace Loans after Natural Disasters

In this section, we aim to investigate the impact of natural disasters on the demand for marketplace loans.

A.1. The Average Effect of Natural Disasters on Marketplace Loans Demand

To investigate the effect of natural disasters on marketplace loan demand, we employ a panel regression analogous to the approach used by Cortés and Strahan (2017). The regression model includes *Pre-Event*, *Event*, and *Post-Event* dummy variables to capture the effects of natural disasters on loan demand:

$$Y_{z,t} = \beta_0 \mathrm{Pre-Event}_{z,t} + \beta_1 \mathrm{Event}_{z,t} + \beta_2 \mathrm{Post-Event}_{z,t} + Controls_{z,t} + \alpha_z + \gamma_t + \epsilon_{z,t} \quad (1)$$

Where z denotes three digits of the zip code, and t denotes year-month. The dependent variable $Y_{z,t}$ represents either the *Number of Loan Applications* or the *Loan Volume Demanded*, both aggregated on a monthly basis for each zip code. *Pre-Event* is a dummy variable equal to one for five months before a natural disaster. *Event* is a dummy variable equal to one for a month that a natural disaster occurred, and *Post-Event* is equal to one for three months after a natural disaster. We follow previous studies and adopt a three–month window to capture the post-disaster effect

(Garmaise and Moskowitz (2009), Runyan (2006), Baltas et al. (2022)). $Controls_{z,t}$ include zip code controls consist of *Share of Small Banks*, *HHI*, *Share of National Banks*, *Share of Systemically Important Banks*, *Geo. Diversification*, *Deposits*, *Number of Branches, Population*, *Unemployment*, *House Price Index*, *Income*, and *Ave. FICO Score*. We draw from both Jagtiani and Lemieux (2018) and Tang (2019) for the control variables and also control for *Share of Systemically Important Banks* and *Ave. FICO Score*. The definitions of the variables can be found in Table I. α_z and γ_t represent the zip code and the year-month fixed effects, respectively.

A.2. Marketplace Loans Demand and Banking Market Structure

To examine the influence of small banks' presence in a given zip code on demand for marketplace loans, we introduce an interaction term between the event indicators (*Pre-Event*, *Event*, and *Post-Event*) and the *Share of Small Banks*. This approach allows us to investigate whether the effect of natural disasters on loan demand from the marketplace lender depends on the market share of small banks operating in a zip code. The regression model is as follows:

$$Y_{z,t} = \beta_0 \mathrm{Pre-Event}_{z,t} + \beta_1 \mathrm{Event}_{z,t} + \beta_2 \mathrm{Post-Event}_{z,t} + \beta_3 \mathrm{Share\ of\ Small\ Banks}_{z,t} + \beta_4 \mathrm{Pre-Event}_{z,t} \times \mathrm{Share\ of\ Small\ Banks}_{z,t} + \beta_5 \mathrm{Event}_{z,t} \times \mathrm{Share\ of\ Small\ Banks}_{z,t} + \beta_6 \mathrm{Post-Event}_{z,t} \times \mathrm{Share\ of\ Small\ Banks}_{z,t} + Controls_{z,t} + \alpha_z + \gamma_t + \epsilon_{z,t} \quad (2)$$

Where z denotes three-digit zip codes, and t denotes the year-month. The dependent variable $Y_{z,t}$ represents either the *Number of Loan Applications* or the *Loan Volume Demanded*. The rest of the model is the same as Equation (1).

Continuing our analysis, we now examine the interplay between marketplace loan demand and the banking market concentration within each zip code. Our objective is to understand how the level of market concentration impacts the demand for marketplace loans following natural disasters. We use the Herfindahl-Hirschman Index (HHI) to measure market concentration in the model. The model employed in this analysis closely resembles the one discussed in Equation (2). We merely replace the variable $Share\ of\ Small\ Banks_{z,t}$ with the $HHI_{z,t}$.

B. Quality of Marketplace Loans Applicants and Natural Disasters

Next, we study the quality of applicants who demand marketplace loans in the aftermath of natural disasters. The potential change in the quality of borrowers can be attributed to potential migration from banks to marketplace lending (see Tang (2019) for more information).[7] We measure the quality of applicants by their FICO score and use the following regression model.

$$Zip\ Code\ FICO\ Score_{z,t} = \beta_0 Pre - Event_{z,t} + \beta_1 Event_{z,t} + \beta_2 Post - Event_{z,t} + Controls_{z,t} + \alpha_z + \gamma_t + \epsilon_{z,t} \tag{3}$$

Where z denotes three digits of the zip code, and t denotes the year-month. $Zip\ Code\ FICO\ Score_{z,t}$ represents the average FICO score of applicants on a monthly basis for each zip code. $Controls_{z,t}$ include zip code controls consist of *Share of Small Banks*, *HHI*, *Share of National Banks*, *Share of Systemically Important Banks*, *Geo. Diversification*, *Deposits*, *Number of Branches, Population*, *Unemployment*, *House Price Index*, and *Income*. The rest of the model is the same as Equation (1).

C. Response of Marketplace Lending

[7] Unfortunately, due to data constraints, we cannot delve into migration dynamics between these entities in this study. Specifically, we could not analyze whether borrowers with weaker or no relationship banking lean more towards marketplace lending.

Following our examination of the effect of natural disasters on marketplace loan demand, it is essential to investigate the response of the marketplace lending platform to potential changes in demand in the aftermath of such events. In this section, we analyze the impact of natural disasters on the approval rate of marketplace loans using a probit regression model.

$$\mathrm{Reject}_{\mathrm{i,z,t}} = \beta_0 Pre - \mathrm{Event}_{z,t} + \beta_1 E\mathrm{vent}_{z,t} + \beta_2 P\mathrm{ost} - \mathrm{Event}_{z,t} + \mathrm{Controls}_{i,z,t} + \alpha_z + \gamma_t + \epsilon_{i,z,t} \tag{4}$$

Here applications are indexed by i, zip codes by z, and the year-month by t; the dependent variable in our model is denoted as $Reject_{i,z,t}$, takes a value of one if the applicant's loan is rejected and zero otherwise. Our objective is to understand how the occurrence of natural disasters influences the likelihood of a loan rejection. The individual and loan control variables include *Amount*, *FICO Score*, *Debt-to-Income*, and *Length of Employment*. The rest of the model is the same as in Equation (1). The complete list of variables can be found in Table I.

Moving forward with our analysis, we investigate the effect of natural disasters on the marketplace lending subgrades assigned to each loan application. The marketplace lending subgrade serves as an indicator of the perceived risk associated with a borrower determined by the marketplace lending algorithm. By analyzing the changes in marketplace lending subgrades in response to natural disasters, we acquire insights into how marketplace lending assesses and adjusts its risk evaluation process.

We opt to use subgrade data instead of grade data due to its greater precision compared to grade data. The grade data ranges from 1 (worst) to 7 (best), whereas the subgrade data ranges from 1 to 35. We employ a regression model incorporating the marketplace lending subgrade as the dependent variable to assess this relationship and use the OLS technique to estimate it. The regression model is specified as follows:

$$Subgrade_{i,z,t} = \beta_0 Pre - Event_{z,t} + \beta_1 \text{Event}_{z,t} + \beta_2 P\text{ost} - \text{Event}_{z,t} + \text{Controls}_{i,z,t} + \alpha_z + \gamma_t + \epsilon_{i,z,t} \quad (5)$$

In the above equation, $Subgrade_{i,z,t}$ represents the marketplace lending subgrade assigned to the loan application of borrower i in zip code z during the year-month t. $Controls_{i,z,t}$ includes *Amount*, *FICO Score*, *Debt-to-Income*, *Length of Employment*, *Maturity*, *Length of Credit*, *Homeownership*, *Revolving Balance, Total Credit Lines*, *Open Accounts*, *Revolver Utilization*, *Annual Income*, *Inquiries Last 6 Months*, *Delinquency Last 2 Years*, *Delinquency*, and *Application Type*. The zip code control variables are the same as Equation (1). The variable definition is provided in Table I.

Next, we examine the impact of natural disasters on the interest rates of marketplace loans. Our objective is to study whether the occurrence of natural disasters leads to significant changes in the interest rates charged by the marketplace lender. To analyze this relationship, we employ a regression model similar to the one described in Equation (5), with the interest rate as the dependent variable. We also control for *Subgrade* in our analysis.

D. Performance of Borrowers

Lastly, we study the performance of borrowers who obtain loans during natural disasters. By assessing the borrower's loan repayment behavior, we seek to acquire insights into the effectiveness of marketplace lender’s selection process in identifying creditworthy borrowers during natural disasters. We employ the following probit regression model.

$$\text{Bad Loan}_{i,z,t} = \beta_0 Pre - Event_{z,t} + \beta_1 \text{Event}_{z,t} + \beta_2 Post - \text{Event}_{z,t} + \text{Controls}_{i,z,t} + \alpha_z + \gamma_t + \epsilon_{i,z,t} \quad (6)$$

The dependent variable, $Bad\ Loan_{i,z,t}$, is defined as an indicator that takes the value of one if the loan has been charged off, defaulted, or is late between 31 and 120 days; otherwise, it is assigned the value of zero. It represents the performance indicator for the loan obtained by borrower i in zip code z during year-month t. The control variables are the same as those used in the previous specification, with the addition of *Interest Rate*.

IV. Empirical Results

A. The Demand for Marketplace Loans after Natural Disasters

First, we present the empirical results of our analysis of the demand for marketplace loans in the aftermath of natural disasters. Our objective is to examine whether there is a significant change in loan demand following these events and to identify its specific temporal patterns.

A.1. The Average Effect of Natural Disasters on Marketplace Loans Demand

We estimate Equation (1) to explore whether there is any abnormal demand for marketplace loans for three months after natural disasters. Estimation results are reported in Table V. As one of the most critical assumptions in our analysis, we first check whether the pre-treatment parallel trend assumption holds. The estimated coefficient of *Pre-Event* is insignificant, indicating that the assumption is not violated. We investigate the changes in loan demand in the month that a natural disaster occurs and in the three months following the event, which prior research suggests are crucial periods for assessing the impact (Garmaise and Moskowitz (2009), Runyan (2006), Baltas et al. (2022)).

[Insert table V here]

In the first column, we consider the *Number of Loan Applications* as the dependent variable. We find that the number of loan applications for marketplace loans decline by 0.019 (9.5% of the average number of loan applications in our sample) during the month of a natural disaster (*Event*). However, in the three months following a natural disaster, we observe more than a 0.02 (about 10.5% of the average) increase in the *Number of Loan Applications* for marketplace loans. In the second column, the dependent variable is the *Loan Volume Demanded*. The results show that, on average, there is a $248 (about 8% of the average loan volume request in our sample) decrease in the *loan volume demanded* in the month when a natural disaster occurs and a $307 (9.8% of the average) increase in the three months following natural disasters.

In our analysis, we substitute the event indicators with their corresponding monthly data to investigate the temporal dynamics of demand fluctuations. To further scrutinize the post-event period and ascertain the lasting impact of natural disasters, we extend our analysis by incorporating an additional two-month timeframe. As illustrated in Figure (3), the coefficients are insignificant beyond the third month after natural disasters (when the dependent variable is either the *Number of Loan Applications* or the *Loan Volume Demanded*), indicating that the influence of the natural disaster wanes after the initial three-month interval following the occurrence of the event. This finding reinforces the validity of selecting the three months following natural disasters as an appropriate time frame to observe their effects. These findings are consistent with prior studies, including Berg and Schrader (2012), which demonstrate an increased demand for microfinance credit following natural disasters. Additionally, they align with the research conducted by Cortés and Strahan (2017), which highlights an increase in loan demand from banks after natural disasters.

[Insert figure 3 here]

A.2. Marketplace Loans Demand and Banking Market Structure

To investigate the relationship between the presence of small banks in a zip code and the demand for marketplace loans, we estimate Equation (2). The results are presented in Table VI. In column (1), we consider the *Number of Loan Applications* as the dependent variable. The interaction term between *Post-Event* and *Share of Small Banks* is significantly negative, indicating that a higher share of small banks in a zip code is associated with a smaller increase in loan demand. One percent increase in the share of small banks will offset about 2% of the increase in the *Number of Loan Applications* after natural disasters. In the second column, we examine the *Loan Volume Demanded* and find that the results remain consistent. One percent increase in the share of small banks will offset about 2% of the increase in the *Loan Volume Demanded* after natural disasters. This phenomenon can be attributed to the business model employed by small banks, which emphasizes relationship banking (DeYoung et al. (2004)). This finding is consistent with previous studies, including Abedifar et al. (2022) and Koetter et al. (2020), which have shown that borrowers who have established relationships with banks are more likely to secure loans following natural disasters.

[Insert table VI here]

In the following, we explore the relationship between the concentration of the banking market and the demand for marketplace loans. This step is motivated by two primary reasons. Firstly, to determine whether the more general concept of banking, banking market concentration, is relevant to demand for marketplace loans. Second, to discover whether the more concentrated areas in which the demand for marketplace loans is higher are different from other areas in terms of credit demand in natural disaster times. We estimate Equation (2) by replacing the variable $Share\ of\ Small\ Banks_{z,t}$ with the $HHI_{z,t}$. Table VII depicts the estimation result. We find that the coefficients of interaction terms between *HHI* and event-time indicators are statistically insignificant when the dependent variable is either the *Number of Loan Applications* or the *Loan Volume Demanded*. These results suggest that there is no significant difference in loan demand between areas with a more concentrated banking market and those with less concentration. Jagtiani and Lemieux (2018) indicate that the demand for marketplace loans is higher in the areas with more concentrated banking markets, in which traditional banks may underserved. Albeit, the Table VII results show that regardless of concentrated banking areas, the patterns of change in loan demand remain relatively consistent with our previous findings.

[Insert table VII here]

B. Quality of Marketplace Loans Applicants and Natural Disasters

After natural disasters, there is a rise in demand for marketplace loans. It is important to investigate whether the average quality of loan applicants, as measured by their FICO scores, changes. Examining this aspect of loan applicants following natural disasters is essential for comprehending potential changes in borrower type, which can subsequently impact our further analysis.

We estimate Equation (3), and the outcome is presented in Table VIII. Our analysis suggests that there is no statistically significant change in the quality of loan applications within the three months period following natural disasters. These results suggest that the composition of applicants remains unchanged following natural disasters.

[Insert table VIII here]

C. Response of Marketplace Lending

After studying the impact of natural disasters on loan demand and confirming that the type of borrowers remains unchanged, we investigate whether marketplace lender decreases access to finance in the aftermath of natural disasters. Following the approach used by Berg and Schrader (2012), we utilize the approval rate as a proxy for measuring access to finance and estimate Equation (4). The results are presented in Table IX. Surprisingly, our results reveal that the approval rate does not experience a significant change following natural disasters. Marketplace lender does not change the approval rate because, as highlighted in Berg et al. (2022), FinTech lending increases lenders' elasticity to demand shocks. The outcome contrasts with the findings of Berg and Schrader (2012), who observe limited access to traditional microfinance resources despite an increase in credit demand after natural disasters, and Collier and Babich (2019), that find a reduction in bank lending. Our results suggest that marketplace lending's response to the increase in loan demand is characterized by maintaining a stable approval rate, indicating better access to finance relative to traditional institutions during natural disasters.

[Insert table IX here]

As we show earlier, we observe that the demand for marketplace loans experiences an increase following natural disasters while access to finance remains relatively stable. In the following, we delve into the assessment of credit risk and examine whether marketplace lending changes the loan subgrades assigned to each application after natural disasters. To investigate this, we estimate Equation (5) and report the result in Table X. The analysis shows that the loan subgrades do not exhibit a significant change in the aftermath of natural disasters. This finding suggests that, despite the financial vulnerability that individuals may face because of natural disasters, the marketplace lender's credit risk assessment remains consistent.

[Insert table X here]

It appears that marketplace lender does not alter subgrades, but there is a possibility that they systematically increase interest rates to appease suppliers of credit amid natural disasters. In the following, we explore whether marketplace lender changes the interest rates of loans in response to natural disasters. We employ a regression model akin to that outlined in Equation (5), with the *Interest Rate* serving as the dependent variable. However, our model also accounts for *Subgrade*, in addition to the controls specified in Equation (5), and presents the estimation results in Table XI. Our findings show no significant change in interest rates during and after natural disasters.

This result stands in contrast to previous studies of traditional banks, which commonly observe an increase in loan spreads in response to natural disasters (Huang et al. (2020), Correa et al. (2020)).

[Insert table XI here]

D. Performance of Borrowers

Finally, we study the performance of borrowers who obtain loans after natural disasters. After establishing the increase in the marketplace loan demand and observing the unchanged access to finance, loan assessment, and loan pricing, it is pivotal to assess the performance of borrowers. To achieve this, we estimate Equation (6) and present the result in Table XII. We find that the performance of borrowers who obtain loans during and after natural disasters shows no significant change relative to similar loans granted in normal times. This finding suggests that the marketplace lender demonstrates a remarkable ability to identify and select creditworthy individuals even in challenging circumstances. The consistent performance of the marketplace lender can be attributed to its strategic use of advanced technologies. New technologies use more data, such as digital footprints (Berg et al. (2019)) in addition to traditional data and machine learning techniques to enhance the informational value of available data (Fuster et al. (2022)).

[Insert table XII here]

V. Conclusion

Access to credit is crucial in the aftermath of natural disasters. Marketplace lenders, as a novel source of financing with distinct characteristics, may exhibit unique behaviors in response to such events. This study examines the behavior of individuals affected by natural disasters and the corresponding response of marketplace lenders to these shocks.

We have uncovered several noteworthy findings using a sample of more than one and half million observations from LendingClub and 33 major natural disasters that occurred in the U.S. First, we observe a decrease in the demand for marketplace loans immediately in the month that a natural disaster happens and then an increase in the demand for marketplace loans within three months after natural disasters. The type of borrowers, as measured by their FICO scores, does not change after natural disasters.

Importantly, our results show that marketplace lending provides better financial access than traditional institutions during natural disasters, where some studies have shown a decrease in the probability of loan approval as loan demand increases due to natural disasters (Berg and Schrader (2012), Collier and Babich (2019)). Additionally, marketplace lending's subgrades and interest rates assigned to each profile remain unchanged, unlike traditional banks, which have been found to increase loan spreads when exposed to natural disasters (Huang et al. (2020), Correa et al. (2020)). More importantly, our analysis reveals that the performance of borrowers who obtain loans during natural disasters remains unchanged relative to those borrowing under normal circumstances. These results can be attributed to the use of non-traditional datasets in addition to traditional datasets (Berg et al. (2019), Gambacorta et al. (2019), Di Maggio et al. (2022)) and the adoption of advanced technologies by marketplace lending that enhance application processing (Fuster et al. (2022)).

Furthermore, we delve deeper into specific factors that may influence the demand for marketplace loans. Our results indicate that areas with a more significant share of small banks experience a smaller increase in demand for marketplace loans. This suggests that the presence of small banks matters for access to credit during natural disasters as they rely more on relationship banking. Additionally, we examine the role of banking market concentration, as existing literature suggests that the demand for marketplace loans is higher in more concentrated areas. We find that the demand for marketplace loans does not significantly differ in concentrated versus un-concentrated markets. This insight adds depth to our understanding of lending dynamics in the aftermath of catastrophic events and contributes to the broader discourse on how various banking factors shape post-disaster financing patterns.

The key message for policymakers is that (1) marketplace lending demonstrates resilience and effectiveness in meeting increased loan demand after natural disasters. (2) While the global trend is to reduce the number of branches, the existence of small banks can help affected individuals.

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Table I. Variable Description

Panel A presents the description of variables related to zip codes, providing insights into the characteristics of the geographical areas. Panel B describes variables related to the loans and borrowers in the dataset.

Panel A: Dependent Variables	
Variable	Description
Number of Loan Applications	The number of applications which apply for marketplace loans per thousand inhabitants
Loan Volume Demanded	The volume of loan demanded by applications per thousand inhabitants
Zip Code FICO Score	The average FICO score of all applicants within a given zip code for a given month
Reject	A dummy variable which takes a value of one if the applicant's loan is rejected and zero otherwise
Subgrade	The categorization of borrowers' credit risk levels in marketplace lending
Interest Rate	Interest rate proposed by LendingClub and accepted by borrowers and lenders
Bad Loan	It is an indicator that takes the value of one if the loan has been charged off, defaulted, or is late between 31 and 120 days; otherwise, it is assigned the value of zero
Pre-Event	It is a dummy variable that equals one for the five months before a natural disaster and zero otherwise
Event	It is a dummy variable that equals one for the month that a natural disaster happened and zero otherwise
Post-Event	It is a dummy variable that equals one for the three months after a natural disaster and zero otherwise
Panel B: Control Variables	
Variable	Description
Share of Small Banks	Deposit share of small banks with total assets of less than $1 billion, in the three digits zip code level
HHI	Herfindahl–Hirschman index of the banking market at the three digits zip code level (based on deposit shares)
Share of National Banks	Deposit share of national banks in the three digits zip code level
Share of Systemically Important Banks	Deposit share of banks with total assets of greater than $50 billion, in the three digits zip code level
Geo. Diversification	A median number of states in which the local zip code’s banks operate
Deposits	The dollar amount of deposits per thousand zip code inhabitants
Number of Branches	Number of branches per one hundred thousand of people in the three digits zip code
Population	The total population in the three digits zip code
Unemployment	The unemployment rate in the three digits zip code
House Price Index	House price index in three digits zip code
Income	The average income in the three digits zip code
Ave. FICO Score	The mean FICO score of all loan applicants within a specific zip code, calculated on a monthly basis
Amount	Dollar amount of the requested loan by a borrower
FICO Score	The FICO score of applicants
Debt-to-Income	Debt-to-income ratio is calculated as the borrower’s total monthly debt payments (excluding any mortgage and the requested LendingClub loan) divided by the borrower’s self-reported monthly income
Length of Employment	Length of employment reported by the borrower; it can take one of ten values: less than one year, 1 year, 2 years, 3 years, . . ., at least 10 years
Maturity	The indicator variable is set to one if the original maturity is 60 months, and zero otherwise

Table I. (Continued)

Panel B: Control Variables (Continued)	
Variable	Description
Length of Credit	Length (in years) of the borrower's credit history
Homeownership	Homeownership status of borrowers
Revolving Balance	Total outstanding balance that the borrower owes on open credit cards or other revolving credit accounts reported by the credit bureau
Total Credit Lines	The total number of credit lines currently in the borrower's credit file
Open Accounts	The number of open credit lines in the borrower's credit file
Revolver Utilization	Amount of credit that the borrower is using relative to all available revolving credit
Annual Income	The self-reported annual income provided by the borrower during registration
Inquiries Last 6 Months	The number of inquiries within the preceding six months (excluding auto and mortgage inquiries) reported by the credit bureau
Delinquency Last 2 Years	Number of borrower delinquencies within the preceding two years
Delinquency	It is equal to one if the delinquency is positive and zero otherwise
Application Type	It is equal to one if an application is joint and zero otherwise

Table II. Summary Statistics - Zip Code Characteristics

This table presents the summary statistics of various zip code level variables. Our sample consists of 5,040 zip code-month observations from 84 zip codes, where a major natural disaster occurs. It covers the 2013 to 2017 period. For the variable definition, please refer to Table I.

Variables	N	Mean	S.D.	Min	Max
Number of Loan Applications	5,040	0.2	0.14	0	1.13
Loan Volume Demanded	5,040	3,135	2,210	0	17,630
Share of Small Banks	5,040	23.15	22.14	0.543	86.51
HHI	5,040	413.3	517.9	47.01	3,466
Share of National Banks	5,040	44.61	18.52	4.989	83.36
Share of Systemically Important Banks	5,040	48.95	25.45	0	98.25
Geo. Diversification	5,040	2.244	1.733	1	12
Deposits	5,040	20,713	11,743	8,377	75,353
Number of Branches	5,040	22.98	5.587	10.93	45.42
Population	5,040	625,631	520,577	48,925	2.706M
Unemployment	5,040	9.394	2.807	3.963	25.62
House Price Index	5,040	192.3	39.22	125.1	351.0
Income	5,040	67,578	14,734	42,807	119,490
Ave. FICO Score	5,026	648.2	20.77	501	784

Table III. Summary Statistics - LendingClub Loans

This table presents summary statistics of LendingClub loan characteristics for all loan applications in Panel A and the funded loans in Panel B. For variable definitions, please refer to Table I.

Variables	N	Mean	S.D.	Min	Max
	Panel A. All Applications				
Amount	1.56M	12,987	10,555	1,000	40,000
FICO Score	1.56M	642.5	63.44	300	850
Debt-to-Income	1.56M	23.42	18.40	0	100
Length of Employment	1.56M	1.47	3.25	0	11
	Panel B. Funded Loans				
Amount	261,352	14,854	8,834	1,000	40,000
FICO Score	261,352	695.0	30.90	660	845
Debt-to-Income	261,352	18.59	8.664	0	99.76
Length of Employment	261,352	6.249	4.096	0	11
Maturity	261,352	0.283	0.450	0	1
Subgrade	261,352	24.29	6.307	1	35
Interest Rate	261,352	13.24	4.766	5.320	30.99
Length of Credit	261,352	16.11	7.363	3	63
Revolving Balance	261,352	16,337	20,193	0	959,754
Total Credit Line	261,352	24.60	11.95	2	150
Open Accounts	261,352	11.90	5.665	1	82
Revolver Utilization	261,352	51.20	23.78	0	100
Annual Income	261,352	75,040	40,068	5,000	275,000
Inquiries Last 6 Months	261,352	0.623	0.915	0	6
Delinquency Last 2 Years	261,352	0.327	0.898	0	30
Delinquency	261,352	0.00414	0.0642	0	1
Application Type	261,352	0.0268	0.161	0	1

Table IV. Frequency of Natural Disasters

This table provides an overview of the frequency of different types of natural disasters observed in the dataset. We retrieve this data from FEMA. The natural disasters occurred during the 2013 - 2017 period.

Incident Type	Frequency
Flood	12
Severe Storm	8
Hurricane	6
Fire	3
Tornado	3
Earthquake	1
Total	33

Table V. The Average Effect of Natural Disasters on Marketplace Loans Demand

This table reports the results of estimating Equation (1) using the OLS technique. In column (1), the dependent variable is the *Number of Loan Applications*, and in column (2), the dependent variable is the *Loan Volume Demanded*. The study period is from 2013 to 2017. We use a sample of 5,026 zip code-month observations. *Pre-Event* equals one for the five months before the event and zero otherwise. *Event* is equal to one for the month a natural disaster occurs and zero otherwise. *Post-Event* equals one for the three months after the event and zero otherwise. ZIPCode Controls include *Share of Small Banks*, *HHI*, *Share of National Banks*, *Share of Systemically Important Banks*, *Geo. Diversification*, *Deposits, Number of Branches, Population*, *Unemployment, House Price Index*, *Income*, and *Ave. FICO Score*. For the definition of the variables, please refer to Table I. The pre-parallel trend assumption is satisfied, indicating the validity of our analysis. The zip code and the year-month fixed effects are included. Standard errors, given in parentheses, are clustered at the zip code level. *, ** and *** indicate significance at 10%, 5%, and 1%.

	(1) Number (#)	(2) Amount ($)
Pre-Event	0.00310	58.70
	(0.00324)	(54.85)
Event	-0.0191***	-248.3***
	(0.00498)	(85.99)
Post-Event	0.0209***	307.1***
	(0.00629)	(98.91)
Constant	-0.826***	-16,964***
	(0.200)	(3,427)
Observations	5,026	5,026
Adjusted R-squared	0.922	0.898
ZIPCode Controls	Yes	Yes
ZIPCode Fixed Effects	Yes	Yes
Year-Month Fixed Effects	Yes	Yes

Table VI. Marketplace Loans Demand and Small Banks

This table reports the results of estimating Equation (2). In column (1), the dependent variable is the *Number of Loan Applications*, and in column (2), the dependent variable is the *Loan Volume Demanded*. The study period is from 2013 to 2017. We use a sample of 5,026 zip code-month observations. *Pre-Event* equals one for the five months before the event and zero otherwise. *Event* is equal to one for the month a natural disaster occurs and zero otherwise. *Post-Event* equals one for the three months after the event and zero otherwise. ZIPCode Controls include *HHI*, *Share of National Banks*, *Share of Systemically Important Banks*, *Geo. Diversification*, *Deposits, Number of Branches, Population*, *Unemployment, House Price Index*, *Income*, and *Ave. FICO Score*. For the definition of the variables, please refer to Table I. The pre-parallel trend assumption is satisfied, indicating the validity of our analysis. The zip code and the year-month fixed effects are included. Standard errors, given in parentheses, are clustered at the zip code level. *, ** and *** indicate significance at 10%, 5%, and 1%.

	(1) Number (#)	(2) Amount ($)
Pre-Event	0.00596	109.1
	(0.00459)	(77.12)
Share of Small Banks	0.000248	6.783
	(0.000568)	(9.048)
Pre-Event × Share of Small Banks	-0.000128	-2.247
	(0.000107)	(1.897)
Event	-0.0199***	-258.0**
	(0.00731)	(114.4)
Event × Share of Small Banks	4.00e-05	0.529
	(0.000271)	(4.516)
Post-Event	0.0371***	566.5***
	(0.0109)	(165.1)
Post-Event × Share of Small Banks	-0.000700***	-11.24***
	(0.000248)	(3.982)
Constant	-0.819***	-16,854***
	(0.197)	(3,383)
Observations	5,026	5,026
Adjusted R-squared	0.922	0.898
ZIPCode Controls	Yes	Yes
ZIPCode Fixed Effects	Yes	Yes
Year-Month Fixed Effects	Yes	Yes

Table VII. Marketplace Loans Demand and Concentration of Banking Market

This table reports the results of estimating Equation (2) by replacing the *Share of Small Banks* with the *HHI*. In column (1), the dependent variable is the *Number of Loan Applications*, and in column (2), the dependent variable is the *Loan Volume Demanded*. The study period is from 2013 to 2017. We use a sample of 5,026 zip code-month observations. *Pre-Event* equals one for the five months before the event and zero otherwise. *Event* is equal to one for the month a natural disaster occurs and zero otherwise. *Post-Event* equals one for the three months after the event and zero otherwise. ZIPCode Controls include *Share of Small Banks*, *Share of National Banks*, *Share of Systemically Important Banks*, *Geo. Diversification*, *Deposits, Number of Branches, Population*, *Unemployment, House Price Index*, *Income*, and *Ave. FICO Score*. For the definition of the variables, please refer to Table I. The pre-parallel trend assumption is satisfied, indicating the validity of our analysis. The zip code and the year-month fixed effects are included. Standard errors, given in parentheses, are clustered at the zip code level. *, ** and *** indicate significance at 10%, 5%, and 1%.

	(1) Number (#)	(2) Amount ($)
Pre-Event	0.00476	102.5*
	(0.00362)	(61.48)
HHI	1.02e-05	0.338
	(2.20e-05)	(0.349)
Pre-Event × HHI	-4.02e-06	-0.107
	(3.80e-06)	(0.0689)
Event	-0.0212***	-266.9***
	(0.00513)	(88.51)
Event × HHI	4.62e-06	0.0391
	(6.53e-06)	(0.116)
Post-Event	0.0248***	421.2***
	(0.00807)	(127.3)
Post-Event × HHI	-9.20e-06	-0.273
	(1.29e-05)	(0.171)
Constant	-0.830***	-17,106***
	(0.202)	(3,463)
Observations	5,026	5,026
Adjusted R-squared	0.922	0.898
ZIPCode Controls	Yes	Yes
ZIPCode Fixed Effects	Yes	Yes
Year-Month Fixed Effects	Yes	Yes

Table VIII. Quality of Marketplace Loans Applicants and Natural Disasters

This table reports the results of estimating Equation (3). The dependent variable is *Zip Code FICO Score,* which is defined as the average FICO score of all applicants within a given zip code for a given month. The study period is from 2013 to 2017. We use a sample of 5,026 zip code-month observations. *Pre-Event* equals one for the five months before the event and zero otherwise. *Event* is equal to one for the month a natural disaster occurs and zero otherwise. *Post-Event* equals one for the three months after the event and zero otherwise. ZIPCode Controls include *Share of Small Banks*, *HHI*, *Share of National Banks*, *Share of Systemically Important Banks*, *Geo. Diversification*, *Deposits, Number of Branches, Population*, *Unemployment, House Price Index*, *Income*. For the definition of the variables, please refer to Table I. The pre-parallel trend assumption is satisfied, indicating the validity of our analysis. The zip code fixed effects and the year-month fixed effects are included. Standard errors, given in parentheses, are clustered at the zip code level. *, ** and *** indicate significance at 10%, 5%, and 1%.

	(1) Zip Code FICO Score	(2) Zip Code FICO Score
Pre-Event	-0.00350	0.00555
	(0.788)	(0.792)
Event	2.445**	2.444**
	(0.998)	(0.987)
Post-Event	0.592	0.576
	(0.908)	(0.926)
Constant	648.2***	697.3***
	(0.102)	(20.81)
Observations	5,026	5,026
Adjusted R-squared	0.740	0.741
ZIPCode Controls	No	Yes
ZIPCode Fixed Effects	Yes	Yes
Year-Month Fixed Effects	Yes	Yes

Table IX. Approval Rate

This table reports the results of estimating Equation (4). The dependent variable is *Reject*, which takes a value of one if the applicant's loan is rejected and zero otherwise. The study period is from 2013 to 2017. *Pre-Event* equals one for the five months before the event and zero otherwise. *Event* is equal to one for the month a natural disaster occurs and zero otherwise. *Post-Event* equals one for the three months after the event and zero otherwise. Column (1) indicates results without controlling for the zip codes' characteristics, while column (2) includes zip code control variables. ZIPCode Controls include *Share of Small Banks*, *HHI*, *Share of National Banks*, *Share of Systemically Important Banks*, *Geo. Diversification*, *Deposits, Number of Branches, Population*, *Unemployment, House Price Index*, *Income*, and *Ave. FICO Score*. The individual and loan control variables include *Amount*, *FICO Score*, *Debt-to-Income*, and *Length of Employment*. For the definition of the variables, please refer to Table I. The pre-parallel trend assumption is satisfied, indicating the validity of our analysis. The zip code fixed effects and the year-month fixed effects are included. Standard errors, given in parentheses, are clustered at the zip code level. *, ** and *** indicate significance at 10%, 5%, and 1%.

	(1) Reject	(2) Reject
Pre-Event	0.0197*	0.011
	(0.0102)	(0.007)
Event	0.0252	0.018
	(0.0265)	(0.025)
Post-Event	8.46e-05	-0.006
	(0.0141)	(0.0141)
Constant	-1.218***	-0.32
	(0.109)	(0.53)
Observations	693,494	693,494
ZIPCode Controls	No	Yes
Borrower and Loan Controls	Yes	Yes
ZIPCode Fixed Effects	Yes	Yes
Year-Month Fixed Effects	Yes	Yes
Pseudo R-squared	0.422	0.422

Table X. Loan Subgrades and Natural Disasters

This table reports the results of estimating Equation (5). The dependent variable is *Subgrade*, which takes a range of values from 1 to 35. The study period is from 2013 to 2017. *Pre-Event* equals one for the five months before the event and zero otherwise. *Event* is equal to one for the month a natural disaster occurs and zero otherwise. *Post-Event* equals one for the three months after the event and zero otherwise. Column (1) indicates results without controlling for the zip codes' characteristics, while column (2) includes zip code control variables. ZIPCode Controls include *Share of Small Banks*, *HHI*, *Share of National Banks*, *Share of Systemically Important Banks*, *Geo. Diversification*, *Deposits, Number of Branches, Population*, *Unemployment, House Price Index*, *Income*, and *Ave. FICO Score*. The individual and loan control variables include *Amount*, *FICO Score, Debt-to-Income, Length of Employment, Maturity, Length of Credit, Homeownership, Revolving Balance, Total Credit Line, Open Accounts, Revolver Utilization, Annual Income, Inquiries Last 6 Months, Delinquency Last 2 Years, Delinquency,* and *Application Type*. For the definition of the variables, please refer to Table I. The pre-parallel trend assumption is satisfied, indicating the validity of our analysis. The zip code fixed effects and the year-month fixed effects are included. Standard errors, given in parentheses, are clustered at the zip code level. *, ** and *** indicate significance at 10%, 5%, and 1%.

	(1) Subgrade	(2) Subgrade
Pre-Event	-0.0550	-0.0694
	(0.0430)	(0.0463)
Event	0.0268	0.0139
	(0.0861)	(0.0859)
Post-Event	0.0890*	0.0772
	(0.0482)	(0.0531)
Constant	-20.29***	-18.77***
	(0.796)	(2.229)
Observations	261,352	261,352
Adjusted R-squared	0.435	0.435
ZIPCode Controls	No	Yes
Borrower and Loan Controls	Yes	Yes
ZIPCode Fixed Effects	Yes	Yes
Year-Month Fixed Effects	Yes	Yes

Table XI. Interest Rate

This table reports the results of estimating Equation (5) by replacing the *Subgrade* with the *Interest Rate* as the dependent variable; additionally, we control for the *Subgrade* in this specification. The study period is from 2013 to 2017. *Pre-Event* equals one for the five months before the event and zero otherwise. *Event* is equal to one for the month a natural disaster occurs and zero otherwise. *Post-Event* equals one for the three months after the event and zero otherwise. Column (1) indicates results without controlling for the zip codes' characteristics, while column (2) includes zip code control variables. ZIPCode Controls include *Share of Small Banks*, *HHI*, *Share of National Banks*, *Share of Systemically Important Banks*, *Geo. Diversification*, *Deposits, Number of Branches, Population*, *Unemployment, House Price Index*, *Income*, and *Ave. FICO Score*. The individual and loan control variables include *Amount*, *FICO Score, Debt-to-Income, Length of Employment, Maturity, Subgrade, Length of Credit, Homeownership, Revolving Balance, Total Credit Line, Open Accounts, Revolver Utilization, Annual Income, Inquiries Last 6 Months, Delinquency Last 2 Years, Delinquency,* and *Application Type*. For the definition of the variables, please refer to Table I. The pre-parallel trend assumption is satisfied, indicating the validity of our analysis. The zip code fixed effects and the year-month fixed effects are included. Standard errors, given in parentheses, are clustered at the zip code level. *, ** and *** indicate significance at 10%, 5%, and 1%.

	(1) Interest Rate	(2) Interest Rate
Pre-Event	0.00627	0.00114
	(0.00818)	(0.00814)
Event	0.00971	0.00433
	(0.0138)	(0.0131)
Post-Event	0.0149	0.00894
	(0.0110)	(0.0111)
Constant	29.49***	30.00***
	(0.173)	(0.373)
Observations	261,352	261,352
Adjusted R-squared	0.976	0.976
ZIPCode Controls	No	Yes
Borrower and Loan Controls	Yes	Yes
ZIPCode Fixed Effects	Yes	Yes
Year-Month Fixed Effects	Yes	Yes

Table XII. Performance of Borrowers

This table reports the results of estimating Equation (6). The dependent variable is *Bad Loan,* which is an indicator that takes the value of one if the loan has been charged off, defaulted, or is late between 31 and 120 days; otherwise, it is assigned the value of zero. The study period is from 2013 to 2017. *Pre-Event* equals one for the five months before the event and zero otherwise. *Event* is equal to one for the month a natural disaster occurs and zero otherwise. *Post-Event* equals one for the three months after the event and zero otherwise. Column (1) indicates results without controlling for the zip codes' characteristics, while column (2) includes zip code control variables. ZIPCode Controls include *Share of Small Banks*, *HHI*, *Share of National Banks*, *Share of Systemically Important Banks*, *Geo. Diversification*, *Deposits, Number of Branches, Population*, *Unemployment, House Price Index*, *Income*, and *Ave. FICO Score*. The individual and loan control variables include *Amount*, *FICO Score, Debt-to-Income, Length of Employment, Maturity, Interest Rate, Subgrade, Length of Credit, Homeownership, Revolving Balance, Total Credit Line, Open Accounts, Revolver Utilization, Annual Income, Inquiries Last 6 Months, Delinquency Last 2 Years, Delinquency,* and *Application Type*. For the definition of the variables, please refer to Table I. The pre-parallel trend assumption is satisfied, indicating the validity of our analysis. The zip code fixed effects and year-month fixed effects are included. Standard errors, given in parentheses, are clustered at the zip code level. *, ** and *** indicate significance at 10%, 5%, and 1%.

	(1) Bad Loan	(2) Bad Loan
Pre-Event	0.0225*	0.0242*
	(0.0131)	(0.0139)
Event	-0.0343	-0.0336
	(0.0271)	(0.0269)
Post-Event	0.0101	0.0123
	(0.0137)	(0.0131)
Constant	1.171***	0.275
	(0.267)	(0.656)
Observations	261,352	261,352
ZipCode Controls	No	Yes
Borrower and Loan Controls	Yes	Yes
ZIPCode Fixed Effects	Yes	Yes
Year-Month Fixed Effects	Yes	Yes
Pseudo R-squared	0.0814	0.0816

Figure 1. Number of the FDIC-insured Commercial Bank Branches

This figure shows the number of FDIC-insured commercial bank branches in the United States from 2000 to 2020. The figure indicates that the number of branches increased until 2009, after which the overall trend was a reduction in the number of branches.

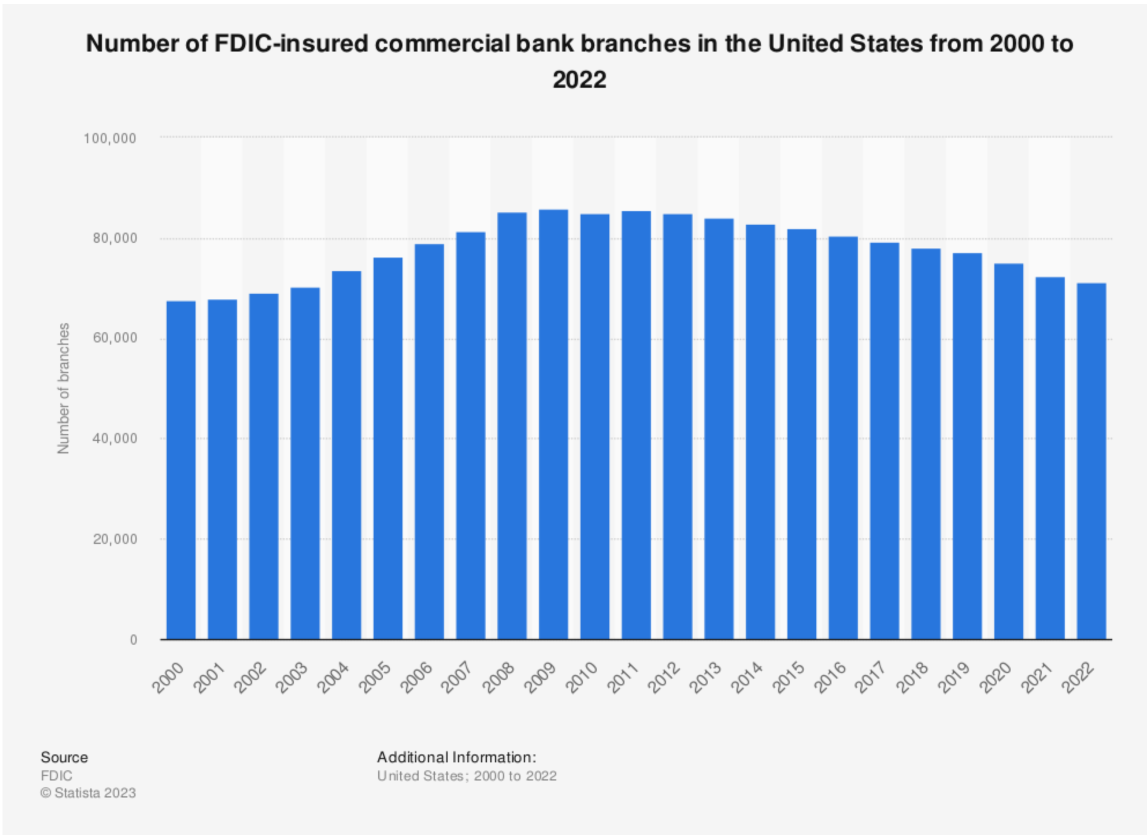


Figure 2. Geographical Distribution of Affected Zip Codes

This figure illustrates a visual representation of the distribution of zip codes affected by natural disasters between the years 2013 and 2017 at the first three-digit zip code level.

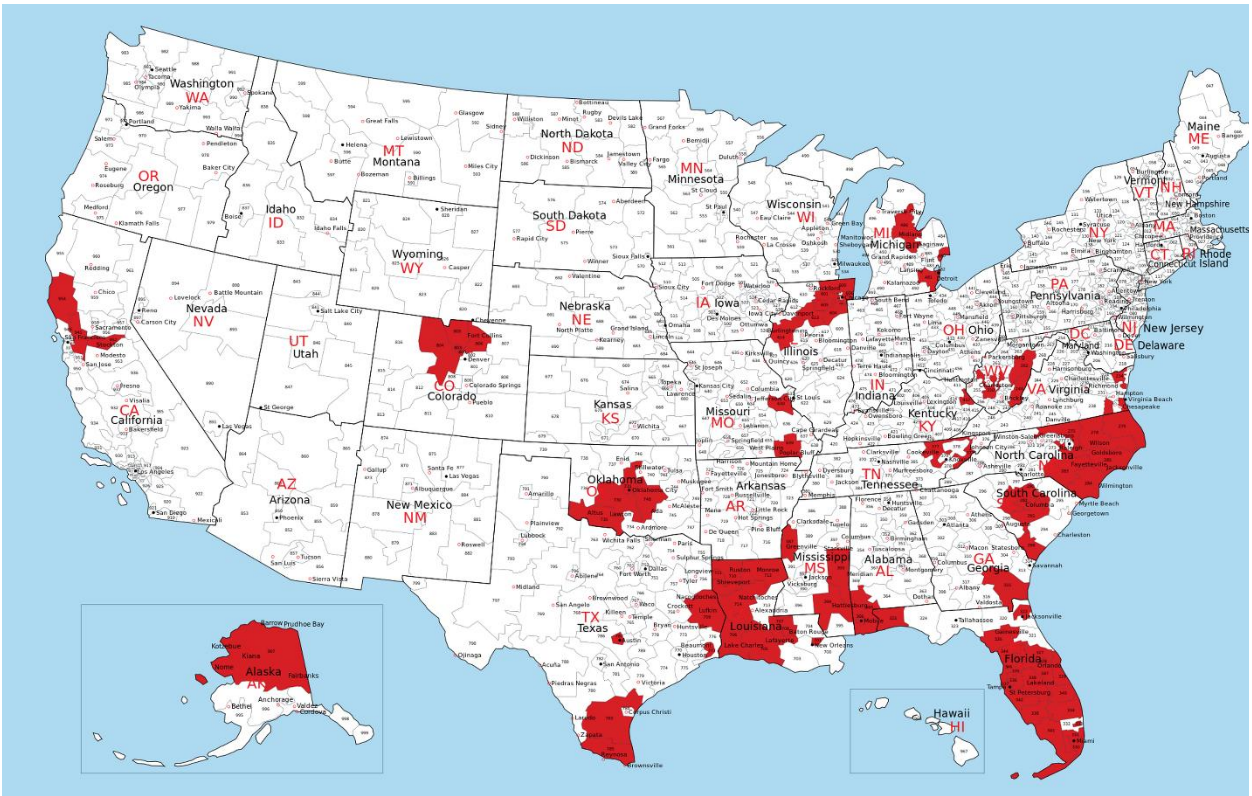
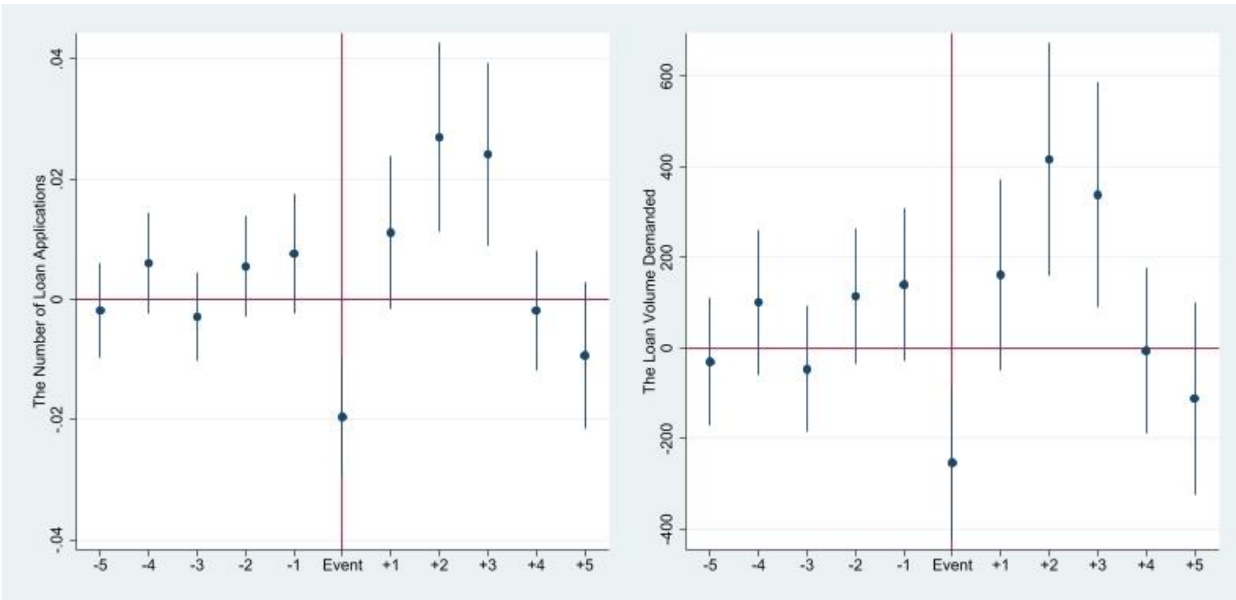


Figure 3. The Dynamics of the Effect of Natural Disasters on the Demand for Marketplace Loans

This figure illustrates the outcomes of estimating Equation (1) by substituting the event indicators with their corresponding monthly indicators while also taking into account the five months following a natural disaster. The left panel of the figure displays the results when the dependent variable is the *Number of Loan Applications*, while the right panel shows the results when the dependent variable is the *Loan Volume Demanded*.



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