

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

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ABSTRACT

What role does marketplace lending play in the aftermath of natural disasters? Using robust staggered difference-in-differences estimators on more than seven million LendingClub loan applications across 61 U.S. disasters over the key expansion phase of marketplace lending, we find that loan demand increases by nearly 11% in the months following a disaster. During the disaster month itself, the platform becomes only marginally more selective. Borrower quality exhibits only a modest statistically significant improvement following natural disasters. Approved applicants receive almost the same subgrades as before, and interest rates remain unchanged. Importantly, the repayment performance of loans originated in the months after a disaster does not deteriorate. Overall, the findings indicate that marketplace lending efficiently absorbs the surge in credit demand following natural disasters, offering useful insights for policymakers.

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

JEL Classifications: D14, E51, G2, Q54

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1. Introduction

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. \(2024\)](#)); 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

[Insert figure 1 here]

The rate at which branches are closed is expected to be even higher 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.

Marketplace lending began in the early 2000s, and it has been grown at a faster pace since 2009 ([Vallee and Zeng \(2019\)](#)). Precedence Research reports that the global peer-to-peer (P2P) lending market was valued at USD 139.80 billion in 2024 and is expected to exceed USD 1,400 billion by

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

² The number of bank branches EU member declines by more than 50% from 2008 to 2024. From 2012 to 2025, the UK saw a sharp reduction in bank branches, dropping from 11,355 to around 4,302.

2034.³ This growth is fueled 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

³ According to the report by [Precedence Research](#).

⁴ According to the report by [Precedence Research](#).

methodologies. These differences have notable implications, particularly in natural disasters. Marketplace lending is immune to 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, small banks and local branches can provide credit to households affected by natural disasters based on relationship banking ([Abedifar et al. \(2024\)](#)). 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 61 natural disasters - hurricanes, severe storms, tornadoes, floods, and others – from 2013 to 2017, a period marked by a sharp contraction in bank branch networks and a rapid expansion of marketplace lending activities.⁵ We use more than seven million loan applications from LendingClub over this period. We also use the FEMA dataset to determine the affected ZIP

⁵ According to the *Global Alternative Finance Market Benchmarking Report* (Ziegler et al., 2021), the global online alternative finance market expanded dramatically from USD 11 billion in 2013 to USD 418 billion in 2017, with peer-to-peer (marketplace) consumer lending accounting for approximately 60 percent of total market volume in 2017.

codes.⁶ To address concerns about bias in conventional two-way fixed effects estimators, we adopt recent advances in staggered difference-in-differences methods. For continuous outcomes, we follow [Callaway and Sant'Anna \(2021\)](#), which accounts for variation in treatment timing and avoids the negative weighting problem of standard approaches. For binary outcomes, we apply the framework of [Wooldridge \(2025\)](#). This approach estimates treatment effects as changes in outcome probabilities, aggregated based on event-time, and allows for formal testing of pre-trends to ensure the validity of our identification strategy.

Our findings reveal a significant, though delayed, surge in credit demand on the platform following a natural disaster. While there is no statistically significant change in loan volume during the event month itself, demand increases substantially in the subsequent months, peaking at approximately \$350 per thousand inhabitants (an increase of nearly 11%) in the three months post-event. This effect is most pronounced in areas with a lower share of small banks, supporting the hypothesis that marketplace lending serves as a key substitute for traditional credit in markets where relationship banking is less prevalent.

The quality of marketplace loan applicants shows a small but statistically significant improvement after natural disasters. Average credit scores in our sample are around 651, and the post-disaster increase amounts to roughly 0.4% of the mean. Although the approval rate declines by 0.42 percentage points in the disaster month—a change that is statistically significant—the magnitude of the effect is economically small, even irrelevant. By contrast, evidence from traditional financing suggests that loan approval probabilities tend to decline when demand rises following natural shocks ([Berg and Schrader \(2012\)](#); [Collier and Babich \(2019\)](#)). The comparison

⁶ 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.

suggests that marketplace lending continues to provide access to finance, unlike traditional institutions, during such events. Moreover, the marketplace platform generally does not assign worse subgrades or higher interest rates to applicants, a response that contrasts with banks, which typically widen loan spreads when exposed to natural disasters ([Huang et al. \(2020\)](#); [Correa et al. \(2020\)](#))).

The consistent response of the marketplace lending during natural disasters, as observed in the unchanged approval rate after natural disasters, 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 no worse than those borrowing under normal conditions. 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. Section 2 provides a comprehensive review of the existing literature. Section 3 presents information about the dataset used in the study, while Section 4 outlines the methodology employed in the analysis. In Section 5, the results of the research are discussed and examined. Finally, Section 6 presents the concluding remarks and summarizes the paper's key findings.

2. 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 asymmetric information with 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. \(2024\)](#), [Koetter et al. \(2020\)](#)).

With the emergence of disruptive innovation in lending, and the rise of FinTech, 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.

3. 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.

Our analysis covers all major natural disasters recorded by FEMA that resulted in positive financial assistance. This comprehensive coverage ensures that we capture the full spectrum of disaster shocks affecting U.S. households and communities during the sample period. Figure (2) presents a geographical visualization that illustrates the distribution of ZIP codes affected by natural disasters.

[Insert figure 2 here]

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 incorporate a range of banking sector control variables derived from the Federal Deposit Insurance Corporation's (FDIC) Summary of Deposits database. Additionally, we consider variables including the dollar amount of deposits per thousand ZIP code inhabitants, the share of small banks and national banks and systemically 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.

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 systemically 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 and aggregate data based on the ZIP code. Therefore, we have 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.

We first create time indicators around each natural disaster to capture periods before and after the event. To ensure the exclusion of potential overlaps, we then remove ZIP codes that experience overlapping indicators between five months before a disaster and twelve months after. We also exclude ZIP codes that exhibited no demand for marketplace loans for more than two consecutive months. The final dataset includes all ZIP codes available in the LendingClub records, where some are classified as treated because they were affected by a disaster, while others remain untreated and serve as controls. Finally, we merge this dataset with ZIP code-level control variables to account for local banking market structure and demographic characteristics.

3.1. Summary statistics

The sample consists of 701 unique ZIP codes with 7,356,997 applications, out of which 1,308,033 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 \$3,200, with values ranging from a

minimum of about \$0 to a maximum of \$20,887. The HHI for the ZIP codes in our sample has an average value of 677, with a minimum of 43 and a maximum of 9,154. The proportion of small banks in a given ZIP code varies from 0% to 100%, with an average of approximately 28%. The population of a ZIP code is, on average, around 367,000 residents, with a minimum of about 11,877 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 644 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 11 open accounts and pay approximately 13% interest rate 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 61 events in our sample. Floods and severe storms are the most frequently observed disasters in the sample, each occurring seventeen times.

[Insert table IV here]

4. Methodology and econometric specification

This study employs modern econometric approaches to estimate the causal impact of natural disasters on marketplace lending outcomes in a staggered difference-in-differences setting. Because disasters occur at different times across ZIP codes, standard two-way fixed effects models may yield biased estimates due to treatment effect heterogeneity and negative weighting (Goodman and Bacon (2021)). To address this, we adopt recent frameworks developed by Callaway and Sant’Anna (2021) and Wooldridge (2025), which are well-suited to our context and the nature of our dependent variables.

For continuous outcomes—including the amount of loans, number of loans, average loan quality, subgrades, and interest rates—we use the estimator proposed by Callaway and Sant’Anna (2021). Their approach identifies average treatment effect on the treated (ATT(g,t)), where groups are defined by the period of first treatment (i.e., the timing of the disaster). The method allows for treatment effect heterogeneity across groups and over time, accommodates both panel and repeated cross-sectional data, and avoids the biases of traditional TWFE models. In line with their framework, we present group-time average treatment effects as well as aggregated effects, structured in an event-study dynamic format.

In Callaway and Sant’Anna (2021), the causal parameter of interest is the group-time average treatment effect:

$$ATT(g, t) = \mathbb{E}[Y_t(g) - Y_t(0) \mid G = g] \quad (1)$$

where $Y_t(g)$ is the potential outcome at time t if first treated in month g , and $Y_t(0)$ is the untreated potential outcome.

To estimate these effects, we use the doubly robust inverse probability weighting (DR-IPW) estimator of [Sant’Anna and Zhao \(2020\)](#). It is particularly well-suited to our context with repeated cross-sections and heterogeneous treatment effects. As the comparison group, we use never-treated ZIP codes as control units. Aggregated effects are then obtained by averaging the estimates $ATT(g, t)$ across groups and event times.

For binary dependent variables—including loan approval and loan performance status—we employ the estimator proposed by [Wooldridge \(2025\)](#). [Wooldridge \(2025\)](#) provides a regression-based framework for estimating causal effects in staggered adoption settings that avoids the negative-weighting problem of conventional TWFE estimators.

In our application, we estimate a linear probability model (LPM) with treatment defined by the first month of a disaster at the ZIP code level. The model can be expressed as:

$$Y_{i,z,t} = \alpha_z + \gamma_t + \sum_{g \in G} \sum_{s=g}^T \beta_{g,s} D_{i,g,s} + X'_{i,z,t} \delta + \varepsilon_{i,z,t} \quad (2)$$

where $Y_{i,z,t}$ is the binary outcome for unit i in ZIP code z in month t , α_z are ZIP code fixed effects, γ_t are year-month fixed effects, the summation is the sum of treatment effect terms over all treatment cohorts g and periods s . Each $\beta_{g,s}$ is a treatment effect for the cohort g in a period s . $D_{i,s,g}$ is an indicator (dummy) equal to 1 if the ZIP code z belongs to cohort g and the current time s is on or after g ; otherwise, 0. $X'_{i,z,t}$ is the transpose of the covariate vector, used to multiply with the coefficient vector δ . $\varepsilon_{i,z,t}$ is the error term.

This specification embeds the staggered timing structure directly into the regression model and allows us to recover cohort- and time-specific treatment effects. The linear probability formulation

provides easily interpretable estimates, where coefficients can be read directly as changes in approval or default probabilities (in percentage points). We then aggregate these estimates to obtain average treatment effects on the treated (ATTs), as well as event-study profiles that show the dynamic path of effects around disaster exposure.

For both approaches, inference is based on robust standard errors clustered at the ZIP code level.

4.1. The demand for marketplace loans after natural disasters

In this section, we investigate the impact of natural disasters on the demand for marketplace loans. Our focus is on whether loan applications and loan volumes increase in affected areas following disaster events, and how these responses evolve over time.

4.1.1. The average effect of natural disasters on marketplace loans demand

To estimate the causal effect of natural disasters on loan demand, we use the staggered difference-in-differences framework of [Callaway and Sant’Anna \(2021\)](#) to calculate $ATT(g,t)$. This approach is well-suited for our setting, where different ZIP codes experience disasters at different times. Specifically, we implement the doubly robust inverse probability weighting (DR-IPW) estimator of [Sant’Anna and Zhao \(2020\)](#), which combines outcome regression with stabilized inverse probability weights.

Treatment cohorts are defined by the first month in which a ZIP code experiences a natural disaster. ZIP codes that never experience a disaster during our sample period serve as the control group. This setup allows us to estimate group-time average treatment effects ($ATT(g,t)$), which

measure the difference in loan demand between treated and never-treated ZIP codes in each period relative to the treatment date.

Control variables include ZIP code-level controls, following the literature (e.g., [Jagtiani and Lemieux \(2018\)](#) and [Tang \(2019\)](#)). These 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*. The definitions of the variables can be found in Table I. Robust standard errors are clustered at the ZIP code level.

4.1.2. Marketplace loans demand and banking market structure

To investigate whether the effect of natural disasters on marketplace loan demand depends on local banking structure, we analyze heterogeneity by the share of small banks in each ZIP code. We split the dataset into two mutually exclusive subsamples. ZIP codes with a share of small banks below 45% are classified as *low small-bank areas*, while those with a share above 55% are classified as *high small-bank areas*. To ensure a clean comparison, ZIP codes with shares between 45% and 55% are excluded from this analysis.

For each subsample, we re-estimate the [Callaway and Sant’Anna \(2021\)](#) staggered DiD model with DR-IPW, using never-treated ZIP codes as controls. This design allows us to compare whether marketplace loan demand reacts differently to natural disasters depending on the local prevalence of relationship banking. We employ the same set of control variables as in Section A.1. Robust standard errors are clustered at the ZIP code level.

4.2. *Quality of marketplace loans applicants and natural disasters*

Next, we study how borrower quality responds to natural disasters in the marketplace lending sector. A shift in average borrower quality may reflect migration from banks toward marketplace platforms in disaster-affected areas (see [Tang \(2019\)](#)). To measure quality, we use the average FICO score of all loan applicants at the three-digit ZIP code–month level.

To estimate causal effects, we apply the staggered DiD framework of [Callaway and Sant’Anna \(2021\)](#), implemented with the doubly robust inverse probability weighting (DR-IPW) estimator of [Sant’Anna and Zhao \(2020\)](#). Treatment cohorts are defined by the month in which a ZIP code first experiences a disaster, while never-treated ZIP codes serve as the control group.

Control variables 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*. Robust standard errors are clustered at the ZIP code level.

4.3. *Response of marketplace lending*

Following our examination of the effect of natural disasters on marketplace loan demand, it is essential to investigate the response of marketplace lending platforms to potential changes in demand. Specifically, we study whether access to credit changes by analyzing the loan approval rate.

For this binary outcome, we apply the [Wooldridge \(2025\)](#) staggered DiD estimator. Estimation is carried out using a linear probability model (LPM), which provides directly interpretable estimates of changes in approval probabilities (measured in percentage points). Treatment cohorts

are defined by the first disaster month at the ZIP code level, and never-treated ZIP codes serve as the comparison group.

We apply the staggered DiD framework of [Wooldridge \(2025\)](#), where the dependent variable is $\text{Reject}_{i,z,t} = 1$ if the loan application i in ZIP code z and month t is rejected, and 0 otherwise. α_z and γ_t are ZIP code and time fixed effects, respectively, while $\beta_{g,t}$ captures the treatment effect for cohort g at time t .

Our objective is to understand how the occurrence of natural disasters influences the likelihood of a loan rejection. The control variables consist of borrower- and loan-specific characteristics—such as requested loan amount, FICO score, debt-to-income ratio, and length of employment—alongside banking structure variables and ZIP code level factors. Standard errors are computed robustly and clustered at the ZIP code level.

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 use subgrade data instead of grade data because it provides greater precision in measuring credit risk. While grade data ranges from 1 (worst) to 7 (best), subgrades range from 1 to 35, offering a more granular assessment of borrower risk. To study whether natural disasters influence

the credit risk evaluation of marketplace lending, we treat the assigned subgrade as the outcome variable.

Estimation is carried out within the [Callaway and Sant’Anna \(2021\)](#) staggered DiD framework, using the doubly robust inverse probability weighting (DR-IPW) estimator of [Sant’Anna and Zhao \(2020\)](#). Treatment cohorts are defined by the first disaster month at the ZIP code level, and never-treated ZIP codes serve as the control group. Control variables include *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 also included. The variable definition is provided in Table I.

Next, we examine whether natural disasters influence the interest rates charged by the marketplace lender. Our objective is to assess whether lending platforms adjust loan pricing in response to increased credit demand and potential risk following disasters.

We estimate this relationship using the [Callaway and Sant’Anna \(2021\)](#) staggered DiD framework with the doubly robust inverse probability weighting (DR-IPW) estimator of [Sant’Anna and Zhao \(2020\)](#). Treatment cohorts are defined by the first disaster month for each ZIP code, and never-treated ZIP codes serve as the control group.

In this specification, the interest rate on funded loans is the dependent variable, and we add subgrade as a key control to our model to capture borrower risk classification. Borrower-level controls and ZIP code level variables are included. Robust standard errors are clustered at the ZIP level.

4.4. Performance of borrowers

Lastly, we study the performance of borrowers who obtain loans during and after natural disasters. Borrower repayment outcomes provide insight into the effectiveness of marketplace lender’s screening process in identifying creditworthy applicants under heightened demand conditions and potential risk of default following natural disasters.

For this binary outcome, we employ the [Wooldridge \(2025\)](#) staggered DiD estimator with a linear probability model (LPM). Treatment cohorts are defined by the month in which a ZIP code first experiences a disaster, and never-treated ZIP codes serve as the comparison group.

We apply the staggered DiD framework of [Wooldridge \(2025\)](#), we use equation (2) where the dependent variable is *BadLoan*. $BadLoan_{i,z,t} = 1$ if a loan *i* in the ZIP code *z* and month *t* has been charged off, defaulted, or is late between 31 and 120 days, and 0 otherwise. ZIP code and time fixed effects are included, and robust standard errors are clustered at the ZIP code level.

5. Empirical results

5.1. 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.

5.1.1. The average effect of natural disasters on marketplace loan demand

We estimate $ATT(g, t)$ using Equation (1), following the [Callaway and Sant'Anna \(2021\)](#) framework with the DR-IPW estimator, to examine whether marketplace loan demand exhibits abnormal changes 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 coefficients from four to two months prior to the event are statistically insignificant, suggesting that the parallel trends assumption holds.

[Insert table [V](#) here]

In the first column, we consider the *Number of Loan Applications* as the dependent variable. The results show no significant change in the disaster month itself, indicating that loan application flow remains stable during the event. However, in the three months following a disaster, the number of applications increases significantly (11.7% of the average number of loan applications in our sample). In the second column, the dependent variable is the *Loan Volume Demanded*. Similar to the number of application results, we do not observe a statistically significant change during the disaster month. In contrast, the three months after a disaster are characterized by a significant increase in the volume of loan applications (10.9% of the average), consistent with households turning to marketplace lending to finance recovery needs.

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.

5.1.2. Marketplace loans demand and banking market structure

To examine whether the effect of natural disasters on marketplace loan demand depends on local banking structure, we analyze heterogeneity by the share of small banks in each ZIP code. We split the dataset into two subsamples.

We estimate the [Callaway and Sant’Anna \(2021\)](#) staggered DiD model with the DR-IPW estimator for each subsample, using never-treated ZIP codes as controls. The results, reported in [Table VI](#), show that the post-disaster increase in the *Number of Loan Applications* and *Loan Volume Demanded* is concentrated in *low small-bank areas*. By contrast, in high small-bank areas, the increase in the *Number of Loan Applications* and *Loan Volume Demanded* is smaller and statistically weaker, consistent with the idea that relationship banking provided by small banks helps absorb part of the post-disaster credit need. This interpretation aligns with earlier studies ([DeYoung et al. \(2004\)](#); [Abedifar et al. \(2024\)](#); [Koetter et al. \(2020\)](#)), which emphasize the role of small banks in supporting local borrowers during periods of distress.

[Insert [table VI](#) here]

5.2. 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 the effect of natural disasters on borrower quality using Equation (1) within the framework of [Callaway and Sant’Anna \(2021\)](#), implemented with the DR-IPW estimator of [Sant’Anna and Zhao \(2020\)](#). The dependent variable is the *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 results are reported in Table [VII](#). Our analysis shows that borrower quality, measured by the average FICO score, remains broadly stable around the time of natural disasters. The only significant effect arises two and three months after the event ($t + 2$; $t + 3$), where we observe a modest improvement in applicant quality. The magnitude of this increase is small—about 0.4% relative to the average FICO score in the sample (coefficient = 3.01; average = 651.7)—indicating that, the overall composition of borrowers does not change materially following natural disasters.

[Insert Table [VII](#) here]

5.3. *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 [Berg and Schrader \(2012\)](#), we use the loan approval rate as a proxy for access to finance and estimate its response to natural disasters. We use [Wooldridge \(2025\)](#) staggered DiD framework, implemented with a linear probability model (LPM). The dependent variable is *Reject*, which equals one if the applicant’s loan is rejected and zero otherwise. The results are presented in Table [VIII](#). We find evidence of a short-lived tightening in credit supply during the disaster month. Specifically, the rejection rate increases significantly by about 0.42 percentage points relative to the baseline (the month before a natural disaster), indicating that marketplace lender becomes slightly more selective at the time of the

shock. However, this effect is transitory: in the months following a disaster, approval rates return to pre-disaster levels, and no significant differences are observed.

This pattern stands in contrast with findings from traditional finance. [Berg and Schrader \(2012\)](#) document a sustained reduction in access to microfinance after natural disasters, while [Collier and Babich \(2019\)](#) show that banks reduce lending more persistently under similar conditions. Our results suggest that marketplace lending platforms behave differently. Although there is a brief increase in rejection rates at the moment of the disaster, the marketplace lender quickly reverts to stable approval behavior, consistent with the notion that FinTech models provide greater elasticity in responding to demand shocks ([Berg et al. \(2022\)](#)).

Overall, these findings highlight the resilience of marketplace lending: access to finance remains largely stable, with only a modest and temporary adjustment during the disaster month.

[Insert table [VIII](#) 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 (1) using the [Callaway and Sant’Anna \(2021\)](#) framework with the DR-IPW estimator of [Sant’Anna and Zhao \(2020\)](#), where the dependent variable is *Subgrade*. The results are reported in Table [IX](#). Overall, the analysis shows that the loan subgrades assigned by the marketplace lending platform remain broadly stable around natural disasters. The only significant effect arises three months after the event ($t + 3$), where we observe a small increase in subgrades—about 1.47% relative to the sample mean (coefficient = 0.35; average = 651.7).

[Insert table IX here]

It appears that the marketplace lender does not substantially alter subgrades in response to natural disasters, but they could potentially adjust interest rates to reassure investors supplying capital to the platform. To examine this, we estimate Equation (1) under the Callaway and Sant’Anna (2021) framework with the DR-IPW estimator of Sant’Anna and Zhao (2020), using the interest rate as the dependent variable. Subgrade is included as a key control to account for borrower risk classification, alongside the standard borrower- and ZIP level controls. The results are presented in Table X.

The results show that the coefficients are insignificant, implying that that interest rates do not increase during or 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 X here]

5.4. Performance of borrowers

Finally, we study the performance of borrowers who obtain loans after natural disasters. Having established that marketplace loan demand increases, while access to finance, loan assessment, and loan pricing remain broadly stable, it is crucial to assess whether credit quality changes in the aftermath of these events. To do so, we use the Wooldridge (2025) staggered DiD framework, using a linear probability model (LPM). The dependent variable is *Bad Loan*, which equals one if the applicant’s loan is rejected and zero otherwise. The results are presented in Table XI.

Overall, borrower performance remains largely unchanged during and after natural disasters. The only exception occurs at one month after the disaster ($t + 1$), where we observe a statistically significant decline in default probability of about 1.6 percentage points, suggesting a slight improvement in repayment outcomes. The consistent performance of the marketplace lender can be attributed to its strategic use of advanced technologies. New technologies combine alternative data and traditional data with machine learning techniques to enhance the informational value of available data ([Fuster et al. \(2022\)](#)).

[Insert table [XI](#) here]

6. 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 a marketplace lender to these shocks.

We have uncovered several noteworthy findings using a sample of more than seven million observations from LendingClub and 61 natural disasters that occurred in the U.S. First, we observe an increase in the demand for marketplace loans within three months after natural disasters.

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. 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.

Borrower quality, as measured by FICO scores, slightly improves after natural disasters. Importantly, our results indicate that marketplace lending ensures better financial access than traditional institutions during natural disasters. While prior studies of banks behavior document a decline in loan approval when demand rises after disasters ([Berg and Schrader \(2012\)](#); [Collier and Babich \(2019\)](#)), we find only a minor and temporary increase in rejections by the marketplace lender in the disaster month itself. Additionally, the subgrades and interest rates assigned by the marketplace lender to each borrower profile remain relatively stable, showing no significant deterioration – unlike traditional banks, which tend to widen loan spreads when exposed to natural disasters ([Huang et al. \(2020\)](#), [Correa et al. \(2020\)](#)). More importantly, our analysis shows that the performance of borrowers who obtain loans during natural disasters is no worse than that of borrowers in normal times. These results can be attributed to the use of alternative 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. \(2022\)](#)).

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
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 1. (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 41,926 ZIP code-month observations from 701 ZIP codes, where a major natural disaster occurs. It covers the 2013 to 2017 period. For the variable definition, please refer to Table I. M stands for a million.

Variables	N	Mean	S.D.	Min	Max
Number of Loan Applications	41,926	0.203	0.145	0	1.389
Loan Volume Demanded	41,926	3,198	2,225	0	20,887
Share of Small Banks	41,926	27.87	25.65	0	100
HHI	41,926	677.3	1,011	43.72	9,154
Share of National Banks	41,926	46.93	23.36	0	99.08
Share of Systemically Important Banks	41,926	41.76	26.21	0	99.20
Geo. Diversification	41,926	2.913	3.215	1	35
Deposits	41,926	31,987	115,024	4,112	2.91M
Number of Branches	41,926	25.23	8.427	6.921	79.80
Population	41,926	367,737	391,670	11,877	2.70M
Unemployment	41,926	8.145	2.666	1.345	25.62
House Price Index	41,926	195.5	45.36	95.64	452.8
Income	41,926	71,685	21,142	34,601	190,741
Ave. FICO Score	41,926	651.7	20.87	448	832

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. M stands for a million.

Variables	N	Mean	S.D.	Min	Max
Panel A. All Applications					
Amount	7.35M	13,127	10,541	1,000	40,000
FICO Score	7.35M	644.1	63.60	300	850
Debt-to-Income	7.35M	23.45	19.26	0	100
Length of Employment	7.35M	1.56	3.35	0	11
Panel B. Funded Loans					
Amount	1.30M	14,999	8,860	1,000	40,000
FICO Score	1.30M	695.7	31.25	660	845
Debt-to-Income	1.30M	18.46	8.683	0	100
Length of Employment	1.30M	6.369	4.113	0	11
Maturity	1.30M	0.293	0.455	0	1
Subgrade	1.30M	24.34	6.320	1	35
Interest Rate	1.30M	13.20	4.767	5.320	30.99
Length of Credit	1.30M	16.22	7.312	3	83
Revolving Balance	1.30M	16,720	20,709	0	1.19M
Total Credit Line	1.30M	24.61	11.88	2	176
Open Accounts	1.30M	11.81	5.588	1	97
Revolver Utilization	1.30M	52.15	24.02	0	100
Annual Income	1.30M	76,243	40,369	600	275,000
Inquiries Last 6 Months	1.30M	0.598	0.896	0	6
Delinquency Last 2 Years	1.30M	0.341	0.917	0	39
Delinquency	1.30M	0.00416	0.0643	0	1
Application Type	1.30M	0.0278	0.164	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	17
Severe Storm	17
Hurricane	14
Tornado	5
Fire	4
Typhoon	1
Mud/Landslide	1
Earthquake	1
Other	1
Total	61

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

This table reports the results of estimating Equation (1) using the [Callaway and Sant'Anna \(2021\)](#) staggered DiD framework with the doubly robust inverse probability weighting (DR-IPW) estimator of [Sant'Anna and Zhao \(2020\)](#). 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 covers 2013–2017. We use a sample of 41,926 ZIP code-month observations.

Treatment cohorts are defined by the first disaster month at the ZIP code level, while ZIP codes that never experience a disaster serve as the control group. The pre-treatment coefficients are statistically insignificant, supporting the parallel trends assumption. ZIP code 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 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 (\$)
t-4	0.00819 (0.00501)	136.5 (97.06)
t-3	0.00591 (0.00375)	33.73 (84.04)
t-2	0.00205 (0.00553)	38.05 (81.25)
t	-0.00470 (0.00431)	-122.7 (83.17)
t+1	0.00964* (0.00544)	116.8 (100.6)
t+2	0.0181*** (0.00567)	269.3*** (100.4)
t+3	0.0239*** (0.00610)	349.5*** (106.8)
t+4	-0.00169 (0.00681)	-8.585 (124.3)
t+5	-0.00657 (0.00746)	-193.2 (142.8)
t+6	0.00278 (0.00809)	-24.60 (129.5)
ZIP Code Controls	Yes	Yes
ZIP Code Fixed Effects	Yes	Yes
Year-Month Fixed Effects	Yes	Yes

Table VI. Marketplace Loans Demand and Presence of Small Banks

This table reports the results of estimating Equation (1) using the Callaway and Sant’Anna (2021) staggered DiD framework with the DR-IPW estimator of Sant’Anna and Zhao (2020). The analysis is conducted separately for ZIP codes with a low share of small banks ($\leq 45\%$) and those with a high share of small banks ($\geq 55\%$), excluding intermediate cases for clarity. In columns (1) and (3), the dependent variable is the *Number of Loan Applications*, and in columns (2) and (4), the dependent variable is the *Loan Volume Demanded*. The study period is 2013–2017. We use 18,872 and 18,861 ZIP code-month observations for *low small-bank areas* and *high small-bank areas*, respectively.

Treatment cohorts are defined by the first disaster month at the ZIP code level, while ZIP codes that never experience a disaster serve as the control group. The pre-treatment coefficients are statistically insignificant, supporting the parallel trends assumption. ZIP code 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 1. 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%.

	Low Small-Bank Areas		High Small-Bank Areas	
	(1)	(2)	(3)	(4)
	Number (#)	Amount (\$)	Number (#)	Amount (\$)
t-4	-0.00458 (0.00532)	-138.5 (105.5)	0.00159 (0.0242)	223.1 (385.4)
t-3	0.000557 (0.00575)	-79.94 (121.7)	0.00778 (0.00548)	206.8* (114.8)
t-2	-0.00298 (0.00562)	-82.36 (109.0)	0.00959 (0.00761)	234.1 (148.0)
t	-0.0178** (0.00709)	-303.8** (127.4)	0.00836 (0.00547)	134.3 (104.0)
t+1	0.0111 (0.00979)	134.2 (167.3)	-0.000802 (0.00604)	115.1 (114.9)
t+2	0.0220** (0.00886)	310.9** (149.4)	0.0131 (0.00862)	349.9** (170.0)
t+3	0.0383*** (0.0102)	556.8*** (177.3)	0.00865 (0.00944)	159.3 (153.0)
t+4	0.00936 (0.00815)	340.6** (150.1)	-0.00320 (0.00856)	17.71 (147.5)
t+5	0.00160 (0.00760)	95.43 (150.9)	-0.00273 (0.00882)	2.300 (168.5)
t+6	0.00651 (0.00774)	212.2 (138.5)	-0.00440 (0.0107)	-34.45 (180.7)
ZIP Code Controls	Yes	Yes	Yes	Yes
ZIP Code Fixed Effects	Yes	Yes	Yes	Yes
Year-Month Fixed Effects	Yes	Yes	Yes	Yes

Table VII. Quality of Marketplace Loans Applicants and Natural Disasters

This table reports the results of estimating Equation (1) using the [Callaway and Sant’Anna \(2021\)](#) staggered DiD framework with the doubly robust inverse probability weighting (DR-IPW) estimator of [Sant’Anna and Zhao \(2020\)](#). The dependent variable is the *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 covers 2013–2017. We use a sample of 41,926 ZIP code-month observations.

Treatment cohorts are defined by the first disaster month at the ZIP code level, while ZIP codes that never experience a disaster serve as the control group. The pre-treatment coefficients are statistically insignificant, supporting the parallel trends assumption. Column (1) reports results without controlling for the ZIP code characteristics, whereas column (2) includes ZIP code control variables. 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*. They are included in column (2). For the definition of the variables, please refer to Table I. 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
t-4	0.579 (1.291)	0.416 (1.535)
t-3	0.891 (0.878)	1.160 (1.075)
t-2	0.416 (0.904)	0.580 (1.127)
t	0.645 (0.968)	1.205 (1.307)
t+1	0.729 (1.034)	1.637 (1.216)
t+2	2.059* (1.092)	3.011** (1.378)
t+3	1.994 (1.362)	3.322* (1.725)
t+4	0.0543 (1.697)	0.984 (1.945)
t+5	-1.592 (1.770)	0.814 (1.951)
t+6	-2.784 (2.016)	-3.328 (4.348)
ZIP Code Controls	No	Yes
ZIP Code Fixed Effects	Yes	Yes
Year-Month Fixed Effects	Yes	Yes

Table VIII. Approval Rate

This table reports the results of estimating Equation (2) under the [Wooldridge \(2025\)](#) staggered DiD framework, implemented with a linear probability model (LPM). The dependent variable is *Reject*, which equals one if the applicant's loan is rejected and zero otherwise. The study period is 2013–2017, with 7,356,997 individual observations.

Treatment cohorts are defined by the first disaster month at the ZIP code level, while never-treated ZIP codes serve as the control group. The pre-treatment coefficients are statistically insignificant, supporting the parallel trends assumption. Column (1) reports results without controlling for the ZIP code characteristics, whereas column (2) includes ZIP code control variables. ZIP code 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 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
t-4	0.00106 (0.00155)	0.00110 (0.00153)
t-3	0.00231 (0.00153)	0.00232 (0.00151)
t-2	-0.000559 (0.00151)	-0.000553 (0.00150)
t	0.00439*** (0.00151)	0.00418*** (0.00150)
t+1	0.00235 (0.00160)	0.00245 (0.00158)
t+2	0.00211 (0.00162)	0.00216 (0.00160)
t+3	0.00169 (0.00168)	0.00166 (0.00164)
t+4	0.000318 (0.00263)	9.46e-05 (0.00265)
t+5	-0.00308 (0.00261)	-0.00303 (0.00262)
t+6	-0.00389 (0.00256)	-0.00378 (0.00254)
Observations	7,356,997	7,356,997
R-squared	0.52	0.52
ZIP Code Controls	No	Yes
Borrower and Loan Controls	Yes	Yes
ZIP Code Fixed Effects	Yes	Yes
Year-Month Fixed Effects	Yes	Yes

Table IX. Loan Subgrades and Natural Disasters

This table reports the results of estimating Equation (1) using the [Callaway and Sant’Anna \(2021\)](#) staggered DiD framework with the doubly robust inverse probability weighting (DR-IPW) estimator of [Sant’Anna and Zhao \(2020\)](#). The dependent variable is the *Subgrade*. The study period covers 2013–2017. We use a sample of 1,308,033 individual observations.

Treatment cohorts are defined by the first disaster month at the ZIP code level, while ZIP codes that never experience a disaster serve as the control group. In the first column, where no ZIP code controls are included, some pre-treatment coefficients are significant; however, after adding ZIP code controls, the parallel trends assumption holds. Column (1) indicates results without controlling for the ZIP codes’ characteristics, while column (2) includes ZIP code control variables. ZIP code 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 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
t-4	-0.151** (0.0714)	-0.234 (0.203)
t-3	-0.0200 (0.0728)	-0.0679 (0.207)
t-2	0.0391 (0.0795)	-0.000636 (0.148)
t	-0.111 (0.105)	0.0278 (0.134)
t+1	0.00233 (0.0861)	0.0918 (0.173)
t+2	-0.0978 (0.0637)	0.127 (0.0973)
t+3	-0.00938 (0.0852)	0.359** (0.174)
t+4	-0.0643 (0.192)	0.344 (0.503)
t+5	0.0844 (0.187)	0.348 (0.709)
t+6	0.0982 (0.194)	0.456 (1.304)
ZIP Code Controls	No	Yes
Borrower and Loan Controls	Yes	Yes
ZIP Code Fixed Effects	Yes	Yes
Year-Month Fixed Effects	Yes	Yes

Table X. Interest Rate

This table reports the results of estimating Equation (1) using the [Callaway and Sant’Anna \(2021\)](#) staggered DiD framework with the doubly robust inverse probability weighting (DR-IPW) estimator of [Sant’Anna and Zhao \(2020\)](#). The dependent variable is the *Interest Rate*. The study period covers 2013–2017. We use a sample of 1,308,033 individual observations.

Treatment cohorts are defined by the first disaster month at the ZIP code level, while ZIP codes that never experience a disaster serve as the control group. The pre-treatment coefficients are statistically insignificant, supporting the parallel trends assumption. Column (1) indicates results without controlling for the ZIP codes’ characteristics, while column (2) includes ZIP code control variables. ZIP code 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 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
t-4	-0.0308 (0.0416)	-0.0561 (0.0457)
t-3	-0.00417 (0.0135)	-0.0308 (0.0202)
t-2	-0.00136 (0.00782)	-0.0126 (0.00947)
t	0.00798 (0.0141)	-0.00986 (0.0129)
t+1	-0.0190 (0.0150)	-0.0271* (0.0164)
t+2	-0.0334* (0.0201)	0.00440 (0.0185)
t+3	-0.00760 (0.0236)	-0.0232 (0.0237)
t+4	-0.431*** (0.111)	-1.989 (1.226)
t+5	-0.211*** (0.0625)	-1.369 (1.078)
t+6	-0.101 (0.0720)	-1.555 (1.097)
ZIP Code Controls	No	Yes
Borrower and Loan Controls	Yes	Yes
ZIP Code Fixed Effects	Yes	Yes
Year-Month Fixed Effects	Yes	Yes

Table XI. Performance of Borrowers

This table reports the results of estimating Equation (2) under the [Wooldridge \(2025\)](#) staggered DiD framework, implemented with a linear probability model (LPM). The dependent variable is *Bad Loan*, an indicator that takes the value of one if the loan has been charged off, defaulted, or is between 31 and 120 days late; otherwise, it equals zero. The study period is 2013–2017, with 1,308,033 individual observations.

Treatment cohorts are defined by the first disaster month at the ZIP code level, while never-treated ZIP codes serve as the control group. The pre-treatment coefficients are statistically insignificant, supporting the parallel trends assumption. Column (1) indicates results without controlling for the ZIP codes' characteristics, while column (2) includes ZIP code control variables. ZIP code 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 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 Loans	(2) Bad Loans
t-4	-0.00110 (0.00490)	-0.00103 (0.00493)
t-3	-0.00334 (0.00494)	-0.00327 (0.00495)
t-2	-0.00389 (0.00428)	-0.00378 (0.00429)
t	-0.00729 (0.00696)	-0.00717 (0.00686)
t+1	-0.0159*** (0.00504)	-0.0156*** (0.00505)
t+2	-0.00297 (0.00442)	-0.00267 (0.00442)
t+3	-0.00740 (0.00594)	-0.00711 (0.00592)
t+4	-0.00285 (0.00726)	-0.00267 (0.00730)
t+5	-0.000132 (0.00781)	0.000192 (0.00781)
t+6	-0.00338 (0.00709)	-0.00331 (0.00714)
Observations	1,308,033	1,308,033
R-squared	0.07	0.07
ZIP Code Controls	No	Yes
ZIP Code Fixed Effects	Yes	Yes
Year-Month Fixed Effects	Yes	Yes

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 2024. The figure indicates that the number of branches increased until 2009, after which the overall trend was a reduction in the number of branches.

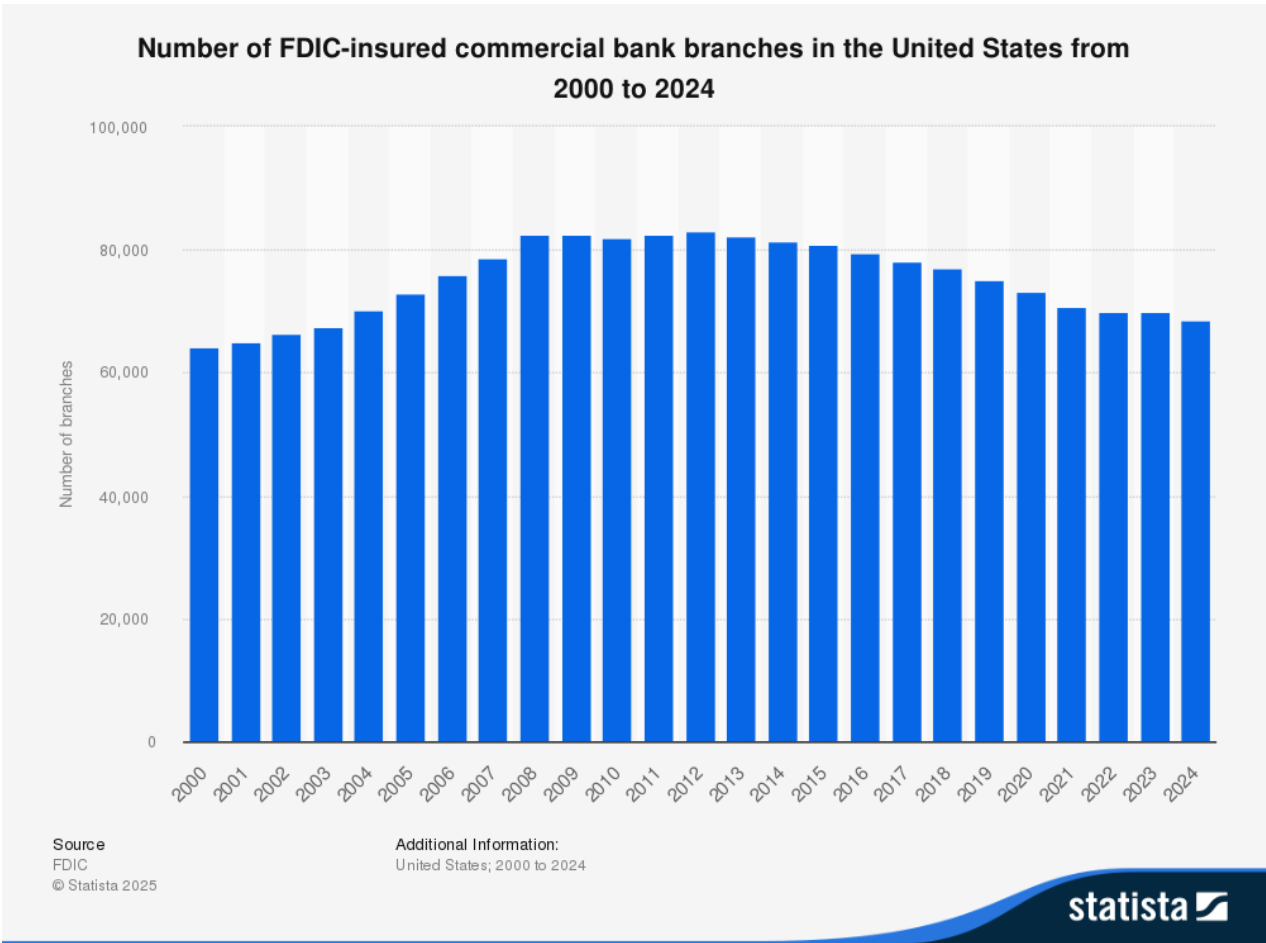


Figure 2. Geographical Distribution of Affected Zip Codes

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.

