The social welfare of marketplace lending: Evidence from natural disasters*

Daniel Bradley

Matthew Henriksson

Sarath Valsalan‡

September 2022

Abstract: Using natural disasters as exogenous shocks to the peer-to-peer (P2P) loan market, we document a local increase in loan demand post-disaster. Interest rates and delinquencies from loans approved during this demand shock are similar to pre-event levels. Loans allocated prior to a disaster are more likely to suffer delinquency over the life of the loan, but loans granted a hardship accommodation delay of payment reduce the likelihood of future delinquency providing relief to borrowers and reduced delinquency costs to investors. Contrary to regulatory concerns that P2P lending is predatory, our results suggest they provide positive social welfare benefits.

Keywords: Marketplace lending, natural disasters, P2P lending, personal loans, FinTech

* We thank Xiao Cen (discussant), Runjing Lu (discussant), seminar participants at Wake Forest University, and conference participants at the 2022 MFA Annual Meeting and 2022 EFA Annual Meeting for their comments and suggestions.

‡ Contact: Daniel Bradley, University of South Florida, Muma College of Business, (Email) danbradley@usf.edu; Matthew Henriksson, University of Mississippi, School of Business Administration, (Email) mhenriksson@bus.olemiss.edu; Sarath Valsalan, University of Mississippi, School of Business Administration, (Email) svalsalan@bus.olemiss.edu.

The social welfare of marketplace lending: Evidence from natural disasters

1. Introduction

Peer-to-peer (P2P) lending, also known as marketplace lending, has emerged as one of the predominant innovations in the FinTech space. These platforms match private lenders with borrowers that may not have been served by traditional financial service providers. The P2P lending market has experienced explosive growth in the past decade that is expected to continue. For instance, in 2019 the P2P market was valued at $68 billion and is anticipated to reach $559 billion by 2027.[1] Proponents of P2P markets argue that they provide borrowers more options and access to financial markets with less inefficiencies and hurdles compared to other financial market channels. Opponents suggest that it is a form of predatory lending with little regulatory oversight. Our paper adds to this debate.

We examine the dynamics and consequences of P2P lending of borrowers residing in locales hit by a natural disaster. Natural disasters represent a plausibly exogenous shock to the demand for local funding, and from an empirical perspective, our research design exploits this shock allowing us to draw causal inferences (i.e., Bernile et al., 2017; Morse, 2011). Second, from an economic point of view, natural disasters are events that likely result in unexpected cash flow shocks to households. Thus, natural disasters represent an event where many local households may be particularly desperate and vulnerable, giving rise to predatory lending opportunities. Indeed, as we discuss later, some borrowers do apply for hardship accommodations. For such accommodations, natural disasters are by far the most common reason borrowers are approved. Thus, natural disasters are ideal for our setting.

We first test to see if there is a significant increase in loan demand in impacted local (using 3-digit zip code) areas following a natural disaster. We find an economically large and statistically significant increase in loan applications immediately and for the three months following a disaster event. Our estimates imply an increase in loan demand of approximately 7% in the three months

[1] https://www.alliedmarketresearch.com/peer-to-peer-lending-market

following the disaster. The effect is transitory. Loan demand remains elevated but is statistically insignificant in months four through six following the disaster.

After demonstrating a shock to loan demand following a disaster, we next turn to characteristics of the loans approved post-disaster. In particular, we examine interest rates and delinquency probabilities for these loans. Despite the surge in loan demand, we find no significant change in interest rates around the disaster event. Thus, our results are not consistent with the view that investors seek to take advantage of vulnerable borrowers by demanding excessive interest rates following a disaster. Likewise, for loans granted following the disaster, we find no increase in delinquency rates, suggesting that these borrowers are not riskier *ex* post. Thus, borrowers granted loans post-disaster maintain a similar payment status. As a result, investors who fund loans during the disaster-driven demand shock bear no additional cost. These findings are robust to a state-matched difference-in-difference design.

Motivated in part by studies that show how capital is reallocated when local demand for capital changes (i.e., Cortes and Strahan, 2017), we examine the cross-sectional impact of our findings in low versus high deposit areas. In areas with low levels of deposits, local capital may not be sufficient to meet loan demand. In such cases P2P lending may be a viable substitute. Consistent with this notion, we find loan demand is exacerbated in low deposit areas following a disaster. For instance, we find loan applications increase by 28 percentage points higher in low deposit areas versus high deposit areas after a natural disaster. Moreover, we find weak evidence that interest rates are lower in low deposit areas suggesting that, if anything, P2P lending benefits borrowers. This benefit also does not seem to come at additional cost to investors since loans approved after a natural disaster in low deposit areas are no more likely to display delinquency behaviors.

The first part of our paper examines the impact of natural disasters on the demand for loans and the attributes of those loans approved post-disaster. This empirical framework allowed us to address the social welfare consequences of the P2P lending market. Collectively, we find no evidence of predatory lending. In fact, our evidence suggests that P2P lending increases access to borrowers and results in positive welfare benefits. In the second part of this study, we examine how natural disasters impact borrowers with existing P2P loans.

For active loans, we find that loans in areas impacted by a natural disaster have higher delinquency probabilities. For instance, our estimates imply an approximately 67 basis points higher default probability and 85 basis points higher late payment probability for active loans in areas struck by a natural disaster. This delinquent behavior provides direct costs to investors as well as borrowers who have to pay late penalties and higher borrowing costs in the future. These estimates are economically large and highly statistically significant providing further evidence that natural disasters indeed represent an unexpected negative cash flow shock to households.

An interesting feature of the P2P lending platform is that it allows borrowers to seek a hardship accommodation that delays loan payments for up to 3 months. Borrowers must apply and be approved for such a provision. We find that conditional on being granted a hardship accommodation, borrowers affected by a natural disaster are significantly less likely to subsequently default. Thus, granting a hardship accommodation benefits both borrowers from having to default on the loan and investors from having to suffer significant losses.

Our paper contributes to the burgeoning marketplace lending literature. Hulme and Wright (2006) offer an overview to the ancestries of online social lending. Early works, primarily using Prosper data, study sociodemographic variables of loans (Ravina, 2012; Pope and Sydnor, 2011) as well as trustworthiness of borrowers (Duarte et al., 2012) using pictures associated with loan listings. Additionally, Herzenstein et al. (2011), Michels (2012), and Nowak et al. (2017) study the roles of narratives in P2P lending while Zhang and Liu (2012) find evidence of rational herding among investors. Lin et al. (2013) investigate the impact of friendship networks and find that these networks signal credit quality. However, Hildebrand et al. (2017) finds that group leader bids are only good signals when they have a substantial amount invested. Lin and Viswanathan (2016) find a home bias in the loan choices of investors. Moreover, Iyer et al. (2016) examine how lenders predict borrowers default likelihood from soft information, and Butler et al. (2017) find borrowers in areas with more access to traditional financing request lower rates. Tang (2019) tests whether P2P lenders are substitutes or complements to traditional banks by exploiting a negative shock to bank credit supply. Wei and Lin (2017) study the two ways (auction and posted prices) in which P2P lending platforms generate interest rates and find auction structures receive lower interest rates, generate lower default likelihoods, but are funded with a lower probability. Our paper differs by analyzing how this marketplace reacts to positive loan demand shocks. Given the speed at which this industry has developed, our study has important implications for researchers, practitioners, and policymakers.

The use of natural disasters in financial studies has also increased in recent years presumably because it offers a plausibly exogenous setting to examine unexpected shocks on financial outcomes. Bernile et al. (2017) examine how early-life disasters impact CEO behaviors and find a nonlinear relationship. Dessaint and Matray (2017) investigate how managers respond to hurricane events through perceived risk versus actual risk. Cen (2021) shows individuals are less likely to take the risk of working for startups after being impacted by climate disasters. Gall et al. (2011) find that direct losses from natural disasters have increased substantially even when controlling for population and wealth growth. Because of the growing impacts of natural disasters, many studies have used natural disasters as shocks to credit conditions. Berg and Schrader (2012) use a volcanic eruption in Ecuador to study how banks shift credit after a loan demand shock. Loayza et al. (2012) find that some moderate disasters can have positive economic growth effects, and Boustan et al. (2017) find floods and droughts to be positively associated with migration patterns. Reasons for such behavior are likely caused by an influx of disaster relief funding or other area specific factors.

The three papers arguably most related to ours are Morse (2011), Cortes and Strahan (2017), and Allen, Shan, and Shen (2020). Morse (2011) studies the payday lending environment and finds the existence of payday lenders increases the welfare for California households likely to face foreclosure following a natural disaster. Besides the obvious structural differences between P2P lending and payday loans, from an econometric perspective, P2P lending has the benefit that it is not geographically confined to a physical location. In our setting, we do not have to worry about differences in local economic conditions where payday lenders reside. Further, borrowers in our sample are from all 50 states making our evidence generalizable across the US. Cortes and Strahan (2017) study home mortgage loans in the US following a natural disaster and find that banks shift credit from non-connected areas to meet the increased demand in disaster areas. Moreover, they find banks lessen the impact of demand shocks by bidding up the rate of deposits in connected markets and increase the sale of more liquid loans. Allen, Shan, and Shen (2020) also study home mortgage loans following a natural disaster and compare the response of FinTech mortgage lenders versus traditional banks and non-FinTech shadow banks. They find that FinTech mortgage lenders increase supply more aggressively to high-demand areas. Both Cortes and Strahan (2017) and Allen, Shan, and Shen (2020) focus on *mortgage* originations and the plausible increase in new home buying and refinancing following a disaster perhaps because of a supply shock. Instead, the P2P lending market are small loans more likely to be driven directly by natural disaster impacts for *existing* borrowers.

Collectively, our paper has important policy implications. As FinTech innovation disrupts the industry, it faces increased regulatory attention and scrutiny. For P2P lending, one major concern regulators have is that P2P platforms will exploit desperate borrowers by charging excessive interest rates. Our paper's focus on natural disasters is an ideal setting to investigate such concerns as disasters represent an unexpected negative cash flow shock where borrowers may be especially vulnerable and desperate for financing, thus turning to alternative funding sources. Our evidence suggests this concern is unfounded. If anything, borrowers benefit from the increase in loan supply from P2P lending.

The rest of the paper is organized as follows. Section 2 discusses the main data sources. We examine the P2P lending market response to natural disaster shocks in section 3. Section 4 analyzes the relationship between active loans, natural disasters, and hardship accommodations, and section 5 concludes.

2. Data

2.1. Marketplace Lending Data

We analyze the P2P lending market using loan data from Lending Club during 2007-2018.[2] Lending Club is a leading marketplace lender in the United States. P2P lending, also known as marketplace lending, is essentially crowdfunding for personal microloans.[3] These platforms allow lenders to easily diversify their investment across a variety of loans, and they provide the borrower with a financing environment free from many hurdles of traditional banks. Unlike traditional banks, P2P platforms do not require collateral but instead minimize risk by screening out high-risk borrowers and capping the loan amount.

To become a borrower on Lending Club, one must have a US social security number and at least a 640 FICO score. After a borrower applies for a loan, they are classified into one of 35 categories based on various credit metrics (FICO score, loan amount, credit inquiries, credit history length, number of open credit accounts, credit utilization, etc.). Each category, referred to as subgrade, is

[2] This sample period is the maximum intersection with the loan and natural disaster data, discussed further in section 2.2.

[3] During our sample, both individuals and institutional investors can invest in Lending Club loans. However, as of December 31, 2020, access for individual investors was terminated, and now only institutional investors can invest in these personal loans. Thus, P2P lending is now a misnomer, but we still use the term and marketplace lending interchangeably since individuals were able to invest during our sample period.

offered an interest rate based on Lending Club's internal algorithm. Each loan has 14 days to gain funding and only gets funded if it attracts enough investors. Over our sample period, loan requests must be between $500 and $40,000 (the maximum amount has increased over time) for either three- or five-year terms. All interest rates are fixed, and loans are paid with equal monthly payments. A borrower is not penalized for paying off the loan early. In addition to interest, borrowers must also pay a one-time fee when the loan is approved, typically 1% to 4% of the loan amount. If borrowers are late with a payment, they are charged a late fee. If payment is more than 120 days late, the loan is in default, and Lending Club sends the loan to collections.

The main appeal to an investor is the ability to increase expected returns with a perceived low level of risk, which is minimized using Lending Club's diversification optimization tool. Investors over our sample period can allocate funds in two ways: semi-automatically and manually. Semi-automatic allocation is achieved by choosing a diversification strategy based upon loan grades. Lending Club then disperses the investment funds for the investor. Manual allocation is done by choosing the individual loan from a listing page.[4] The minimum investment per investor for each loan is $25. According to Paravisini et. al. (2017), for portfolio allocations up to June 2009, "39.6% was suggested by the optimization tool, 47.1% was initially suggested by the tool and then altered by the investor, and the remaining 13.3% was chosen manually."

We choose Lending Club over other marketplace lenders due to the location level detail of borrowers, which is vital to identifying natural disaster exposure. Unlike Prosper, where the borrower has the option of including their city, Lending Club provides three-digit zip codes and states for all loan originations. Over our sample period, Lending Club reports 29.9 million loan originations which include 2.3 million approved loans (or an approval probability of 7.6%) for a total of $34 billion in

[4] Appendix Figure A1 shows a snapshot of a Lending Club listing on December 1, 2017. This figure provides an example of what an investor would see if researching available loans to fund.

approved loan amounts. For these approved loans, the average loan amount is $15,047, and the average interest rate charged is 13.1%. It is also worth noting that we have three point-in-time snapshots of the approved loans: 11/28/2017, 4/10/2019, and 9/13/2020. We make use of all these snapshots to define variables related to loan performance. Detailed descriptions of all loan variables are available in Appendix Table A1.

[Insert Table 1 Here]

Table 1 reports loan statistics by year. While the average interest rate charged has not varied substantially over the years, the approval probability has fluctuated quite a bit with the highest year (2013) reporting an approval probability of 15.1% and the lowest year (2018) reporting an approval probability of 5.0%. The popularity of this platform (similar to many other P2P platforms) has grown exponentially since its inception in 2007 as the majority of loan originations and approved loans occur in the last three years of the sample. In all of our tests, we include month-year fixed effects to control for the clear time trend at Lending Club.

2.2. Natural Disasters Data

We collect natural disaster events hazard data at the county-level from the Spatial Hazard Events and Losses Database for the United States (SHELDUS). SHELDUS data are created from the records of the National Climatic Data Center (NCDC). The data are available at a monthly frequency. To ensure the natural disasters identified are significant to individuals, we require Presidential Disaster Declarations similar to Cortes and Strahan (2017). Disaster types include hurricanes, earthquakes, thunderstorms, blizzards, hail, drought, landslides, floods, wildfires, volcanoes, and tornadoes. Although SHELDUS provides data dating back to 1960, we use natural disasters between 2007 and

2018 due to the overlap in Lending Club data. In addition to restricting the time period, we also aggregate the natural disaster damage data to the three-digit zip code level, the lowest geographic level available at Lending Club.[5]

[Insert Table 2 Here]

Table 2 reports natural disaster damages during our sample period by year and disaster type. Although natural disaster damages are weakly increasing across time, they are certainly more sporadic than P2P loan volume. The years with the most damage are 2017, 2012, 2011 and 2008, respectively. Natural disaster hazards span many different types, but the most damaging over our sample period occur due to flooding ($202.2 billion), hurricanes/tropical storms ($91.4 billion), and tornadoes ($34.2 billion).[6]

3. The Response to Loan Demand Shocks

3.1. Identifying Demand Shocks

The first step in measuring the P2P market response to a demand shock is identifying the demand shock. We use natural disasters as plausibly exogenous shocks to personal loan demand likely to manifest in the P2P lending market. Affected individuals may need personal loans to repair damaged property or to help pay bills in the event of a short-term economic slowdown that could affect employment and wages. We use a panel data set constructed at the zip code-month level of total loan originations to determine the relative loan demand around disaster events. Similar to Cortes and

[5] Throughout the paper, zip code area always refers to the first three digits of a US ZIP code since this is the lowest geographic level available for the loan data.

[6] Even though SHELDUS groups damages into mutually exclusive hazard types, it is likely that many types listed (such as hurricanes and flooding) occur simultaneously. Therefore, we make no restrictions based on hazard type when aggregating damages to the zip code-month level.

Strahan (2017), we regress loan originations on a list of event-month indicator variables defined around the date of each natural disaster with zip code and month-year fixed effects as follows:

$$Log(1 + Loan\ Originations)_{j,t} = \sum_k \beta^k D^k{}_{j,t} + \alpha_j + \gamma_t + \varepsilon_{j,t} \tag{1}$$

where *j* indexes zip codes and *t* indexes month-years. Zip code level fixed effects are denoted by α_j, and month-year fixed effects are denoted by γ_t. Event-month indicators ($D^k_{j,t}$) are included from three months before to 12 months after the disaster. In other words, 16 monthly indicators are included from k = -3 to k = 12, where k = 0 at the month in which the disaster occurred.

[Insert Figure 1 Here]

Figure 1 displays the β coefficients from the estimation of equation (1) along with boundaries of 95% confidence intervals for those coefficients. The abnormal loan originations around natural disasters indicate no abnormally high or low levels of lending before the disaster providing evidence that the disaster event is exogenous and unexpected. However, the figure shows that during the disaster month and for the next 3 months after a disaster event, there is a significant increase in the levels of loan originations. The demand increase is highest and most significant two months after the disaster when a 6.51% (t-stat 3.37) increase occurs. Compared to Cortes and Strahan (2017) who study the home mortgage loan market and document a peak demand increase in month six after the event, we document a closer demand shock peaking two months after the event. Additionally, we document a stronger demand shock as their market increases by about 3% at its peak. This economically quicker and larger response indicates that the P2P marketplace may be a more immediate channel for lending required in the aftermath of a natural disaster. The next sections aim at understanding how the P2P lending market reacts to such a demand shock.[7]

3.2. *Interest Rates*

If P2P lenders were predatory in nature, then they might exploit a demand shock by charging significantly higher prices as indicated by the interest rates of approved loans. On the other hand, if P2P lenders do not discriminate across geographic areas, then interest rates may be unaffected by the local demand shock we document in section 3.1. Moreover, if the lending platform is especially sympathetic to disaster-affected borrowers, then we may even expect to see relatively low interest rates during this demand shock. To determine the P2P market response, we use loan-level data for all approved loans.

[Insert Table 3 Here]

[7] A natural response to examine at this point is the approval probability during the documented demand shock. However, the Lending Club data does not provide significant information on declined loans. This limitation makes inference about the drivers of approval probabilities challenging and problematic. Appendix Table A2 reports summary statistics for all available variables associated with requested loans. 67% of declined loans do not have a credit score associated with their origination. This likely occurs because they were declined prior to this stage in the process. That leaves only the loan amount, borrower's employment length, and DTI% as control variables. Nonetheless, we report approval probability tests in Appendix Table A3 with limited control variables. Columns 1 and 2 use the full sample of requested loans, and columns 3 and 4 use the sample with at least a credit score. Columns 1 and 3 test each sample with no loan/borrower controls and columns 2 and 4 add all controls that are available for each sample. The two samples tell conflicting stories, and the controls seem to have very little impact on the disaster coefficients. Instead, the sample reduction drives the conflicting stories, suggesting potential omitted variable bias in both tests. When using the full sample of originations, we document weakly positive approval probabilities during the disaster-induced demand shock. However, when restricting to the 33% of originations that have a credit score associated, we document lower approval probabilities following a disaster event, but the inclusion of the additional control variable does not drive this change. Therefore, we omit these results from the main sections of the paper due to the limitations of this analysis but still report it descriptively in the Appendix. It is worth noting that the demand shock documented in Figure 1 is robust to the reduced sample of loan originations with a credit score. We report the same figure for this subsample in Appendix Figure A2, and the pattern is similar with a significant demand shock beginning in the disaster month and lasting for the next three months.

Table 3 reports the summary statistics of the approved loans during our sample period. The variables are grouped into three categories: (1) loan characteristics, (2) borrower characteristics, and (3) loan performance variables.[8] The average loan is for $15,047 and pays an interest rate of 13.09%. Approximately, 29% (71%) of all loans are for 5-year (3-year) terms. The average borrower reports an annual income of $77,992 and a credit score of 701. About 60% of borrowers are homeowners. The debt-to-income ratio and revolving utilization for the sample have a mean of 18.66% and 50.34%, respectively. More generally, we observe that these are relatively small personal loans for borrowers that hold significant debt but generally have a good history of paying it back.

To test the relative interest rates charged around a natural disaster, we regress interest rates on the event-month indicators surrounding a disaster as well as other loan and borrower characteristics with zip code and month-year fixed effects as follows:

$$Interest\ Rate_i = \sum_k \beta^k D^k{}_{j,t} + \alpha_j + \gamma_t + \lambda_i + \varepsilon_i \qquad (2)$$

where *i* indexes loans, *j* indexes zip codes, and *t* indexes month-years. *Interest Rate* is the interest rate charged on the loan in percentage points. Similar to equation (1), event-month indicators ($D^k_{j,t}$) are included from three months before to 12 months after the disaster, zip code level fixed effects are denoted by α_j, and month-year fixed effects are denoted by γ_t. We also add λ_i, which includes control variables related to loan/borrower characteristics that are likely to influence charged interest rates.

[Insert Table 4 Here]

[8] A detailed description of these variables and others is available in Appendix Table A1.

Table 4 reports the results of equation (2) without the loan/borrower controls in column 1 and with all controls in column 10. Columns 2-9 add each loan/borrower characteristic individually. To determine the response during the demand shock, we focus on disaster indicators 0-3 (the shaded area). All coefficients except for one during this period are statistically insignificant from zero. When we control for all loan/borrower characteristics, we find a statistically significant increase during the disaster month of 4.3 basis points (t-stat 2.34). Although this coefficient is statistically significant at the 5% level, it is economically small as the average interest rate is about 13%. Moreover, the brief elevated interest rate in the disaster month under this specification does not last, as we observe that the following months are all statistically insignificant from zero. Furthermore, the peak of the demand shock (k=2) actually has a negative but statistically insignificant coefficient. Table 4 also provides the direction and magnitude of important control variables in the analysis, and all signs are as expected. The interest rate charged is positively (negatively) related to loan amount, debt-to-income ratio, revolving utilization, and loan term (credit scores, income, employment length, and homeownership.)

Overall, we find no evidence of predatory lending reflected by the interest rates charged during the demand shock following a natural disaster. Admittedly, it does not seem that the P2P marketplace is especially sympathetic to disaster-affected borrowers either since rates are not materially affected. Instead, the evidence supports the idea that this marketplace does not discriminate across geographic areas. Thus, disaster-affected P2P borrowers are charged similar levels during the documented demand shock following a natural disaster event.

3.3. Delinquency Probability

Although we find no evidence of predatory pricing of interest rates during a disaster-induced demand shock, there may be costs to investors if borrowers are financially constrained post-disaster and therefore more likely to display delinquent behavior. Higher interest rates could have potentially offset delinquency costs, but since we did not observe higher interest rates charged following a natural disaster, delinquent behavior could be especially costly to investors. In this section, we examine the probability of delinquency for loans approved during the disaster-induced demand shock documented in section 3.1.

Again, we use the loan-level data to analyze the future delinquency of these loans. For this test we regress equation (2), except that we replace *Interest Rate* with two delinquency variables: *Default* and *Late Payment*. *Default* equals one if the loan is past due for more than 120 days at any time during the life of the loan and zero otherwise. *Late Payment* equals one if the loan is past due any number of days during the life of the loan and zero otherwise. To control for other characteristics likely to affect a loan's interest rate, we include all loan/borrower characteristics from section 3.2 as well as subgrade fixed effects. When a loan is approved at Lending Club, it is assigned into one of 35 groups based on its expected risk level. This risk is likely determined by the marketplace lender using the borrower/loan characteristics we observe but also potentially additional unobserved information. The loan's interest rate is then assigned based on the loan's subgrade. Therefore, subgrade fixed effects help control for observed and potentially unobserved characteristics related to loan risk that influenced the loan's interest rate. Essentially, subgrade fixed effects allow us to test delinquency behavior independent of the interest rate charged since interest rates are charged based on the subgrade category.

[Insert Table 5 Here]

Table 5 reports the results of equation (2) with delinquency variables replacing *Interest Rate* as the dependent variable. In column 1, control variables related to loan/borrower characteristics, λ_i, from equation (2), are omitted. In column 2, they are included, and in column 3, they are included with subgrade fixed effects additionally. We find that loans approved during the disaster-induced demand shock are no more likely to display future delinquent behavior. All coefficients during the demand shock (k=0 to k=3) are statistically insignificant from zero across all variations of controls. The results are qualitatively similar whether we use *Late Payment* or *Default*. Therefore, borrowers approved during the disaster-induced demand shock are no more likely to pay late or default over the life of their loan. This table also provides the direction and magnitude of other control variables in the analysis. The probability of delinquency is positively (negatively) related to loan amount, debt-to-income ratio, and loan term (credit scores, income, employment length, revolving utilization, and homeownership.)

An additional finding of Table 5 that we document is a slightly significant positive probability of late payment in the months leading up to a natural disaster. For instance, loans approved two months before a natural disaster (k=-2) have a 40 basis points higher probability of late payment after controlling for all listed borrower/loan characteristics and subgrade fixed effects. Essentially, although loans approved after a natural disaster are no more likely to be delinquent, loans approved *before* are more likely to be delinquent. This finding is further explored in section 4, where we analyze loans that are active when a natural disaster occurs.

3.4. State-Matched Difference-in-Difference Robustness

Thus far, we have found evidence in the P2P lending market that a local loan demand shock occurs following a natural disaster, yet interest rates for local loans approved during this demand shock are similar to pre-disaster levels, and moreover, those approved loans are no more likely to display delinquent behavior. If the P2P lender was acting in a predatory nature, we might see significant interest rate increases during the demand shock in the affected area, but we do not. Furthermore, investors do not seem to bear any additional cost from lending during this demand shock since borrowers approved during it have similar payment statuses throughout the loan. Instead, it seems that the P2P market provides access to funding in disaster-stricken areas at no additional cost to borrowers or investors by quickly and efficiently meeting the demand in high-need areas.

In this section, we test the robustness of these results by using a difference-in-difference (DID) framework similar in spirit to Allen, Shan, and Shen (2020). We define *Post* equal to one (zero) for the period after (before) the disaster event. Based on the demand shock documented in Section 3.1, we analyze the six-month period around (or one quarter before and after) each disaster event. We define *Treat* to equal one for zip codes hit by a natural disaster and zero for control zip codes that are unaffected by a natural disaster. We match control zip codes to treatment zip codes for each disaster by selecting within the same state and minimizing pre-disaster loan demand to ensure parallel trends prior to disaster events.

A crucial assumption for the DID design is that pre-disaster trends of P2P loan demand should be similar in treatment and control areas. Following Allen, Shan, and Shen (2020), we run the following regression to satisfy this assumption:

$$Log(1 + Loan\ Originations)_{j,t} = \beta_1 Treat_j \times D^{-2}{}_{j,t} + \beta_2 Treat_j \times D^{0}{}_{j,t} + \beta_3 Treat_j + \beta_4 D^{-2}{}_{j,t} + \beta_5 D^{0}{}_{j,t} + \alpha_j + \gamma_t + \varepsilon_{j,t} \tag{3}$$

where observations occur at the zip code (*j*) and month (*t*) level. Zip code level fixed effects are denoted by α_j, and month-year fixed effects are denoted by γ_t. $D^{k}{}_{j,t}$ are the event time indicators where *k* is the number of quarters after the disaster. Since $D^{-1}{}_{j,t}$ is omitted, β_1 and β_2 measure the difference in loan demand of treatment and control zip codes relative to the loan demand in the period prior to the disaster (*k* = -1).

[Insert Figure 2 Here]

Figure 2 reports β_1 and β_2 from equation (3) with 95% confidence intervals. We observe no significant difference in P2P loan demand in the pre-disaster time period consistent with the required parallel trends assumption. However, we see a significant increase from the quarter before to the quarter after the disaster event consistent with the loan demand shock following a disaster event documented in Section 3.1.

Next, we test the robustness of the results reported in Section 3.2 and 3.3 by running the DID test with the following dependent variables: *Approved, Interest Rate, Late Payment, and Default*. *Approved* equals one if the loan application was approved and zero otherwise. *Interest Rate* is the interest rate charged on the loan in percentage points. *Late Payment* equals one if the loan is past due any number of days during the life of the loan and zero otherwise. *Default* equals one if the loan is past due for more than 120 days at any time during the life of the loan and zero otherwise. We also include all relevant control variables from the preceding sections to account for borrower/loan characteristics that influence these dependent variables.

[Insert Table 6 Here]

Table 6 reports the results of the DID robustness tests. Overall, the evidence is consistent with previous results. That is, we document a significant loan demand shock in the quarter following a natural disaster. Under this specification, we report an increase of 3.8% (t-stat 2.11) in treated areas relative to untreated areas following a disaster event. Regarding approval probabilities, we find consistently insignificant evidence under this DID specification. While Appendix Table A3 reports conflicting results under the main specification due to the large number of originations without a reported credit score, the DID design shows consistent positive (but insignificant) approval probabilities for disaster-affected areas relative to unaffected areas following the disaster event.

Although this positive relationship is not statistically significant, predatory lending behavior predicts a significant negative effect. In columns 6 and 7, we analyze interest rates charged on approved loans and find an insignificant negative effect. Predatory lending predicts significantly higher interest rates charged after this demand shock, but instead, we find that interest rates are lower (albeit insignificantly) for treatment areas relative to untreated areas following a natural disaster. Finally, we find no evidence that the loans approved during this demand shock are more likely to exhibit delinquent behavior. In fact, we report negative interaction coefficients for all delinquency measures although none of these are statistically significant. Therefore, investors do not seem to bear any material costs as the P2P lending platform quickly meets loan demand in high-need areas. Together, this state-matched DID design provides robustness in documenting a significant demand shock following a natural disaster event, but no signs of predatory lending.

3.5. Low Deposit Areas

While we find no evidence of predatory lending in the P2P loan market following a loan demand shock from natural disasters, in this section, we analyze if these findings vary by local access to traditional funding options such as local bank deposits. If the P2P loan market is complementary to traditional funding options, then we would expect to see stronger demand in low deposit areas. Additionally, low deposit areas may contain borrowers that are especially vulnerable to predatory lending practices as their limited options may make them desperate for funding following an unexpected disaster. Therefore, we analyze loan demand, interest rates charged, and delinquency probabilities cross sectionally across low and high deposit areas.

We collect local bank branch deposits from the Federal Deposit Insurance Corporation (FDIC) Summary of Deposits (SOD) file. We download the SOD file for each year, which reports the branch office deposits as of June 30th. We then define *Low Deposit Area* to be one if the deposit level for that zip code is below the median across all zip codes in that given year.[9] Next, we run the same tests from sections 3.1-3.3 but now include *Low Deposit Area* as well as interaction terms with each of the event-month indicators (D^k) and *Low Deposit Area.* Under this specification, the coefficients of interest (the interaction terms) are the difference in the event-month indicators for low and high deposit areas. Thus, the event-month indicators now represent the coefficients in high deposit areas. Positive (negative) interaction coefficients mean higher (lower) event effects for areas with low branch deposits.

[Insert Table 7 Here]

Table 7 reports the demand, interest rate, and delinquency probability tests including the *Low Deposit Area* variables. As a reminder, the results in Panel A (demand) occur at the zip-month level, while the results in Panel B (interest rate and delinquency) occur at the loan level. In Panel A, we observe all interaction coefficients are positive and statistically significant at the 1% level. This pattern indicates that areas with low levels of local bank deposits are more likely to seek lending options in the P2P market at all times around a natural disaster, not just afterwards. These results suggest that this marketplace is likely a complement to traditional lending at all times, not just after a natural disaster. However, the coefficients are larger during the natural disaster demand spike with the largest interaction occurring in the disaster month (*Low Deposit Area**D_0) with a coefficient of 27.66 (t-stat 5.96). These results indicate that low deposit areas experience a 27.66 higher percentage point increase in loan applications than high deposit areas during a disaster month. Moreover, the complementary

[9] We define *Low Deposit Area* by year to account for potential changes in deposit levels across time, but this restriction does not materially affect the results. We find that very few zip codes cross the median thresholds from year to year.

nature of marketplace lending in low deposit areas is especially strong when an unexpected demand shock occurs.

In Panel B, we observe that despite a stronger increase in loan demand, low deposit areas actually experience slightly lower costs of borrowing as depicted by the interest rates they are charged. In column 2, after including controls for loan/borrower characteristics, we report that during the disaster month, approved loans in low deposit areas pay 10.67 basis points less than high deposit areas. Although the lower interest rates are not statistically significant in the following month, the coefficients of the interaction terms remain negative throughout the demand shock. This pattern suggests that the P2P market not only provides a complement source of funding in low deposit areas following a disaster, but also, it does so at slightly *reduced* costs to borrowers.

Given the evidence of reduced interest rates charged in low deposit areas, investors may bear the cost of providing funding to these areas if the borrowers are less likely to make timely payments. To test the impact of these lending practices on investors, we replace *Interest Rate* with our previous measures of delinquency as the dependent variable: *Default* and *Late Payment*. However, in columns 3-8, we find no difference in the subsequent delinquency behavior of loans approved in low deposit areas during the demand shock. Using *Default* or *Late Payment* as the dependent variable yields similar insignificant results between low and high deposit areas as indicated by the interaction coefficients in the shaded area. Although abnormal loan demand is larger for low deposit areas after a natural disaster, interest rates charged are actually slightly lower, and future delinquency probabilities are not significantly affected.

Together, we find no evidence of predatory lending, even in low deposit areas where borrowers may be especially vulnerable. In fact, this marketplace lender seems to act as a complement to traditional funding and provides relatively lower costs to borrowers in areas with greater relative loan demand at no additional cost to investors.

4. Natural Disasters and Active Loans

4.1. Disaster Exposure after Approval

In this section, we analyze how natural disaster exposure is related to active P2P loans. Active loans are likely to be negatively impacted by a local disaster due to the plausible reduction of household cash flow following a natural disaster. This reduction may come in the form of property repairs or it may occur because of reduced economic activity likely to occur immediately following the disaster event. Additionally, even if the area remains economically active, borrowers may have to miss work to take care of children who are out of school or help to rebuild/recover damaged property. In short, we hypothesize that loans impacted by a natural disaster are more likely to display delinquency behaviors such as late payments or default. To test this hypothesis, we run the following regression equation:

$$Delinquency_i = Loan\ Disaster_i + \alpha_j + \gamma_t + \varepsilon_i \quad (3)$$

where *i* indexes loans, *j* indexes zip codes, and *t* indexes month-years. *Loan Disaster* equals one if the borrower lives in an area impacted by a Presidential Disaster Declaration while the loan is active, and zero otherwise. Zip code fixed effects are denoted by α_j, and month-year fixed effects are denoted by γ_t. Delinquency is measured with two levels of severity: *Default* and *Late Payment*. *Late Payment* takes the value of one if the loan makes any payments after the due date, and zero otherwise. *Default* equals one if the loan is past due for more than 120 days at any point during the life of the loan and zero otherwise.[10] We also report the results of equation (3) after adding λ_i, which includes control variables

[10] The P2P loan data we collect includes one time stamp during our sample period, 11/28/2017. The other time stamps occur after the sample period, 4/10/2019 and 9/13/2020. Additionally, the natural disaster data ends on 12/31/2018. For these reasons, we use only the loan time stamp closest to the end of our natural disaster data to reduce noise that may occur because of disasters that we do not capture occurring after 2018.

related to loan/borrower characteristics. Furthermore, we also add subgrade fixed effects as our strongest specification. Investors are grouped into one of 35 subgroups when approved and their interest rate is decided based on this grouping. Therefore, including subgrade fixed effects likely controls for information from the other loan/borrower characteristics as well as potentially unobserved characteristics and soft information not included in the data.

[Insert Table 8 Here]

Table 8 reports the results of equation (3) in columns 1 and 4. The probability of the loan going into default (paying late) increases by 67 (85) basis points for active loans that experience a natural disaster and is statistically significant at the 1% level with a t-stat of 4.98 (6.08). In columns 2 and 5, we add loan/borrower characteristics to observe if these relationships are robust when controlling for observed characteristics likely to be associated with delinquency. All of these controls are highly significant in the expected direction. Even still, we see that the probability of a loan going into default (paying late) increases by 32 (41) basis points and is statistically significant at the 1% level with a t-stat of 2.59 (3.35). In columns 3 and 6, we add subgrade fixed effects to further control for unobserved borrower characteristics as well as the interest rate paid on loans since they are assigned at the subgrade level. Under this specification, the relationship with default is no longer statistically significant, but the coefficient of interest remains positive at 17 basis points (t-stat 1.45). However, the increased probability of late payment is still significant at the 5% level with an increase of 24 basis points (t-stat 2.04). These results indicate that active loans impacted by a natural disaster are more likely to display delinquency behavior. These behaviors may result in additional costs to investors and

---

Also, we are careful not to claim that the natural disaster exposure directly *causes* the delinquent behaviors, only that they are associated since we cannot identify how soon after the natural disaster the delinquent behavior occurs.

raise the costs of future borrowing for delinquent borrowers since their credit worthiness is likely to be affected.

4.2. Hardship Accommodations

In the previous section, we find evidence that active loans struck by a natural disaster are more likely to be delinquent. This behavior likely will prevent the delinquent borrowers from future borrowing opportunities (or at least increase the cost of those opportunities). Additionally, investors bear the immediate cost of the late payments and defaults. However, if the delinquency behavior is temporary, then it may be beneficial to allow a short delay of payment to reduce the likelihood of additional payment delays or default. Beginning in 2012, Lending Club allows borrowers affected by unfortunate circumstances to apply for a hardship accommodation. If this accommodation is approved, then the borrower is allowed a payment delay of up to three months.

[Insert Figure 3 Here]

Figure 3 shows a pie chart of the reasons given for approved hardship accommodations. *Natural Disaster* (27%) is the most common reason given for an approved hardship accommodation, followed by *Excessive Obligations* (20%) and *Unemployment* (18%). Admittedly, these reasons are not mutually exclusive, but instead provide a representation of the reasons Lending Club might approve an accommodation.

A hardship accommodation provides an immediate cost to investors through delayed payments. However, if the borrower is able to improve their financial position in those three months allotted, then they may be less likely to have future delinquencies. For these tests, we only measure the reduction of future default since the accommodation itself provides direct relief for late payments. To test the impact of the hardship accommodation on future defaults of disaster-affected borrowers, we define *Hardship* to equal one if the loan is granted a hardship accommodation and zero otherwise. We then add *Hardship* and an interaction term (*Hardship*Loan Disaster*) to equation (3). Under this specification, the interaction term is the difference in default probabilities of disaster-affected loans granted a hardship accommodation and those not granted an accommodation.

[Insert Table 9 Here]

In Table 9, we examine the relationship between the hardship accommodation and the default probability of disaster-affected loans. Because the hardship reasons are not mutually exclusive, we do not exclude any reasons that are likely experienced because of a natural disaster. We first define *Hardship* using all reasons in columns 1-3. In columns 4-6, we remove those less likely, such as divorce, family death, medical, and disability. In columns 7-9, we keep only natural disasters and excessive obligations. Across all specifications, we observe a lower default probability for disaster-affected loans granted a hardship accommodation. Even once controlling for observed loan/borrower characteristics and subgrade FEs, the hardship accommodation reduces the default probability for a disaster-affected loan by 3.12% (t-stat 1.96) to 4.43% (t-stat 2.56). Across all tests, the hardship accommodation lowers the delinquency probability for active loans impacted by a natural disaster. Therefore, the three-month payment delay cost to investors is at least somewhat offset by savings in future costs of default. While we cannot comment on the relative size of these opposing forces since we cannot examine the details of defaults, we do find evidence that the hardship accommodation provides relief to borrowers and mitigates costs to investors through a reduction of the future default probability.

5. Conclusions

We study the impact of marketplace lending following natural disasters. Our setting is ideal for testing whether P2P platforms engage in predatory lending practices for two reasons: 1) natural disasters represent a plausibly exogenous shock to lending and 2) individuals impacted by natural disasters suffer an unexpected cash flow shock making borrowers potentially vulnerable to predatory lending. Despite regulators concerns that P2P lending platforms are akin to payday loans, we find the market is efficient in responding to demand shocks without any evidence of predatory lending practices. In fact, this marketplace seems to provide social welfare benefits to natural disaster-affected borrowers at minimal costs to investors.

References

Allen, L., Y. Shan, and T. Shen, 2020, Do FinTech Mortgage Lenders Fill the Credit Gap?, working paper.

Berg, G. and J. Schrader, 2012, Access to credit, natural disasters, and relationship lending, *Journal of Financial Intermediation* 21, 549-568.

Bernile, G., V. Bhagwat, and P. R. Rau, 2017, What Doesn't Kill You Will Only Make You More Risk-Loving: Early-Life Disasters and CEO Behavior, *Journal of Finance* 72, 167-206.

Boustan, L. P., M. E. Kahn, P. W. Rhode, and M. L. Yanguas, 2017, The Effect of Natural Disasters on Economic Activity in US Counties: A Century of Data, *working paper*.

Butler, A. W., J. Cornaggia, and U. G. Gurun, 2017, Do Local Capital Market Conditions Affect Consumers' Borrowing Decisions, *Management Science* 63, 4175-4187.

CEMHS, 2019. Spatial Hazard Events and Losses Database for the United States, Version 18.1. [Online Database]. Phoenix, AZ: Center for Emergency Management and Homeland Security, Arizona State University.

Cen, X., 2021, Household Wealth and Entrepreneurial Career Choices: Evidence from Climate Disasters, working paper.

Cortes, K. R. and P. E. Strahan, 2017, Tracing out capital flows: How financially integrated banks respond to natural disasters, *Journal of Financial Economics* 125, 182-199.

Dessaint, O. and A. Matray, 2017, Do managers overreact to salient risks? Evidence from hurricane strikes, *Journal of Financial Economics* 125, 97-121.

Duarte, J., S. Siegel, and L. Young, 2012, Trust and Credit: The Role of Appearance in Peer-to-peer Lending, *Review of Financial Studies* 25, 2455-2484.

Gall, M., K. A. Borden, C. T. Emrich, and S. L. Cutter, 2011, The Unsustainable Trend of Natural Hazard Losses in the United States, *Sustainability* 3, 2157-2181.

Herzenstein, M., S. Sonenshein, and U. M. Dholakia, 2011, Tell me a Good Story and I May Lend You Money: The Role of Narratives in Peer-to-Peer Lending Decisions, *Journal of Marketing Research* 68, S138-S149.

Hildebrand, T., M. Puri, and J. Rocholl, 2017, Adverse Incentives in Crowdfunding, *Management Science* 63, 587-608.

Hulme M. K. and C. Wright, 2006, Internet Based Social Lending: Past, Present and Future, *Social Futures Observatory*, London.

Iyer, R., A. I. Khwaja, E. F. P. Luttmer, and K. Shue, 2016, Screening Peers Softly: Inferring the Quality of Small Borrowers, *Management Science* 62, 1554-1577.

Lin, M., N. Prabhala, and S. Viswanathan, 2013, Judging Borrowers by the Company They Keep: Friendship Networks and Information Asymmetry in Online Peer-to-Peer Lending, *Management Science* 59, 17-35.

Lin, M. and S. Viswanathan, 2016, Home Bias in Online Investments: An Empirical Study of an Online Crowdfunding Market, *Management Science* 62, 1393-1414.

Loayza, N., E. Olaberria, J. Rigolini, and L. Christiaensen, 2012, Natural Disasters and Growth: Going Beyond the Averages, *World Development* 40, 1317-1336.

Michels, J., 2012, Do Unverifiable Disclosures Matter? Evidence from Peer-to-Peer Lending, *The Accounting Review* 87, 1385-1413.

Morse, A., 2011, Payday lenders: Heroes or villains?, *Journal of Financial Economics* 102, 28-44.

NOAA National Centers for Environmental Information (NCEI) U.S. Billion-Dollar Weather and Climate Disasters (2017). https://www.ncdc.noaa.gov/billions/

Nowak, A., A. Ross, and C. Yencha, 2017, Small Business Borrowing and Peer-to-Peer Lending: Evidence from Lending Club, *Contemporary Economic Policy*, doi:10.1111/coep.12252.

Paravisini, D., V. Rappoport, and E. Ravina, 2017, Risk Aversion and Wealth: Evidence from Person-to-Person Lending Portfolios, *Management Science* 63, 279-297.

Pope, D. G. and J. R. Sydnor, 2011, What's in a Picture? Evidence of Discrimination from Prosper.com, *Journal of Human Resources* 46, 53-92.

Ravina, E., 2012, Love & Loans: The Effect of Beauty and Personal Characteristics in Credit Markets, *working paper*.

Tang, H., 2019, Peer-to-Peer Lenders Versus Banks: Substitutes or Complements?, *Review of Financial Studies* 32, 1900-1938.

Wei, Z. and M. Lin, 2017, Market Mechanisms in Online Peer-to-Peer Lending, *Management Science* 63, 4236-4257.

Zhang, J. and P. Liu, 2012, Rational Herding in Microloan Markets, *Management Science* 58, 892-912.

Figure 1: Loan Demand Around Natural Disasters

This figure displays abnormal loan originations around natural disasters. The solid line reflects the β_k coefficients (k=0 in the disaster month) from equation (1). The dotted lines report the boundaries of 95% confidence intervals for those coefficients. All standard errors are clustered at the zip code level.

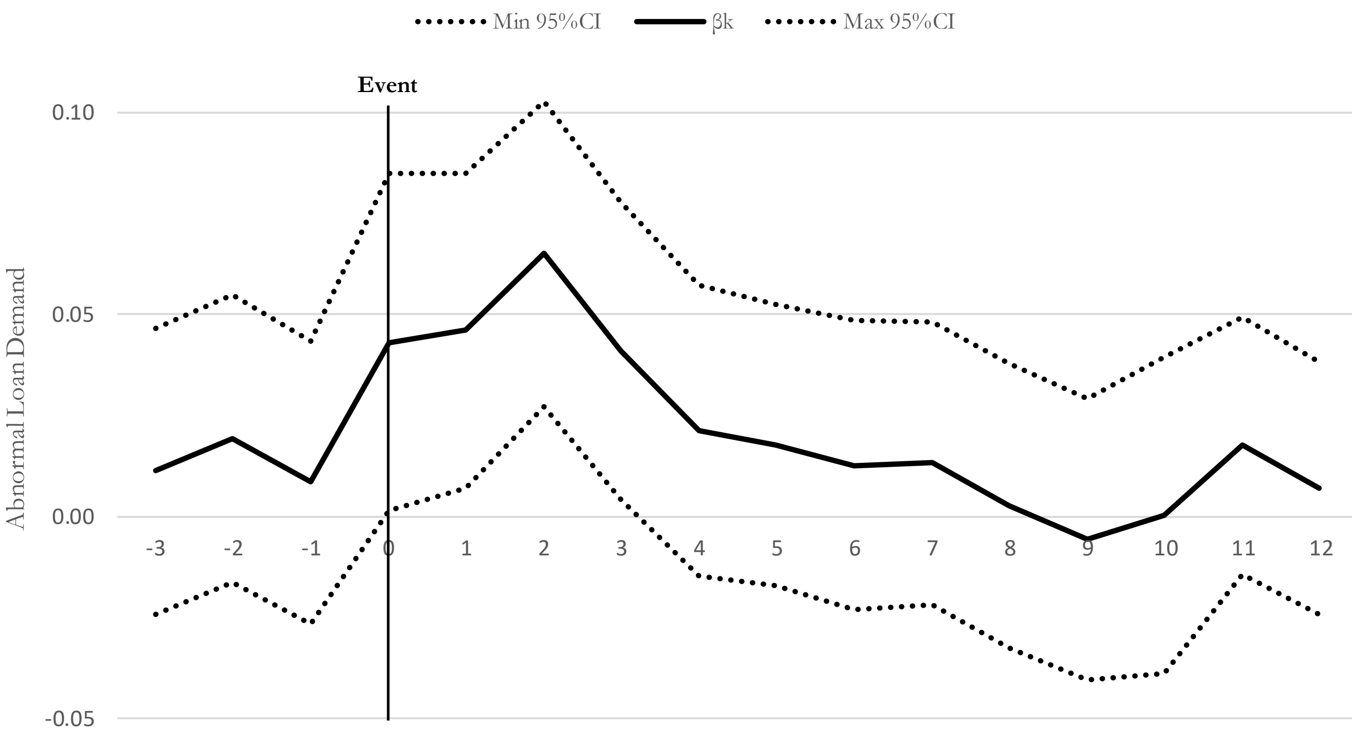


Figure 2: Parallel Trends of Loan Demand

This figure measures the difference in treatment and control area loan demand leading up to a natural disaster shock. More specifically, this figure reports the interaction coefficients (β_1 and β_2) from equation (3) along with 95% confidence intervals. That is, this figure shows the difference in P2P loan demand of treatment and control zip codes in the quarter after the disaster occurs (quarter 0) and two quarters before the disaster event (quarter -2) relative to the quarter before the event (quarter -1). Standard errors are clustered at the zip code level.

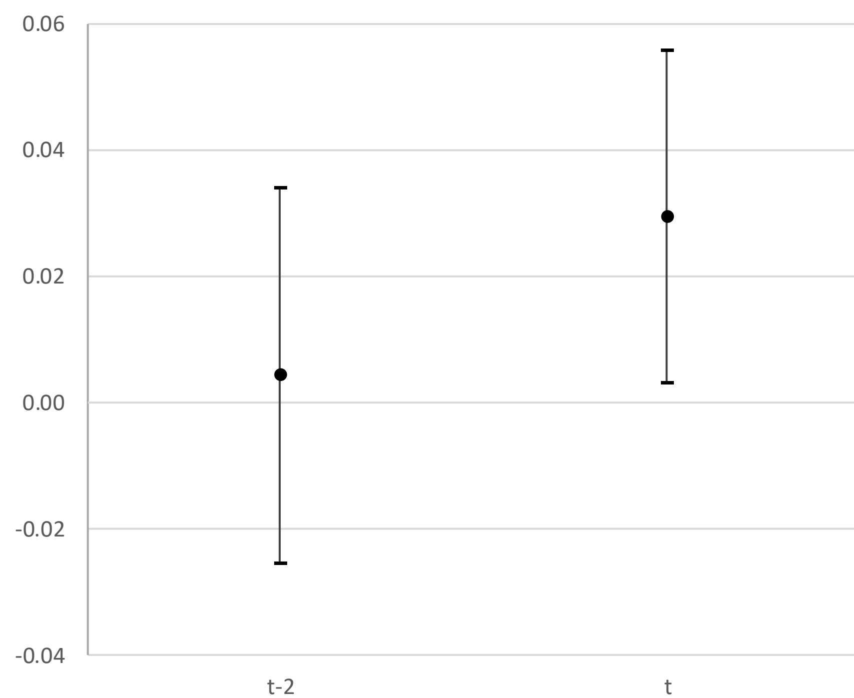


Figure 3: Hardship Accommodation Reasons

This figure displays the relative amount for each reason loans are granted a hardship accommodation. The hardship accommodation includes up to a 3-month payment delay to account for the approved hardship in order to provide relief to affected borrowers.

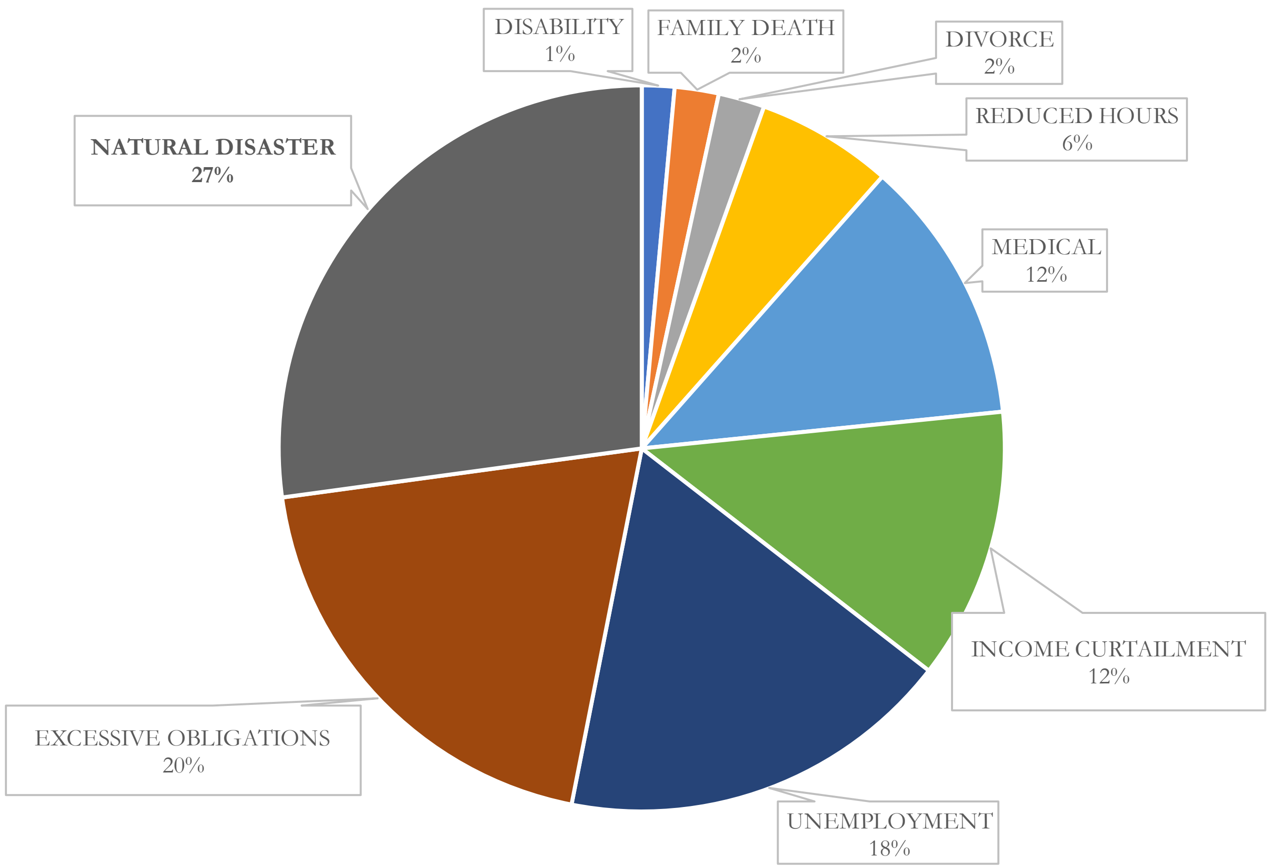


Table 1: Loan Summary Statistics by Year

This table reports the total loans requested, total loans approved, approval probability, approved amount, average loan amount, and average interest rate by year and in total during the sample period.

Year	Total Loans Requested (in Thousands)	Total Loans Approved (in Thousands)	Approval Probability (%)	Approved Amount (in $USD Millions)	Average Loan Amount ($USD)	Average Interest Rate (%)
2007	6	1	10.3	5	8,255	11.8
2008	28	2	8.6	21	8,825	12.1
2009	62	5	8.5	52	9,833	12.4
2010	125	13	10.0	132	10,528	12.0
2011	239	22	9.1	262	12,047	12.2
2012	391	53	13.7	718	13,462	13.6
2013	896	135	15.1	1,983	14,707	14.5
2014	2,168	236	10.9	3,504	14,870	13.8
2015	3,280	421	12.8	6,417	15,240	12.6
2016	5,203	434	8.3	6,400	14,734	13.0
2017	7,515	444	5.9	6,585	14,845	13.2
2018	9,991	495	5.0	7,936	16,025	12.7
Total	**29,904**	**2,261**	**7.6**	**34,015**	**15,047**	**13.1**

Table 2: Natural Disaster Summary Statistics by Year and Hazard Type

This table reports Presidential Disaster Declaration natural disaster damage estimates during the loan sample period. We report damage totals by year and hazard type. The largest contributors to *Other* includes severe storm, hail, earthquake, and landslide.

		Disaster Type (in Millions)					
Year	**Total Damage (in $USD Billions)**	**Flooding**	**Hurricane/ Tropical Storm**	**Tornado**	**Drought, Wildfire, Heat**	**Blizzard/ Winter Weather**	**Other**
2007	7.1	1,638.7	0.0	1,246.0	1,819.4	2,113.0	268.6
2008	31.8	19,015.3	8,648.5	2,674.6	307.5	258.2	887.0
2009	3.4	724.8	0.0	646.1	52.4	1,695.2	319.2
2010	6.4	5,251.0	2.8	551.7	267.0	282.0	54.5
2011	36.6	17,019.4	2,600.9	14,791.8	1,975.4	94.8	153.8
2012	58.5	46,485.2	293.4	9,450.4	1,963.7	154.3	128.3
2013	6.9	2,563.9	0.0	3,351.1	645.8	280.7	22.8
2014	4.2	2,228.9	1.0	511.7	469.9	33.9	993.0
2015	4.4	3,736.5	6.9	145.1	10.5	115.0	350.3
2016	18.4	12,068.8	6,080.8	56.5	175.0	9.1	8.1
2017	141.2	87,676.2	52,782.2	406.1	189.5	48.4	140.8
2018	26.5	3,814.7	20,941.1	399.5	740.8	2.1	613.3
Total	**345.4**	**202,223.4**	**91,357.6**	**34,230.6**	**8,616.9**	**5,086.6**	**3,939.5**

Table 3: Summary Statistics of Approved Loans

This table reports summary statistics for all approved loans at Lending Club over the sample period, 2007-2018. Appendix Table A1 provides detailed definitions of the variables listed.

Variable	Obs	Missing	Mean	Std Dev	Min	10%	25%	Median	75%	90%	Max
Loan Characteristics											
Loan Amount (in thousands)	2,260,586	0	15.05	9.19	0.50	5.00	8.00	12.90	20.00	30.00	40.00
Interest Rate (%)	2,260,586	0	13.09	4.83	5.31	7.26	9.49	12.62	15.99	19.42	30.99
5 Year Loan	2,260,586	0	0.29	0.45	0	0	0	0	1	1	1
Borrower Characteristics											
Credit Score	2,260,586	0	701	33	612	667	677	692	717	747	848
Annual Income (in thousands)	2,260,582	4	77.99	112.70	0.00	34.00	46.00	65.00	93.00	130.00	110000.00
Log Income	2,260,582	4	11.09	0.63	0.00	10.43	10.74	11.08	11.44	11.78	18.52
Homeowner	2,259,354	1,232	0.60	0.49	0	0	0	1	1	1	1
DTI (%)	2,258,873	1,713	18.66	9.68	0.00	7.28	11.89	17.84	24.49	30.50	99.00
Revolving Utilization (%)	2,258,784	1,802	50.34	24.71	0.00	16.70	31.50	50.30	69.40	84.20	892.30
Employment Length	2,113,681	146,905	6.02	3.59	1	1	2	6	10	10	10
Loan Performance Variables											
Default	2,260,586	0	0.16	0.37	0	0	0	0	0	1	1
Late Payment	2,260,586	0	0.19	0.39	0	0	0	0	0	1	1
Hardship	2,260,586	0	0.00	0.07	0	0	0	0	0	0	1

Table 4: Interest Rates Charged Around Natural Disasters

This table displays the results for linear regressions using equation (2). *Interest Rate* is the interest rate charged on the loan in percentage points. Event-month indicators ($D^{k}_{j,t}$) are included from three months before (k = -3) to 12 months after (k=12) the disaster. In column 1, control variables related to loan/borrower characteristics, λ_i, from equation (2), are omitted. In columns 2-9, they are added independently, and in column 10, they are all included. Detailed descriptions of control variables are available in Appendix Table A1. Standard errors are clustered at the zip code level.

Dependent Variable:	Interest Rate									
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
D_{-3}	0.0517	0.0531	0.0216	0.0538	0.0442	0.0438	0.0423	0.0523	0.0499	0.0037
	(1.49)	(1.54)	(0.72)	(1.49)	(1.27)	(1.30)	(1.37)	(1.50)	(1.42)	(0.14)
D_{-2}	0.0448	0.0432	0.0338	0.0439	0.0527	0.0628**	0.0536*	0.0427	0.0493	0.0568**
	(1.36)	(1.34)	(1.16)	(1.30)	(1.64)	(2.03)	(1.81)	(1.31)	(1.50)	(2.28)
D_{-1}	0.0089	0.0060	0.0146	0.0086	0.0173	0.0316	0.0136	0.0089	0.0104	0.0229
	(0.27)	(0.18)	(0.50)	(0.25)	(0.55)	(0.98)	(0.43)	(0.27)	(0.32)	(0.84)
D_{0}	0.0175	0.0172	0.0279	0.0227	0.0234	0.0266	0.0177	0.0156	0.0224	0.0430**
	(0.74)	(0.74)	(1.37)	(0.91)	(1.01)	(1.17)	(0.80)	(0.67)	(0.96)	(2.34)
D_{1}	-0.0119	-0.0161	-0.0066	-0.0003	-0.0074	0.0022	-0.0148	-0.0135	-0.0085	0.0041
	(-0.51)	(-0.69)	(-0.31)	(-0.01)	(-0.32)	(0.10)	(-0.67)	(-0.58)	(-0.37)	(0.21)
D_{2}	-0.0246	-0.0313	-0.0256	-0.0061	-0.0086	-0.0187	-0.0373	-0.0266	-0.0170	-0.0075
	(-0.96)	(-1.23)	(-1.16)	(-0.23)	(-0.33)	(-0.79)	(-1.60)	(-1.05)	(-0.66)	(-0.37)
D_{3}	0.0326	0.0311	0.0161	0.0392	0.0418*	0.0375	0.0282	0.0281	0.0327	0.0240
	(1.34)	(1.29)	(0.72)	(1.55)	(1.72)	(1.56)	(1.26)	(1.16)	(1.35)	(1.12)
D_{4}	0.0245	0.0149	0.0202	0.0207	0.0226	0.0293	-0.0032	0.0233	0.0312	-0.0136
	(0.91)	(0.56)	(0.82)	(0.75)	(0.84)	(1.12)	(-0.13)	(0.87)	(1.16)	(-0.64)
D_{5}	0.0209	0.0157	0.0048	0.0170	0.0248	0.0219	0.0212	0.0210	0.0255	0.0038
	(0.86)	(0.66)	(0.20)	(0.69)	(0.98)	(0.92)	(1.03)	(0.87)	(1.03)	(0.19)
D_{6}	0.0202	0.0158	0.0315	0.0251	0.0234	0.0249	0.0011	0.0187	0.0245	0.0175
	(0.73)	(0.57)	(1.29)	(0.89)	(0.85)	(0.91)	(0.04)	(0.68)	(0.88)	(0.78)
D_{7}	0.0674**	0.0662**	0.0599**	0.0785***	0.0713***	0.0760***	0.0566**	0.0662**	0.0702***	0.0547**
	(2.56)	(2.55)	(2.45)	(2.85)	(2.76)	(3.00)	(2.36)	(2.52)	(2.68)	(2.48)
D_{8}	-0.0188	-0.0145	-0.0228	-0.0290	-0.0120	-0.0142	-0.0112	-0.0263	-0.0183	-0.0204
	(-0.70)	(-0.54)	(-0.94)	(-1.04)	(-0.46)	(-0.56)	(-0.44)	(-0.97)	(-0.69)	(-0.90)
D_{9}	0.0296	0.0262	0.0298	0.0262	0.0292	0.0393	0.0387	0.0274	0.0321	0.0397*
	(1.06)	(0.95)	(1.25)	(0.91)	(1.07)	(1.47)	(1.49)	(0.98)	(1.15)	(1.86)
D_{10}	0.0177	0.0139	0.0021	0.0186	0.0147	0.0238	0.0055	0.0160	0.0212	-0.0059
	(0.64)	(0.50)	(0.08)	(0.65)	(0.54)	(0.91)	(0.21)	(0.58)	(0.77)	(-0.24)
D_{11}	0.0389	0.0362	0.0132	0.0399	0.0466	0.0343	0.0204	0.0325	0.0439	-0.0028
	(1.27)	(1.17)	(0.49)	(1.24)	(1.55)	(1.19)	(0.72)	(1.06)	(1.45)	(-0.12)
D_{12}	0.0032	0.0061	-0.0002	0.0040	0.0090	0.0205	0.0028	-0.0035	-0.0029	-0.0050
	(0.12)	(0.24)	(-0.01)	(0.15)	(0.36)	(0.83)	(0.11)	(-0.14)	(-0.11)	(-0.22)
Loan Amount		0.0561***								0.0335***
		(83.85)								(58.49)
Credit Score			-0.0614***							-0.0584***
			(-462.27)							(-456.17)
Employment Length				-0.0237***						-0.0066***
				(-10.83)						(-5.28)
DTI					0.0926***					0.0530***
					(156.39)					(106.30)
Revolving Utilization						0.0513***				0.0064***
						(237.80)				(35.04)
5 Year Loan							4.0602***			3.9537***
							(390.79)			(414.71)
Home Owner								-0.8622***		-0.4321***
								(-60.92)		(-36.43)
Log Income									-0.8215***	-1.1372***
									(-71.45)	(-87.17)
Constant	13.0882***	12.2449***	56.0866***	13.2231***	11.3587***	10.5028***	11.9207***	13.6095***	22.1978***	63.9446***
	(4,920.40)	(1,175.69)	(602.22)	(986.65)	(1,016.93)	(940.94)	(3,077.48)	(1,521.40)	(174.09)	(368.83)
Observations	2,260,566	2,260,566	2,260,566	2,113,661	2,258,853	2,258,764	2,260,566	2,259,335	2,260,562	2,110,829
R-squared	0.023	0.034	0.193	0.023	0.056	0.089	0.165	0.030	0.034	0.376
Zip FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Date FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Table 5: Delinquency Probability for Loans Approved Around Natural Disasters

This table reports linear regressions using equation (2), except replacing *Interest Rate* with two loan performance variables measuring delinquency. *Default* equals one if the loan becomes more than 120 days past due over the life of the loan and zero otherwise. *Late Payment* equals one if the loan is past due at any point during the life of the loan and zero otherwise. Event-month indicators ($D^k_{j,t}$) are included from three months before (k = -3) to 12 months after (k=12) the disaster. In column 1, control variables related to loan/borrower characteristics, λ_i, from equation (2), are omitted. In column 2, they are included, and in column 3, they are included with subgrade fixed effects additionally. Detailed descriptions of control variables are available in Appendix Table A1. Standard errors are clustered at the zip code level.

Dependent Variable:	Default			Late Payment		
	(1)	(2)	(3)	(4)	(5)	(6)
D_{-3}	0.0001	-0.0004	-0.0007	0.0004	-0.0004	-0.0006
	(0.05)	(-0.19)	(-0.28)	(0.14)	(-0.15)	(-0.24)
D_{-2}	0.0031	0.0034	0.0027	0.0045*	0.0048**	0.0040*
	(1.36)	(1.53)	(1.22)	(1.85)	(2.00)	(1.69)
D_{-1}	0.0022	0.0023	0.0023	0.0043*	0.0044*	0.0043*
	(0.93)	(0.96)	(0.95)	(1.77)	(1.83)	(1.83)
D_0	-0.0020	-0.0016	-0.0022	-0.0011	-0.0009	-0.0015
	(-1.10)	(-0.86)	(-1.19)	(-0.59)	(-0.47)	(-0.81)
D_1	-0.0004	0.0000	0.0000	0.0006	0.0013	0.0012
	(-0.19)	(0.01)	(0.01)	(0.30)	(0.62)	(0.63)
D_2	-0.0013	-0.0010	-0.0008	0.0002	0.0003	0.0006
	(-0.75)	(-0.59)	(-0.45)	(0.11)	(0.15)	(0.29)
D_3	0.0009	0.0010	0.0006	0.0014	0.0017	0.0013
	(0.51)	(0.55)	(0.35)	(0.80)	(0.91)	(0.72)
D_4	0.0012	0.0010	0.0012	0.0022	0.0017	0.0019
	(0.70)	(0.56)	(0.69)	(1.24)	(0.91)	(1.05)
D_5	0.0020	0.0010	0.0009	0.0027	0.0016	0.0015
	(1.21)	(0.57)	(0.56)	(1.57)	(0.88)	(0.87)
D_6	0.0012	0.0015	0.0014	0.0014	0.0017	0.0015
	(0.64)	(0.80)	(0.71)	(0.74)	(0.84)	(0.75)
D_7	-0.0003	-0.0006	-0.0012	-0.0001	-0.0005	-0.0012
	(-0.15)	(-0.33)	(-0.69)	(-0.07)	(-0.29)	(-0.67)
D_8	-0.0007	-0.0002	0.0000	0.0003	0.0006	0.0009
	(-0.39)	(-0.14)	(0.00)	(0.15)	(0.37)	(0.52)
D_9	0.0012	0.0021	0.0015	0.0020	0.0023	0.0016
	(0.69)	(1.20)	(0.87)	(1.09)	(1.28)	(0.93)
D_{10}	0.0012	0.0005	0.0005	0.0021	0.0013	0.0013
	(0.67)	(0.27)	(0.29)	(1.12)	(0.68)	(0.72)
D_{11}	-0.0006	-0.0011	-0.0011	-0.0004	-0.0006	-0.0006
	(-0.33)	(-0.59)	(-0.61)	(-0.20)	(-0.31)	(-0.32)
D_{12}	0.0006	0.0002	0.0003	0.0007	0.0001	0.0002
	(0.31)	(0.10)	(0.14)	(0.33)	(0.06)	(0.10)
Loan Amount		0.0015***	0.0011***		0.0018***	0.0013***
		(39.85)	(30.11)		(42.58)	(33.48)
Credit Score		-0.0010***	-0.0004***		-0.0011***	-0.0004***
		(-105.94)	(-38.41)		(-107.39)	(-39.52)
Employment Length		-0.0005***	-0.0005***		-0.0007***	-0.0006***
		(-5.05)	(-4.54)		(-6.27)	(-5.84)
DTI		0.0015***	0.0009***		0.0015***	0.0009***
		(43.49)	(25.30)		(42.92)	(23.82)
Revolving Utilization		-0.0003***	-0.0004***		-0.0004***	-0.0005***
		(-28.02)	(-35.66)		(-29.99)	(-38.12)
5 Year Loan		0.0582***	0.0091***		0.0643***	0.0112***
		(90.45)	(13.64)		(94.05)	(15.92)
Homeowner		-0.0298***	-0.0246***		-0.0315***	-0.0259***
		(-33.12)	(-28.61)		(-33.44)	(-28.89)
Log Income		-0.0261***	-0.0133***		-0.0281***	-0.0141***
		(-36.19)	(-19.27)		(-37.11)	(-19.54)
Constant	0.1191***	1.0792***	0.5232***	0.1303***	1.1839***	0.5730***
	(537.77)	(105.86)	(52.48)	(584.56)	(109.45)	(54.63)
Observations	2,260,566	2,110,829	2,110,829	2,260,566	2,110,829	2,110,829
R-squared	0.041	0.065	0.088	0.033	0.059	0.083
Zip FE	Yes	Yes	Yes	Yes	Yes	Yes
Date FE	Yes	Yes	Yes	Yes	Yes	Yes
Subgrade FE	No	No	Yes	No	No	Yes

Table 6: State-Matched Difference-in-Difference Robustness

This table tests the robustness of Figure 1, Table A3, Table 4, and Table 5 using a state-matched difference-in-difference design. *Treat* equals one for zip codes hit by a natural disaster and zero for control zip codes that are unaffected by a natural disaster but reside in the same state. *Post* equals to one (zero) for the period after (before) the disaster event. *Demand* equals the natural logarithm of one plus the number of P2P loan originations. *Approved* equals one if the loan origination was approved and zero otherwise. We report approval results using the full sample of requested loans (columns 2 and 3) and the subset of requested loans with a credit score listed (columns 4 and 5). *Interest Rate* is the interest rate charged on the loan in percentage points. *Late Payment* equals one if the loan is past due any number of days during the life of the loan and zero otherwise. *Default* equals one if the loan is past due for more than 120 days at any time during the life of the loan and zero otherwise. Detailed descriptions of control variables are available in Appendix Table A1. Standard errors are clustered at the zip code level.

Dependent Variable:	Demand	Approved				Interest Rate		Late Payment			Default		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)
Treat	-0.0029	0.0010	-0.0001	-0.0057	-0.0059	0.0609	0.0317	0.0106*	0.0107*	0.0101*	0.0073	0.0075	0.0071
	(-0.08)	(0.39)	(-0.05)	(-1.39)	(-1.58)	(0.85)	(0.63)	(1.73)	(1.92)	(1.84)	(1.30)	(1.42)	(1.38)
Post	-0.0032	-0.0012	-0.0009	-0.0047**	-0.0027**	0.0018	-0.0235	0.0031	0.0014	0.0020	0.0002	-0.0017	-0.0011
	(-0.14)	(-1.12)	(-1.14)	(-2.11)	(-2.30)	(0.03)	(-0.47)	(0.64)	(0.30)	(0.45)	(0.05)	(-0.35)	(-0.25)
Treat*Post	0.0385**	0.0009	0.0012	0.0023	0.0012	-0.0787	-0.0227	-0.0095	-0.0078	-0.0075	-0.0076	-0.0060	-0.0058
	(2.11)	(0.96)	(1.57)	(1.00)	(0.83)	(-1.25)	(-0.42)	(-1.65)	(-1.34)	(-1.39)	(-1.36)	(-1.00)	(-1.05)
Loan Amount			0.0010***		-0.0013***		0.0561***		0.0026***	0.0017***		0.0023***	0.0014***
			(10.02)		(-6.88)		(9.66)		(11.26)	(7.31)		(10.75)	(6.70)
Employment Length			0.0600***		0.0701***		-0.0124***		-0.0018***	-0.0016***		-0.0015***	-0.0014***
			(24.71)		(39.81)		(-3.59)		(-5.27)	(-4.66)		(-4.38)	(-3.84)
DTI			-0.0004***		-0.0012***		0.0443***		0.0020***	0.0012***		0.0019***	0.0013***
			(-13.87)		(-9.86)		(16.59)		(10.83)	(7.31)		(9.63)	(6.83)
Credit Score					0.0011***		-0.0591***		-0.0017***	-0.0008***		-0.0015***	-0.0007***
					(14.10)		(-51.46)		(-30.06)	(-12.17)		(-29.76)	(-12.04)
Revolving Utilization							0.0046***		-0.0005***	-0.0005***		-0.0005***	-0.0006***
							(3.79)		(-6.96)	(-8.50)		(-9.25)	(-11.06)
5 Year Loan							3.9279***		0.0959***	0.0287***		0.0923***	0.0320***
							(67.44)		(18.47)	(5.64)		(16.67)	(5.67)
Home Owner							-0.5065***		-0.0404***	-0.0320***		-0.0419***	-0.0344***
							(-12.08)		(-12.12)	(-9.44)		(-13.40)	(-10.91)
Log Income							-1.3377***		-0.0346***	-0.0133***		-0.0363***	-0.0174***
							(-14.49)		(-10.91)	(-3.93)		(-12.15)	(-5.48)
Constant	3.6075***	0.0766***	-0.0445***	0.1849***	-0.6425***	13.1840***	66.7806***	0.1965***	1.7574***	0.9002***	0.1688***	1.5917***	0.8406***
	(155.58)	(49.89)	(-11.01)	(72.39)	(-14.46)	(281.69)	(80.51)	(51.22)	(33.15)	(15.73)	(45.52)	(32.45)	(15.77)
Observations	13,670	3,008,113	2,737,086	1,285,206	1,252,480	230,930	215,959	230,930	215,959	215,959	230,930	215,959	215,959
R-squared	0.952	0.019	0.282	0.196	0.522	0.025	0.387	0.013	0.055	0.080	0.013	0.053	0.077
Zip FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Date FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Subgrade FE	No	No	No	No	No	No	No	No	No	Yes	No	No	Yes

Table 7: Demand, Interest Rates, and Delinquency Probability for Low Deposit Areas

This table reports the results from Figure 1, Table 4, and Table 5 by local bank deposits in a given area. For Panel A, the dependent variable is loan demand, or log(1+*originations*). *Originations* are the number of loans requested at the zip-month level. For Panel B, the data is at the loan level, and the dependent variables are *Interest Rate* for columns 1 and 2, *Default* for columns 3-5, and *Late Payment* for columns 6-8. *Interest Rate* is the interest rate charged on the loan in percentage points. *Default* equals one if the loan misses a payment for more than 120 days and zero otherwise. *Late Payment* equals one if the loan is past due at any point during the life of the loan and zero otherwise. Event-month indicators (D^k) are included from three months before to 12 months after the disaster where k=0 for the disaster month. *Low Deposit Area* equals one if the zip code's total deposits in the given year are below the median across all zip codes in that year and zero otherwise. Detailed descriptions of all variables are available in Appendix Table A1. All standard errors are clustered by zip code.

Panel A: Demand

Dependent Variable:	log(1+originations)
Low Deposit Area*D_{-3}	0.0991***
	(2.71)
Low Deposit Area*D_{-2}	0.1128***
	(3.07)
Low Deposit Area*D_{-1}	0.1279***
	(3.54)
Low Deposit Area*D_{0}	0.2766***
	(5.96)
Low Deposit Area*D_{1}	0.2107***
	(4.97)
Low Deposit Area*D_{2}	0.2014***
	(4.92)
Low Deposit Area*D_{3}	0.1874***
	(4.67)
Low Deposit Area*D_{4}	0.1775***
	(4.49)
Low Deposit Area*D_{5}	0.1776***
	(4.82)
Low Deposit Area*D_{6}	0.1534***
	(3.99)
Low Deposit Area*D_{7}	0.1423***
	(3.86)
Low Deposit Area*D_{8}	0.1565***
	(4.26)
Low Deposit Area*D_{9}	0.1329***
	(3.59)
Low Deposit Area*D_{10}	0.1420***
	(3.89)
Low Deposit Area*D_{11}	0.1158***
	(3.39)
Low Deposit Area*D_{12}	0.0932***
	(2.80)

D_{-3}	-0.0365
	(-1.57)
D_{-2}	-0.0345
	(-1.52)
D_{-1}	-0.0535**
	(-2.49)
D_{0}	-0.1018***
	(-3.47)
D_{1}	-0.0607**
	(-2.31)
D_{2}	-0.0375
	(-1.51)
D_{3}	-0.0542**
	(-2.11)
D_{4}	-0.0686***
	(-2.78)
D_{5}	-0.0708***
	(-2.99)
D_{6}	-0.0630**
	(-2.53)
D_{7}	-0.0557**
	(-2.27)
D_{8}	-0.0738***
	(-2.96)
D_{9}	-0.0697***
	(-2.81)
D_{10}	-0.0682***
	(-2.81)
D_{11}	-0.0373*
	(-1.71)
D_{12}	-0.0361
	(-1.61)
Low Deposit Area	0.0837
	(1.05)
Constant	3.3179***
	(83.40)
Observations	111,420
R-squared	0.924
Zip FE	Yes
Date FE	Yes

Panel B: Interest Rate and Delinquency

Dependent Variable:	Interest Rate		Default			Late Payment		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Low Deposit Area*D_{-3}	-0.2243**	-0.0689	-0.0017	0.0042	0.0054	-0.0022	0.0049	0.0062
	(-2.37)	(-0.93)	(-0.22)	(0.54)	(0.69)	(-0.27)	(0.56)	(0.72)
Low Deposit Area*D_{-2}	-0.0100	-0.0193	-0.0127*	-0.0108	-0.0103	-0.0156**	-0.0131	-0.0127
	(-0.10)	(-0.26)	(-1.68)	(-1.39)	(-1.33)	(-2.01)	(-1.64)	(-1.60)
Low Deposit Area*D_{-1}	-0.1421	-0.0305	0.0047	0.0072	0.0075	0.0003	0.0032	0.0037
	(-1.58)	(-0.37)	(0.65)	(0.97)	(1.04)	(0.04)	(0.40)	(0.47)
Low Deposit Area*D_0	-0.0964	-0.1067**	0.0021	0.0034	0.0050	0.0006	0.0021	0.0038
	(-1.44)	(-1.98)	(0.39)	(0.63)	(0.93)	(0.11)	(0.36)	(0.67)
Low Deposit Area*D_1	0.0176	-0.0061	0.0029	0.0045	0.0044	0.0009	0.0014	0.0013
	(0.26)	(-0.11)	(0.50)	(0.74)	(0.75)	(0.14)	(0.21)	(0.20)
Low Deposit Area*D_2	-0.1645**	-0.0685	0.0013	0.0040	0.0052	0.0003	0.0044	0.0058
	(-2.51)	(-1.17)	(0.24)	(0.73)	(0.95)	(0.05)	(0.74)	(0.97)
Low Deposit Area*D_3	-0.0970	-0.0780	0.0019	0.0066	0.0079	0.0007	0.0066	0.0079
	(-1.46)	(-1.35)	(0.38)	(1.24)	(1.47)	(0.13)	(1.10)	(1.33)
Low Deposit Area*D_4	-0.0932	-0.0500	-0.0005	0.0016	0.0028	-0.0004	0.0020	0.0032
	(-1.39)	(-0.90)	(-0.11)	(0.30)	(0.54)	(-0.06)	(0.35)	(0.57)
Low Deposit Area*D_5	-0.0100	-0.0713	0.0017	-0.0012	-0.0002	0.0018	-0.0018	-0.0006
	(-0.14)	(-1.21)	(0.31)	(-0.22)	(-0.04)	(0.32)	(-0.31)	(-0.11)
Low Deposit Area*D_6	-0.0638	-0.0272	-0.0046	-0.0016	-0.0008	-0.0135**	-0.0104*	-0.0096
	(-0.94)	(-0.47)	(-0.83)	(-0.27)	(-0.14)	(-2.24)	(-1.70)	(-1.60)
Low Deposit Area*D_7	-0.1054	-0.0124	-0.0031	0.0004	0.0006	-0.0006	0.0031	0.0033
	(-1.33)	(-0.19)	(-0.55)	(0.07)	(0.11)	(-0.10)	(0.46)	(0.53)
Low Deposit Area*D_8	-0.1382*	-0.0579	-0.0012	0.0004	0.0010	-0.0061	-0.0038	-0.0031
	(-1.93)	(-1.04)	(-0.20)	(0.06)	(0.16)	(-0.93)	(-0.57)	(-0.48)
Low Deposit Area*D_9	-0.1468*	-0.1303**	-0.0053	-0.0036	-0.0017	-0.0074	-0.0056	-0.0034
	(-1.82)	(-2.05)	(-0.96)	(-0.64)	(-0.30)	(-1.26)	(-0.92)	(-0.58)
Low Deposit Area*D_{10}	0.0521	0.0111	-0.0007	-0.0022	-0.0023	0.0012	-0.0004	-0.0006
	(0.77)	(0.18)	(-0.11)	(-0.37)	(-0.40)	(0.20)	(-0.07)	(-0.10)
Low Deposit Area*D_{11}	-0.0091	-0.0128	-0.0050	-0.0020	-0.0012	-0.0051	-0.0010	-0.0002
	(-0.12)	(-0.19)	(-0.94)	(-0.37)	(-0.22)	(-0.86)	(-0.17)	(-0.04)
Low Deposit Area*D_{12}	-0.0437	-0.0052	0.0065	0.0059	0.0061	0.0052	0.0041	0.0043
	(-0.60)	(-0.08)	(1.03)	(0.95)	(1.00)	(0.77)	(0.62)	(0.66)
D_{-3}	0.0811**	0.0126	0.0019	0.0004	0.0000	0.0016	-0.0005	-0.0009
	(2.16)	(0.44)	(0.64)	(0.14)	(0.01)	(0.48)	(-0.17)	(-0.31)
D_{-2}	0.0458	0.0592**	0.0060**	0.0068**	0.0058**	0.0078***	0.0080***	0.0069**
	(1.31)	(2.23)	(2.20)	(2.51)	(2.16)	(2.73)	(2.87)	(2.51)
D_{-1}	0.0273	0.0266	0.0037	0.0028	0.0026	0.0039	0.0027	0.0025
	(0.76)	(0.91)	(1.24)	(0.96)	(0.91)	(1.23)	(0.88)	(0.81)
D_0	0.0301	0.0570***	-0.0010	-0.0010	-0.0018	-0.0003	-0.0001	-0.0011
	(1.20)	(2.94)	(-0.47)	(-0.43)	(-0.85)	(-0.14)	(-0.04)	(-0.48)
D_1	-0.0146	0.0047	-0.0015	-0.0014	-0.0015	0.0003	0.0010	0.0009
	(-0.59)	(0.22)	(-0.67)	(-0.62)	(-0.66)	(0.13)	(0.41)	(0.38)
D_2	-0.0029	0.0014	-0.0002	-0.0001	-0.0000	0.0026	0.0021	0.0022
	(-0.10)	(0.06)	(-0.08)	(-0.05)	(-0.01)	(1.01)	(0.81)	(0.87)
D_3	0.0461*	0.0346	0.0016	0.0008	0.0002	0.0017	0.0005	-0.0001
	(1.76)	(1.50)	(0.82)	(0.35)	(0.08)	(0.76)	(0.22)	(-0.05)
D_4	0.0366	-0.0071	0.0028	0.0020	0.0021	0.0031	0.0023	0.0024
	(1.25)	(-0.31)	(1.31)	(0.87)	(0.93)	(1.32)	(0.92)	(0.98)

D_5	0.0220	0.0128	0.0029	0.0024	0.0022	0.0050**	0.0047**	0.0044*
	(0.84)	(0.59)	(1.41)	(1.12)	(1.04)	(2.13)	(2.01)	(1.95)
D_6	0.0282	0.0207	0.0027	0.0023	0.0020	0.0043*	0.0038	0.0035
	(0.93)	(0.85)	(1.18)	(0.93)	(0.80)	(1.70)	(1.41)	(1.29)
D_7	0.0813***	0.0558**	0.0011	0.0005	-0.0003	-0.0003	-0.0004	-0.0013
	(2.90)	(2.37)	(0.53)	(0.22)	(-0.15)	(-0.15)	(-0.18)	(-0.57)
D_8	-0.0002	-0.0129	0.0024	0.0025	0.0027	0.0019	0.0024	0.0026
	(-0.01)	(-0.52)	(1.10)	(1.22)	(1.31)	(0.82)	(1.03)	(1.13)
D_9	0.0490	0.0568**	0.0023	0.0026	0.0016	0.0022	0.0028	0.0017
	(1.64)	(2.51)	(0.98)	(1.12)	(0.70)	(0.95)	(1.23)	(0.74)
D_{10}	0.0096	-0.0078	0.0019	0.0010	0.0011	0.0012	0.0001	0.0002
	(0.32)	(-0.29)	(0.83)	(0.45)	(0.49)	(0.47)	(0.05)	(0.09)
D_{11}	0.0395	-0.0015	0.0033	0.0019	0.0018	0.0020	-0.0002	-0.0002
	(1.17)	(-0.06)	(1.46)	(0.85)	(0.80)	(0.81)	(-0.07)	(-0.10)
D_{12}	0.0088	-0.0046	0.0008	-0.0003	-0.0002	0.0008	-0.0002	-0.0001
	(0.31)	(-0.19)	(0.35)	(-0.14)	(-0.11)	(0.35)	(-0.08)	(-0.04)
Low Deposit Area	0.0021	0.0219	-0.0004	-0.0007	-0.0005	0.0005	0.0004	0.0005
	(0.04)	(0.52)	(-0.09)	(-0.15)	(-0.13)	(0.12)	(0.10)	(0.12)
Loan Amount		0.0335***		0.0023***	0.0017***		0.0026***	0.0020***
		(58.51)		(46.91)	(38.80)		(51.45)	(43.28)
Credit Score		-0.0584***		-0.0014***	-0.0005***		-0.0016***	-0.0006***
		(-456.15)		(-118.01)	(-46.19)		(-123.77)	(-49.77)
Employment Length		-0.0066***		-0.0008***	-0.0007***		-0.0012***	-0.0011***
		(-5.28)		(-6.46)	(-6.08)		(-9.68)	(-9.57)
DTI		0.0530***		0.0017***	0.0009***		0.0017***	0.0008***
		(106.25)		(43.26)	(23.67)		(40.75)	(20.01)
Revolving Utilization		0.0064***		-0.0005***	-0.0006***		-0.0004***	-0.0005***
		(35.02)		(-34.02)	(-42.89)		(-26.44)	(-35.76)
5 Year Loan		3.9537***		0.0831***	0.0231***		0.0885***	0.0212***
		(414.57)		(114.35)	(30.48)		(111.49)	(25.18)
Homeowner		-0.4321***		-0.0388***	-0.0324***		-0.0372***	-0.0300***
		(-36.42)		(-34.22)	(-30.08)		(-32.01)	(-27.53)
Log Income		-1.1373***		-0.0352***	-0.0190***		-0.0344***	-0.0159***
		(-87.15)		(-41.52)	(-24.04)		(-39.98)	(-20.34)
Constant	13.0881***	63.9414***	0.1583***	1.4600***	0.7451***	0.1880***	1.6181***	0.7983***
	(1,691.08)	(368.46)	(256.80)	(121.37)	(63.90)	(283.45)	(126.82)	(66.63)
Observations	2,259,937	2,110,232	2,259,937	2,110,232	2,110,232	2,259,937	2,110,232	2,110,232
R-squared	0.023	0.376	0.012	0.047	0.072	0.011	0.048	0.075
Zip FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Date FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Table 8: Natural Disasters and Delinquency of Active Loans

This table reports regression results from equation (3) to determine to relationship between active loans and natural disasters. More specifically, this table analyzes the relationship with natural disaster exposure of active loans and delinquency using two measures of severity. *Default* equals one if the loan misses a payment for more than 120 days and zero otherwise. *Late Payment* equals one if the loan is past due at any point and zero otherwise. *Loan Disaster* equals one if the borrower's zip code was hit with a natural disaster while the loan was active and zero otherwise. Detailed descriptions of control variables are available in Appendix Table A1. All standard errors are clustered by zip code.

Dependent Variable:		Default			Late Payment	
	(1)	(2)	(3)	(4)	(5)	(6)
Loan Disaster	0.0067***	0.0032***	0.0017	0.0085***	0.0041***	0.0024**
	(4.98)	(2.59)	(1.45)	(6.08)	(3.35)	(2.04)
Loan Amount		0.0015***	0.0011***		0.0019***	0.0014***
		(39.87)	(30.13)		(45.32)	(35.61)
Credit Score		-0.0010***	-0.0004***		-0.0013***	-0.0005***
		(-105.89)	(-38.38)		(-112.04)	(-42.38)
Employment Length		-0.0005***	-0.0005***		-0.0011***	-0.0010***
		(-5.05)	(-4.53)		(-9.59)	(-9.42)
DTI		0.0015***	0.0009***		0.0015***	0.0008***
		(43.47)	(25.31)		(41.10)	(20.44)
Revolving Utilization		-0.0003***	-0.0004***		-0.0003***	-0.0004***
		(-28.00)	(-35.62)		(-21.53)	(-29.82)
5 Year Loan		0.0581***	0.0090***		0.0666***	0.0066***
		(90.33)	(13.54)		(90.90)	(8.57)
Homeowner		-0.0298***	-0.0246***		-0.0296***	-0.0232***
		(-33.13)	(-28.62)		(-30.79)	(-25.74)
Log Income		-0.0261***	-0.0133***		-0.0267***	-0.0106***
		(-36.18)	(-19.25)		(-35.23)	(-14.92)
Constant	0.1169***	1.0782***	0.5227***	0.1534***	1.3125***	0.6052***
	(259.23)	(106.48)	(52.71)	(329.94)	(115.30)	(56.14)
Observations	2,260,566	2,110,829	2,110,829	2,260,566	2,110,829	2,110,829
R-squared	0.042	0.065	0.088	0.035	0.061	0.087
Zip FE	Yes	Yes	Yes	Yes	Yes	Yes
Date FE	Yes	Yes	Yes	Yes	Yes	Yes
Subgrade FE	No	No	Yes	No	No	Yes

Table 9: Hardship Accommodation Impact on Loans Exposed to a Natural Disaster

This table tests the impact of the hardship accommodation on the default probability of disaster-affected loans. *Loan Disaster* equals one if the loan is affected by a natural disaster during the life of the loan and zero otherwise. *Hardship* equals one if the loan is granted a hardship accommodation and zero otherwise. This accommodation provides a delay of payment for up to three months. Columns 1-3 define hardship accommodation using all reasons. Columns 4-6 include natural disasters, excessive obligations, unemployment, income curtailment, and reduced hours. Columns 7-9 include only natural disaster and excessive obligations. All standard errors are clustered at the zip code level.

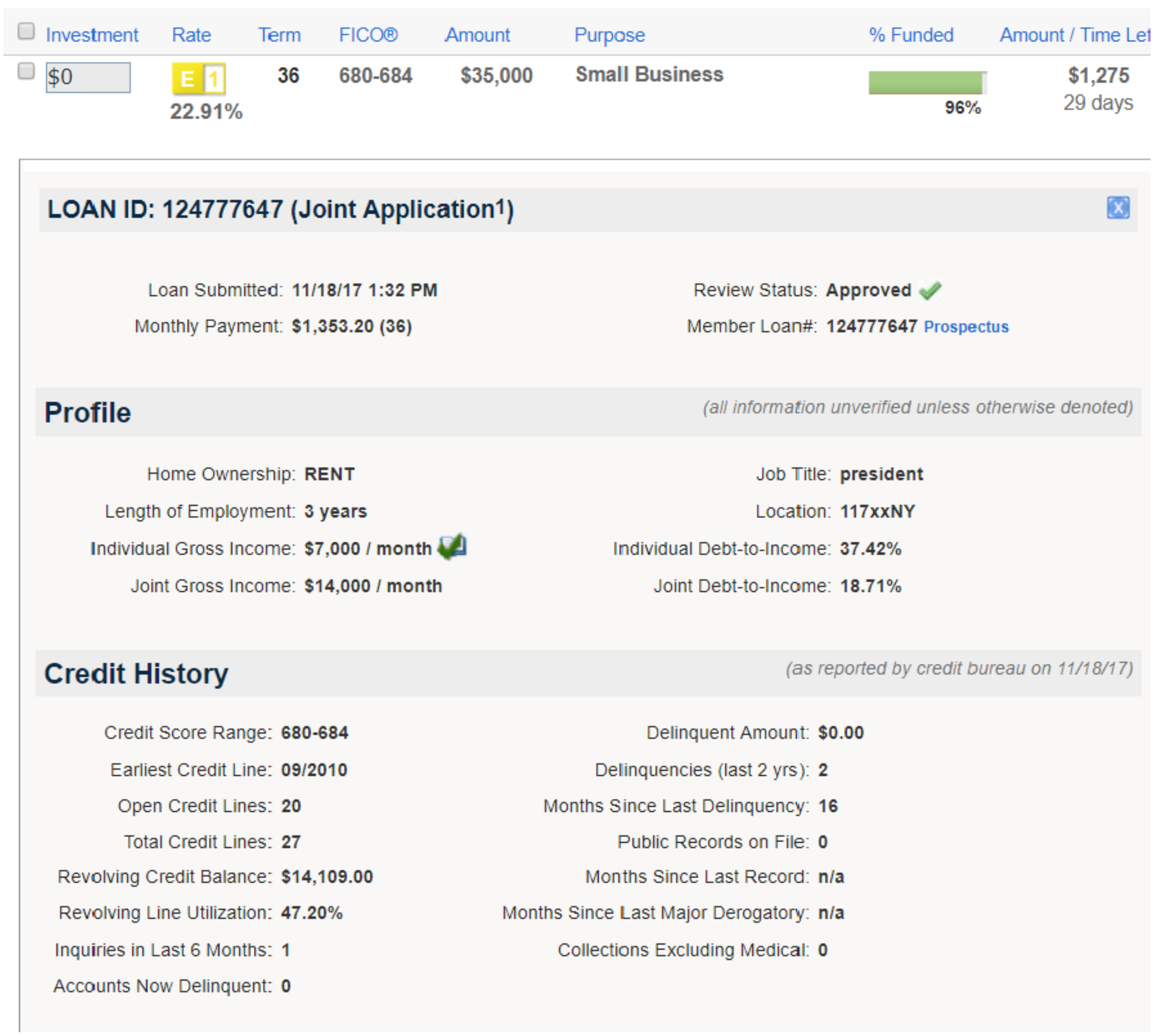
Dependent Variable:	Default								
Hardship Reasons:	All			Natural Disasters, Excessive Obligations, Unemployment, Income Curtailment, Reduced Hours			Natural Disasters and Excessive Obligations		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Loan Disaster	0.0063***	0.0028**	0.0013	0.0063***	0.0028**	0.0013	0.0064***	0.0029**	0.0014
	(4.66)	(2.28)	(1.13)	(4.70)	(2.31)	(1.16)	(4.78)	(2.38)	(1.23)
Hardship	0.2493***	0.2302***	0.2124***	0.2522***	0.2318***	0.2140***	0.2013***	0.1751***	0.1558***
	(29.30)	(26.27)	(24.62)	(25.87)	(23.12)	(21.69)	(13.17)	(11.42)	(10.35)
Hardship*Loan Disaster	-0.0387**	-0.0367**	-0.0312*	-0.0566***	-0.0506***	-0.0443**	-0.0589***	-0.0482**	-0.0392**
	(-2.37)	(-2.20)	(-1.96)	(-3.26)	(-2.82)	(-2.58)	(-2.97)	(-2.38)	(-2.01)
Loan Amount		0.0015***	0.0010***		0.0015***	0.0010***		0.0015***	0.0010***
		(39.08)	(29.28)		(39.28)	(29.48)		(39.76)	(29.95)
Credit Score		-0.0010***	-0.0004***		-0.0010***	-0.0004***		-0.0010***	-0.0004***
		(-104.64)	(-37.83)		(-104.99)	(-37.94)		(-105.52)	(-38.20)
Employment Length		-0.0005***	-0.0004***		-0.0005***	-0.0004***		-0.0005***	-0.0005***
		(-4.85)	(-4.35)		(-4.82)	(-4.32)		(-5.03)	(-4.52)
DTI		0.0015***	0.0009***		0.0015***	0.0009***		0.0015***	0.0009***
		(43.00)	(25.06)		(43.16)	(25.16)		(43.26)	(25.20)
Revolving Utilization		-0.0003***	-0.0004***		-0.0003***	-0.0004***		-0.0003***	-0.0004***
		(-28.03)	(-35.61)		(-28.07)	(-35.65)		(-28.04)	(-35.63)
5 Year Loan		0.0578***	0.0091***		0.0579***	0.0091***		0.0580***	0.0091***
		(89.91)	(13.72)		(90.14)	(13.71)		(90.19)	(13.61)
Homeowner		-0.0296***	-0.0244***		-0.0296***	-0.0244***		-0.0297***	-0.0245***
		(-33.05)	(-28.55)		(-33.06)	(-28.56)		(-33.12)	(-28.61)
Log Income		-0.0260***	-0.0132***		-0.0260***	-0.0133***		-0.0261***	-0.0133***
		(-35.85)	(-19.09)		(-35.89)	(-19.11)		(-36.03)	(-19.19)
Constant	0.1159***	1.0687***	0.5176***	0.1161***	1.0708***	0.5188***	0.1166***	1.0756***	0.5214***
	(258.51)	(105.17)	(52.16)	(258.71)	(105.51)	(52.26)	(259.81)	(106.07)	(52.57)
Observations	2,260,566	2,110,829	2,110,829	2,260,566	2,110,829	2,110,829	2,260,566	2,110,829	2,110,829
R-squared	0.044	0.067	0.090	0.043	0.066	0.089	0.042	0.065	0.088
Zip FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Date FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Subgrade FE	No	No	Yes	No	No	Yes	No	No	Yes

Appendix

"The social welfare of marketplace lending: Evidence from natural disasters"

Figure A1: Lending Club Listing Snapshot

This figure shows a snapshot taken from a randomly chosen Lending Club loan listing on December 1, 2017. It is not a typical loan as the grade is lower than average and consequently pays a higher-than-average interest rate. Instead, it provides an example of the investor's view when researching potential loans to fund. This view is no longer publicly available as Lending Club only allows institutional (not individual) investors to fund the platform as of December 31, 2020.



Investment	Rate	Term	FICO®	Amount	Purpose	% Funded	Amount / Time Let
$0	E 1 22.91%	36	680-684	$35,000	Small Business	96%	$1,275 29 days

LOAN ID: 124777647 (Joint Application1)

Loan Submitted: **11/18/17 1:32 PM**
Monthly Payment: **$1,353.20 (36)**
Review Status: **Approved**
Member Loan#: **124777647** Prospectus

Profile *(all information unverified unless otherwise denoted)*

Home Ownership: **RENT**
Length of Employment: **3 years**
Individual Gross Income: **$7,000 / month**
Joint Gross Income: **$14,000 / month**
Job Title: **president**
Location: **117xxNY**
Individual Debt-to-Income: **37.42%**
Joint Debt-to-Income: **18.71%**

Credit History *(as reported by credit bureau on 11/18/17)*

Credit Score Range: **680-684**
Earliest Credit Line: **09/2010**
Open Credit Lines: **20**
Total Credit Lines: **27**
Revolving Credit Balance: **$14,109.00**
Revolving Line Utilization: **47.20%**
Inquiries in Last 6 Months: **1**
Accounts Now Delinquent: **0**
Delinquent Amount: **$0.00**
Delinquencies (last 2 yrs): **2**
Months Since Last Delinquency: **16**
Public Records on File: **0**
Months Since Last Record: **n/a**
Months Since Last Major Derogatory: **n/a**
Collections Excluding Medical: **0**

Figure A2: Loan Demand Around Natural Disasters Robustness

This figure displays abnormal loan originations around natural disasters using only those originations with an associated credit score. Some originations do not make it to this stage in the approval process because they are declined prior. The solid line reflects the β_k coefficients from equation (1). The dotted lines report the boundaries of 95% confidence intervals for those coefficients. All standard errors are clustered at the zip code level.

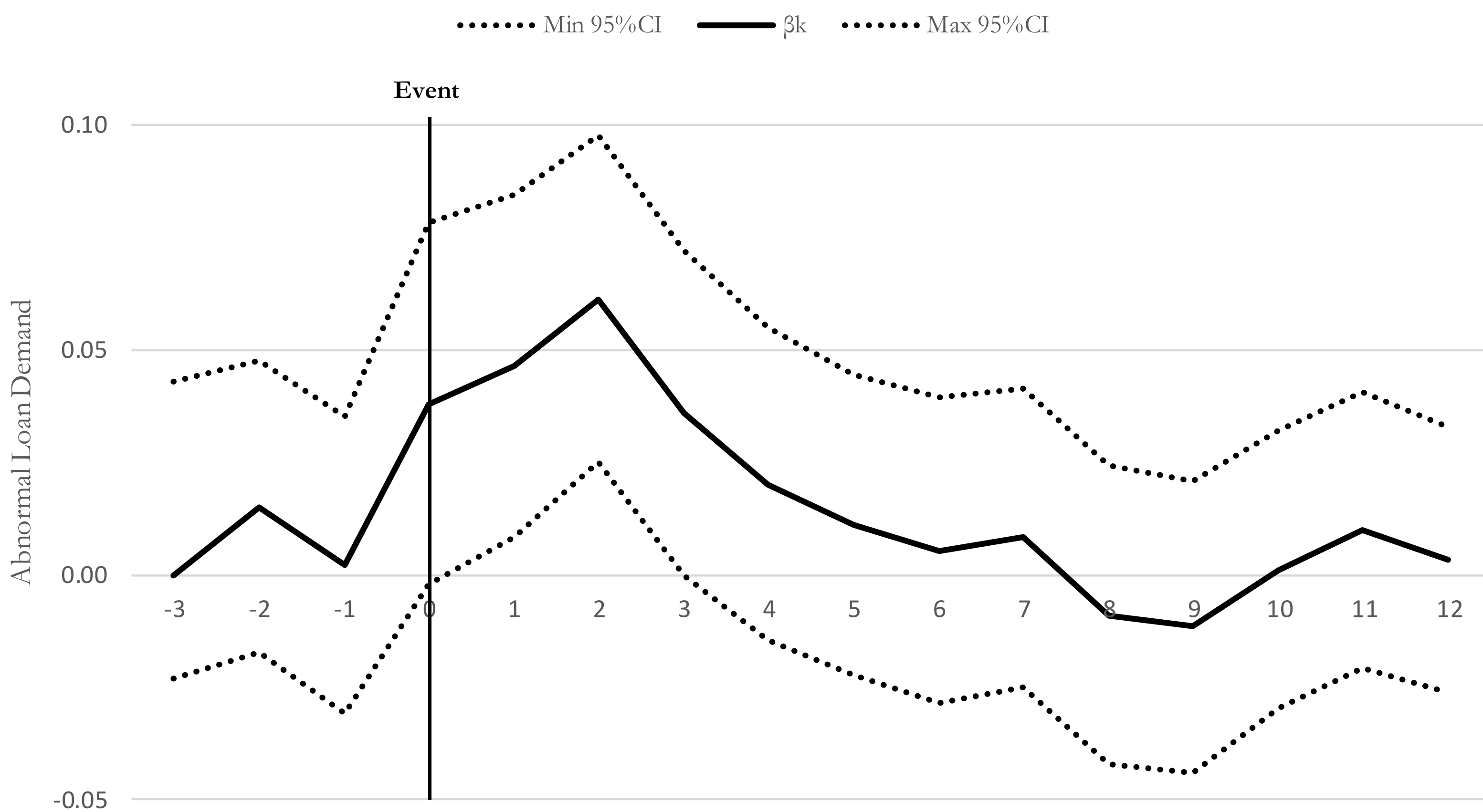


Table A1: Variable Descriptions

Variable	Description
Loan Amount	The approved loan amount in $USD thousands.
Interest Rate (%)	The interest rate charged on the loan in percentage points.
5 Year Loan	Equals one for 5-year loans and zero for 3-year loans. All loan terms are either 3 years or 5 years.
Annual Income	The self-reported annual income (in $USD thousands) provided by the borrower during the application process.
DTI (%)	The ratio of the borrower's total monthly debt payments on the total debt obligations (excluding home mortgage) to their self-reported monthly income.
Revolving Utilization (%)	The amount of credit the borrower is using relative to all available revolving credit in percentage points.
Credit Score	The borrower's FICO score at the time of loan origination. This is calculated as the average of the upper and lower boundary range the borrower's FICO belongs to at loan origination.
Employment Length	The borrower's employment length in years. Possible values are between 0 and 10 where 0 means less than one year and 10 means ten or more years.
Homeowner	Equals one if the borrower owns a home during the application process and zero otherwise.
Subgrade	Once borrowers loan applications are approved, they are assigned into one of 35 groups based on their expected risk level. These groups are referred to as subgrades. Interest rates are internally calculated based assigned subgrades.
Default	Equals one if the borrower's loan was ever considered in default during the life of the loan, and zero otherwise. Lending Club considers all loans more than 120 days past due in default.
Late Payment	Equals one if the loan is considered past due at any point during the life of the loan and zero otherwise.
Hardship	Equals one is the loan was approved for a hardship accommodation and zero otherwise.
D_k	Zip code* level disaster event-month indicators. We include 16 monthly indicators from k = -3 to k = 12, where k = 0 at the month in which the disaster occurred.
Loan Originations	The zip-month total count of all (approved and rejected) loan applications received by Lending Club.
Loan Disaster	Equals one if the borrower's zip code was struck by a disaster during the life of the loan and zero otherwise.
Low Deposit Area	Equals one if the borrower's zip code has fewer local bank deposits than the median across all zip codes in the given year and zero otherwise.

*Note, all references to a zip code area are the first three digits of the borrower's reported zip code.

Table A2: Requested Loan Summary Stats

This table displays summary statistics for all requested loans (Panel A) and declined loans (Panel B) broken out separately. *Approved* equals one if the loan origination was approved and zero otherwise. *Loan Amount* is the requested loan amount in $USD thousands. *Employment Length* is the borrower's employment length in years. Possible values are between zero and ten where zero means less than one year and 10 means ten or more years. *DTI* is the ratio of the borrower's total monthly debt payments on the total debt obligations (excluding home mortgage) to their self-reported monthly income. *Credit Score is* the borrower's FICO score at the time of loan origination. This is calculated as the average of the upper and lower boundary range the borrower's FICO belongs to at loan origination.

Panel A: Requested Loans

Variable	Obs	Missing	Mean	Standard Deviation	10%	25%	Median	75%	90%
Approved	29,904,329	0	0.08	0.26	0	0	0	0	0
Loan Amount (in thousands)	29,903,010	1,319	13.28	14.66	2	5	10	20	30
Employment Length	28,806,098	1,098,231	1.90	2.20	1	1	1	1	5
DTI %	28,701,010	1,203,319	27.94	26.28	2.5	10.0	20.6	36.0	64.5
Credit Score	11,294,793	18,609,536	646.83	65.33	556	606	655	689	722

Panel B: Declined Loans

Variable	Obs	Missing	Mean	Standard Deviation	10%	25%	Median	75%	90%
Loan Amount (in thousands)	27,642,424	1,319	13.13	15.01	2	5	10	20	30
Employment Length	26,692,417	951,326	1.57	1.66	1	1	1	1	5
DTI %	26,442,137	1,201,606	28.73	27.08	2.2	9.7	21.1	37.6	70.2
Credit Score	9,034,207	18,609,536	633.38	64.49	545	593	637	675	711

Table A3: Approval Probabilities Around Natural Disasters

This table reports results of equation (2), except the dependent variable is replaced with *Approved*. *Approved* equals one if the loan origination was approved and zero otherwise. Event-month indicators ($D^k_{j,t}$) are included from three months before (k = -3) to 12 months after (k=12) the disaster. We report using the full sample of requested loans (columns 1 and 2), and the subset of requested loans with a credit score listed (columns 3 and 4). In column 2 and 4 (1 and 3), available control variables related to loan/borrower characteristics are included (omitted). Detailed descriptions of control variables are available in Appendix Table A1. Standard errors are clustered at the zip code level.

Dependent Variable:	Approved			
	(1)	(2)	(3)	(4)
D_{-3}	0.0001	0.0005	-0.0010	-0.0014
	(0.20)	(0.74)	(-0.69)	(-1.21)
D_{-2}	0.0001	-0.0003	-0.0003	-0.0015
	(0.12)	(-0.40)	(-0.19)	(-1.26)
D_{-1}	-0.0007	-0.0006	-0.0033**	-0.0028**
	(-1.06)	(-0.96)	(-2.10)	(-2.34)
D_0	-0.0005	-0.0003	-0.0031**	-0.0034***
	(-0.83)	(-0.43)	(-2.43)	(-2.86)
D_1	0.0005	0.0007	-0.0021*	-0.0030***
	(0.88)	(1.44)	(-1.73)	(-2.83)
D_2	0.0010*	0.0011**	0.0005	-0.0013
	(1.76)	(2.05)	(0.45)	(-1.28)
D_3	0.0001	0.0004	-0.0008	-0.0015
	(0.12)	(0.91)	(-0.74)	(-1.51)
D_4	0.0010	0.0008	0.0009	-0.0008
	(1.44)	(1.36)	(0.72)	(-0.79)
D_5	0.0007	0.0010*	-0.0008	-0.0013
	(1.20)	(1.86)	(-0.69)	(-1.16)
D_6	0.0000	0.0005	-0.0026**	-0.0011
	(0.03)	(0.84)	(-2.04)	(-1.01)
D_7	0.0007	0.0007	-0.0008	-0.0003
	(1.22)	(1.26)	(-0.55)	(-0.29)
D_8	0.0003	0.0002	-0.0038***	-0.0016
	(0.49)	(0.39)	(-2.77)	(-1.56)
D_9	0.0009	0.0008	-0.0029*	-0.0019
	(1.59)	(1.47)	(-1.88)	(-1.50)
D_{10}	0.0010*	0.0005	-0.0046***	-0.0028**
	(1.86)	(0.97)	(-3.30)	(-2.46)
D_{11}	0.0010*	0.0005	-0.0036***	-0.0025**
	(1.75)	(0.91)	(-3.12)	(-2.51)
D_{12}	0.0008	0.0005	-0.0003	0.0002
	(1.32)	(0.88)	(-0.23)	(0.17)
Loan Amount		0.0010***		-0.0010***
		(41.76)		(-36.98)
Employment Length		0.0630***		0.0682***
		(262.07)		(303.41)
DTI		-0.0004***		-0.0013***
		(-58.56)		(-76.33)
Credit Score				0.0012***
				(100.11)
Constant	0.0755***	-0.0443***	0.2006***	-0.7140***
	(649.95)	(-87.53)	(891.35)	(-97.78)
Observations	29,904,329	27,642,172	11,294,793	10,981,363
R-squared	0.020	0.300	0.219	0.532
Date FE	Yes	Yes	Yes	Yes
ZIP3 FE	Yes	Yes	Yes	Yes