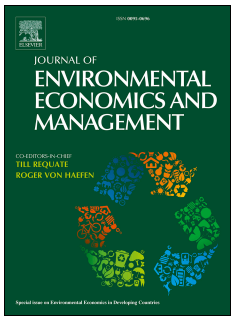
Journal Pre-proof



Do non-damaging earthquakes shake mortgage lenders' risk perception?

Minhong Xu, Yilan Xu

PII: S0095-0696(22)00113-9

DOI: https://doi.org/10.1016/j.jeem.2022.102760

Reference: YJEEM 102760

To appear in: *Journal of Environmental Economics and Management*

Received Date: 8 February 2021

Revised Date: 22 September 2022

Accepted Date: 8 November 2022

Please cite this article as: Xu, M., Xu, Y., Do non-damaging earthquakes shake mortgage lenders' risk perception?, *Journal of Environmental Economics and Management* (2022), doi: https://doi.org/10.1016/j.jeem.2022.102760.

Do Non-damaging Earthquakes Shake Mortgage Lenders' Risk Perception?*

Minhong Xu†
New York University
Wilf Hall
139 MacDougal Street, Third Floor
New York, NY 10012
minhong.xu@nyu.edu

Yilan Xu
University of Illinois at Urbana-Champaign
309 Mumford Hall
1301 W. Gregory
Urbana, IL 61801
yilanxu@illinois.edu

* Declarations of interest: none. This research did not receive any specific grant from funding agencies in the public, commercial, or not-for-profit sectors.

† Corresponding author. Wilf Hall, 139 MacDougal Street, Third Floor, New York, NY 10012.

Do Non-damaging Earthquakes Shake Mortgage Lenders' Risk Perception?

Abstract

This study examines how banks respond to earthquakes that convey seismic risk salience but do not cause damage, i.e., noticeable non-damaging earthquakes (NNDEs). Using evidence from California, we find loans more likely to be denied or sold after increased NNDEs. Banks with fewer assets, more diversified branching markets, or stronger sales capability relied more on securitization to transfer the perceived seismic risk. We show evidence that banks likely learned about the NNDEs through personal experience and local news. The effects of NNDEs persisted up to three years. Meanwhile, the NNDEs only caused moderate and temporary collateral devaluation but did not increase the observable default risk. Thus, banks' responses most likely resulted from the increased risk salience of future damaging earthquakes during the mortgage term. Our findings call for reevaluations of the heuristics in banks' risk-perception updating and have implications for designing more efficient disaster risk-sharing mechanisms in the financial market.

Keywords: Earthquake risk; bank lending; disaster risk-sharing

JEL Classification: G14; G21; G41; Q54

1. Introduction

Understanding how economic agents update risk perception is important in promoting efficient disaster risk mitigation and adaptation. Existing studies find that homeowners could learn from recent floods to update their risk perception of future floods (Kousky, 2010; Gallagher, 2014). Banks also learned from billion-dollar hurricane events and originated more conforming mortgage loans to be sold to the Government-Sponsored Enterprises (GSEs) in response (Ouazad and Kahn, 2022). Moreover, disasters affect the risk perception of homeowners even when physical damage was negligible (Liu et al., 2018), when no dis-amenity effects occurred (McCoy and Walsh, 2018), and when the events were geographically distant (Muller and Hopkins, 2019). It is unknown, however, whether banks also take precautionary measures in response to disasters that send risk signals but do not cause actual losses. Banks' disaster risk management deserves research and policy attention because of their critical role in promoting economic growth and disaster resilience as financial institutions. This study uses noticeable non-damaging earthquakes ("NNDEs") to examine how banks react to the risk information of seismic shocks independent of financial losses.

Earthquakes subject banks to losses such as collateral depreciation and foreclosure expenses when borrowers default on damaged properties (Anderson and Weinrobe, 1986). However, unlike flood insurance, earthquake insurance is not required to cover loans secured by buildings in seismic zones, leading to a low take-up rate of about 10 percent (Marshall, 2017). Moreover, banks are more vulnerable to uninsured seismic risk in non-recourse states like California, where banks are prohibited from suing borrowers to make up the difference between the collateral value and the outstanding balance in the event of foreclosure. Our study exploits NNDEs in California as costless risk signals that convey the salience of seismic risk but do not cause property damage.

We examine changes in banks' credit decisions on home mortgage loans after NNDEs to reveal their risk perception updating process and the associated risk management strategies.

When perceiving seismic risk, banks are expected to reevaluate the risk of default and collateral devaluation for loans in the affected neighborhoods. The increased anticipated credit losses may lead to reduced loan provisions (Garmaise and Moskowitz, 2009; Berg and Schrader, 2012; Xu and Xu, 2020). Alternatively, banks may choose to charge higher interest rates to price the risk (Garmaise and Moskowitz, 2009) or securitize more to transfer the risk of the originated loans (Xu and Xu, 2020; Ouazad and Kahn, 2022). In particular, the major buyers in the secondary market, the GSEs, lack local disaster information. Banks are thus more likely to exploit the information asymmetry to shift the risk. In this study, we develop a theoretical model that allows a bank to make an adjustment in the probability of future damaging earthquakes on top of the existing knowledge after NNDEs. The model explicitly disentangles two channels of potential financial losses, i.e., default risk and collateral devaluation, and three risk management strategies, i.e., loan denial, interest rate adjustment, and securitization. Our model concludes that banks perceiving seismic risk do not necessarily cut the loan supply if they can use the pricing and securitization tools to manage the risk. We then empirically examine banks' responses to seismic shocks using 2010-2016 California home mortgage loans from the Home Mortgage Disclosure Act (HMDA) data. In our loan-level analysis, we measure seismic shocks by the within-Census-tract variations in the number of NNDEs in the previous year. Our model captures time-invariant Census-tract-level characteristics by controlling for the Census tract fixed effects and the county-level demand changes by controlling for the bank by year by county fixed effects.

The baseline results show increases in the likelihoods of a loan being denied or sold after NNDEs. Given one more NNDE in the previous year, the likelihood of a loan being denied

increased by 0.1 percentage points (p-value<0.05), equivalent to a 0.7 percent increase in the loan denial rate. The results indicate that the perceived risk from NNDEs led to a credit supply cut of a small magnitude. By comparison, Garmaise and Moskowitz (2009) find that the presence of objective earthquake risk, measured by the associated annual loss, could reduce the probability of bank loan provision in California by 12.4 percentage points, equivalent to a 22 percent of the mean probability. Meanwhile, we find that one more NNDE in the previous year raised the likelihood of a loan being sold to the GSEs by 0.3 percentage points (p-value<0.05), or a 0.6 percent increase in the rate of GSEs securitization. The adjustment in loan securitization was more pronounced among banks with fewer assets, more diversified branching markets, or stronger connections with the secondary market. As we further explore two alternative measures of seismic shocks, our evidence suggests that banks' decisions on loan denial were more responsive to the shaking intensity of earthquakes, whereas their decisions on loan securitization relied more on the concentration of seismic activity. Our findings of banks' *ex-ante* precautionary behavior when no damage costs occur expand the existing literature on banks' *ex-post* strategies to recover from damaging disasters, such as capital reallocation across markets (Cortés and Strahan, 2017), relationship-based lending (Berg and Schrader, 2012; Koetter et al., 2019), and asset portfolio adjustment (Schüwer et al., 2018; Bos et al., 2022). In particular, we add to Ouazad and Kahn (2022) by showing that banks could respond to the disaster risk information *per se* in non-damaging disasters even when the market conditions and loan quality were unaffected.

Next, we explore the potential channels from which banks could source seismic information. We show that banks likely sourced seismic information from both personal experience and soft information such as real-time local news. Specifically, banks did not respond to unnoticeable

earthquakes but reacted to noticeable ones and especially to those in their branching markets. They also responded to earthquakes in neighboring counties within the same media network. Our findings indicate that banks can use local soft information to detect environmental risks, which are linked to the broader literature on bank branching and relationship-based lending (Ergungor, 2010; Berg and Schrader, 2012; Gilje et al., 2016; Koetter et al., 2019).

We then examine how banks update their risk perception after NNDEs. We find that banks only responded to NNDEs up to the past three years, which might be explained by the availability bias (Tversky and Kahneman, 1973; Tversky and Kahneman, 1974) or a Bayesian learning process that heavily discounts the past information (Gallagher, 2014). Meanwhile, we find no changes in the observable default risk or immediate collateral devaluation. Specifically, we find no evidence of sorting by less creditworthy borrowers into neighborhoods exposed to NNDEs. In addition, we only identify a moderate and temporary housing price drop that persisted nine months after NNDEs, which barely imposed credit risks unless collaterals were forced to be sold due to foreclosure before housing prices rebounded. However, the risk is extremely low given that foreclosure within one year of loan origination is rare even during the global financial crisis (Xu, 2014). Moreover, homeowners are unlikely to walk away from such a moderate collateral devaluation, especially when the housing price fluctuation period is even shorter than the typical foreclosure timeline (Cordell et al., 2015). Thus, banks' responses to NNDEs were more likely to result from the concern about an increased chance of damaging earthquakes during the mortgage term.

2. Theoretical Model

In this section, we set up a theoretical model to demonstrate how banks adjust credit decisions in response to perceived seismic risk. We extend the models of Collier (2020) and Bos et al. (2022) in three ways. First, we allow banks' credit decisions to be affected by an adjustment of seismic risk relative to the existing earthquake probability. Second, we introduce loan pricing and securitization as part of banks' risk management strategies. Third, we build the model in a non-recourse loan context in which banks can foreclose defaulted loans to recover the outstanding balance but need to bear the deficiency losses due to collateral devaluation, i.e., the difference between the collateral value and the outstanding balance.

Assume that a bank manages a stock of equity k. In each period, the bank makes loans l with an interest rate $\hat{r} = r + \epsilon^r$, where r is the mean value and ϵ^r is a random shock. The costs of searching, screening, and monitoring borrowers when originating loans are $h(l) = \eta l + \frac{\varphi}{2} l^2$, where $\eta > 0$ and $\varphi > 0$, indicating increased marginal costs with the loan amount. Meanwhile, the bank takes deposits d with a deposit interest rate r^d. The bank also sells a fraction, $\hat{s} = s + \epsilon^s$, of the originated loans to the secondary market as a risk-transfer strategy, where s is the mean value and ϵ^s is an unexpected shock. The bank acquires revenue $\hat{s} l \gamma$ from the loans sold, where $\gamma \in (0,1)$. The balance sheet identity thus implies the following equation:

$$(1 - \hat{s})l = d + k \tag{1}$$

Loans kept in the portfolio default at a rate, $\hat{\xi} = \xi + \epsilon^{\xi}$, where ξ is the mean value and ϵ^{ξ} is an unexpected shock. When borrowers default, banks sell the collaterals to recover the loan balance while bearing the foreclosure deficiency losses, which occur as a fraction $\hat{c}$ of the

defaulted loan amount. The collateral losses rate $\hat{c}$ takes the mean value c with a random shock ϵ^c in each period.

The net income of the bank, I, thus equals the income from the securitized loans, plus the interest income from the performing loans in the portfolio, less the foreclosure deficiency losses from the defaulted loans, the deposit interest payments, and the origination costs as follows:

$$I = \hat{s}l\gamma + \left(1 - \hat{\xi}\right)(1 - \hat{s})l\hat{r} - \hat{\xi}(1 - \hat{s})l\hat{c} - r^d d - h(l) \tag{2}$$

The bank's objective is to maximize its current and discounted future dividend payments to shareholders over an infinite horizon. In the equilibrium, we impose the zero-profit condition so that income equals dividend payments.

$$I = vk \tag{3}$$

where k is the current equity and v is the dividend rate.

The bank expects a damaging earthquake to happen with a probability p during the mortgage term: $p = p^o + \tilde{p}$. The probability of damaging earthquake p^o is assessed by the best available science and usual experience. In an efficient risk-sharing market, banks fully price the risk by incorporating the full information of past earthquakes. Banks make an adjustment $\tilde{p}$ relative to the existing knowledge due to perceived risk after seismic shocks. Part of the adjustment may capture changes in the objective earthquake probability if NNDEs indeed affect the chance of future damaging earthquakes (Petersen et al., 2014).

The earthquake probability affects the bank's potential losses due to default and devaluation. In the equilibrium, the default rate is $\xi = \mu_\xi + p\tilde{\xi}$ and the collateral losses rate is $c = \mu_c + p\tilde{c}$, where μ_ξ and μ_c are the rates without any earthquake whereas $\tilde{\xi}$ and $\tilde{c}$ are the increments in the

event of a damaging earthquake. We expect NNDEs to affect the expected credit risk through p rather than μ_ξ or μ_c, unless borrowers' creditworthiness worsens or the collateral properties depreciate permanently after NNDEs.

We allow the bank to adjust the interest rate and the securitization rate in response to perceived seismic risk. The interest rate is $r = \mu_r + p\tilde{r}$ and the securitization rate is $s = \mu_s + p\tilde{s}$, where μ_r and μ_s are the earthquake-free rates and $\tilde{r}$ and $\tilde{s}$ represent the risk premium and the additional share of loans sold, respectively, when a damaging earthquake occurs.

Substituting equations (1)-(2) into equation (3) solves the optimal loan amount in equilibrium $l = \frac{-B+\sqrt{B^2-2\varphi(r^d-v)d}}{\varphi}$, where $B = [\eta + v(1-s) + \xi(1-s)c - (1-\xi)(1-s)r - s\gamma]$. Taking the total derivative of l with respect to $\tilde{p}$ yields:

$$\frac{dl}{d\tilde{p}} = \frac{\partial l}{\partial c}\frac{dc}{d\tilde{p}} + \frac{\partial l}{\partial \xi}\frac{d\xi}{d\tilde{p}} + \frac{\partial l}{\partial r}\frac{dr}{d\tilde{p}} + \frac{\partial l}{\partial s}\frac{ds}{d\tilde{p}} = \frac{\partial l}{\partial c}\tilde{c} + \frac{\partial l}{\partial \xi}\tilde{\xi} + \frac{\partial l}{\partial r}\tilde{r} + \frac{\partial l}{\partial s}\tilde{s} \quad (4)$$

Given that $\tilde{c}$, $\tilde{\xi}$, $\tilde{r}$, and $\tilde{s}$ are all positive, the sign of equation (4) depends on the direction of each of the following derivatives:[1]

i. $\frac{\partial l}{\partial c} < 0$. The loan supply decreases as the expected collateral losses rate increases.
ii. $\frac{\partial l}{\partial \xi} < 0$. The loan supply decreases as the expected default rate increases.
iii. $\frac{\partial l}{\partial r} > 0$. The loan supply increases as the loan interest rate increases.

[1] See Appendix A for detailed derivation.

iv. The sign of $\frac{\partial l}{\partial s}$ is undetermined. The effect of securitization on the loan supply depends on the relative magnitudes of the loan interest rate, the default rate, the collateral losses rate, the dividend rate, and the proportional revenue of loan securitization.

The results above indicate that an increment in perceived seismic risk, $\tilde{p}$, may lead to undetermined changes in the credit supply. On the one hand, banks are incentivized to cut the supply due to a higher expected collateral losses rate (part i) and a higher expected default rate (part ii). On the other hand, banks have the option of pricing (part iii) and securitization (part iv) strategies to mitigate the risk of the originated loans and thus do not necessarily reduce loan provisions.

3. Data

3.1 Earthquake Data

We source the earthquake catalog from the U.S. Geological Survey (USGS). The USGS ShakeMap contours the severity of earthquakes by the Modified Mercalli Intensity (MMI) to measure the pointwise shaking intensity, which decreases with distance from the earthquake epicenter. To measure the intensity of an earthquake perceived in a Census tract, we overlap the Shakemap of an earthquake with the Census tract boundaries of California (Figure 1). We then calculate the average MMI across all the polygons intersected with the Census tract, weighted by the area of each intersecting polygon relative to that of the entire Census tract. To supplement earthquakes missing Shakemap data, we calculate the perceived intensity of each earthquake at the centroids of nearby Census tracts using an attenuation function, which is based on the

magnitude, the depth, and the distance from the epicenter of the earthquake.[2] Combining the earthquake intensity information obtained using the two methods, we count the total number of earthquakes with an average MMI between 2 and 6 perceived in a Census tract every year, i.e., NNDEs that are salient enough to be noticed but do not damage any property (USGS, 2016). We also calculate the annual total number of earthquakes with an average MMI above 6 as damaging earthquakes and those with an average MMI below 2 as unnoticeable earthquakes for each Census tract. As alternative measures for seismic shocks, we weight the number of NNDEs by the inverse of the interval between the current and the immediately previous earthquakes to capture the concentration of seismic activity in a year. We also weight the earthquake counts by the intensity of each earthquake in MMI to capture the effects of shaking severity.

Figure 2 plots the temporal variations in the annual number of earthquakes covered in our analyses. From 2010 to 2016, California was affected by 2,010 NNDEs and 29 damaging earthquakes, including those with epicenters in California or neighboring states. Figure 3 illustrates the spatial distribution of the cumulative number of NNDEs over this period across Census tracts in California, which shows that seismic risk is higher near the coastline and the state border. Figure C1 plots the geographic distribution of the annual earthquake counts across Census tracts for each year over 2011-2016, which illustrates the temporal variations in the number of NNDEs within a Census tract upon which our identification strategy is based.

[2] See Appendix B for the detailed calculation method.

3.2 Home Mortgage Loan Data

We access home mortgage lending activities from the Home Mortgage Disclosure Act data, which cover 80% of the total mortgage originations nationwide (Berkovec and Zorn, 1996; Avery et al., 2007). The data report borrowers' loan amount, income, and demographic information but do not contain factors related to creditworthiness such as credit histories, debt burdens, and the loan-to-value ratio (Munnell et al. 1996). We rule out the effects of creditworthiness by examining changes in observable characteristics such as race and ethnicity, given that on average minority applicants have less wealth, weaker credit histories, and higher loan-to-value ratios (Munnell et al. 1996). To the extent that borrowers' creditworthiness is uncorrelated with the observable characteristics, we may understate the potential sorting by less creditworthy borrowers into shaking areas after seismic shocks.

We focus on loans from depository institutions, including commercial banks, savings and loan associations, savings banks, and credit unions, which are referred to as "banks" in this study. Our analysis is based on a sample of conventional, conforming,[3] one- to four-family, owner-occupied, and first-lien home purchase loans. We first keep loan applications from natural persons by dropping those from businesses, corporations, or partnerships. We then keep loan applications that were originated, denied, or approved but not accepted in status. Among the originated loans, we identify higher-priced loans as first-lien loans with an annual percentage rate exceeding the rate on the Treasury securities of comparable maturity by at least 1.5 percentage points. We identify the securitization status of a loan by whether a purchaser type was

[3] We follow the county-level conforming loan limit published by the Federal Housing Finance Agency at https://www.fhfa.gov/DataTools/Downloads/Pages/Conforming-Loan-Limits.aspx

recorded in the data. In particular, a loan is identified to be sold to the GSEs if the purchaser was Fannie Mae, Ginnie Mae, Freddie Mac, or Farmer Mac. We then use the background information of banks to identify their branching and banking characteristics. Specifically, we identify local banks by the presence of branch offices in the Metropolitan Statistical Area (MSA) where the mortgaged property was located. We measure the branching diversity of banks by the number of MSAs where they had local branches. In addition, we measure banks' capital allocation ability by their assets and their sales capability by the share of loans sold throughout the national secondary market in the previous year.

3.3 Summary Statistics

Table 1 reports the summary statistics of the loan application sample and the loan origination sample respectively. The loan application sample covers 532,858 loan applications from 908 banks. The average probability for a loan to be denied was 14.2 percent. Among the originated loans, 1.7 percent were higher-priced loans; 55.8 percent were sold to the secondary market, most of which were sold to the GSEs. In the loan application sample, a mortgaged property experienced an average of 1.6 and a maximum of 67 NNDEs in a year in the Census tract where it was located. Specifically, about 64 percent of the loans experienced at least one NNDE in a year with an average intensity of 2.8 in MMI, whereas the rest of the loans were not subject to seismic shocks of the year. Damaging earthquakes occurred at a lower chance with an annual average of 0.002 in a Census tract, whereas unnoticeable earthquakes happened in large numbers with an annual average of 10.

4. Empirical Model

In this section, we empirically estimate how banks perceiving seismic risk exploit loan denial, pricing, and securitization strategies to ensure the returns of investments using the following linear probability model:

$$y_{ijt} = \beta Seismic\ shocks_{ijt} + \gamma \mathbf{x}_{ijt} + \varphi \mathbf{z}_{jt} + C_j + Y_{lt} + \varepsilon_{ijt} \quad (6)$$

where i indexes loan, j indexes Census tract, and t indexes year. The dependent variables y_{ijt} are the credit outcomes showing whether a loan was originated and whether it was a higher-priced loan or sold after origination. The key explanatory variable $Seismic\ shocks_{ijt}$ indicates the number of NNDEs in the previous year. The vector $\mathbf{x}_{ijt}$ includes the log form of the loan amount, the loan-to-income ratio, the presence of co-applicants, and the applicant's gender, race, and ethnicity. The vector $\mathbf{z}_{jt}$ controls for the Census-tract-level characteristics including the number of damaging earthquakes in the previous year, the population density, the log form of the median family income, the minority population percentage, the number of owner-occupied units, and the number of one- to four-family units. The model controls for the Census tract fixed effects C_j to capture time-invariant characteristics of local neighborhoods and the bank by year by county fixed effects Y_{lt} to capture potential changes in regional loan demand. We cluster standard errors at the county level.

5. Empirical Results

5.1 The Effects of NNDEs on Banks' Credit Decisions

5.1.1 NNDEs Increased the Likelihoods of Loan Denial and the GSEs Securitization

Table 2 reports the baseline effects of NNDEs on banks' credit decisions. The dependent variables are dummies indicating whether a loan was originated, whether it was originated as a higher-priced loan, whether it was sold to the secondary market, and whether it was sold to the GSEs. In the last three cases, we restrict the sample to the originated loans. Panel A shows that one more NND earthquake in the previous year increased the likelihood of a loan being denied by 0.1 percentage points (p-value<0.05) (Columns 1). The estimate translates into a 0.7 percent increase in the loan denial rate given that on average 14.2 percent of loans were denied in our sample. Meanwhile, the likelihood of a loan being sold to the secondary market increased by 0.3 percentage points (p-value<0.1) (Column 3). In particular, the likelihood of a loan being sold to the GSEs increased by 0.3 percentage points (p-value<0.05), equivalent to a 0.6 percent increase in the rate of GSEs securitization.[4]

Next, we factor in two types of risk salience signals conveyed by NNDEs. In Panel B, we weight the number of NNDEs in the previous year by the inverse of the interval between the current and the immediately previous earthquake. We find significant effects of NNDEs on the likelihood of a loan being sold (p-value<0.01) but an insignificant effect on loan denial. In Panel C, we further weight the earthquake counts in the previous year by the intensity of each earthquake in MMI. The effect of NNDEs on loan denial remains significant (p-value<0.05) whereas the effects on loan securitization are insignificant. As loan denial is a more radical

[4] See Table C1 for the baseline full regression results.

strategy to reduce the risk exposure directly compared with loan securitization to transfer the risk, our findings suggest that banks might perceive shaking severity as a more salient signal of seismic risk than shaking concentration.

5.1.2 Heterogeneous Responses by Banking Characteristics

In this section, we examine the heterogeneous effects of NNDEs across various banking characteristics to identify which types of banks are more capable to manage the perceived seismic risk. First, capital constraints may incentivize smaller banks to securitize more so that they can use the income from securitization to meet the post-disaster credit demand (Cortés, 2017). Second, banks with more diversified branching markets have higher costs of investing in soft information compared with more concentrated banks (Loutskina and Strahan, 2011). The former is thus more likely to exploit securitization as a risk-transfer channel to avoid the disadvantage in soft information collection. Third, banks with stronger connections with the secondary market may also exploit their sales capability to shift seismic risk through securitization (Xu and Zhang, 2014).

Table 3 reports the effects of NNDEs across banks' assets, the number of branching markets, and the share of loans sold in the national secondary market in the previous year. Given one more NNDE in the previous year, the probability of a loan being sold to the GSEs decreased by an additional 0.3 percentage points (p-value<0.1) when banks' assets increased by one trillion dollars. Meanwhile, the likelihood of the GSEs securitization increased by an additional 0.005 percentage points (p-value<0.01) for banks with one more branching MSA and by an additional 0.013 percentage points (p-value<0.01) for banks with a higher previous securitization rate by one percentage point. Our findings indicate that banks with fewer assets, more diversified

branching markets, or stronger sales capability were more likely to exploit securitization to transfer the perceived seismic risk.

5.1.3 The Effects of NNDEs Persisted Three Years

To examine how banks update risk perception after NNDEs, we estimate the persistent effects of NNDEs by adding more lead and lag terms to the baseline model. We find that the effects of NNDEs on loan securitization lasted up to three years before turning statistically insignificant (Figure 4), indicating that banks weighted older earthquakes less heavily than more recent ones. The findings support the availability heuristics, in which case recent NNDEs serve as salience signals that elevate banks' risk perception temporarily (Tversky and Kahneman, 1973; Tversky and Kahneman, 1974). Alternatively, banks' responses can be explained by a Bayesian learning process that allows banks to weight recent earthquake activity more heavily than earlier ones, in which case banks learn the new information from recent earthquakes, make short-term adjustments, and forget quickly (Gallagher, 2014). In either case, our results show that banks focused on the short-term information salience rather than the long-term full information of past earthquakes in risk perception updating.

5.2 Information Source of NNDEs

Compared with commercial lenders, residential lenders are less likely to systematically monitor and evaluate seismic risk as earthquake insurance is not required in residential lending. We perform three tests to explore the potential channels from which banks could source seismic information in Table 4. First, if banks acquired seismic information mainly from personal

experience rather than official records, they would not respond to unnoticeable earthquakes. We indeed find insignificant correlations between the credit outcomes and the number of unnoticeable earthquakes in the previous year (Panel A). Next, we find that banks were more responsive to NNDEs by loan securitization if they had local branches in the same MSA as the mortgaged property. The findings suggest that banks might use private information known to local decision-makers to detect seismic information (Panel B). As these local banks could be in the same MSA but not the same county where the mortgaged property was located, they might access earthquake information in neighboring counties through local media network. Consistent with the expectation, we find that banks raised the securitization rate in response to NNDEs in neighboring counties within the same media network (Panel C), indicating that banks might source the information from local media as well (Gallagher, 2014). Thus, banks were likely to acquire seismic information from both personal experience and soft information such as real-time local news.

5.3 Immediate risk or perceived future risk?

While NNDEs elevated the salience of future seismic risk, they could also lead to immediate credit risks by worsening the credit pool or reducing the collateral value. In this section, we examine changes in these aspects to explore whether banks' responses to NNDEs resulted from instant losses or concern about a higher chance of future damaging earthquakes during the mortgage term.

5.3.1 No Evidence of Worsened Borrowers' Creditworthiness or Changes in Loan Demand

If less creditworthy borrowers self-selected into shaking neighborhoods after NNDEs, banks would change loan decisions due to increased default risk. To test the potential compositional effects, we re-estimate the baseline model by replacing the dependent variables with a series of observable borrowers' characteristics. The key independent variable is the number of NNDEs in the previous year, controlling for the same Census-tract-level characteristics and fixed effects as the baseline model. Table 5 shows insignificant changes in the observable characteristics of loan applicants after NNDEs occurred except for a lower likelihood of Latino applicants in both loan application and origination samples and a lower likelihood of Asian applicants among the originated loans. Thus, the baseline findings are unlikely to be explained by deteriorated creditworthiness of borrowers. In addition, we do not find significant changes in the total number of loan applications at the Census tract level after NNDEs,[5] ruling out the confounding changes in regional loan demand.

5.3.2 Temporary and Moderate Housing Price Drop

In non-recourse states, collateral value is perceived even more important than borrowers' creditworthiness, because banks cannot request additional assets from defaulted borrowers other than collaterals (Garmaise and Moskowitz, 2009). If revealed seismic risk lowered homeowners' willingness to pay for earthquake-prone properties, a subsequent housing price drop would threaten the collateral value of existing and potential loans. Banks thus might change credit decisions due to the immediate risk of collateral devaluation.

[5] The results are available upon request.

To estimate the extent of collateral depreciation after NNDEs, we exploit the seasonally adjusted median sale prices from the Zillow Research housing data. Given that zip code is the lowest geographic level available in the data, we construct a panel consisting of zip codes with available median sale prices and earthquake incidences for every month from 2010 to 2016. Figure 5 plots the estimates of the time-varying effects of NNDEs on the log form of housing prices, which controls for the zip code by year fixed effects and the year-month fixed effects with standard errors clustered at the zip code level. The figure shows that housing prices drop started from the 2nd month after NNDEs and returned to the pre-shock level in the 10th month. Given one more NNDE, the monthly price reduction ranges between 0.1 and 0.2 percent. The largest drop of 0.2 percent occurred in the 9th month after NNDEs, which was equivalent to $833 given the sample average housing price of $416,518. Furthermore, given a sample average of 0.134 and a maximum of 35 NNDEs in a month, a zip code incurred an average loss of $112 (=416,518*0.2%*0.134) and a maximum loss of $29,156 (=416,518*0.2%*35) due to NNDEs every month; 99% of zip codes lost less than $1,666 with less than 2 NNDEs per month (=416,518*0.2%*2). The results indicate that homebuyers became more cautious after seismic risk was revealed. However, the resulting collateral depreciation barely imposed credit risks to either banks or the GSEs as borrowers were unlikely to walk away due to such a moderate collateral loss. Even if they did, housing prices would have rebounded before the collaterals were sold given an average foreclosure timeline of around one year (Cordell et al., 2015).

6 Conclusions

This study exploits NNDEs in California, which convey the risk salience but do not cause property damage, to examine how banks manage perceived seismic risk before actual losses

occur. We find that more NNDEs resulted in reduced credit supply and increased securitization. Our findings add to the literature by showing that banks could respond to the risk information *per se* conveyed by non-damaging disasters. We provide further evidence to show that banks most likely sourced earthquake information through personal experience and soft information such as real-time local news. Banks' response was based on NNDEs in the past three years, indicating their focus on recent earthquake information rather than the full information of the long-term seismic activity. We do not find evidence of worsened borrowers' creditworthiness after NNDEs. Moreover, collateral losses barely occurred as the moderate housing price drop rebounded ten months after NNDEs. Thus, banks' responses were more likely to result from the increased salience of future damaging earthquakes rather than immediate credit losses, which points out the risk information value of NNDEs in banks' seismic risk management.

Our study contributes to the public discussion on seismic risk-sharing given an inefficiently low earthquake insurance coverage rate in the current private insurance market. Although insurers have been mandated to offer residential earthquake insurance in California since 1985 (Marshall, 2017), most homeowners are unwilling to insure themselves against the low-probability risk given the voluntary purchase nature and the high costs. Our findings demonstrate that, to a certain extent, banks can exploit their advantages in information acquisition and risk transfer to share seismic risk with homeowners through non-recourse loans, providing homeowners implicit earthquake insurance in the event of foreclosure after damaging earthquakes. To the extent that NNDEs influence the likelihood of future damaging earthquakes and the associated credit risks during the mortgage term, the risk-shifting channel of securitization prevented a further credit crunch while transferring the risk to the GSEs (Elenev et al., 2016; Ouazad and Kahn, 2022).

Our study calls for reevaluations of the heuristics in banks' disaster risk-perception updating. Given banks' current seismic risk management strategies, borrowers are more likely to be denied when applying for loans after more frequent NNDEs, everything else equal. With a higher likelihood of being sold, these loans could also be serviced with lower quality in the sense of a higher foreclosure probability and a lower modification probability in the event of delinquency (Zhang, 2013; Kruger, 2018). Moreover, banks' focus on earthquake information in the recent three years may lead to inconsistent credit decisions on loans from the same neighborhood but applied at different time points despite the same future seismic risk within the mortgage term. To promote more efficient seismic risk management, designing affordable insurance policies in the private insurance market can help improve earthquake insurance coverage among homeowners. Alternatively, risk-sharing through the mortgage market would be more efficient if banks priced seismic risk systematically based on the long-term seismic hazard assessment while the GSEs tightened the underwriting standards and incorporated the risk into the guarantee fee. Fully pricing seismic risk, through private insurance or higher interest rates and fees, can lower the willingness of homeowners to move to high-risk regions and encourage hazard mitigation investment (Bakkensen and Ma, 2020; Chen et al., 2021).

References

Anderson, D.R. and M. Weinrobe. 1986. Mortgage Default Risks and the 1971 San Fernando Earthquake. *Real Estate Economics* 14(1): 110–135.

Avery, R., K. Brevoort and G. Canner. 2007. Opportunities and Issues in Using HMDA Data. *Journal of Real Estate Research* 29(4): 351–380.

Bakkensen, L.A. and L. Ma. 2020. Sorting Over Flood Risk and Implications for Policy Reform. *Journal of Environmental Economics and Management* 104:102362.

Berg, G. and J. Schrader. 2012. Access to Credit, Natural Disasters, and Relationship Lending. *Journal of Financial Intermediation* 21(4): 549–568.

Berkovec, J. and P. Zorn. 1996. How Complete is HMDA? HMDA Coverage of Freddie Mac Purchases. *Journal of Real Estate Research* 11(1): 39–56.

Bos, J.W., R. Li and M.W. Sanders. 2022. Hazardous Lending: The Impact of Natural Disasters on Bank Asset Portfolio. *Economic Modelling* 108: 105760.

Chen, Z., C. Towe and N. Bockstael. 2021. How Does the Coastal Housing Market View Flood Zone - A Risk Signal or Mandatory Costs? Working paper. https://drive.google.com/file/d/11vptmQ1wrJ7TPyqE1EFtIYxJIRr_lcee/view.

Collier, B.L. 2020. Strengthening Local Credit Markets Through Bank-level Index Insurance. *Journal of Risk and Insurance* 87(2): 319-349.

Cordell, L., L. Geng, L.S. Goodman and L. Yang. 2015. The Cost of Foreclosure Delay. *Real Estate Economics* 43(4): 916-956.

Cortés, K. 2017. How Small Banks Deal with Large Shocks. *Economic Commentary* 2017-08.

Cortés, K.R. and P.E. Strahan. 2017. Tracing Out Capital Flows: How Financially Integrated Banks Respond to Natural Disasters. *Journal of Financial Economics* 125(1): 182–199.

Elenev, V., T. Landvoigt and S.V. Nieuwerburgh. 2016. Phasing Out the GSEs. *Journal of Monetary Economics* 81: 111-132.

Ergungor, O.E. 2010. Bank Branch Presence and Access to Credit in Low- to Moderate-Income Neighborhoods. *Journal of Money, Credit, and Banking* 42, 1321–1349.

Gallagher, J. 2014. Learning About an Infrequent Event: Evidence from Flood Insurance Take-up in the United States. *American Economic Journal: Applied Economics* 6(3): 206–233.

Garmaise, M. and T. Moskowitz. 2009. Catastrophic Risk and Credit Markets. *The Journal of Finance* (64)2: 657–707.

Gilje, E. P., E. Loutskina and P. E. Strahan. 2016. Exporting Liquidity: Branch Banking and Financial Integration. *The Journal of Finance* 71(3): 1159-1184.

Koetter, M., F. Noth and O. Rehbein. 2019. Borrowers Under Water! Rare Disasters, Regional Banks, and Recovery Lending. *Journal of Financial Intermediation* 100811.

Koster, H.R. and J. van Ommeren. 2015. A Shaky Business: Natural Gas Extraction, Earthquakes and House Prices. *European Economic Review* 80: 120–139.

Kousky, C. 2010. Learning from Extreme Events: Risk Perceptions After the Flood. *Land Economics* 86(3): 395–422.

Kruger, S. 2018. The Effect of Mortgage Securitization on Foreclosure and Modification. *Journal of Financial Economics* 129 (3): 586-607.

Liu, H., S. Ferreira and B. Brewer. 2018. The Housing Market Impacts of Wastewater Injection Induced Seismicity Risk. *Journal of Environmental Economics and Management* 92: 251–269.

Loutskina, E. and P.E. Strahan. 2011. Informed and Uninformed Investment in Housing: The Downside of Diversification. *The Review of Financial Studies* 24(5): 1447-1480.

Marshall, D. 2017. The California Earthquake Authority. Resources for the Future Discussion Paper 17-05. https://media.rff.org/archive/files/document/file/RFF-DP-17-05.pdf

McCoy, S.J. and R.P. Walsh. 2018. Wildfire Risk, Salience & Housing Demand. *Journal of Environmental Economics and Management* 91: 203–228.

Muller, N.Z. and C.A. Hopkins. 2019. Hurricane Katrina Floods New Jersey: The Role of Information in the Market Response to Flood Risk. NBER Working Paper No. w25984.

Munnell, A., G.M.B. Tootell, L.E. Browne and J. McEneaney. 1996. Mortgage Lending in Boston: Interpreting HMDA Data. *The American Economic Review* 86(1): 25–53.

Ouazad, A. and M.E. Kahn. 2022. Mortgage Finance and Climate Change: Securitization Dynamics in the Aftermath of Natural Disasters. *The Review of Financial Studies* 35(8): 3617–3665.

Petersen, M.D., M.P. Moschetti, P.M. Powers, C.S. Mueller, K.M. Haller, A.D. Frankel, Y. Zeng, S. Rezaeian, S.C. Harmsen, O.S. Boyd, N. Field, R. Chen, K.S. Rukstales, N. Luco, R.L. Wheeler, R.A. Williams and A.H. Olsen. 2014. Documentation for the 2014 Update of the United States National Seismic Hazard Maps. U.S. Geological Survey Open-File Report 2014–1091. https://dx.doi.org/10.3133/ofr20141091.

Schüwer, U., C. Lambert and F. Noth. 2018. How Do Banks React to Catastrophic Events? Evidence from Hurricane Katrina. *Review of Finance* 23(1): 75–116.

Tselentis, G.A. and L. Danciu. 2008. Empirical Relationships Between Modified Mercalli Intensity and Engineering Ground-motion Parameters in Greece. *Bulletin of the Seismological Society of America* 98(4): 1863-1875.

Tversky, A. and D. Kahneman. 1973. Availability: A Heuristic for Judging Frequency and Probability. *Cognitive Psychology* 4: 207–232.

Tversky, A. and D. Kahneman. 1974. Judgment Under Uncertainty: Heuristics and Biases. *Science* 185: 1124–1131.

U.S. Geological Survey. 2016. The Severity of an Earthquake. USGS General Interest Publication, 1989-288-913. https://pubs.usgs.gov/gip/earthq4/severitygip.html.

Xu, M. and Y. Xu. 2020. Environmental Hazards and Mortgage Credit Risk: Evidence from Texas Pipeline Incidents. *Real Estate Economics* 48(4): 1096–1135.

Xu, Y. 2014. Does Mortgage Deregulation Increase Foreclosures? Evidence from Cleveland. *Regional Science and Urban Economics* 46: 126-139.

Xu, Y. and Zhang, J. 2014. Nonlocal Mortgage Lending and The Secondary Market Involvement. *Journal of Real Estate Literature* 20(2):307–322.

Zhang, Y., 2013. Does Loan Renegotiation Differ by Securitization Status? A Transition Probability Study. *Journal of Financial Intermediation* 22(3): 513-527.

Table 1. Summary Statistics

	Mean	Standard Deviation	Min	Max	Mean	Standard Deviation	Min	Max
	Loan Application Sample				Loan Origination Sample			
Dependent Variables								
Denied	0.142	0.349	0	1				
Higher-priced					0.017	0.130	0	1
Sold					0.558	0.497	0	1
Sold to the GSEs					0.486	0.500	0	1
Independent Variables								
Borrowers' Characteristics								
Loan amount (in $10,000)	44.295	25.486	0.100	140.300	45.106	25.444	0.300	140.300
Loan-to-income ratio	3.475	4.443	0.001	1190.000	3.354	1.71	0.014	602.000
Co-applicants	0.488	0.5	0	1	0.5	0.5	0	1
Latino	0.108	0.31	0	1	0.101	0.301	0	1
Male	0.721	0.449	0	1	0.725	0.446	0	1
Asian	0.298	0.457	0	1	0.299	0.458	0	1
Black	0.018	0.132	0	1	0.016	0.125	0	1
White	0.67	0.47	0	1	0.673	0.469	0	1
Census Tracts' Characteristics								
#NNDEs	1.562	2.082	0	67	1.554	2.069	0	52
#Damaging earthquakes	0.002	0.041	0	2.000	0.002	0.040	0	2.000
#Unnoticeable earthquakes	10.293	9.629	0	342	10.401	9.604	0	286
Population density (thousand/km^2)	0.463	0.238	0.040	0.998	0.459	0.235	0.040	0.998
%Minority population	9.896	3.889	0.770	28.202	10.005	3.864	0.770	28.202
Median family income (in $10,000)	1.28	0.687	0.003	6.345	1.289	0.685	0.003	6.345
#Owner-occupied units (in 1,000)	1.654	0.832	0.004	9.894	1.659	0.826	0.004	9.894
#One- to four-family units (in 1,000)	1.528	1.925	0	45	1.533	1.931	0	45
Banks' Characteristics								

Local bank	0.761	0.426	0	1	0.766	0.423	0	1
#MSAs	133.51	112.575	1	265	134.746	112.938	1	265
Assets (in $trillion)	0.753	0.716	0	2.075	0.762	0.716	0	2.075
Previous sale	0.505	0.342	0	1	0.509	0.34	0	1
Observations				532,858				428,781

Notes: The table reports the summary statistics of the baseline sample. Each observation is a conventional, conforming, one- to four-family, owner-occupied, and first-lien home purchase loan from depository institutions in California from 2010-2016. *#NNDEs* is the annual number of noticeable non-damaging earthquakes. *Local bank* is a dummy indicating whether a loan was applied with a local bank identified by the presence of branch offices in the MSA where the mortgaged property was located. *#MSAs* is the number of MSAs where a bank had branches. *Previous sale* is the share of loans sold by a bank to the national secondary market in the previous year.

Table 2. The Effects of NNDEs on Banks' Credit Decisions

	(1) Denied	(2) Higher-priced	(3) Sold	(4) Sold to the GSEs
Sample mean	0.142	0.017	0.558	0.486
	Panel A: Annual Earthquake Counts			
#NNDEs	0.001**	-0.000	0.003*	0.003**
	(0.000)	(0.000)	(0.001)	(0.001)
#Damaging earthquake	-0.008	0.002	0.006	0.029*
	(0.008)	(0.003)	(0.016)	(0.016)
Census tract FE	YES	YES	YES	YES
Bank by year by county FE	YES	YES	YES	YES
Observations	525,355	421,753	421,753	421,753
R-squared	0.120	0.630	0.467	0.478
	Panel B: Weighted by concentration			
Weighted by concentration	0.001	-0.000	0.009***	0.009***
	(0.001)	(0.000)	(0.003)	(0.002)
Census tract FE	YES	YES	YES	YES
Bank by year by county FE	YES	YES	YES	YES
Observations	525,355	421,753	421,753	421,753
R-squared	0.120	0.630	0.467	0.478
	Panel C: Weighted by intensity			
Weighted by intensity	0.000**	-0.000	0.001	0.001
	(0.000)	(0.000)	(0.001)	(0.000)
Census tract FE	YES	YES	YES	YES
Bank by year by county FE	YES	YES	YES	YES
Observations	525,355	421,753	421,753	421,753
R-squared	0.120	0.630	0.467	0.478

Notes: Column 1 uses the loan application sample, whereas Columns 2-4 use the loan origination sample. The dependent variables are dummies indicating the credit outcomes listed as the column titles. *#NNDEs* is the number of noticeable non-damaging earthquakes in the previous year. *Weighted by concentration* is the number of NNDEs in the previous year weighted by the inverse of the interval between the current and the immediately previous earthquake. *Weighted by intensity* is the number of NNDEs in the previous year weighted by the intensity of each earthquake in MMI. The model controls for the loan-level characteristics including the log form of the loan amount, the loan-to-income ratio, the presence of co-applicants, and the applicant's gender, race, and ethnicity, and the Census-tract-level characteristics including the number of damaging earthquakes in the previous year, the population density, the log form of the median family income, the minority population percentage, the number of owner-occupied units, and the number of one- to four-family units. The estimates of the coefficients are presented in the table with standard errors clustered by county. *** p<0.01, ** p<0.05, * p<0.1.

Table 3. Heterogeneous Responses by Banking Characteristics

	(1) Denied	(2) Higher-priced	(3) Sold	(4) Sold to the GSEs
Sample mean	0.142	0.017	0.558	0.486
#NNDEs*Assets	0.001	-0.000	0.001	-0.003*
	(0.001)	(0.000)	(0.002)	(0.002)
#NNDEs*#MSAs	0.000	0.000	0.002*	0.005***
	(0.001)	(0.000)	(0.001)	(0.002)
#NNDEs*Previous sale	-0.001	-0.000	0.010***	0.013***
	(0.001)	(0.000)	(0.003)	(0.004)
#NNDEs	0.001**	-0.000	0.003*	0.003**
	(0.000)	(0.000)	(0.001)	(0.001)
Census tract FE	YES	YES	YES	YES
Bank by year by county FE	YES	YES	YES	YES
Observations	525,355	421,753	421,753	421,753
R-squared	0.120	0.630	0.467	0.479

Notes: Column 1 uses the loan application sample, whereas Columns 2-4 use the loan origination sample. The dependent variables are dummies indicating the credit outcomes listed as the column titles. *#NNDEs* is the number of noticeable non-damaging earthquakes in the previous year. *Assets* is a bank's assets in trillion dollars subtracted by the sample mean. *#MSAs* is the number of MSAs in 100s where banks had branches subtracted by the sample mean. *Previous sale* is the share of loans sold by a bank to the national secondary market in the previous year subtracted by the sample mean. The coefficients of *Assets*, *#MSA*, and *Previous sale* are absorbed by the bank by year by county fixed effects. The model includes the same baseline control variables as in Table 2. The estimates of the coefficients are presented in the table with standard errors clustered by county. *** p<0.01, ** p<0.05, * p<0.1.

Table 4. Information Source of NNDEs

	(1) Denied	(2) Higher-priced	(3) Sold	(4) Sold to the GSEs
Sample mean	0.142	0.017	0.558	0.486
Panel A: No Response to Unnoticeable Earthquakes				
#Unnoticeable earthquakes	0.000	0.000	-0.001	-0.001
	(0.000)	(0.000)	(0.001)	(0.001)
#NNDEs	0.001**	-0.000	0.003**	0.003**
	(0.000)	(0.000)	(0.001)	(0.001)
Census tract FE	YES	YES	YES	YES
Bank by year by county FE	YES	YES	YES	YES
Observations	525,355	421,753	421,753	421,753
R-squared	0.120	0.630	0.467	0.478
Panel B: More Responsive to NNDEs in Branching Markets				
#NNDEs× Local bank	-0.000	0.001	0.005***	0.005***
	(0.001)	(0.001)	(0.001)	(0.001)
#NNDEs	0.001*	-0.001	-0.002	-0.001
	(0.001)	(0.000)	(0.001)	(0.001)
Census tract FE	YES	YES	YES	YES
Bank by year by county FE	YES	YES	YES	YES
Observations	525,355	421,753	421,753	421,753
R-squared	0.120	0.630	0.470	0.480
Panel C: Respond to NNDEs in the Same Media Network				
Network #NNDEs	-0.000	0.000	0.002***	0.002***
	(0.000)	(0.000)	(0.000)	(0.000)
#NNDEs	0.001	0.000	0.003*	0.002
	(0.000)	(0.000)	(0.002)	(0.002)
Census tract FE	YES	YES	YES	YES
Bank by year FE	YES	YES	YES	YES
Observations	532,044	427,924	427,924	427,924
R-squared	0.097	0.601	0.440	0.450

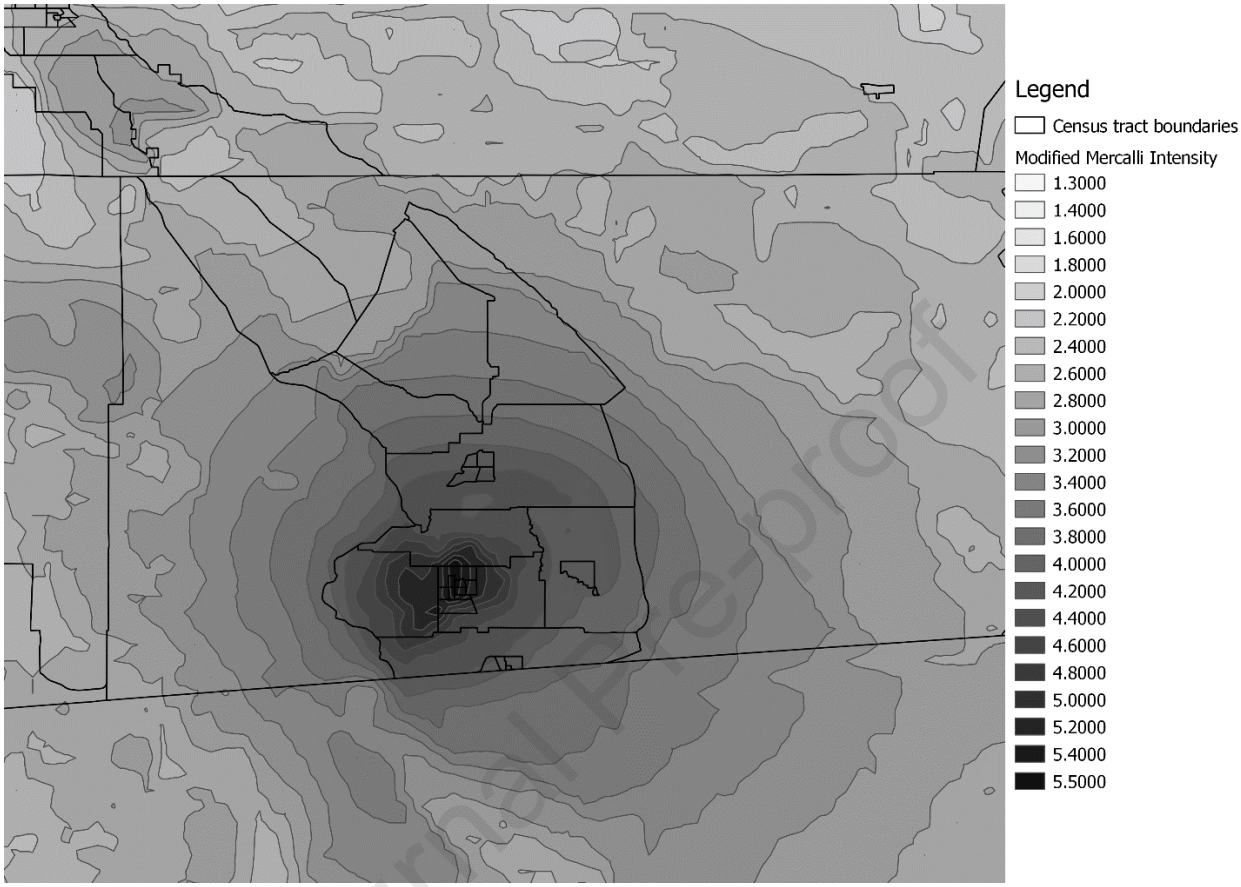
Notes: Column 1 uses the loan application sample, whereas Columns 2-4 use the loan origination sample. The dependent variables are dummies indicating the credit outcomes listed as the column titles. *#Unnoticeable earthquakes* is the number of unnoticeable earthquakes in the previous year. *#NNDEs* is the number of noticeable non-damaging earthquakes in the previous year. *Local bank* is a dummy indicating whether a loan was applied with a local bank identified by the presence of branch offices in the MSA where the mortgaged property was located. *Network #NNDEs* is the number of NNDEs in counties within the same media network excluding those in the seated county. Panels A and C include the same baseline control variables as in Table 2. Panel B includes the baseline control variables and those interacted with *Local bank*. The estimates of the coefficients are presented in the table with standard errors clustered by county. *** p<0.01, ** p<0.05, * p<0.1.

Table 5. No Evidence of Worsened Borrowers' Creditworthiness After NNDEs

VARIABLES	(1) Loan Amount (in $10,000)	(2) Loan-to-income ratio	(3) Co-applicants	(4) Latino	(5) Male	(6) Asian	(7) Black	(8) White
			Panel A: Loan application sample					
#NNDEs	-0.010	-0.003	-0.001	-0.001**	-0.001	-0.000	0.000	0.000
	(0.065)	(0.010)	(0.001)	(0.000)	(0.001)	(0.000)	(0.000)	(0.001)
Census tract FE	YES	YES	YES	YES	YES	YES	YES	YES
Bank by year by county FE	YES	YES	YES	YES	YES	YES	YES	YES
Observations	525,355	525,355	525,355	525,355	525,355	525,355	525,355	525,355
R-squared	0.646	0.058	0.101	0.262	0.079	0.370	0.131	0.348
			Panel B: Loan origination sample					
#NNDEs	-0.007	-0.003	-0.001	-0.001*	-0.000	-0.001**	0.000	0.001
	(0.064)	(0.005)	(0.002)	(0.000)	(0.001)	(0.000)	(0.000)	(0.001)
Census tract FE	YES	YES	YES	YES	YES	YES	YES	YES
Bank by year by county FE	YES	YES	YES	YES	YES	YES	YES	YES
Observations	421,753	421,753	421,753	421,753	421,753	421,753	421,753	421,753
R-squared	0.651	0.088	0.105	0.258	0.083	0.375	0.123	0.354

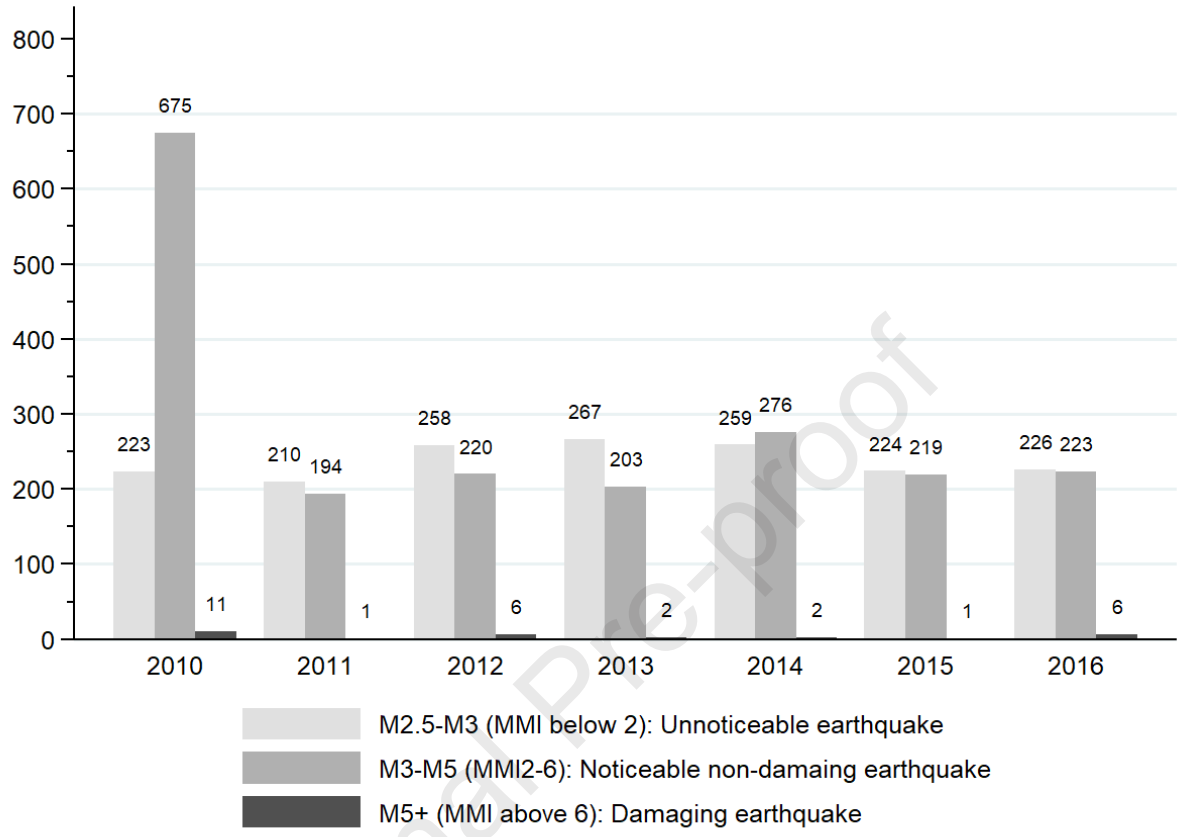
Notes: Panel A use the loan application sample, whereas Panel B uses the loan origination sample. *#NNDEs* is the number of noticeable non-damaging earthquakes in the previous year. The model includes the same baseline Census-tract-level characteristics as in Table 2. The estimates of the coefficients are presented in the table with standard errors clustered by county. *** p<0.01, ** p<0.05, * p<0.1.

Figure 1. Illustration of An Earthquake Intersecting with the Census Tract Boundaries



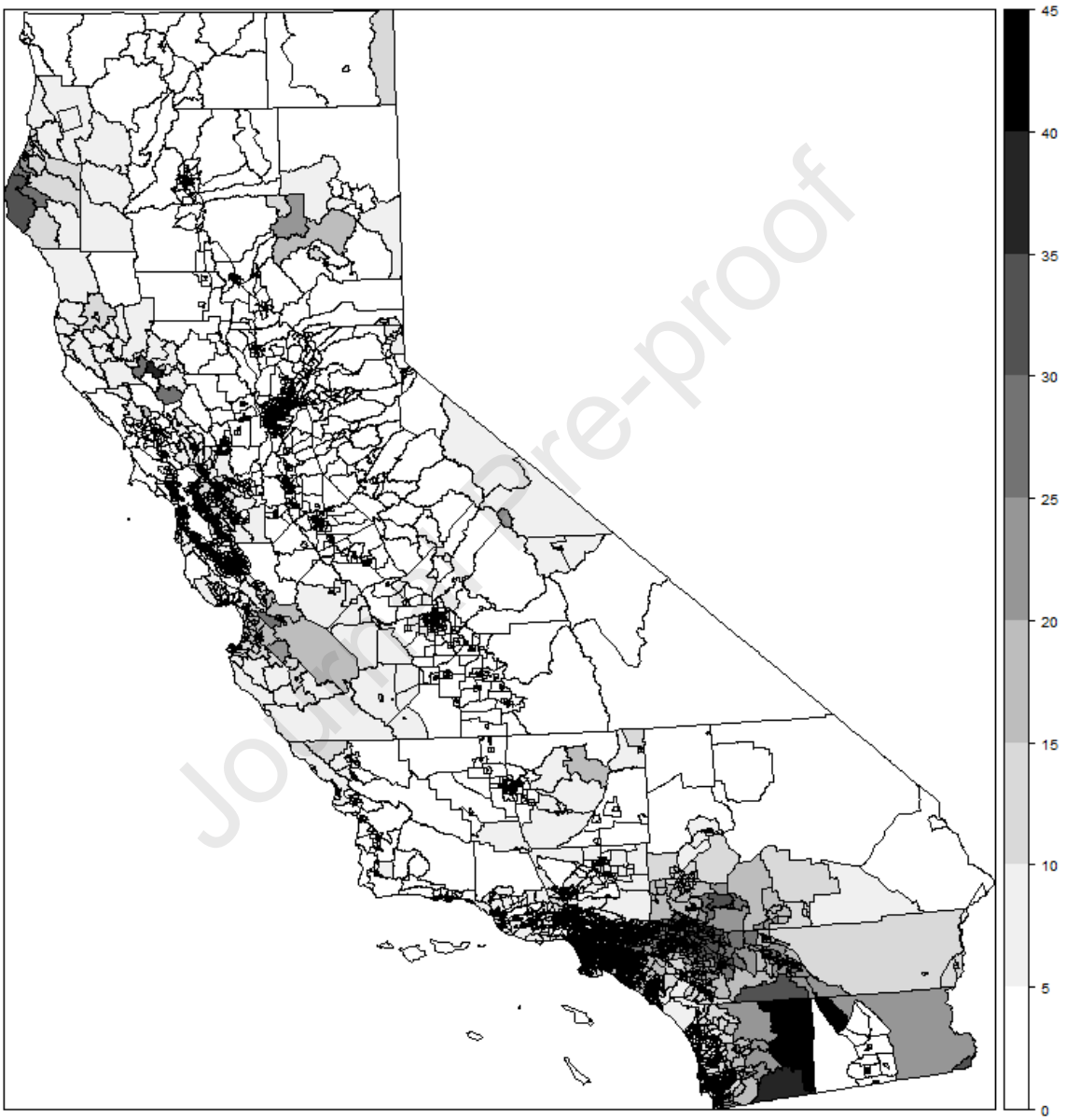
Notes: Generated by the authors using data from the U.S. Geological Survey. The earthquake illustrated in the figure happened on April 5, 2010, near Ocotillo, CA. We measure the intensity of an earthquake in a Census tract by its average MMI across all the ShakeMap polygons intersected with the Census tract, weighted by the area of each intersecting polygon relative to that of the entire Census tract.

Figure 2. The Annual Number of Earthquakes in California



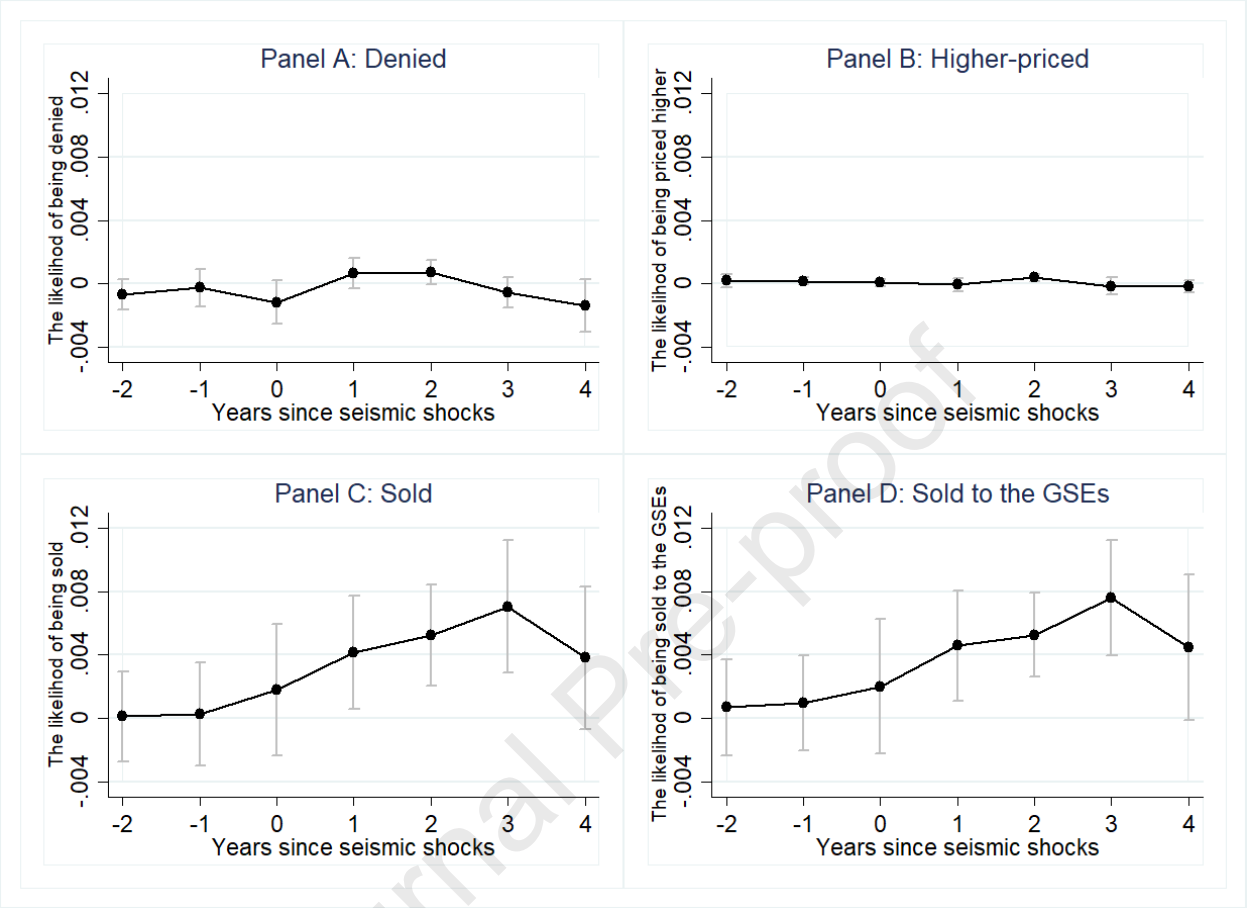
Notes: Generated by the authors using data from the U.S. Geological Survey. The figure plots the annual number of earthquakes covered in our analyses, including earthquakes generating positive shaking intensity in California with epicenters in California or in neighboring states.

Figure 3. Spatial Distribution of the 2010-2016 Cumulative Number of NNDEs in California



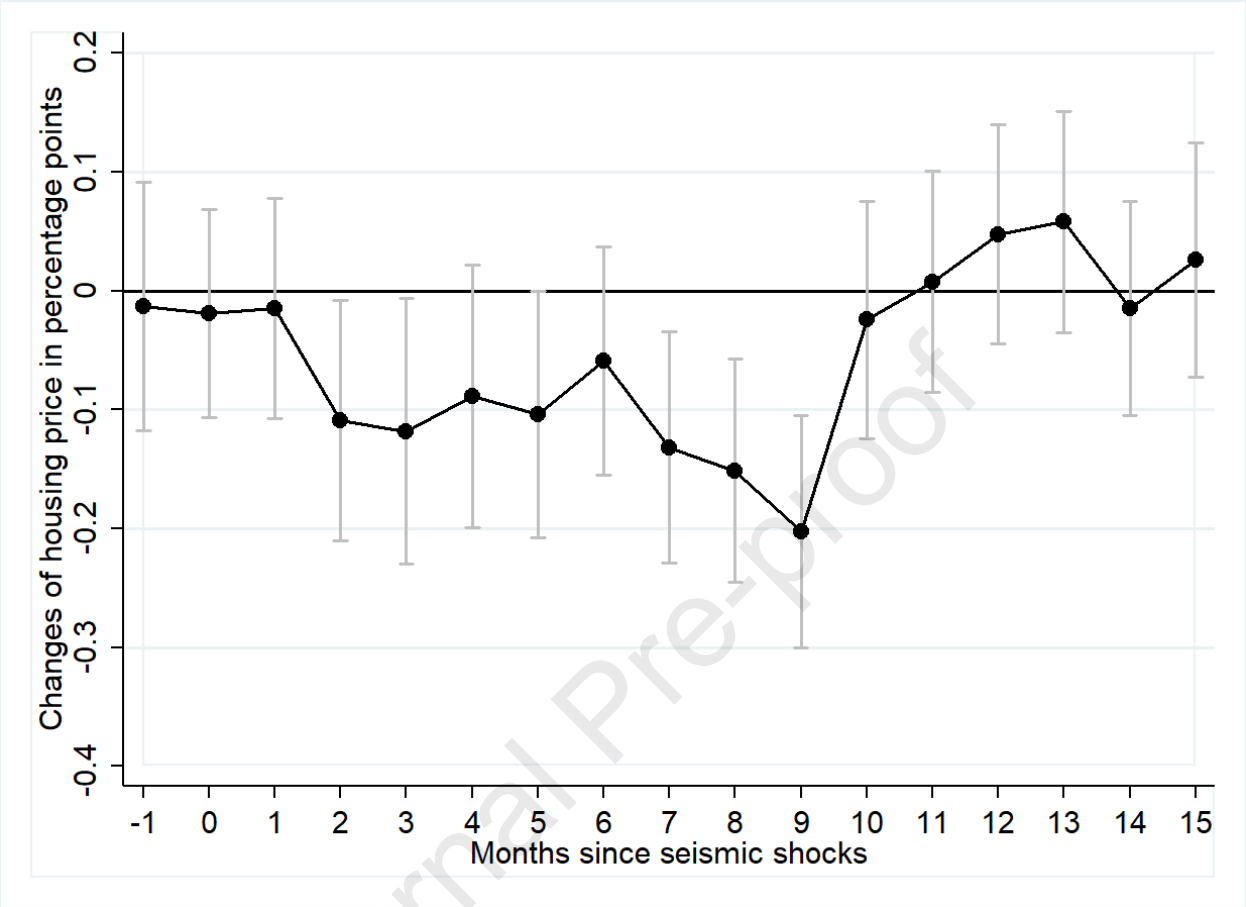
Notes: Generated by the authors using data from the U.S. Geological Survey. The figure plots the spatial distribution of the cumulative number of NNDEs from 2010 to 2016 across Census tracts in California.

Figure 4. Persistent Effects of NNDEs



Notes: The figure plots the coefficient estimates and the 95% confidence intervals of the number of NNDEs in the future two, the current, and the previous four periods. Panel A is based on the loan application sample, whereas Panels B-D are based on the loan origination sample. The dependent variables are dummies indicating the credit outcomes listed as the plot titles. The model controls for the same baseline control variables and fixed effects as in Table 2.

Figure 5. Temporary and Moderate Housing Price Drop



Notes: The figure plots the coefficient estimates and the 95% confidence intervals of the effects of NNDEs on housing prices based on a 2010-2016 zip code by year-month subsample with available Zillow housing sale prices data. The dependent variable is the log form of the median sale price. The key independent variable is the number of NNDEs. The model controls for the zip code by year fixed effects and the year-month fixed effects with standard errors clustered by zip code.

Appendix A

Substituting equations (1)-(2) into equation (3) yields:

$$\frac{\varphi}{2}l^2 + [\eta + v(1-s) + \xi(1-s)c - (1-\xi)(1-s)r - s\gamma]l + (r^d - v)d = 0 \quad \text{(a1)}$$

which solves the optimal loan amount in equilibrium as $l = \frac{-B+\sqrt{B^2-2\varphi(r^d-v)d}}{\varphi}$, where $B = [\eta + v(1-s) + \xi(1-s)c - (1-\xi)(1-s)r - s\gamma]$. Note that $\sqrt{B^2 - 2\varphi(r^d - v)d} > 0$, since $\varphi > 0$, $r^d < v$,[1] and $d > 0$ by assumption. Thus, taking the first derivative of l with respect to c, ξ, r, and s respectively yields the following results:

$$\frac{\partial l}{\partial c} = A\left(-\frac{\partial B}{\partial c}\right) = A[-\xi(1-s)] \quad \text{(a2)}$$

$$\frac{\partial l}{\partial \xi} = A\left(-\frac{\partial B}{\partial \xi}\right) = A[-(1-s)(c+r)] \quad \text{(a3)}$$

$$\frac{\partial l}{\partial r} = A\left(-\frac{\partial B}{\partial r}\right) = A(1-\xi)(1-s) \quad \text{(a4)}$$

$$\frac{\partial l}{\partial s} = A\left(-\frac{\partial B}{\partial s}\right) = A[\mathrm{v} + \gamma + \xi\mathrm{c} - (1-\xi)\mathrm{r}] \quad \text{(a5)}$$

where $A = \frac{\sqrt{B^2-2\varphi(r^d-v)d}-B}{\varphi\sqrt{B^2-2\varphi(r^d-v)d}}$. Note that $\sqrt{B^2 - 2\varphi(r^d - v)d} - B > \sqrt{B^2} - B$, since $\varphi > 0$, $r^d < v$, and $d > 0$ by assumption. If $B \leq 0$, then $\sqrt{B^2} - B = -2B \geq 0$; If $B > 0$, then $\sqrt{B^2} - B = 0$. In either case, $\sqrt{B^2 - 2\varphi(r^d - v)d} - B > 0$ and thus $A > 0$. Hence,

from equation (a2), $\frac{\partial l}{\partial c} < 0$, since $-\xi(1-s) < 0$;

[1] We impose the assumption for simplicity to derive the optimal loan amount, which is a sufficient rather than a necessary condition for the existence of a unique optimal loan amount.

from equation (a3), $\frac{\partial l}{\partial \xi} < 0$, since $-(1-s)(c+r) < 0$;

from equation (a4), $\frac{\partial l}{\partial r} > 0$, since $(1-\xi)(1-s) > 0$;

from equation (a5), $\frac{\partial l}{\partial s}\begin{cases} \geq 0, & if\ \mathrm{r} \leq \frac{\mathrm{v}+\gamma+\xi \mathrm{c}}{1-\xi} \\ < 0, & if\ \ r > \frac{\mathrm{v}+\gamma+\xi \mathrm{c}}{1-\xi} \end{cases}$.

Appendix B

To calculate the perceived intensity of earthquakes missing Shakemap data, which are all small earthquakes below M4.5, we follow Koster and van Ommeren (2015) to convert the magnitude to the pointwise intensity of an earthquake at the centroids of nearby Census tracts using the following attenuation function:

$$log_{10}v_{it} = -1.53 + 0.74M_{Ljt} - 1.33log_{10}r_{ijt} - 0.00139r_{ijt} \quad \text{(b1)}$$

where v_{it} is the peak ground velocity (PGV) in cm/s of an earthquake perceived in location i in year t. M_{Ljt} is the magnitude of the earthquake that occurred at the epicenter j in year t. $r_{ijt} = \sqrt{d_{ijt}^2 + s_{ijt}^2}$ is the hypocentral distance, where d_{ijt} is the distance between location i and the epicentral location j in kilometers, and $s_{ijt}$is the depth of the earthquake in kilometers.

We then convert the calculated PGV to MMI using the following conversion equation estimated by Tselentis and Danciu (2008):

$$MMI_{it} = 3.3 + 3.358log_{10}v_{it} \quad \text{(b2)}$$

where MMI_{it} and v_{it} are the intensity in Modified Mercalli Intensity and PGV (cm/s), respectively, of an earthquake perceived in location i in year t.

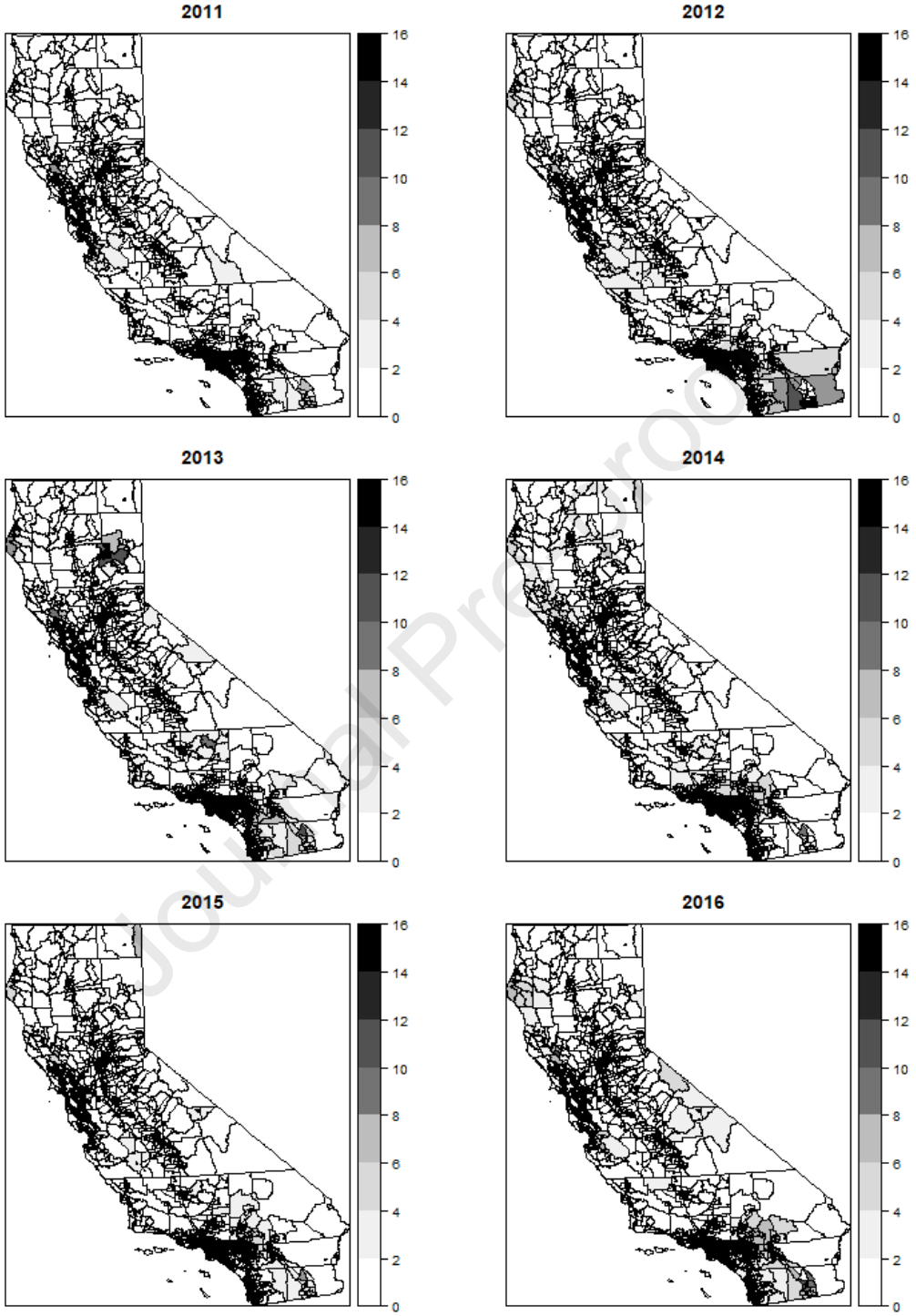
Appendix C

Table C1. Baseline Full Regression Results

	(1) Denied	(2) Higher-priced	(3) Sold	(4) Sold to the GSEs
Sample mean	0.142	0.017	0.558	0.486
#NND earthquake	0.001**	-0.000	0.003*	0.003**
	(0.000)	(0.000)	(0.001)	(0.001)
#Damaging	-0.008	0.002	0.006	0.029*
	(0.008)	(0.003)	(0.016)	(0.016)
log(loan amount)	-0.007***	0.000	-0.233***	-0.220***
	(0.002)	(0.001)	(0.014)	(0.013)
Loan-to-income ratio	0.005***	-0.001**	0.002	0.003
	(0.001)	(0.000)	(0.002)	(0.002)
Co-applicants	-0.014***	0.001**	0.002	0.001
	(0.002)	(0.001)	(0.002)	(0.002)
Latino	0.036***	0.005***	0.010***	0.011***
	(0.003)	(0.001)	(0.003)	(0.003)
Male	-0.003**	-0.000	0.003**	0.002
	(0.001)	(0.000)	(0.002)	(0.002)
Asian	-0.015***	-0.004*	-0.005	-0.007
	(0.003)	(0.002)	(0.008)	(0.007)
Black	0.025***	0.007***	-0.012	-0.001
	(0.007)	(0.002)	(0.010)	(0.010)
White	-0.027***	-0.003	-0.001	-0.006
	(0.004)	(0.002)	(0.008)	(0.008)
Population density	0.005	-0.001	-0.000	-0.001
	(0.004)	(0.001)	(0.005)	(0.005)
Minority population%	0.016	0.009*	0.103	0.095
	(0.016)	(0.005)	(0.156)	(0.152)
log(median family income)	0.002	-0.003	-0.055*	-0.051*
	(0.007)	(0.002)	(0.029)	(0.030)
#Owner-occupied units	-0.011	0.001	-0.057**	-0.058***
	(0.012)	(0.002)	(0.022)	(0.019)
#One- to four-family units	0.005	-0.001	0.025	0.026
	(0.009)	(0.002)	(0.028)	(0.025)
Census tract FE	YES	YES	YES	YES
Bank by year by county FE	YES	YES	YES	YES
Observations	525,355	421,753	421,753	421,753
R-squared	0.120	0.630	0.467	0.478

Notes: Column 1 uses the loan application sample, whereas Columns 2-4 use the loan origination sample. The dependent variables are dummies indicating the credit outcomes listed as the column titles. *#NND earthquake* is the number of noticeable non-damaging earthquakes in the previous year. The estimates of the coefficients are presented in the table with standard errors clustered by county. *** p<0.01, ** p<0.05, * p<0.1.

Figure C1. Spatial Distribution of the Annual Number of NNDEs in California



Notes: Generated by the authors using data from the U.S. Geological Survey. The figure plots the spatial distribution of the annual number of NNDEs for each year over 2011-2016 across Census tracts in California.