Sea Level Rise Risk and Mortgage Lending Standards

Chengbo Fu[a], Qiping Huang[b], Meimei Lin[c], Salman Tahsin [d]

[a]School of Business, Faculty of Business and Economics, University of Northern British Columbia, Prince George, BC, Canada V2N 4Z9

[b]Department of Economics and Finance, School of Business Administration, University of Dayton, Dayton, OH, USA 45469

[c]Department of Geology and Geography, Georgia Southern University, Savannah, GA, USA 31419

[d]Department of Accounting and Finance, Lucas College and Graduate School of Business, San José State University, San José, CA, USA 95192

Sea Level Rise Risk and Mortgage Lending Standards

Abstract

We study the relationship between sea level rise (SLR) risk and access to residential mortgage credit at the census tract level from 2018 to 2020. Three different levels of SLR risk, ranging from imminent to long-term risks, are estimated using the elevations from sea level. We find significantly lower loan approval rates in census tracts that are exposed to all three different levels of SLR risks. Additionally, we find that the climate risk beliefs do not matter if the location is under imminent risk. However, in areas under medium or long-term risks, approval rates are affected by SLR only if climate risk beliefs are high. We also find that both local and diversified banks reduce loan acceptance rates in locations that are under imminent risk, but local banks approve significantly more loans if the risks are more medium to long term. The local bank effects are not driven by the size of banks. Overall, we uncover a significant impact of SLR risks on mortgage approval rates and we also find that the effects vary based on the level of SLR risks.

JEL Classifications: G20, G21, and Q54.

Key Words: Sea level rise, mortgage, loan acceptance, belief, climate risk.

1. Introduction

Rise in sea level can increase the frequency of flooding, coastal erosion and other natural disasters, leading to loss of life and property. It can also have an adverse effect on local infrastructure and the economy. During the 1993-2021 period, global sea level has increased by 3.4 mm per year.[1] This trend is accelerating globally and the melting of glaciers and ice sheets are now the primary source of the increase (IPCC, 2019). Risk of sea level rise (SLR) will become worse in the future due to global warming, which is expected to increase 3 to 5°C by the end of this century, posing a serious threat to the lives and livelihoods of people near the coast.[2] In the U.S., around 40% of the population live in coastal counties, and these areas have significantly higher population density that the national average.[3] Thus, a notable percentage of the U.S. population is vulnerable to SLR risk.[4]

In this paper, we study the relationship between SLR risk and access to residential mortgage credit at the census tract level from 2018 to 2020.[5] SLR can directly affect residential property prices and local economic activities. It can also increase the belief among mortgage lenders that the area is at high risk of future natural disasters.[6] Several papers find a negative relationship between natural disasters and the economy. Hsiang and Jina (2014) show that tropical cyclone hit areas experience lower economic growth and decline in income level. Similarly,

[1] Satellite sea level observations. NASA's Goddard Space Flight Center. https://climate.nasa.gov/vital-signs/sea-level/.
[2] Statement on the State of the Global Climate by World Meteorological Organization (WMO) in 2018.
[3] NOAA. What percentage of the American population lives near the coast? National Ocean Service website, https://oceanservice.noaa.gov/facts/population.html, accessed on 11/29/21.
[4] Globally, around 267 million people live in coastal areas that are less than 2 meters above sea level; by 2100, this is expected to reach at least 410 million, even if there is no population growth and only a 1-meter increase in sea level (Hooijer and Vernimmen, 2021).
[5] We limit our sample period from 2018 to 2020, since our mortgage data, which is collected from the HMDA dataset, do not include important borrower characteristics such as loan-to-value and debt-to-income ratios for loan applications before 2018.
[6] People who have experienced the adverse effects of climate change are more likely to believe in the risk of climate change (Myers et al., 2012; Akerlof et al., 2013; Zaval et al., 2014).

Boustan et al. (2017) find that extreme natural disasters can cause decline in home prices and rise in poverty rates. If loan officers believe SLR will hurt the local economy and the housing market, they will tighten mortgage lending standards to reduce the risk of borrower default.

Decline in local economic activities and income can also cause higher foreclosure rates, contributing to lower home prices (Lee, 2008; Schuetz, Been and Ellen, 2008; Frame, 2010). For example, Lin, Rosenblatt and Yao (2009) show that foreclosures are associated with an 8.7% decline in surrounding home prices. Similarly, Immergluck and Smith (2006) find that foreclosures lead to a 0.9% decline in nearby home values. Higher foreclosure rates and lower home prices can increase the risk of mortgage defaults (Agarwal, Ambrose, Chomsisengphet, and Sanders, 2012; Ding, Quercia, and Ratcliffe, 2010). For example, Capozza and Van Order (2011) show that deteriorating economic conditions during the financial crisis, that led to lower home prices, was a major contributor to the surge in mortgage defaults during that period. Similarly, Kau et al. (2011) argue that the crash in home prices during the financial crisis led to high defaults in subprime mortgages. The probability of borrower default increases if home price drops below the mortgage amount (Jackson and Kasserman, 1980; Foster and Van Order; 1984; and Kau, Keenan and Kim, 1994).

We study the relationship between SLR and mortgage lending standards using three different levels of elevation from sea level: (i) 0 ft above sea level represents imminent risk, (ii) 1 ft above sea level represents medium-term risk, and (iii) 2 ft above sea level represents long-term risk. For all three levels of elevation, we find a negative effect of SLR on loan acceptance rates, indicating that lenders take into account both immediate and longer-term climate risk of these locations. Past papers show that SLR also affects the cost of borrowing. For example, Painter (2020) finds that issuance costs of long-term municipal bonds are higher for counties exposed to

SLR risk. On the other hand, Jiang, Li, and Qian (2019) find that businesses operating in areas with SLR risk pay higher interest rates for long-term loans. To the best of our knowledge, we are the first to study the impact of SLR risk, using three different levels of elevation, on residential mortgage lending standards. This approach allows us to examine changes in loan acceptance rates for different levels of SLR risk.

The relationship between SLR and loan acceptance rates may be affected by belief in climate risk.[7] To examine the impact of climate risk belief on our results, we divide our sample into High Belief and Low Belief areas using the percentage of survey respondents in a matching county who believe global warming is happening.[8] We find that SLR leads to tighter lending standards in both High Belief and Low Belief census tracts, if there is an immediate threat of SLR (areas that are 0 ft above sea level). However, in locations where risk is more long-term (areas that are 1 to 2 ft above sea level), SLR leads to lower loan acceptance rates only in High Belief census tracts. The results suggest that belief in climate risk doesn’t matter when the threat of SLR is imminent. However, when risk is not immediate, SLR leads to lower loan acceptance rates only in areas where belief in climate risk is already high. On the other hand, lenders do not reduce loan acceptance rates in Low Belief census tracts since these locations are perceived to have low climate risk. Consistent with our results, several papers show that the real estate market is affected by belief in climate change. For example, Baldauf et al. (2020) argue that the belief in long-term climate risk in an area is reflected in its residential home prices. They find that prices of homes that are expected to be underwater are lower in locations where belief in climate change is high

[7] Personal judgement of loan officers can have an impact on mortgage lending decisions (Cortes, Duchin, and Sosyura, 2016; Tzioumis and Gee, 2013).

[8] The county level survey data is matched with the relevant census tracts. We rank the census tracts based on the percentage of survey respondents in matching counties who believe global warming is happening. We define census tracts in the upper quantile as High Belief and those in the lower quantile as Low Belief. Data comes from the Yale Climate Opinion Maps 2020 (Howe, Mildenberger, Marlon, and Leiserowitz, 2015).

compared to locations where such belief is low. Similarly, Keys and Mulder (2020) find that SLR causes a bigger decline in home prices in locations where belief in climate change is high.

Next, we examine whether the relationship between SLR and loan acceptance rates varies for local versus geographically diversified lenders.[9] We expect local lenders to have a better relationship with the borrowers and greater access to soft information, making it easier for them to continue lending in high SLR risk areas. Past studies show that prior relationship between lenders and borrowers can increase the likelihood of loan approval during periods of external crisis (He, 2018; Puri, Jorg, and Sascha, 2011). Prior relationship can also reduce information asymmetry leading to lower rates of default (Bolton, Freixas, Gambacorta, and Mistrulli, 2016). Our results show that when SLR risk is imminent, the type of lender does not affect the relationship between SLR and loan acceptance rates. However, in locations where SLR risk is more long-term (elevation is 1 to 2 ft above sea level), loan approval is higher among local lenders but lower among diversified lenders. The results suggest that local lenders, using soft information, are able to identify creditworthy borrowers in these locations and maintain their core markets. They also play a supportive role in these census tracts by improving access to mortgage credit. On the other hand, diversified lenders tighten lending standards to avoid long-term SLR risk in these census tracts.

We make several contributions to the literature. First, we study the relationship between SLR risk and residential mortgage lending standards at the census tract level; we divide SLR into three different levels of risk based on elevation from sea level: 0 ft, 1 ft, and 2 ft. For all three levels of risk, we find a negative effect of SLR on loan acceptance rates, indicating that lenders take into consideration both the short-term and long-term threat of SLR on the local economy and

[9] Lenders are defined as local if at least 65% of their total loans originated in the census tract in the previous year, and they are defined as geographically diversified if less than 65% of their total loans originated in the census tract in the previous year.

housing market. The results are consistent with previous studies that show that lenders account for local risk factors such as environmental disasters and contamination when making lending decisions (Xu and Xu, 2020; Jackson, 2001). We believe we are the first to examine the impact of SLR, using different levels of elevation, on mortgage lending standards, allowing us to study the relationship between SLR and loan acceptance rates for different levels of risk. We also examine how climate risk belief and lender type affects this relationship. Our results show that climate risk belief is not important if the threat of SLR is imminent. However, if risk is more long-term and not immediate, SLR negatively affects loan acceptance rates only in census tracts where people have high belief in climate risk. Moreover, we find that the relationship between SLR and lending standards does not differ for local and geographically diversified lenders if the threat of SLR is imminent. However, in locations where risk is not immediate (elevation is 1 to 2 ft above sea level), loan acceptance rates are higher among local lenders but lower among diversified lenders. The results indicate that local lenders play an important role in these census tracts by maintaining higher loan approval rates. Overall, the findings add to our understanding of the effect of SLR on access to mortgage credit in coastal areas, contributing to the literature that studies the impact of climate risk on various financial markets.

We arrange the remaining paper as follows. Section 2 presents the sources of data. Section 3 discusses our methodology and results. Section 4 concludes.

2. Data Sources

Most U.S. financial institutions report data for mortgage applications under the Home Mortgage Disclosure Act (HMDA).[10] Our sample includes all conventional home purchase loan

[10] The data are publicly available at the Federal Financial Institutions Examination Council (FFIEC) website. For additional information about the HMDA data, please visit http://www.ffiec.gov/hmda/hmdaproducts.htm.

applications from 2018 to 2020. It includes information about loan acceptance decision, loan amount requested, and applicant's income, loan-to-value ratio, debt-to-income ratio, race, ethnicity, gender and geographic location. We collect county level population and labor force data from the U.S. Census Bureau and the Bureau of Labor Statistics, respectively. County level median home price data come from Zillow.com and state level median household income data come from the Federal Reserve Bank of St. Louis. We obtained projections of SLR for coastal areas in the lower 48 states from the National Oceanic and Atmospheric Administration (NOAA).[11] These data indicate the potential inundation of coastal areas as a result of a 0 to 10 feet rise in sea level over current Mean Higher High Water (MHHW) conditions. We then generated centroids for all the census tracts within the 48 lower states. Shapefiles of SLR projections of 0 to 2 feet were used to identify the census tracts that would be inundated under zero foot to two feet of SLR. We match the loan level mortgage data with the relevant socioeconomic variables at the county or state level and the SLR variables at the census tract level.

For our sample period, we collect 11,339,228 loan level observations of residential mortgage applications. Table 1 presents the summary statistics of the variables considered in this study. Accept is a dummy indicator that is equal to 1 if the loan application is approved or 0 if declined. The average of Accept shows that loan acceptance ratio is as high as 92 percent. The average loan-to-value ratio is 90 percent, indicating an average 10 percent down payment in the residential property transactions. The mean of debt-to-income ratio shows that applicants have to spend an average of 38 percent of their income on mortgage payment. The mean of natural logarithm of applicants' income is 4.47 and it represents an average income of $87,357 for the loan applicants. Female (Minority) is an indicator variable that is equal to 1 if an applicant is

[11] See Sea level rise (SLR) projections from the National Oceanic and Atmospheric Administration (NOAA): https://coast.noaa.gov/slrdata/

female (a visible minority) and 0 otherwise. Within all the applications, 34 percent of applicants are female and 29 percent of applicants belong to minority group. Based on the mean of natural logarithm of 8.59, the average total number of applications in a county is 5,377. The average house price is $255,250, derived from the natural logarithm of 12.45. Throughout all counties, the average population is 400,312 including the average labor force of 196,811. At state level, the mean of median household income growth is 2 percent.

[Insert Table 1]

Given the accelerating trend in global sea level rise, we measure SLR risk at three different levels based on the elevation of a census tract from sea level. 0ft is a dummy variable that is equal to 1 if the area is zero foot above sea level and 0 otherwise. It generally indicates imminent risk related to sea level rise. Similarly, 1ft is a dummy variable about whether the area is one foot above sea level. It indicates medium-term risk that is expected to become imminent risk in 20 to 30 years. 2ft is a similar dummy variable that indicates long-term risk as it is expected to turn into imminent risk in up to 100 years. Figure 1 provides a map view of the distribution of SLR risk in the U.S. The red colored areas are the counties that have imminent risk. It is observable that counties in west, east and south coast are subject to imminent risk and those areas are close to large cities such as Seattle, San Francisco, New Orleans, Boston, New York City and Washington DC.

[Insert Figure 1]

Table 2 reports the correlation among all important variables studied. While the magnitude is not large, it is noticeable that loan acceptance ratio is significantly correlated with all variables. Due to the significant correlation, we conduct multivariable regressions by controlling all the mortgage application characteristic variables and socioeconomic variables at the census tract or county levels. Besides, it is not surprising that the correlation between population and labor is close to 1. Moreover, it shows that house price is positively correlated with applicant's income, population, and labor force. This is generally the consensus in real estate market.

[Insert Table 2]

3. Empirical Results

3.1 Main Result

In order to investigate the relationship between SLR risk and residential mortgage lending standards, we run regression using the following equation:

$$Accept_{i,t} = \alpha_i + \beta_1 SLR\ Risk_{i,t-1} + Controls_{i,t-1} + \delta_t + \varepsilon_{i,t} \quad (1)$$

where $Accept_{i,t}$ is the dummy variable about whether the mortgage application is approved. $SLR\ Risk_{i,t-1}$ is the measure of sea level rise risk. 0 ft above sea level (0ft) represents imminent risk. 1 ft above sea level (1ft) represents medium-term risk, and 2 ft (2ft) represents long-term risk. The coefficient on the SLR Risk (β_1) indicates the relation between SLR risk and loan acceptance ratio. Control variables include loan level variables such as loan-to-value ratio (LTV), debt-to-income ratio (DTI), applicants' income (Income), Gender (Female), race (Minority), and house price (Price). We also control county level variables including total number of applications (App), Population (Pop) and labor force (Labor), as well as the state level variable, median household income growth (Growth). The county fixed effect, lender fixed effect and year fixed effect are included throughout. The standard errors are clustered at the county and lender level.

The result of multivariable regressions based on equation (1) is reported in Table 3. With 11,339,228 residential mortgage applications, in regression (1), the coefficient on the SLR risk demonstrates a significantly negative relation (t=-5.24) between imminent SLR risk and loan acceptance ratio. It indicates that when a residential mortgage application is from a county with elevation zero foot above sea level, the loan acceptance ratio will be 1.3 percent lower than a similar one from a county without imminent SLR risk. In regression (2), we find a similar negative relation between medium-term SLR risk and loan acceptance rate, significant at 10 percent level (t=-1.92). Moreover, long-term SLR risk also affect lenders' loan acceptance decision. The result in regression (3) shows that when from a county subject to long-term SLR risk, a mortgage application is less likely to be approved by 1.2 percent comparing with an otherwise similar application from a county without SLR risk. This relation is significant at 1 percent level (t=-2.80). Throughout all three regressions, the coefficient on SLR risk suggests that SLR risk negatively affects loan acceptance ratio. If a mortgage application is flagged with imminent, medium-term or long-term SLR risk, lenders tend to apply a more rigorous loan acceptance standard. The evidence implies that lenders take into consideration climate risk associated with sea level rise. Besides the relation between SLR risk and loan acceptance rate, the regressions also reveal additional factors that affect lenders' loan acceptance decision. For example, there is a significantly negative relation between loan-to-value ratio and loan acceptance rate. Debt-to-income ratio negatively affects loan acceptance rate but this is opposite for applicants' income level. These relations intuitively make sense because lenders feel safe when borrowers make more down payment (low loan-to-value), have less debt relative to income (low debt-to-income), and earn higher income. These applications are therefore more likely to pass. Another noticeable point is the significantly negative relation between race and loan acceptance rate. The results shows that minority's mortgage application is less likely to be approved. We will study this relation further under SLR framework in a latter section. Overall, we find a negative relation between SLR risk and loan acceptance rate. This relation holds for imminent, medium-term and long-term SLR risk.

[Insert Table 3]

3.2 The Impacts of Climate Risk Beliefs

As Tzioumis and Gee(2013) and Cortes, Duchin, and Sosyura (2016) imply that the relationship between SLR risk and loan acceptance ratio may be affected by belief in climate risk, it is important to examine the impact of climate risk belief on our results. We divide our sample into subsamples of High Belief and Low Belief areas using the percentage of survey respondents in a matching county who believe global warming is happening. The numbers of residential mortgage applications are 3,831,954 from High Belief census tracts and 3,694,517 from Low Belief census tracts. We run the same regressions described in equation (1) for each subsample and the result is reported in Table 4. Regressions (1) and (2) demonstrate that lenders apply tighter lending standards in both High Belief and Low Belief census tracts, if there is an immediate threat of sea level rise. For mortgage applications from counties with elevation of zero foot above sea level, belief in climate risk seems not affect the relation between SLR risk and loan acceptance ratio. However, SLR risk negatively affect loan acceptance ratio only in High Belief census tracts when facing medium-term SLR risk as presented in regressions (3) and (4). A similar phenomenon is found in counties with long-term SLR risk in regressions (5) and (6). This evidence is consistent with the implication of the literature that relationship between SLR risk and loan acceptance ratio may be affected by belief in climate risk. The result indicates that the negative relation between non-imminent SLR risk (1ft or 2ft) and loan acceptance ratio seems to be affected by beliefs. On the other hand, loan acceptance rate in Low Belief census tracts is not affected since people in these locations are less likely to believe in the climate risk associated with sea level rise. In sum, the result suggests that belief in climate risk doesn’t play a role when the SLR risk is imminent. However, when risk is not immediate, SLR risk leads to lower loan acceptance rates only in areas where belief in climate risk is already high. Our result supports that the real estate market is affected by belief in climate change.

[Insert Table 4]

3.3 The Impacts of Lender Characteristics

Evidence in prior sections reveals a negative relation between SLR risk and loan acceptance rate. In this section, we further study this relation by interacting SLR risk with loan level characteristics from both lender side and borrower side. Studies in the literature suggest that prior relationship between lenders and borrowers can increase the likelihood of loan approval (He, 2018; Puri, Jorg, and Sascha, 2011) and can reduce information asymmetry (Bolton, Freixas, Gambacorta, and Mistrulli, 2016). Comparing with non-local lenders, it is expected that local lenders have a better relationship with the borrowers and have greater access to soft information, enabling them to continue lending in high SLR risk areas. Specifically, we examine whether the relationship between SLR and loan acceptance rates varies for local versus geographically diversified non-local lenders. We run regression tests using the following Equation (2).

$$Accept_{i,t} = \alpha_i + \beta_1\left(SLR\ Risk_{i,t-1} * Local_{i,t}\right) + \beta_2 SLR\ Risk_{i,t-1} + \beta_3 Local_{i,t} + Controls_{i,t-1} + \delta_t + \varepsilon_{i,t} \quad (2)$$

where $Accept_{i,t}$ is the dummy variable about whether the mortgage application is approved. Similar to Equation (1), $SLR\ Risk_{i,t-1}$ is the measure of sea level rise risk. 0 ft above sea level (0ft) represents imminent risk. 1 ft above sea level (1ft) represents medium-term risk, and 2 ft represents long-term risk. $Local_{i,t}$ is a dummy variable equal to 1 for local lenders if at least 65% of their total loans originated in the census tract in the previous year and 0 for geographically diversified lenders if less than 65% of their total loans originated in the census tract in the previous year. The coefficient on the interaction term (β_1) indicates the relation between SLR risk and loan acceptance ratio when an application is submitted to a local lender. Control variables are the same as those in Equation (1). Table 5 reports the results of regression tests based on Equation (2). In regression (1), the coefficient on the interaction term is close to zero and insignificant (t=0.08). It indicates that when facing imminent SLR risk, local lenders and geographically diversified lenders treat mortgage applications in a similar standard. There is no significant difference in loan acceptance rate between these two groups of lenders. However, it turns out that (β_1) is equal to 0.08 in regression (2), significant at 1 percent level with a t value of 4.20. It means that local lenders have higher loan acceptance ratio than diversified lenders when SLR risk is medium-term. With a coefficient of 0.05 (t=1.89, significant at 10 percent level), a similar result is found in regression (3) for long-term SLR risk. Overall, the empirical result suggests that local lenders apply a looser standard on mortgage applications when SLR risk is not imminent. It is consistent with the results in prior studies that prior relationship between borrowers and lenders affects the chance of loan approval.

[Insert Table 5]

While we do find that local banks are more favorite to borrowers than diversified banks in medium to long term SLR risk areas, what we do not know is whether the effect stem from their size? Local banks tend to be smaller than the diversified banks. We would like to understand whether the results are driven by smaller banks which do not want to lose clients by not declining the applications that they are supposed to reject, or it is truly because local banks have established relationship and know their clients better so that medium or long term SLR risk plays a less role in the mortgage approval decisions. To do that, we divide the mortgage loan application sample based on the size of lenders. We define a lender as large size if the value of its asset is at least 10 billion dollars. Then regression tests are used based on the following equation.

$$Accept_{i,t} = \alpha_i + \beta_1(SLR\ Risk_{i,t-1} * Large\ Size_{i,t}) + \beta_2 SLR\ Risk_{i,t-1} + \beta_3 Large\ Size_{i,t} + Controls_{i,t-1} + \delta_t + \varepsilon_{i,t} \quad (3)$$

where $Large\ Size_{i,t}$ is a dummy variable that is equal to 1 for large size lender and 0 otherwise. Controlling variables are the same as those discussed in Equation (1). The result is reported in Table 6. Among three regressions, the coefficient of interaction term is insignificant for imminent and long-term SLR risk and marginally significant for medium-term SLR risk. It indicates that lender size does not affect the relation between SLR risk and loan acceptance rate significantly, suggesting that the effect of local versus non-local lenders is not likely driven by their size.

[Insert Table 6]

3.4 The Impacts of Borrower Characteristics

In Table 3, we find that minority applicants are significantly less likely to be approved, controlled by all other factors. Therefore, we wonder if race might play a role in the relationship between SLR and approval rate. We would like to understand whether minority would be further punished if their house under contract are under imminent to long term SLR risks, or they would fair similarly or better than other race groups under different SLR risk levels. To examine whether the relation between SLR risk and loan acceptance rate is affected by borrower race, we run regressions using the following equation.

$$Accept_{i,t} = \alpha_i + \beta_1(SLR\ Risk_{i,t-1} * Minority_{i,t}) + \beta_2 SLR\ Risk_{i,t-1} + \beta_3 Minority_{i,t} + Controls_{i,t-1} + \delta_t + \varepsilon_{i,t} \quad (4)$$

where $Minority_{i,t}$ is a dummy variable equal to 1 if the borrowers belongs to minority group and 0 otherwise. Table 7 presents the regression tests result. The relation between SLR risk and loan acceptance rate is insignificant and close to none, indicating that lenders apply a similar standard for minority borrowers and non-minority borrowers when SLR risk is either imminent (0ft) or non-imminent (1ft and 2ft). In sum, our result of the effect of SLR risk on loan acceptance rate is not affect by borrower race.

[Insert Table 7]

4. Conclusion

Coastal counties, which are home to 127 million people in the United States, are at higher risk of natural disasters due to seal level rise.[12] Natural disasters can negatively affect the local housing market as well as economic activities; they can also increase the climate risk perception among lenders. We examine the effect of SLR on mortgage loan acceptance rates using three different levels of elevation from sea level: (i) 0 ft above sea level indicates imminent risk, (ii) 1 ft above sea level indicates medium-term risk, and (iii) 2 ft above sea level indicates long-term risk.

Our results show that SLR is associated with tighter residential mortgage lending standards for all three levels of elevation, suggesting that lenders take into account both immediate and long-term climate risk of these locations. We also find that belief in climate risk does not affect this relationship between SLR and loan acceptance rates if SLR risk is imminent. However, if risk is long-term (areas that are 1 to 2 ft above sea level), SLR leads to lower loan acceptance rates only in places where people have high belief in climate risk. Overall, our results show the importance

[12] NOAA. What percentage of the American population lives near the coast? National Ocean Service website, https://oceanservice.noaa.gov/facts/population.html, accessed on 11/29/21.

of SLR risk for the residential mortgage market, contributing to the literature that examines the effect of climate risk on various financial markets.

References

Akerlof, Karen, Edward W. Maibach, Dennis Fitzgerald, Andrew Y. Cedeno, and Amanda Neuman, 2013, Do People "Personally Experience" Global Warming, and if so How, and Does it Matter?, Global Environmental Change, 23(1): 81–91.

Agarwal, Sumit, Brent W. Ambrose, Souphala Chomsisengphet, and Anthony B. Sanders, 2012, Thy Neighbor's Mortgage: Does Living in a Subprime Neighborhood Affect One's Probability of Default? Real Estate Economics, 40(1): 1–22.

Baldauf, Markus, Lorenzo Garlappi, and Constantine Yannelis, 2020, Does Climate Change Affect Real Estate Prices? Only If You Believe In It, Review of Financial Studies, 33(3):1256-1295.

Bolton, Patrick, Xavier Freixas, Leonardo Gambacorta, and Paolo E. Mistrulli, 2016, Relationship and Transaction Lending in a Crisis, Review of Financial Studies, 29(10): 2643-2676.

Boustan, Leah P., Matthew E. Kahn, Paul W. Rhode, and Maria L. Yanguas, 2017, The Effect of Natural Disasters on Economic Activity in US Counties: A Century of Data, NBER Working Papers 23410, National Bureau of Economic Research.

Capozza, Dennis R., and Robert Van Order, 2011, The Great Surge in Mortgage Defaults 2006–2009: The Comparative Roles of Economic Conditions, Underwriting and Moral Hazard, Journal of Housing Economics, 20(2): 141–51.

Cortes, Kristle R., Ran Duchin, and Denis Sosyura, 2016, Clouded Judgment: The Role of Sentiment in Credit Origination, Journal of Financial Economics, 121(2): 392-413.

Ding, Lei, Roberto G. Quercia, and Janneke Ratcliffe, 2010, Neighborhood Subprime Lending and the Performance of Community Reinvestment Mortgages, Journal of Real Estate Research, 32(3): 341–76.

Frame, W. Scott, 2010, Estimating the Effect of Mortgage Foreclosures on Nearby Property Values: A Critical Review of the Literature, Economic Review, Federal Reserve Bank of Atlanta, 95(3).

Foster, Chester, and Robert Van Order, 1984, An Option Based Model of Mortgage Default, Housing Finance Review, 3(4): 351–372.

Howe, Peter, Matto Mildenberger, Jennifer Marlon, and Anthony Leiserowitz, 2015, Geographic Variation in Opinions on Climate Change at State and Local Scales in the USA, Nature Climate Change, 5: 596–603.

Hsiang, Solomon M., and Amir S. Jina, 2014, The Causal Effect of Environmental Catastrophe on Long-Run Economic Growth: Evidence from 6,700 Cyclones, NBER Working Papers 20352, National Bureau of Economic Research.

Immergluck, Dan, and Geoff Smith, 2006, The External Costs of Foreclosure: The Impact of Single-Family Mortgage Foreclosures on Property Values, Housing Policy Debate, 17(1): 57–79.

Jackson, Jerry R., and David L. Kasserman, 1980, Default Risk on Home Mortgage Loans: A Test of Competing Hypotheses, Journal of Risk and Insurance, 47(4): 678–690.

Jackson, Thomas, 2001, Environmental Risk Perceptions of Commercial and Industrial Real Estate Lenders, Journal of Real Estate Research, 22(3):271-288.

Jiang, Feng, C. Wei Li, and Yiming Qian, 2019, Can Firms Run Away from Climate-Change Risk? Evidence from the Pricing of Bank Loans, Available at SSRN: https://ssrn.com/abstract=3477450.

Kau, James B., Donald C. Keenan, and Taewon Kim, 1994, Default Probabilities for Mortgages, Journal of Urban Economics, 35(3): 278–296.

Kau, James B., Donald Keenan, Constantine Lyubimov, and V. Carlos Slawson, 2011, Subprime Mortgage Default. Journal of Urban Economics, 70(2–3): 75–87.

Keys, Benjamin J., and Philip Mulder, 2020, Neglected No More: Housing Markets, Mortgage Lending, and Sea Level Rise, NBER Working Papers 27930, National Bureau of Economic Research.

Lee, Kai-yan, 2008, Foreclosure's Price-Depressing Spillover Effects on Local Properties: A Literature Review, Public and Community Affairs Discussion Papers 2008-1, Federal Reserve Bank of Boston.

Lin, Zhenguo, Eric Rosenblatt, and Vincent W. Yao, 2009, Spillover Effects of Foreclosures on Neighborhood Property Values, The Journal of Real Estate Finance and Economics, 38(4): 387–407.

He, Ai, 2018, Exogenous Shocks and Real Effects of Financial Constraints: Loan-and Firm-Level Evidence around Natural Disasters, Available at SSRN: https://ssrn.com/abstract=3190343.

Hooijer, Aljosja, and Ronald Vernimmen, 2021, Global LiDAR Land Elevation Data Reveal Greatest Sea-level Rise Vulnerability In The Tropics, Nature Communications, 12(1): 1-7.

Myers, Teresa, Matthew Nisbet, Edward Maibach, and Anthony Leiserowitz, 2012, A Public Health Frame Arouses Hopeful Emotions about Climate Change, Climatic Change, 113(3): 1105-1112.

Micheal, Oppenheimer, Bruce Glavovic, Jochen Hinkel, Roderik van de Wal, Alexandre Magnan, Amr Abd-Elgawad, Cai Rongshu, Miguel Cifuentes, Robert DeConto, Tuhin Ghosh, John Hay, Ben Marzeion, Benoit Meyssignac, Zita Sebesvari, 2019, Sea Level Rise and Implications for Low-Lying Islands, Coasts and Communities. IPCC Special Report on the Ocean and Cryosphere in a Changing Climate.

Painter, Marcus, 2020, An Inconvenient Cost: The Effects of Climate Change on Municipal Bonds, Journal of Financial Economics, 135 (2): 468-482.

Puri, Manju, Jörg Rocholl, and Sascha Steffen, 2011, Global Retail Lending in the Aftermath of the US Financial Crisis: Distinguishing Between Supply and Demand Effects, Journal of Financial Economics, 100(3):556-578.

Schuetz, Jenny, Vicki Been, and Ingrid G. Ellen, 2008, Neighborhood Effects of Concentrated Mortgage Foreclosures, Journal of Housing Economics, 17(4): 306–319.

Tzioumis, Konstantinos, and Matthew Gee, 2013, Nonlinear Incentives and Mortgage Officers' Decisions, Journal of Financial Economics, 107(2): 436-453.

Xu, Minhong, and Yilan Xu, 2020, Environmental Hazards and Mortgage Credit Risk: Evidence from Texas Pipeline Incidents, Real Estate Economics, 48(4): 1096-1135.

Zaval, Lisa, Elizabeth A. Keenan, Eric J. Johnson, and Elke U. Weber, 2014, How Warm Days Increase Belief in Global Warming, Nature Climate Change, 4:143-147.

Table 1. Summary Statistics

This table reports the summary statistics for the variables in mortgage applications and counties. Accept is a dummy indicator that is equal to 1 if the loan application is approved or 0 if declined. LTV is the loan-to-value ratio. DTI is the debt-to-income ratio. Income is the natural logarithm of applicant annual before tax income. Female is an indicator variable that is equal to 1 if an applicant is female and 0 otherwise. Minority is an indicator variable that is equal to 1 if an applicant is a visible minority and 0 otherwise. App is the natural logarithm of total application in a county. Price is the natural logarithm of house price. Pop and Labor are the natural logarithm of population and labor force in a county. Growth represents median household income growth at state level.

	Mean	S.D.	1%	25%	50%	75%	99%
Accept	0.92	0.28	0.00	1.00	1.00	1.00	1.00
LTV	90.14	1657.79	30.19	80.00	94.19	96.50	103.30
DTI	37.59	12.28	10.00	33.00	38.00	44.00	80.00
Income	4.47	0.68	3.09	4.01	4.42	4.86	6.34
Female	0.34	0.47	0.00	0.00	0.00	1.00	1.00
Minority	0.29	0.45	0.00	0.00	0.00	1.00	1.00
App	8.59	1.42	4.74	7.77	8.82	9.54	11.25
Price	12.45	0.50	11.37	12.12	12.43	12.73	13.72
Pop	12.90	1.42	9.49	11.98	13.01	13.81	16.11
Labor	12.19	1.45	8.68	11.24	12.34	13.14	15.41
Growth	0.02	0.06	-0.11	-0.02	0.00	0.06	0.16

Table 2. Correlations

This table shows the correlation matrix for the variables in Table 1. 0 ft, 1 ft, and 2 ft are dummy variables that are equal to 1 if a county is zero foot, one foot, or two feet above sea level and 0 otherwise. P-values are reported in the matrix. Asterisks *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

	Accept	0ft	1ft	2ft	LTV	DTI	Income	Female	Minority	App	Price	Pop	Labor
0ft	-0.005***	1											
	[0]												
1ft	-0.002***	-0.003***	1										
	[0]	[0]											
2ft	-0.002***	-0.003***	-0.001***	1									
	[0]	[0]	[0]										
LTV	-0.002***	-0.000	-0.000	-0.000	1								
	[0]	[0.163]	[0.616]	[0.660]									
DTI	-0.232***	-0.005***	0.001***	0.002***	0.002***	1							
	[0]	[0]	[0.002]	[0]	[0]								
Income	0.099***	0.063***	0.014***	0.013***	-0.003***	-0.319***	1						
	[0]	[0]	[0]	[0]	[0]	[0]							
Female	-0.012***	-0.004***	-0.003***	-0.002***	0.000	0.045***	-0.139***	1					
	[0]	[0]	[0]	[0]	[0.757]	[0]	[0]						
Minority	-0.083***	-0.021***	-0.001***	-0.005***	0.001***	0.156***	-0.085***	0.045***	1				
	[0]	[0]	[0]	[0]	[0]	[0]	[0]	[0]					
App	0.013***	0.008***	-0.004***	0.001***	-0.001***	0.077***	0.177***	0.025***	0.217***	1			
	[0]	[0]	[0]	[0]	[0]	[0]	[0]	[0]	[0]				
Price	0.019***	0.045***	0.008***	0.011***	-0.003***	0.063***	0.353***	-0.007***	0.140***	0.508***	1		
	[0]	[0]	[0]	[0]	[0]	[0]	[0]	[0]	[0]	[0]			
Pop	0.001***	0.001***	-0.005***	-0.001***	-0.002***	0.078***	0.183***	0.027***	0.259***	0.968***	0.506***	1	
	[0.002]	[0.001]	[0]	[0]	[0]	[0]	[0]	[0]	[0]	[0]	[0]		
Labor	0.003***	0.000	-0.006***	-0.002***	-0.002***	0.074***	0.189***	0.028***	0.253***	0.968***	0.523***	0.998***	1
	[0]	[0.302]	[0]	[0]	[0]	[0]	[0]	[0]	[0]	[0]	[0]	[0]	
Growth	0.003***	0.003***	0.003***	0.001***	-0.001***	0.020***	0.010***	-0.010***	0.004***	0.001***	0.016***	0.018***	0.023***
	[0]	[0]	[0]	[0]	[0.020]	[0]	[0]	[0]	[0]	[0]	[0]	[0]	[0]

Table 3. SLR Risk and Loan Acceptance

This table presents the regression results of loan acceptance ratio on SLR risk. 0 ft, 1 ft, and 2 ft are dummy variables that are equal to 1 if a census tract is zero foot, one foot, or two feet above sea level and 0 otherwise. 0 ft above sea level indicates imminent risk. 1 ft above sea level indicates medium-term risk and 2 ft above sea level indicates long-term risk. LTV is the loan-to-value ratio. DTI is the debt-to-income ratio. Income is the natural logarithm of applicant annual before tax income. Female is an indicator variable that is equal to 1 if an applicant is female and 0 otherwise. Minority is an indicator variable that is equal to 1 if an applicant is a visible minority and 0 otherwise. App is the natural logarithm of total application in a county. Price is the natural logarithm of house price. Pop and Labor are the natural logarithm of population and labor force in a county. Growth represents median household income growth at state level. The county fixed effect, lender fixed effect and year fixed effect are included throughout models. The standard errors are clustered at the county and lender level. Statistical t-values are reported in the brackets. Asterisks *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

	1	2	3
		Loan Acceptance	
0ft	-0.0129***		
	[-5.236]		
1ft		-0.0093*	
		[-1.924]	
2ft			-0.0122***
			[-2.804]
LTV	-0.0000***	-0.0000***	-0.0000***
	[-2.619]	[-2.619]	[-2.618]
DTI	-0.0051***	-0.0051***	-0.0051***
	[-17.848]	[-17.846]	[-17.845]
Income	0.0109***	0.0109***	0.0109***
	[7.121]	[7.078]	[7.080]
Female	0.0002	0.0002	0.0002
	[0.462]	[0.449]	[0.450]
Minority	-0.0294***	-0.0293***	-0.0293***
	[-18.804]	[-18.762]	[-18.770]
App	-0.0042	-0.0043	-0.0042
	[-0.764]	[-0.774]	[-0.772]
Price	0.0094	0.0094	0.0094
	[0.750]	[0.751]	[0.752]
Pop	-0.0736***	-0.0738***	-0.0738***
	[-2.605]	[-2.611]	[-2.612]
Labor	0.0307	0.0309	0.0310
	[1.346]	[1.354]	[1.356]
Growth	0.0069	0.0069	0.0069
	[1.374]	[1.381]	[1.381]
Constant	1.5614***	1.5616***	1.5614***
	[3.849]	[3.850]	[3.850]
County FE	Yes	Yes	Yes
Lender FE	Yes	Yes	Yes
Year FE	Yes	Yes	Yes
Two-way cluster	Yes	Yes	Yes
Observations	11,339,228	11,339,228	11,339,228
R-squared	0.106	0.106	0.106

Table 4. SLR Risk and Beliefs

This table presents the subsample regression results of loan acceptance ratio on SLR risk. The sample is divided into subsamples of High Belief and Low Belief areas using the percentage of survey respondents in a matching county who believe global warming is happening. 0 ft, 1 ft, and 2 ft are dummy variables that are equal to 1 if a county is zero foot, one foot, or two feet above sea level and 0 otherwise. 0 ft above sea level indicates imminent risk. 1 ft above sea level indicates medium-term risk and 2 ft above sea level indicates long-term risk. Control variables are the same as described in Table 3. The county fixed effect, lender fixed effect and year fixed effect are included throughout models. The standard errors are clustered at the county and lender level. Statistical t-values are reported in the brackets. Asterisks *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

	1	2	3	4	5	6
	Loan Acceptance					
	High Beliefs	Low Beliefs	High Beliefs	Low Beliefs	High Beliefs	Low Beliefs
0ft	-0.0114**	-0.0147***				
	[-2.335]	[-4.391]				
1ft			-0.0206*	0.0005		
			[-1.676]	[0.106]		
2ft					-0.0193**	-0.0072
					[-1.981]	[-1.143]
LTV	-0.0000	-0.0000***	-0.0000	-0.0000***	-0.0000	-0.0000***
	[-0.748]	[-3.074]	[-0.749]	[-3.073]	[-0.748]	[-3.073]
DTI	-0.0058***	-0.0044***	-0.0058***	-0.0044***	-0.0058***	-0.0044***
	[-14.554]	[-21.711]	[-14.552]	[-21.707]	[-14.551]	[-21.708]
Income	0.0033	0.0202***	0.0033	0.0202***	0.0033	0.0202***
	[1.523]	[13.007]	[1.500]	[12.966]	[1.496]	[12.974]
Female	0.0008	-0.0003	0.0008	-0.0003	0.0008	-0.0003
	[1.513]	[-0.592]	[1.495]	[-0.599]	[1.504]	[-0.599]
Minority	-0.0263***	-0.0327***	-0.0262***	-0.0327***	-0.0262***	-0.0327***
	[-10.847]	[-17.954]	[-10.793]	[-17.942]	[-10.807]	[-17.943]
App	0.0002	-0.0158***	0.0002	-0.0159***	0.0002	-0.0159***
	[0.021]	[-2.921]	[0.017]	[-2.938]	[0.020]	[-2.938]
Price	-0.0148	0.0282*	-0.0148	0.0283*	-0.0148	0.0283*
	[-0.676]	[1.785]	[-0.675]	[1.789]	[-0.676]	[1.789]
Pop	-0.1368**	-0.1278***	-0.1367**	-0.1280***	-0.1369**	-0.1280***
	[-2.519]	[-4.171]	[-2.517]	[-4.184]	[-2.519]	[-4.183]
Labor	0.1471***	0.0800***	0.1470***	0.0802***	0.1473***	0.0801***
	[3.552]	[3.199]	[3.546]	[3.205]	[3.563]	[3.205]
Growth	0.0412***	0.0246***	0.0413***	0.0246***	0.0412***	0.0246***
	[4.025]	[3.577]	[4.030]	[3.579]	[4.026]	[3.580]
Constant	1.2705	1.3931***	1.2717	1.3930***	1.2705	1.3928***
	[1.435]	[3.674]	[1.437]	[3.679]	[1.435]	[3.678]
County FE	Yes	Yes	Yes	Yes	Yes	Yes
Lender FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Two-way cluster	Yes	Yes	Yes	Yes	Yes	Yes
Observations	3,831,954	3,694,517	3,831,954	3,694,517	3,831,954	3,694,517
R-squared	0.118	0.099	0.118	0.099	0.118	0.099

Table 5. Local versus Geographically Diversified Lenders

This table presents the regression results of loan acceptance ratio on the interaction between SLR risk and localness of lenders. Local is a dummy variable equal to 1 for local lenders if at least 65% of their total loans originated in the census tract in the previous year and 0 for geographically diversified lenders if less than 65% of their total loans originated in the census tract in the previous year. Control variables are the same as described in Table 3. Statistical t-values are reported in the brackets. Asterisks *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

	1	2	3
		Loan Acceptance	
0ft*Local	0.0009		
	[0.079]		
0ft	-0.0129***		
	[-5.262]		
1ft*Local		0.0810***	
		[4.196]	
1ft		-0.0095*	
		[-1.951]	
2ft*Local			0.0458*
			[1.892]
2ft			-0.0124***
			[-2.828]
Local	0.0029*	0.0029*	0.0029*
	[1.690]	[1.696]	[1.699]
LTV	-0.0000***	-0.0000***	-0.0000***
	[-2.619]	[-2.618]	[-2.618]
DTI	-0.0051***	-0.0051***	-0.0051***
	[-17.848]	[-17.845]	[-17.845]
Income	0.0109***	0.0109***	0.0109***
	[7.122]	[7.079]	[7.081]
Female	0.0002	0.0002	0.0002
	[0.461]	[0.448]	[0.449]
Minority	-0.0294***	-0.0293***	-0.0293***
	[-18.803]	[-18.762]	[-18.769]
App	-0.0042	-0.0043	-0.0043
	[-0.765]	[-0.775]	[-0.773]
Price	0.0095	0.0095	0.0095
	[0.755]	[0.756]	[0.757]
Pop	-0.0740***	-0.0742***	-0.0742***
	[-2.621]	[-2.627]	[-2.628]
Labor	0.0308	0.0310	0.0310
	[1.348]	[1.357]	[1.359]
Growth	0.0069	0.0069	0.0069
	[1.372]	[1.379]	[1.379]
Constant	1.5652***	1.5654***	1.5652***
	[3.859]	[3.861]	[3.861]
County FE	Yes	Yes	Yes
Lender FE	Yes	Yes	Yes
Year FE	Yes	Yes	Yes
Two-way cluster	Yes	Yes	Yes
Observations	11,339,228	11,339,228	11,339,228
R-squared	0.106	0.106	0.106

Table 6. Lender Size and SLR Risk

This table presents the regression results of loan acceptance ratio on the interaction between SLR risk and size of lenders. Large Size is a dummy variable that is equal to 1 if the value of lender's asset is at least 10 billion dollars and 0 otherwise. Control variables are the same as described in Table 3. Statistical t-values are reported in the brackets. Asterisks *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

	1	2	3
		Loan Acceptance	
0ft*Large Size	0.0008		
	[0.234]		
0ft	-0.0132***		
	[-6.151]		
1ft*Large Size		-0.0151*	
		[-1.826]	
1ft		-0.0044	
		[-1.125]	
2ft* Large Size			-0.0075
			[-1.012]
2ft			-0.0099**
			[-2.454]
Large Size	-0.0094**	-0.0094**	-0.0094**
	[-2.008]	[-1.993]	[-1.995]
LTV	-0.0000***	-0.0000***	-0.0000***
	[-2.619]	[-2.618]	[-2.618]
DTI	-0.0051***	-0.0051***	-0.0051***
	[-17.848]	[-17.846]	[-17.845]
Income	0.0109***	0.0109***	0.0109***
	[7.121]	[7.080]	[7.080]
Female	0.0002	0.0002	0.0002
	[0.460]	[0.448]	[0.449]
Minority	-0.0294***	-0.0293***	-0.0293***
	[-18.802]	[-18.760]	[-18.769]
App	-0.0042	-0.0043	-0.0043
	[-0.766]	[-0.776]	[-0.774]
Price	0.0094	0.0094	0.0094
	[0.749]	[0.750]	[0.750]
Pop	-0.0734***	-0.0735***	-0.0736***
	[-2.594]	[-2.601]	[-2.601]
Labor	0.0306	0.0308	0.0308
	[1.339]	[1.348]	[1.350]
Growth	0.0069	0.0069	0.0069
	[1.370]	[1.377]	[1.377]
Constant	1.5627***	1.5630***	1.5627***
	[3.851]	[3.852]	[3.852]
County FE	Yes	Yes	Yes
Lender FE	Yes	Yes	Yes
Year FE	Yes	Yes	Yes
Two-way cluster	Yes	Yes	Yes
Observations	11,339,228	11,339,228	11,339,228
R-squared	0.106	0.106	0.106

Table 7. Race and SLR Risk

This table presents the regression results of loan acceptance ratio on the interaction between SLR risk and borrower race. Minority is a dummy variable that is equal to 1 if the borrower is minority and 0 otherwise. Control variables are the same as described in Table 3. Statistical t-values are reported in the brackets. Asterisks *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

	1	2	3
		Loan Acceptance	
0ft*Minority	-0.0075		
	[-1.595]		
0ft	-0.0115***		
	[-5.561]		
1ft*Minority		0.0018	
		[0.288]	
1ft		-0.0098*	
		[-1.919]	
2ft*Minority			-0.0014
			[-0.155]
2ft			-0.0119***
			[-2.828]
Minority	-0.0293***	-0.0293***	-0.0293***
	[-18.696]	[-18.763]	[-18.771]
LTV	-0.0000***	-0.0000***	-0.0000***
	[-2.619]	[-2.619]	[-2.618]
DTI	-0.0051***	-0.0051***	-0.0051***
	[-17.848]	[-17.846]	[-17.845]
Income	0.0109***	0.0109***	0.0109***
	[7.121]	[7.078]	[7.080]
Female	0.0002	0.0002	0.0002
	[0.463]	[0.449]	[0.450]
Minority	0.0000	0.0000	0.0000
	[0.000]	[0.000]	[0.000]
App	-0.0042	-0.0043	-0.0042
	[-0.763]	[-0.774]	[-0.772]
Price	0.0094	0.0094	0.0094
	[0.751]	[0.752]	[0.752]
Pop	-0.0736***	-0.0738***	-0.0738***
	[-2.606]	[-2.611]	[-2.612]
Labor	0.0307	0.0309	0.0310
	[1.346]	[1.354]	[1.356]
Growth	0.0069	0.0069	0.0069
	[1.374]	[1.381]	[1.380]
Constant	1.5616***	1.5615***	1.5614***
	[3.849]	[3.850]	[3.850]
County FE	Yes	Yes	Yes
Lender FE	Yes	Yes	Yes
Year FE	Yes	Yes	Yes
Two-way cluster	Yes	Yes	Yes
Observations	11,339,228	11,339,228	11,339,228
R-squared	0.106	0.106	0.106

Figure 1.

This figure provides a map view of the distribution of SLR risk in the U.S. The red-colored areas are the counties with imminent SLR risk that have elevation zero foot above sea level. The orange-colored areas are the counties with medium-term SLR risk that have elevation one foot above sea level. The yellow-colored areas are the counties with long-term SLR risk that have elevation two feet above sea level.