Climate Change Risk and the Cost of Mortgage Credit

Duc Duy Nguyen
Durham University

Steven Ongena
University of Zurich, Swiss Finance Institute, KU Leuven, and CEPR

Shusen Qi
School of Management, Xiamen University

Vathunyoo Sila
University of Edinburgh

ABTRACT

We show that lenders charge higher interest rates for mortgages on properties exposed to a greater risk of sea level rise (SLR). This SLR premium is not evident in short-term loans and is not related to borrowers' short-term realized default or creditworthiness. Further, the SLR premium is smaller when the consequences of climate change are less salient and in areas with more climate change deniers. Overall, our results suggest that mortgage lenders view the risk of SLR as a long-term risk, and that attention and beliefs are potential barriers through which SLR risk is priced in residential mortgage markets.

JEL Classification: G21, G22, Q54
Keywords: bank loans, residential mortgages, climate change risk, sea level rise, securitization

Duc Duy Nguyen: Millhill Lane, Durham DH1 3LB, United Kingdom, email: duc.d.nguyen@durham.ac.uk; Steven Ongena: Plattenstrasse 14, CH-8032 Zurich, Switzerland, e-mail: steven.ongena@bf.uzh.ch; Shusen Qi: Chengfeng Building, 422 Siming South Road, Xiamen 361005, China, email: shusenqi@xmu.edu.cn; Vathunyoo Sila: 29 Buccleuch Place, Edinburgh EH8 9JS, UK, email: ben.sila@ed.ac.uk. We are grateful to Marcin Kacperczyk (the Editor), an anonymous editor, and an anonymous referee for very helpful comments and suggestions. We also thank Pedro Cuadros, Miguel De Jesus, Tarik Driouchi, Johanna Garzon, Martin Gotz, Xinming Li (discussant), Joy Lyu, Jose Martin-Flores, Danny McGowan, Huyen Nguyen, Yuchao Peng (discussant), Ludovico Rossi, Nianhang Xu (discussant), Jacky Zhang, Viktoriya Zotova (discussant), and participants at the 2021 IFABS conference, the 2nd Birmingham Responsible Business Symposium, the 5th Edinburgh-Shanghai Green Finance virtual conference, the 1st Banking and Financial Intermediation Forum, the 18th Chinese Finance Annual Meeting, the 2020 China Financial Researcher Forum, and seminar participants at Cardiff and CUNEF for helpful comments and suggestions. Ongena acknowledges financial support from ERC ADG 2016 - GA 740272 lending. Shusen Qi acknowledges financial support from the National Natural Science Foundation of China (71903164, 71790601).

Climate Change Risk and the Cost of Mortgage Credit

ABSTRACT

We show that lenders charge higher interest rates for mortgages on properties exposed to a greater risk of sea level rise (SLR). This SLR premium is not evident in short-term loans and is not related to borrowers' short-term realized default or creditworthiness. Further, the SLR premium is smaller when the consequences of climate change are less salient and in areas with more climate change deniers. Overall, our results suggest that mortgage lenders view the risk of SLR as a long-term risk, and that attention and beliefs are potential barriers through which SLR risk is priced in residential mortgage markets.

JEL Classification: G21, G22, Q54
Keywords: bank loans, residential mortgages, climate change risk, sea level rise, securitization

1. Introduction

A growing literature examines the impact of sea level rise (SLR) risk on prices of residential properties (e.g., Baldauf et al., 2020; Bernstein et al., 2019; Keys and Mulder, 2021; Murfin and Spiegel, 2020). While Murfin and Spiegel (2020) find limited price effects of SLR risk on coastal homes, Baldauf et al. (2020) detect significant SLR price discounts in areas with high levels of climate change believers. Keys and Mulder (2021) argue that the increased pessimism about climate change risk explains the decline in SLR exposed residential properties in Florida after 2018. The overall mixed evidence could be due to the heterogenous beliefs among market participants, which are mainly retail investors, about how SLR risk may be realized. Bernstein et al. (2019) postulate that sophisticated investors are better able to price SLR risk and document a significant price discount for SLR risk among non-owner-occupied homes.

In this paper, we use the mortgage market to study whether SLR risk in residential properties is priced by financial institutions. While both residential mortgage and residential property markets are exposed to the same risk, i.e., the uncertainty of home values and future cash flows from the long-term change in sea levels, financial institutions should be more sophisticated than an average investor when dealing in residential properties. While an average investor may purchase a house at most a few times in their life, banks process a large volume of mortgage applications every day. Further, banks have sophisticated risk systems in place that appropriately identify, measure, and incorporate climate change risk. There are also abundant data on property exposure to SLR.[1] Indeed, several banks claim that they incorporate climate change scenarios into their risk modelling for residential mortgages. For instance, Bank

[1] For instance, the National Oceanic and Atmospheric Administration (NOAA) provides publicly available geodata on areas that can be affected by SLR, which we use to construct our SLR measure. The Federal Emergency Management Agency (FEMA) makes freely available flood maps for areas that they assess for flood insurance purposes. There are also several data sources that are available on a commercial basis such as those provided by Four Twenty Seven (owned by Moody's), Jupiter Intelligence, and First Street Foundation (a non-profit organization).

of America has been collaborating with a major insurance company to implement climate risk scoring system on its residential mortgages.[2] PNC Financial Services Group has employed spatial SLR data from the National Oceanic and Atmospheric Administration to analyze the impact of potential water inundation on the equity positions of the bank's residential property portfolio.[3] Further, recent studies show that banks incorporate risks related to climate change into commercial lending (e.g., Delis et al., 2021; Jiang et al., 2020).

However, even with the awareness of SLR risk and abundant geographical data on climate-related risks, banks may not be sufficiently able to incorporate this information into their loan pricing. Indeed, the Mortgage Bankers Association cites several challenges for banks to incorporate climate risk indicators in mortgage default modelling. These include the range of potential severity of future climate scenarios, the wide variety of competing climate risk measures, which can lead to conflicting predictions, and overall, the lack of widely accepted best practices in climate risk modelling.[4] Similarly, a recent report by the Board of Governors of the Federal Reserve System (2020) notes that the models used by many banks still lack the necessary geographic granularity or appropriate horizons to price climate risks. Another challenge can be uncertainty regarding the time horizon over which climate risks will materialize (Barnett et al., 2020). Many banks continue to rely on traditional backward-looking models based on historical losses and exposures, which may not adequately account for the complex and continuously changing nature of climate change risks. Furthermore, given the many risks that banks are currently facing (e.g., cybersecurity, geopolitical risks, and risks

[2] "Responsible growth and a low-carbon economy: Bank of America's Task Force on Climate-related Financial Disclosures (TCFD) report", *Bank of America*: https://about.bankofamerica.com/content/dam/about/pdfs/task-force-climate-financial-disclosures-report.pdf.
[3] "2020 TCFD Report", *PNC Financial Services Group*: https://www.pnc.com/content/dam/pnc-com/pdf/aboutpnc/CSR/PNC_TCFD_Report_2020.pdf.
[4] The Mortgage Bankers Association contrasts climate risk modelling to interest rate or default risk modelling, in which there is widely accepted best practice and standardized risk measures such as FICO scores (Becketti, 2021).

associated with the credit cycle) and the relatively long-run horizon around climate change, climate change risk may not be prioritized by banks (Nyberg and Wright, 2015).

Using a sample of 620,244 conventional 30-year mortgages originated in the U.S. between January 1992 and June 2018, we document an "SLR premium" in the residential mortgage market. We find that lenders charge higher interest rate spreads on mortgages for properties exposed to greater SLR risk. Our baseline results suggest that the interest rate spread for mortgages in a zip code where all properties are exposed to SLR risk is approximately 7.5 basis points (bps) higher than the interest rate spread for mortgages in a zip code where none of the properties are exposed to SLR risk.[5] For the average borrower in our sample, this increase in interest rate spread translates into nearly $9,000 increase in financing cost.[6]

All our estimations include granular interacted fixed effects, which allow us to compare mortgages in SLR exposed areas to a control group of unexposed mortgages that are originated in the same year and in the same county, for properties with similar characteristics, i.e., distance to the coast, elevation above sea level, property type (single family home, 2–4 family home, or condo/townhouse), and property appraisal value, and for borrowers with similar risk profiles (i.e., FICO scores and loan-to-value ratios). Importantly, our interacted fixed effects include granular distance-to-coast bins, which allow us to compare mortgages on properties located within the same distance to the coast bands, such as between 0.02 and 0.04 km from the coast. This within-distance-to-coast-bin variation controls for granular local characteristics such as coastal amenities while absorbing some variations in property and mortgage applicant characteristics that may influence the interest rate spread.

---

[5] This effect is sizable in magnitude in comparison to effects identified in prior studies of mortgage loan pricing. For instance, Buchak et al. (2018) document an average difference in interest rates between traditional banks and non-fintech shadow banks of 2.4 bps, and Bhutta et al., (2020) document an interest rate reduction of 7 bps when borrowers apply to more than one lender in search of better loan terms.

[6] The average loan size in our sample is $506,712 and the average annual interest rate is 5.707%. Assuming monthly payments at an interest rate of 5.707%, the total mortgage cost for a 30-year mortgage is $1,059,554 (monthly payment of $2,943 multiplied by 360 months). In contrast, the total mortgage cost at 5.782% is $1,068,243.

We perform various analyses to shed light on three fundamental features underlying the SLR premium. First, consistent with the view that SLR is a long-run risk of slowly rising oceans eventually inundating coastal properties (Bansal et al., 2016), we find that lenders perceive SLR risk as a long-run risk when they incorporate SLR exposure of the underlying property into their mortgage pricing decisions. Specifically, we find that the SLR premium is not statistically significant for short-term 15-year mortgages. We further confirm that the SLR premium does not merely capture lenders' concerns about potential damage caused by short-term flooding events, because our results continue to hold in subsamples of counties that never experience any major coastal or river flood. This is also consistent with our findings that the exposure to SLR risk is unrelated to borrowers' ex ante credit quality or their short-term ex post defaults.

Second, using a frictionless option model, we demonstrate that the estimated SLR spread is associated with a 0.037 percentage point (pp) increase in the implied default probability. This increase in implied default probability is lower than the expected increases in default due to a climate risk mitigation tax (Hong et al., 2021), and the implied increase in default in the municipal bond market (Goldsmith-Pinkham et al., 2021). Our results suggest that financial institutions may not yet incorporate the full extent of SLR risk into their pricing of residential mortgages.

We further show that lenders' attention and attitudes toward climate change risk could be the mechanisms that prevent them from incorporating SLR risk into mortgage pricing. Consistent with the view that climate change risk is less likely to be recognized in the early sample period (Bolton and Kacperczyk, 2021), we find that the SLR premium is less salient in the 1990s. Moreover, while we find that the SLR premium is higher following a hurricane or periods of heightened media attention to climate change, these effects disappear two quarters after the initial event, suggesting that lenders' attention to climate change is short-lived. We also find the effect to be weaker in areas where fewer local residents (including local loan officers) believe that climate change is happening.

Finally, we examine whether different banks price SLR risk differently. We find that the SLR premium is more salient: (1) among smaller and local banks, (2) among banks that engage more intensively in traditional banking activities, and (3) among banks that have more experience in originating mortgage loans and in handling mortgage applications for properties exposed to SLR risk. Our results thus suggest that experience and exposure to SLR risk is an important factor that determines a bank's ability to price this nonconventional risk.

Our paper contributes to the growing literature that analyzes the impact of SLR risk on the residential property market. Several recent studies investigate the impact of SLR risk on residential property values (e.g., Baldauf et al., 2020; Bernstein et al., 2019; Keys and Mulder, 2020; Murfin and Spiegel, 2020). The overall evidence is mixed and suggests that there are barriers that prevent retail investors to incorporate SLR risk into house prices. Bernstein et al. (2019) postulate that sophisticated investors price SLR risk and document a price discount for SLR risk among non-owner-occupied homes.

Focusing on the mortgage markets, we document an SLR risk premium that lenders impose on mortgages for properties exposed to a greater SLR risk. An important contribution of our paper is that, in addition to documenting a price effect, we also evaluate the increase in implied default probability associated with this risk premium. Compared to other benchmarks documented in recent studies, the increase in implied default probability linked to the SLR premium is modest. The modest economic magnitude, together with its sensitivity to factors such as local beliefs, attention, and lenders' experience, highlight the challenges lenders face in incorporating and managing risks related to SLR. Thus, our results overall indicate that while financial institutions are considered sophisticated, their ability to price SLR risk in residential mortgages remains limited. Our finding is especially important from a regulatory perspective because it demonstrates that a more standardized approach to measure and incorporate climate-related risk is needed (Becketti, 2021).

More broadly, our paper also adds to growing evidence that climate-related risks may not be fully incorporated in various asset classes. Hong et al., (2019) find that stock prices of food producers underreact to risk of drought due to climate change. Painter (2020) finds that prices of long-term municipal bonds only incorporate climate risk when the attention about climate change increase after the 2006 Stern Review on climate change.

Our paper is also related to recent works that study how financial institutions consider climate-related risk in their lending decisions. In corporate lending, Delis et al. (2021) and Jiang et al. (2020) show that lenders impose a higher cost of credit for fossil fuel firms exposed to stricter climate policies and for firms exposed to higher SLR risk. We add to this literature by showing that banks are aware and attempt to price this risk in residential mortgage markets. Ouazad and Kahn (2021) show that banks are more likely to initiate mortgages that can be securitized in areas that recently suffered from major natural disasters. We show that climate-related risk also influences pricing of residential mortgages, particularly those mortgages that are not qualified for securitization. Therefore, our results complement theirs by showing that mortgage pricing is another mechanism that banks use to manage potential risk from SLR.

2. Data and Empirical Model

2.1 Data

2.1.1. Mortgage Data. Our loan-level mortgage data are taken from the Black Knight Financial Services Group's McDash dataset. This dataset covers approximately two-thirds of the mortgage market in the U.S. and includes information on several mortgage characteristics (e.g., interest rate, loan amount, and maturity), risk characteristics of borrowers (e.g., FICO score and loan-to-value ratio), mortgage performance since origination (e.g., information on repayments, delinquencies, and loan modifications), and characteristics of the mortgaged properties (e.g., appraised amount, property type, and geographical location). To protect the privacy of homeowners, the data provider codes property locations at the 5-digit zip code level.[7] Because this dataset focuses on loan performance, our primary sample only covers originated loans.

To construct our sample, we begin with the universe of all McDash mortgages originated between January 1992 and June 2018. We restrict our attention to a set of relatively homogenous mortgages, that is, all conventional, 30-year fixed-rate mortgages with non-missing FICO, loan-to-value ratio, debt-to-income ratio, interest rate, appraisal amount, and geographic identifier.[8] We also exclude mortgages with "exotic" features, i.e., those with balloon payments and teaser-rate periods. To minimize possible data errors, we follow Agarwal et al., (2013) in excluding observations with FICO scores below 300 or above 900 and observations with reported loan-to-value ratios above 100%. See Table IA-I in the Internet Appendix for detailed sample construction.

2.1.2. Exposure to SLR Risk. We measure SLR exposure at the 5-digit zip code level to be consistent with property locations in the McDash dataset being geocoded at the 5-digit zip code level. To determine each zip code's exposure to SLR, we use publicly available SLR maps from the U.S. National Oceanic and Atmospheric Administration (NOAA). The NOAA provides detailed geographical shapefiles that describe the latitudes and longitudes that would

[7] One limitation of the McDash dataset is that it does not report information on the lender originating each mortgage. In Section 6.3, we use an alternative loan-level dataset collected under the Home Mortgage Disclosure Act (HMDA) to explore the heterogeneity across banks.
[8] Screening out non-conventional loans, in particular, is crucial because these loans are guaranteed by relevant agencies, i.e., the Federal Housing Administration, the Department of Veterans Affairs, and the Department of Agriculture. For instance, the Veteran Affairs' loan guaranty program pays up to 50% of losses that the lender may suffer from mortgage default (Foote, 2010). Because financial institutions do not bear the all of the losses when these mortgages default, the pricing of these mortgages could be different from how lenders price conventional mortgages.

be inundated following an increase in average global sea level of 1–6 feet compared to the year 2000.

We combine NOAA's SLR maps with zip code tabulation area shapefiles from the Census Bureau. Our measure for SLR exposure, *SLR Exposure*, is defined as the proportion of the zip code tabulation area that would be under water if the global sea level rises by 6 feet. Based on the U.S. Interagency Sea Level Rise Taskforce's worst-case scenario that the global mean sea level rises by 25 millimeters per year, the 6-foot SLR would be realized by approximately 2073.[9,10] Thus, our measure is likely to capture the long-term risk of the properties being inundated by a global rise in the sea level.

Although these sea-level projections cover a period beyond the maturity of mortgages in our sample, banks also face substantial uncertainty regarding the time horizon over which climate change risks will materialize (Barnett et al., 2020; Cai and Lontzek, 2019). For instance, there could be regulatory changes (induced by other climate events unrelated to the mortgaged properties) that force banks to realize SLR risk by recognizing the SLR exposure of these properties on their balance sheets. These events could occur during the lifetime of the mortgage, even when the underlying property remains above sea level. In addition, rising sea levels could also cause more frequent extreme weather events,[11] which could in turn depress house prices and consequently the value of banks' collateral. Therefore, banks are exposed not only to the risk of houses being directly inundated but also to other negative externalities induced by rising sea levels.

---

[9] The U.S. Interagency Sea Level Rise Taskforce publishes six scenarios of increases in the global mean sea level for risk assessment purposes (Sweet et al., 2017). The Taskforce's most conservative scenario projects an SLR rate of 3 millimetres per year, and their intermediate scenario projects 10 millimetres per year. See https://scenarios.globalchange.gov/sea-level-rise.

[10] In untabulated results, we use an alternative measure of SLR exposure, the proportion of the zip code tabulation area that would be under water if the global sea level rises by 4 feet. We find that our results continue to hold. Based on the global mean sea level rising by 25 millimetres per year, the 4-foot SLR would be realized by approximately 2048. The results are available upon request.

[11] For instance, Vitousek et al. (2017) find that an increase in sea level as small as 0.2 meters could double the risk of coastal storm-related flooding and the magnitude of the impact is likely to become increasingly severe as other climate problems worsen.

[Figure 1 around here]

Following Murfin and Siegel (2020), our analyses focus on coastal states in the continental United States. Within these states, we restrict our sample to mortgages on properties located within 30 kilometers of the coast. Figure 1 shows the distribution of our sample observations across zip codes in all coastal states in our sample. In choosing this 30 km bandwidth, we balance the tradeoff between including properties with substantial exposure to SLR risk and maximizing the variation in *SLR Exposure* across zip codes. Indeed, within the 30 km bandwidth, the average exposure to SLR is 9.4% with a standard deviation of 0.193. In contrast, when we consider a 30-60 km bandwidth, these figures drop sharply to a mean *SLR Exposure* of 0.8% and a standard deviation of 0.05. Further, because our identification strategy relies on variation within distance-to-coast bins, our results should not be sensitive to such distance restriction. Consistent with this, we later show in Figure 3 that our results are robust to alternative sample restrictions across both directions of the 30 km threshold such as 5 or 45 km from the coast.

2.1.3. Distance to Coast and Elevation. We employ two geographic variables to control for local conditions that may confound the relation between exposure to SLR and the costs of mortgage credit. The first variable is the distance to the nearest coast, for which we obtain the data from NASA's Ocean Biology Processing Group. The second variable is elevation of the land above sea level, which is provided by the U.S. Geological Survey's Elevation Point Query Service. We measure both variables at the centroid of each zip code. The average zip code in our sample is 10.4 kilometers away from the coast and 64 meters above sea level. These statistics are similar to those reported in prior studies.

2.2 Summary Statistics

Table I presents summary statistics for our key variables. Our main sample includes 620,244 originated mortgages for properties located in 2,743 zip codes representing 238 counties. The average loan amount in our sample is approximately $506,712 and the average interest rate is 5.707% (which corresponds to an average interest spread of 2.122%). The average borrower has a FICO score of 738, a debt-to-income ratio of 34%, and borrows 63% of the property's appraisal value. These statistics are comparable to those reported in the prior literature using the McDash database (e.g., Agarwal et al., 2013).

[Table I and Figure 2 around here]

In our sample, 47.4% of mortgages (293,690 out of 620,244) are issued to applicants buying houses in zip codes with a non-zero SLR exposure. The average exposure to SLR is 9.4%. The statistics on SLR exposure are similar to those in prior studies using the NOAA database (e.g., Kousky, 2017; Montgomery and Kunreuther, 2018). Panel B provides a detailed breakdown of the average SLR exposure and the average interest rate by state. We find substantial variations in SLR exposure across states. Whereas the average SLR exposure in the top three states (North Carolina, South Carolina, and Georgia) is 40%, the average SLR exposure in the bottom three states (Washington, Virginia, and Pennsylvania) is 2%. There is also considerable variation in SLR exposure within smaller geographical units, such as counties and cities. Figure 2 illustrates the levels of SLR exposure in six zip codes in the city of Philadelphia, PA. We show that within this city, the level of SLR exposure ranges from 0% to more than 78%. This demonstrates that there is sufficient variation in SLR exposure within our sample to identify any relation between SLR risk and mortgage interest rates.

2.3 Empirical Model

The goal of our empirical design is to investigate the relation between properties' exposure to SLR (measured at the zip code level) and interest rate spreads. The key empirical challenge we face is that the interest rate spreads may vary along dimensions other than the property's projected exposure to SLR. For instance, given that coastal properties are more expensive, mortgages on these properties may on average have higher debt-to-income ratios, and consequently, have higher interest rate spreads. Alternatively, as coastal homes are generally more valuable than other homes (Bin et al., 2008), these properties may attract more affluent and creditworthy buyers which may result in lower interest spreads. To address this challenge, we specify an empirical model that compares mortgages originated in the same year and in the same county, for properties that are observably equivalent (based on their distance from the coast, elevation above sea level, property type, and appraisal value), and for borrowers with similar risk characteristics (i.e., FICO scores and loan-to-value ratios). We estimate the following regression equation:

$$\{\text{Rate Spread}\}_{izt} = \alpha\{\text{SLR Exposure}\}_z + \mathbf{x}_{it}'\boldsymbol{\beta} + \gamma_t + \delta_{cydepvfl} + \varepsilon_{it} \qquad (1)$$

The dependent variable is $\{\text{Rate Spread}\}_{izt}$, which is the difference between the interest rate on mortgage *i* originated in year *t* in zip code *z* and the 10-year US treasury bond yield.[12] While it would be preferable to use 30-year treasury bond yields to match the maturity of our mortgages, we do not have complete data on 30-year treasury bond yields over our sample period because the U.S. government discontinued issuance of 30-year treasury bonds between 2002 and 2004.[13] $\{\text{SLR Exposure}\}_z$ is the proportion of the property's zip code that will be

[12] Data on treasury bond yields are obtained from the U.S. Department of the Treasury.
[13] It is comforting to note that the 10-year treasury yields are highly correlated with the 30-year treasury yields (0.967). As shown in Table IV, we obtain similar results using 30-year yields as a proxy for risk-free rate.

under water if the global sea level rises by 6 feet; if lenders incorporate SLR risk into their loan pricing decisions, the coefficient on $\{\text{SLR Exposure}\}_z$ will be positive.

$\mathbf{x}'_{it}$ includes several loan-level control variables: *Low Documentation* (a dummy variable that equals 1 if the borrower has less than full documentation of household financials, and 0 otherwise), *Jumbo Loan* (a dummy variable that equals 1 if the loan amount exceeds the conforming loan limit, and 0 otherwise), *Has Prepayment Penalty* (a dummy variable that equals 1 if the mortgage contract stipulates charges for early payments, and 0 otherwise), *FICO* (the FICO score of the applicant), *Loan-to-Value* (the application's loan-to-value ratio), and *Debt-to-Income* (the application's debt-to-income ratio). Finally, we include *Ln(Local Income)* to control for zip code level income per capita.

All regression specifications include $\delta_{cydepvfl}$, which absorbs variation in the cost of mortgage credit related to time, location, applicant risk characteristics, and property and transaction characteristics. Specifically, $\delta_{cydepvfl}$ comprises interacted fixed effects between county (C), year (Y), distance-to-coast bins (D), elevation above sea level decile bins (E), property type indicator variables (P),[14] property appraisal value decile bins (V), 60-point FICO score bins (F), and 10-point loan-to-value ratio bins (L).

Critical to our identification strategy is the inclusion of distance-to-coast bins. Using an approach similar in spirit to Bernstein et al. (2019), we construct 13 distance-to-coast bins of progressively smaller widths closer to the coast. They correspond to the following km-to-coast buckets: [0-0.01], [0.01-0.02], [0.02-0.04], [0.04-0.08], [0.08-0.16], [0.16-0.32], [0.32-0.64], [0.64-1.28], [1.28-2.56], [2.56-5], [5-10], [10-20] and [20-30]. The average bin size is 4.2km wide. To illustrate the importance of including an interaction with distance-to-coast bins of smaller widths closer to the coast, Figure IA-1 in the Internet Appendix plots the relationship

[14] Property types include single family home, 2–4 family home, condo/townhouse, and others.

between distance to the coast and the interest rate spread. We find that the interest rate spread on mortgages quickly decreases as we move closer to the coast. This is expected given that coastal homes have improved amenities (Bin et al., 2008), and this could attract more affluent and creditworthy applicants. Therefore, this within-bin variation not only controls for granular local characteristics such as coastal amenities but can also absorb some variations in property and mortgage applicant characteristics that may influence interest rate spread.

Overall, the inclusion of our full suite of *interacted* fixed effects allow us to compare mortgages that are originated in the same year and in the same county, for properties with similar characteristics (i.e., distance to the coast, elevation above sea level, property type, and for borrowers with similar risk profiles (i.e., FICO scores and loan-to-value ratios). Importantly, even after we include the interacted fixed effects, there remains substantial variation in *SLR Exposure* that allows us to estimate its effect on loan spread. For instance, our regressions would identify the relation between *SLR Exposure* and the loan spread of two mortgages, both for single-family properties, valued between $370,000 and $460,000, elevated between six and nine meters above the sea level, and located between 5 and 10 km from the coast in Harris County, Texas. These two properties are located in zip codes 77571 and 77536. While both zip codes are almost equally as far from the coast, the *SLR Exposure* measure for 77571 is 4% whereas the exposure for 77536 is 20%.

3. SLR Risk and the Costs of Mortgage Credit

3.1 Baseline Results

Table II reports the baseline regression results examining the effect of *SLR Exposure* on the cost of mortgage credit. Model specifications vary across columns in terms of the fixed effects included. The results in Column 1 are shown for illustrative purposes; the coefficient on SLR risk is positive and statistically significant at well below the 1% level and is equal to 0.103.

[Table II around here]

In Column 2 we include year fixed effects and the estimated coefficient on *SLR Exposure* slightly decreases from 0.103 to 0.091. Column 3 includes the interacted fixed effects between county, distance-to-coast bins, elevation bins, FICO bins, loan-to-value bins, property type, and property value bins. These granular interacted fixed effects absorb potential omitted variables that could confound the correlation between SLR risk and distance to the coast. Finally, Column 4 includes the full set of fixed effects; the coefficient on *SLR Exposure* remains statistically significant at below the 1% level, but the magnitude of the coefficient decreases slightly to 0.075. Thus, our evidence demonstrates that lenders charge higher interest rate spreads on mortgage applications for properties exposed to greater SLR risk. This effect is obtained after controlling for various location, time, borrower, and property characteristics.

The magnitudes obtained indicate modest effects, as may be expected. The coefficient estimate in Column 4 indicates that the interest rate spread for mortgages in a zip code where all properties are exposed to SLR risk (*SLR Exposure* = 1) is approximately 7.5 bps higher than the interest rate spread for mortgages in a zip code where none of the properties are exposed to SLR risk (*SLR Exposure* = 0). This increase in interest rate spread translates into a nearly $9,000 increase in financing cost for the average borrower in our sample.[15]

This SLR premium is comparable to the magnitude of effects identified in prior studies examining mortgage loan pricing, for example the average interest rate gap between traditional banks and non-fintech shadow banks (2.4 bps) documented by Buchak et al. (2018) or the interest rate reduction when borrowers apply to more than one bank in search of better loan terms (7 bps) documented by Bhutta et al. (2019). As we show in Section 5, this modest effect

[15] The average loan size in our sample is $506,712, the average annual interest rate (r) is 5.707%, and the duration of the mortgage is 30 years (30 * 12 = 360 months). We obtain the monthly payments using the simple present value formula ($loan = \sum_{t=1}^{30*12} \frac{pmt}{(1+r/12\,)^t}$), where the total mortgage cost is the sum of all monthly payments ($pmt *$ 360). At an interest rate of 5.707%, the total mortgage cost is $1,059,554 ($2,943 * 360). In contrast, at an interest rate of 5.782% the total mortgage cost is $1,068,243 ($2,967 * 360).

is consistent with lenders perceiving SLR as a long-term risk; our results also indicate that not all lenders are prepared to price this nonconventional risk.

The coefficients corresponding to our control variables show the expected relations between loan risk characteristics and the cost of credit. Specifically, a higher interest rate spread on mortgages is associated with borrowers who have a lower FICO score, a higher debt-to-income ratio, and provide less documentation. Loans with a prepayment penalty also attract a higher interest rate spread.

[Figure 3 around here]

Figure 3 illustrates the relationship between SLR risk and interest rate spreads using alternative bandwidths from the coast. In this figure, we report the estimated coefficients and the 95% confidence intervals on *SLR Exposure* when we re-estimate Equation (1) using mortgages on properties located within the following bandwidths from the coast: 5, 10, 15, 20, 25, 30, 35, 40, and 45 km. Across all bandwidths, we observe a statistically significant SLR premium on mortgages for properties exposed to greater SLR risk. This gives us comfort that our results are not sensitive to the choice of bandwidth from the coast.

3.2 Robustness Tests for the Baseline Results

One limitation of our analysis is that property locations are coded at the 5-digit zip code level and not at a more precise geolocation level. The fact that a home's underwater projection is measured at the zip code level induces potential measurement errors in our main variable of interest, *SLR Exposure*.

We alleviate this concern by instrumenting *SLR Exposure* with a different source of variation in a location's exposure to SLR risk. Specifically, our instrument is a dummy variable that equals 1 if there has been a beach nourishment project in a given zip code, and 0 otherwise.[16] The purpose of beach nourishment is to restore the width of an eroding beach as a result of rising sea level. As a result, we expect the presence of a beach nourishment project to be positively correlated with SLR risk. While this instrument is susceptible to similar measurement concerns, we argue that these measurement errors are unlikely to be correlated across two measures.[17] Column (1) of Panel A Table III reports the first-stage estimation. Our instrument is positive and significantly related to a zip code's *SLR Exposure*. The second-stage regression results are reported in Column (2). The coefficient on the IV estimate continues to be positively significant, alleviating the concern that our results are driven solely by measurement errors.

Another concern regarding our results is that the relationship between SLR risk and the cost of mortgage credit may be due to spurious correlations with unobserved local characteristics. Although the inclusion of fixed effects in the main model already absorbs various location characteristics and addresses this problem to a large degree, we further address this concern by performing a placebo test.

Specifically, our placebo test reassigns the values of *SLR Exposure* on the basis of geographical proximity (Jiang et al., 2020). To construct *Placebo SLR Exposure*, we first exclude all loans in zip codes with a positive SLR risk (treatment zip codes). For each of these excluded treatment zip codes, we assign its positive *SLR Exposure* value to the nearest zip code in the same county that is not subject to SLR risk. Thus, observations with positive *Placebo SLR Exposure* are observations that do not have any exposure to SLR but are likely to be in areas that have similar location characteristics (except for SLR exposure) to the treatment zip codes. We re-estimate the specification in Column 4 of Table II using *Placebo SLR Exposure*

[16] We obtain beach nourishment data from the Program for the Study of Developed Shorelines from Western Carolina University. The data cover all beach nourishment projects between 1923 and 2018.

[17] It is comforting to observe that, at the minimum, the two measures are not correlated with the control variables in the same direction. For instance, while *SLR Exposure* is negatively correlated with zip code level income (−0.06), the beach nourishment indicator is positively correlated with zip code level income (0.02).

and present the results in Panel B of Table III.[18] The estimated coefficient on *Placebo SLR Exposure* is not statistically significant. This result suggests that our main findings in Table II are unlikely to be driven by unobserved location characteristics, because if this were the case, we would expect to observe a large and statistically significant placebo estimate.

[Table III around here]

To further ensure that our results are not driven by imbalances in loan characteristics in zip codes exposed to SLR risk compared to other zip codes, we rebalance our sample using multivariate distance kernel matching. Specifically, we match mortgages in zip codes with a positive SLR risk (treatment zip codes) with mortgages in zip codes with zero SLR risk (control zip codes) on the basis of the following loan and location characteristics: *FICO, Debt-to-income, Loan-to-value, Jumbo loan, Low Documentation, Has Prepayment Penalty* and *Ln(Local Income)*. We further require that the treatment and control observations be for properties in the same county and that the mortgages be originated in the same year.[19] As shown in Panel C of Table III, the coefficient on *SLR Exposure* remains positively significant when we re-estimate Equation (1) using the matched sample.

Panel D performs other robustness tests on the baseline findings in Column 4 of Table II. In Column 1, we include zip code level measures of house prices and house price growth as additional control variables. This is to control for potential confounding effects of local housing demand trends on mortgage pricing, as Keys and Mulder (2021) find that housing transactions in the communities with greatest SLR exposure are 16% lower than transactions in communities with lesser SLR exposure. Column (2) includes zip code level measures of total population and the fraction of the population having at least a bachelor's degree to control for

[18] The number of observations in the placebo sample is smaller than the number of observations in the baseline regressions because we only use observations with zero exposure to SLR. Some single observations are further dropped from the estimation, resulting in a reduction of the number of observations in Panel B of Table III to 318,927.
[19] The covariate-balanced sample includes 574,512 mortgages for properties located in 2,330 zip codes, with an average SLR exposure of 8%.

the quality of the neighborhood. Column (3) includes additional controls for other location and property characteristics: *Non-Owner Occupied*, *Ln(Distance-to-Coast)*, *Ln(Distance-to-Coast)^2*, *Ln(Elevation)*, *Ln(Elevation)^2*, *Ln (Property Value)*, and *Ln (Property Value)^2*.

Columns 4-6 introduce more granular fixed effects. Specifically, we interact the full suite of fixed effects with quarter-year fixed effects (Column 4), month-year fixed effects (Column 5). These granular time fixed effects further control for within-year seasonal variations that could affect mortgage pricing. Column 6 interacts the full suite of fixed effects with 10-point debt-to-income ratio bins. The extensive fixed effects used in Columns 4-6 reduce our sample by approximately 38%, 65%, and 42% respectively, due to the exclusion of large numbers of singleton observations, so we choose the specification in Column 4 of Table II as our baseline specification. Column 7 restricts the sample to zip codes with a positive SLR risk; and Column 8 uses 30-year (instead of 10-year) US treasury bond yield to calculate interest rate spread. Our results are robust across all specifications in Panel D.

4. Interpretation of Magnitudes

To interpret the economic significance of our SLR premium, we use the frictionless option-theoretic model (FOM) (Epperson et al., 1985; Foote and Willen, 2018)—a tractable model based on Merton (1974)—to back out the increase in default probability implied by our SLR spread. Under the FOM, the borrower holds the mortgage as a liability in exchange for two assets: a house (H) and a default put option (P). To keep the default put option alive, the borrower must pay a fixed monthly payment (C) at the end of each month. Alternatively, the borrower can exercise the default put option and sell the house to the lender at a strike price equal to the outstanding balance on the mortgage (M).

Under this setting, default is optimal when the value of the house including the default put option is below the remaining mortgage balance including the next monthly payment, i.e., when the borrower's net position, $H_t + P_t – (M_t + C)$, is negative. Therefore, the put option's payoff at the end of each month (t = 1, 2, …, 360) is $\max(M_t + C – H_t, P_{t+1})$. Because the value of the put option (P_t) depends on the future option values, the default put option must be valued recursively from maturity (t=360) of the mortgage to its initiation (t=0). To this end, we use 360-period binomial option pricing model to estimate the value of the default put option.

From the lender's perspective, the value of the mortgage at origination (M_0) is equal to the value of the risk-free debt (B_0), which is the present value of all future mortgage payments discounted at the risk-free rate, less the value of the default put option (P_0). That is, $M_0 = B_0 – P_0$. To estimate the implied probability of default, we calibrate the put option value from the binomial option pricing model such that P_0 is equal to the difference between the risk-free bond (B_0) and the value of the mortgage (M_0).

[Table IV around here]

Table IV presents the results from our calibration exercise based on the average mortgage in our sample (5.707% mortgage interest rate, 3.585% risk-free rate, and 63.1% loan-to-value ratio). We find that the implied default probability of this mortgage is 46.348% over the lifetime of the mortgage.[20] We then add the SLR premium to the mortgage interest rate based on our estimation in Column 4 of Table II (5.707% + 0.075% = 5.782%) and use this interest rate to recalibrate our binomial option pricing model. The implied default probability

[20] This implied lifetime default probability is slightly higher than those estimated using empirical data. For instance, Bank of America and Merrill Lynch Research reports the lifetime default ratio of 34% for jumbo fixed-interest prime mortgages in 2007 (Edmans, 2010). This is consistent with the observation from prior studies that while the FOM provides a simple and tractable pricing model that allows us to estimate the change in implied probability of default, the implied probability of default from the FOM tends to be higher than those observed in empirical data (see, e.g., Foote et al., 2008; Vandell, 1995). This mismatch between implied and realized default probability arises from the FOM's assumption that borrowers will default immediately when their net position becomes negative ("ruthless" or "strategic" default). There are several reasons why borrowers may continue to make monthly payment even when their net position is negative. First, the FOM does not incorporate costs that are associated with default such as cost of moving home and reduction in credit scores. Second, default may also carry a psychological stigma for some homeowners (Keene et al., 2015). Third, the FOM does not consider individual characteristics of mortgage borrowers (such as their overall wealth or employment status) that may affect the borrower's decision to default. However, our goal is not to estimate the implied probability of default itself, but to estimate the *change* in implied probability of default that is commensurate with the change in loan pricing.

becomes 46.385%. Therefore, the change in default probability implied by the SLR risk premium is 46.385% − 46.348% = 0.037 pp.[21] Further, we find that this increase in implied default probability is concentrated in the period far in the future. As shown in Table IV, the increase in default probability is virtually non-existent in the first 15 years of the mortgage's term and is 0.049 pp in the last 15 years. The increase in the default probability becomes 0.055 pp and 0.076 pp in the last 10 and 5 years respectively.

To further contextualize the economic significance of our SLR premium, we compare the implied increase in default probability due to SLR to two benchmarks from recent studies. The first benchmark is the implied change in default probability if homeowners in SLR-exposed properties are required to pay for costly climate-risk mitigation tax (Hong et al., 2021). While this tax will be used to invest in mitigation technology that can reduce future damages from climate-related disasters, it also leads to an immediate reduction in cash flows to homeowners. Hong et al. (2021) calibrate a stochastic general-equilibrium model which predicts that the climate-risk mitigation tax will reduce property value by 5%. This 5% value impact corresponds to a 0.138 pp increase in implied default probability for the average mortgage in our sample.[22]

The second benchmark is the change in default probability implied by SLR spread in another fixed income market. The estimates in Goldsmith-Pinkham et al. (2021) indicate a 0.26 to 0.58 pp increase in credit spreads on municipal bonds between areas with zero SLR risk and areas with a full exposure to SLR risk.[23] Following their calibration exercise, we use the Merton

[21] Given the average loss given default for residential mortgages of 43.78% (Ross and Shibut, 2015), this increase in default probability implies an average 0.02% loss to the bank due to SLR and represents 6.67% of the loan loss provision for the average bank in our sample.
[22] Specifically, we compare the implied default probability of the average mortgage in our sample (5.707% mortgage interest rate, 3.585% risk-free rate, and 63.1% loan-to-value ratio) to another mortgage that is otherwise identical but with 66.4% loan-to-value, which reflects the 5% decrease in home valuation.
[23] Goldsmith-Pinkham et al. (2021) finds that a one standard deviation increase in SLR Exposure (defined as the proportion of the number of properties exposed to SLR scaled by the total number of properties in the area) is associated with a 0.023 to 0.053 pp increase in the municipal bond spread. Their sample standard deviation of SLR Exposure is 0.09. Therefore, one unit increase in SLR Exposure is associated with a 0.26 to 0.58 pp increase in the municipal bond spread.

(1974) model to estimate the implied default probability on their average bond and calculate the implied change in default probability associated with SLR exposure. [24] We find that these increases in bond yield are equivalent to a 0.420 to 0.960 pp increase in implied probability of default respectively.

These increases in implied default probability documented in recent studies are higher than our baseline calibration. The results suggest that our documented SLR premium implies less pessimistic beliefs about SLR risk in residential properties, or that financial institutions may not yet incorporate the full extent of SLR risk into their pricing of residential mortgages. While we are not able to distinguish between these two possibilities, our results in subsequent sections suggest that beliefs and attention could be the mechanisms that prevent financial institutions from incorporating SLR risk into mortgage pricing.

5. Economic Mechanisms

In this section, we examine heterogeneity in the SLR premium in order to better understand the underlying mechanisms through which SLR risk is incorporated into the cost of mortgage credit. Our analyses reveal that mortgage rates reflect lenders' beliefs and attention to long-run climate change risk as well as their ability to securitize the mortgage.

5.1 Long-run Climate Risk

SLR is a long-run risk that slowly rising oceans will eventually inundate coastal properties. Therefore, the fact that mortgages on properties requiring an SLR of up to 6 feet to be inundated

[24] We set the time to maturity to 7.5 years, the risk-free rate to 3.585%, and bond yield (without SLR exposure) to 3.24% (their sample average of municipal bond yield). Similar to Goldsmith-Pinkham et al. (2021), because we do not have access to data on capital structure of municipal bond issuers and calibrate their model over a wide range of leverage ratios, we set the leverage ratio to 63.1% which is equal to the average loan-to-value in our sample.

command a higher premium suggests that lenders view SLR as a long-horizon risk. In this subsection, we examine this conjecture by performing the following three tests.

First, if SLR exposure affects the costs of mortgage credit through the long-run risk of rising oceans, the effect of SLR premium should be less pronounced among mortgages with a shorter maturity. To test this hypothesis, Column 1 of Panel A, Table V focuses on a sample of conventional short-term 15-year mortgages.[25] The average *SLR Exposure* in this sample is 9.9%, and 60% of the zip codes have a positive SLR exposure, which are similar to our baseline sample. The results in Column 1 indicate that SLR risk has no statistically significant effect on the interest rate spreads of short-term mortgages.

[Table V around here]

Because borrowers that seek short-term mortgages could be different from those that seek long-term mortgages, Column 2 uses a full sample that includes both short- and long-term mortgages and interacts *SLR Exposure* with *Short-term Mortgages*, a dummy variable that equals 1 for short-term 15-year mortgages, and 0 otherwise. Column 3 further controls for the observable differences between short- and long-term mortgages by adding the interactions between *Short-term Mortgages* and all control variables. Consistent with the results in Column 1, the interaction coefficients *SLR Exposure***Short-term Mortgages* are negative and marginally statistically significant (p-value=.051 in Column 3), suggesting that the SLR premium is less salient among mortgages with short durations and that lenders are indeed more concerned about climate risk in the longer term (e.g., Jiang et al. 2020; Painter 2020).

Further, one could argue that the SLR premium may reflect lenders' concerns about the potential damage caused by short-term realized flooding events. To isolate long-run climate risk from short-term flood risk, Panel B of Table V restricts the sample to counties that never

[25] The standard mortgage duration in the US is either 30-year for long-term mortgages or 15-year for short-term mortgages. Therefore, we focus on 15-year mortgages to test for the effect of SLR risk on short-term mortgages.

experience any major river flood (Column 1), coastal flood (Column 2), or either river or coastal flood (Column 3) over the sample period. In Column 4, we restrict the sample to counties that never receive any substantial FEMA assistance, which is triggered when damages occur in FEMA flood zones.[26] These sample restrictions effectively remove all counties that are potentially more exposed to short-term flood risk. Property valuation and mortgage rates in these counties might be different even in the absence of a current flood. Although our sample size is reduced by 9%−70% depending on the specification, the coefficients on *SLR Exposure* remain statistically significant across Columns 1-4.

In Column 5, we follow Baldauf et al. (2020) to control for short-term flood risk by including *Flood10*, which is the height of a flood that has a 10% chance of occurring in a given year. We find that controlling for *Flood10* does not eliminate the statistical significance of the estimated SLR premium. Overall, the results in Panel B of Table V indicate that short-term flooding events are unlikely to explain the SLR premium.

Similarly, if the SLR premium reflects long-term climate risk, *SLR Exposure* should not be related to the applicants' short-run credit risk. To test whether this is the case, we use three proxies to capture applicant risk: the applicant's *FICO* score, *Loan-to-Value* ratio, and *Loan Delinquencies*. Following Cortés et al. (2016), *Loan Delinquencies* is a dummy variable that equals 1 if a loan becomes 90-day delinquent or enters foreclosure during the first five years of its life, and 0 otherwise.[27] The mortgage default regressions include similar control

[26] Data on short-term flood events and FEMA assistance come from the National Centers for Environmental Information and the Federal Emergency Management Agency, respectively. A major flood is one that causes monetary damages in the sample's top quartile. Similarly, a substantial FEMA assistance is defined as monetary assistance that is in the sample's top quartile.
[27] Our results (untabulated for brevity but available upon request) are robust to using alternative default windows, such as two or three years.

variables and fixed effects to those of Column 4 Table II. The *FICO* and *Loan-to-Value* regressions exclude FICO bins and loan-to-value bins.[28]

Panel C of Table V shows the results. Across all outcome variables, the estimated coefficients on *SLR Exposure* are not statistically significant at conventional levels and are economically indistinguishable from zero. Consistent with the argument that SLR is a long-run risk, the results in Column 3 indicate that exposure to SLR does not cause borrowers to default on their mortgages in the short run. Overall, the findings in Panel C indicate that the SLR premium is unlikely to be driven by applicants' credit risk.

5.2 Climate Risk Salience

Our results so far indicate that lenders price long-run climate change risk, consistent with them being sophisticated investors. However, it is natural to expect that not all lenders are equally prepared to price this unconventional risk, the long-term impact of which is highly uncertain (e.g., Nyberg and Wright, 2015). In this subsection, we perform various cross-sectional tests across time and geography to shed light on the roles of lenders' attention to climate change in pricing SLR risk.

First, we explore heterogeneity in the SLR premium over time. We expect the SLR premium to be less salient in the earlier years of our sample period when lenders are less likely to be aware of such risk. For example, Bolton and Kacperczyk (2021) find that there is no significant carbon emission risk premium in the 1990s, consistent with the view that investors back at that time are less aware of climate change risk. To examine this hypothesis, Column 1 of Panel A, Table VI interacts *SLR Exposure* with two time dummies: 1992-1999 and 2000-2018. Expectedly, we find that the interacted SLR premium in the pre-2000 period is not

[28] The FICO, loan-to-value, and debt-to-income regressions have more observations than our baseline regressions in Column 4 Table II because they use fewer fixed effects (FICO and loan-to-value ratio interactions are excluded from the fixed effects) and therefore have fewer singleton observations.

statistically significant, indicating that there is no SLR premium for mortgages originated in the 1990s. In contrast, the SLR premium is significantly positive for mortgages originated on or after 2000.

In Column 2, we use more granular time-series variation: 1992-1999, 2000-2006, and 2007-2018. The interacted SLR premium is -0.013 and insignificant in the pre-2000 period, is 0.068 in the period between 2000 and 2006 (p-value<0.05), and 0.083 in the post-2006 period (p-value<0.05). Overall, while the results suggest a significant increase in SLR premium in the 2000s, the gradual increase thereafter is only marginal.

[Table VI around here]

Given the findings in Panel A, we next evaluate the possibility that the SLR premium reflects lenders' shorter-term reaction to local climate events. Hong et al. (2021) specify that while the belief on climate change discretely increases upward upon a disaster arrival, it decreases deterministically in the absence of disasters. As a first test for this conjecture, we use occurrences of hurricanes to capture lenders' attention to climate change risk. Lenders are more likely to pay attention to climate change risk after a hurricane due to the increased media coverage of its consequences (Krueger et al., 2020). To isolate the direct effect of the hurricane on borrower creditworthiness from the effect on lenders' attention to long-run climate change risk, we exclude states that were directly affected by the hurricane and examine changes in the SLR premium following the hurricane among unaffected states.

We include the worst hurricanes that cause at least $30 billion in damage as reported by the National Hurricane Center (see Table IA-II in the Internet Appendix for the dates and locations affected). We use four indicator variables: *Hurricane (Q1)*, *Hurricane (Q2)*, *Hurricane (Q3)*, and *Hurricane (Q4)* which indicate the first, second, third, and fourth quarter following a hurricane. To examine our hypothesis, we regress *Rate Spread* on the interaction between *SLR Exposure* and the hurricane indicators described above.

Panel B of Table VI reports the results. We find positive and statistically significant coefficients on the interaction term between *SLR Exposure* and *Hurricane (Q2)*. In contrast, the coefficients on the interactions between *SLR Exposure* with other time-period indicators are statistically insignificant. Thus, the results suggest that the magnitude of the SLR premium becomes larger in the second quarter following a hurricane. This delayed effect is expected given that the mortgage origination process could take several months to complete as loan officers need to gather, verify, and process information on the applicants (e.g., Cortés et al., 2016; Tzioumis and Gee, 2013). Moreover, the effect of a hurricane is short-lived as the interaction coefficients between *SLR Exposure* and the time-period indicator for the third and fourth quarters after the hurricane are insignificant.

As a second test, we examine whether lenders pay more attention to SLR risk following periods of increased media attention to climate change risk. We capture media attention using the Wall Street Journal Climate Change News Index (CCNI). Specifically, this index is the residual from an AR(1) autoregressive model of the proportion of the Wall Street Journal dedicated to the topic of climate change (Engle et al., 2020; Jiang et al., 2020). We obtain monthly index values for our sample period from January 1992 to May 2018, and we classify a month as having a "spike" in media attention if the index value is within the top 10% of values for the sample period. We construct four indicator variables: *CCNI Spike (Q1)*, *CCNI Spike (Q2)*, *CCNI Spike (Q3)*, and *CCNI Spike (Q4)*, which indicate the first, second, third, and fourth quarter following the media spike. We then regress *Rate Spread* on the interaction between *SLR Exposure* and the indicators of media attention described above.

The results in Panel C mirror those in Panel B. Specifically, we find that the magnitude of the SLR premium becomes larger in the second quarter following increased media attention to climate change risk. The effect again appears to be short-lived: the coefficient on the interaction with *CCNI Spike (Q3)* becomes marginally significant and the coefficient on the interaction with *CCNI Spike (Q4)* is close to zero and statistically insignificant.

Overall, the results in Panels B and C are consistent with Hong et al. (2021) that the pricing of SLR risk reflects lenders' response to extreme weather events. Similar to Hong et al. (2021) who predict that the attention to climate change decreases overtime in the absence of climate disasters, we find lenders' reaction to climate-related events to be short-lived. This could also potentially explain why we do not find a strong statistical support for a gradual increase in SLR premium over time in the 2000s in Panel A.

5.3 Climate Change Beliefs

Next, we examine how community beliefs regarding climate change risk affect the SLR premium. Studies have shown that climate change beliefs affect how various financial and asset markets price SLR risk (e.g., Baldauf et al., 2020). Even though loan officers are arguably more financially sophisticated than the average population, prior studies show that their decision-making behavior can be influenced by factors such as the outcomes of large sporting events (Agarwal et al., 2013), the amount of local sunshine (Cortés et al., 2016), or loan approval streaks (Chen et al., 2016). Given this, it is worth investigating whether the pricing of SLR risk is influenced by the climate change beliefs of local loan officers who are responsible for making recommendations on loan applications.[29]

To test for this, we measure county-level climate change beliefs using the Yale Climate Opinion Maps (Howe et al., 2015). The first publicly available map uses survey responses conducted in 2014 and are updated every two years. Because our sample period is from 1992 to 2018, we use the earliest 2014 survey data. Our main measure of climate belief, *Climate Believing County*, is a dummy that equals 1 if the percentage of people in the county answering

[29] It is important to note that because rational borrowers will not be willing to pay higher interest rates even if they strongly believe in climate change, our results are unlikely to reflect borrowers' climate change beliefs.

"yes" to the question asking whether they believe that climate change is happening is above the sample's median and 0 otherwise.[30] In the median county in our sample, 69% of surveyed respondents believe that climate change is happening.

[Table VII around here]

We regress *Rate Spread* on the interaction between *SLR Exposure* and *Climate Believing County* and display the results in Table VII. Because variation in climate change beliefs is at the county level, we cluster standard errors for this analysis at the county level. The interaction coefficient between *SLR Exposure* and *Climate Believing County* is positively significant, suggesting that the SLR premium varies with climate change beliefs even among sophisticated decision-makers.

6. Additional Analyses

6.1 Securitization

Our findings so far indicate that a lender earns a higher premium for long-term climate change risk by incorporating the risk into loan pricing. In contrast, Ouazad and Kahn (2021) show that banks pass climate-related risks to Government Sponsored Enterprises (GSEs), such as Fannie Mae and Freddie Mac, by increase their initiation of mortgages that can be securitized in areas that recently suffered from major natural disasters. This section explores whether the SLR premium depends on a loan's eligibility to be sold to Government Sponsored Enterprises (GSEs)—Fannie Mae and Freddie Mac.

The GSEs fully absorb the credit risk of the loans they purchase through their buyback provisions in which loans sold to the GSEs are purchased, packaged, and insured against loss of principal and interest. The GSEs provide a pricing grid which helps bank determine the

[30] Unreported tests confirm that our results are also robust to using alternative survey questions, including the percentage of people who "are worried about global warming" or "think global warming will harm them personally." We also obtain similar results using the survey data from 2016 and from 2018.

credit risk premium charged by the GSEs.[31] Specifically, the pricing of GSE-eligible loans is subject to the GSEs' constant interest rate policy in which interest rates vary based on a borrower's observable credit score, loan-to-value ratio, and other observable borrower characteristics, but exclude factors that systematically affect credit risk across regions (Hurst et al. 2016; McGowan and Nguyen, 2021).[32] Thus, the interest rates devised from a GSE's pricing-grid are unlikely to reflect SLR risk.[33]

In contrast, for loans that do not meet the GSEs' underwriting criteria, lenders must either hold them on their balance sheets or sell them to private institutions such as hedge funds or insurance companies. Because the costs of default are directly borne by lenders or risk-averse private institutions, we expect that lenders would charge higher interest rate spreads to compensate for the greater SLR risk.

To test our prediction, we regress *Rate Spread* on the interaction between *SLR Exposure* and *GSE-ineligible Loans.* GSEs specify the underwriting criteria that a loan must meet to be eligible for sale to a GSE. Following Bayer et al. (2018), *GSE-ineligible Loans* are either (1) jumbo loans, i.e., those with a loan amount greater than the county-level conforming loan limit, or (2) subprime loans, i.e., those with above 45% debt-to-income ratio for manually underwritten loans, or above 50% debt-to-income ratio for non-manually underwritten loans, and those with a loan-to-value ratio above 97% for fixed rate mortgages and above 95% for adjustable-rate mortgages. Because lenders may assign different weights to borrowers' credit

---

[31] See, for example, Fannie Mae's Loan-Level Price Adjustment matrix https://singlefamily.fanniemae.com/media/9391/display.

[32] Additionally, reports indicate that the GSEs only started to "take a closer look" at climate risk as recent as October 2020 (Colman, 2020). This implies that the GSEs have indeed not incorporated climate change risk into their pricing grid in our sample period.

[33] Lenders in general tend to adhere to the GSE pricing guidelines when determining the interest rate on a GSE-eligible loan because a failure to do so may prevent them from selling a loan to the GSEs, thereby reducing loan portfolio liquidity (Loutskina, 2011). Consistent with this, Hurst et al. (2016) find that GSE loans' interest rates do not vary with historic mortgage default rates and McGowan and Nguyen (2021) show that foreclosure laws do not have any effect on GSE loans' interest rates. However, lenders may occasionally quote an interest rate spread that is above what is suggested by the pricing grid for non-credit reasons, such as to exploit its monopoly position in the local area or to extract rent from borrowers who are less likely to shop around (Bartlett et al., 2022).

score and their loan-to-value ratios when pricing GSE-ineligible loans, we also include an interacted fixed effects between *GSE-ineligible Loans* dummy and FICO score bins and loan-to-value bins. Panel A of Table VIII presents the results.

[Table VIII around here]

As shown in Panel A of Table VIII, the estimated coefficient on the interaction term between *SLR Exposure* and *GSE-ineligible Loans* is positive and statistically significant. Thus, consistent with our expectation, lenders are more likely to price SLR risk when the loans are not eligible to be sold to GSEs.

6.2 Flood Insurance

Because insurance payments can offset losses incurred when SLR risks materialize, lenders may charge a lesser premium for insured properties. In this subsection, we examine the role of flood insurance in explaining the SLR premium.

In the U.S., flood insurance is largely provided by the federal government's National Flood Insurance Program. The Federal Emergency Management Agency (FEMA) produces flood hazard maps which indicate the locations of Special Flood Hazard Areas (SFHAs),[34] and the Flood Disaster Protection Act of 1973 mandates flood insurance coverage for properties in SFHAs if they have mortgages with a federally regulated lender or backed by the federal government (Kousky et al., 2020). The mandatory purchase requirement implies that SLR risk for mortgages in SFHAs will largely be covered by flood insurance.[35]

[34] Defined as areas with a 1% chance of flooding in any given year based on flood elevation levels and floodways.
[35] There is a possibility that some borrowers may not comply with the mandatory flood insurance purchase requirements. For instance, borrowers who purchased flood insurance at the origination of their mortgage could allow their policy to lapse, and lenders may not impose any sanction or penalty on these borrowers. FEMA admitted to the Congressional Committee in 2002 that it could not estimate the level of noncompliance with mandatory flood insurance purchase requirements. See US General Accounting Office (2002) Flood insurance: Extent of noncompliance with purchase requirements is unknown (July 21), https://www.govinfo.gov/content/pkg/GAOREPORTS-GAO-02-396/html/GAOREPORTS-GAO-02-396.

Because the mapping process is often political, a large proportion of areas that are exposed to SLR risk are not included in SFHAs and are not covered by flood insurance (Pralle, 2019).[36] Dixon et al. (2006) estimated that half of the houses in SFHAs have flood insurance policies, and that this take-up is overwhelmingly driven by the federal government's flood insurance mandatory purchase requirement. In comparison, the market penetration rate of flood insurance outside SFHAs is only about 1%. We use this asymmetric take-up in flood insurance policies between areas inside and outside SFHAs to analyze the role of flood insurance in moderating the effect of SLR exposure on interest rates.

To assess whether properties in a zip code require flood insurance, we obtain the National Flood Hazard Layer geodata from FEMA's Flood Map Service Center. We construct a zip code level variable, %*SFHA*, which is the proportion of the zip code area that is designated by FEMA as a special flood hazard area. The average %*SFHA* for zip codes with a positive %*SFHA* is 21%. We assume that mortgages in SFHA zip codes are covered by flood insurance, whereas mortgages outside SFHA zip codes are not. We then regress *Rate Spread* on the interaction between *SLR Exposed* and *SFHA ZIP Code*.

As shown in Panel B of Table VIII, the coefficient on the interaction *%SFHA * SLR Exposure* is not statistically significant, suggesting that the SLR premium is not affected by whether or not borrowers are required to buy flood insurance. The fact that some borrowers inside SFHAs are not covered by flood insurance, and some borrowers outside SFHAs are covered, may introduce noise into the estimations, resulting in the non-significant difference in SLR premiums between the two areas. Further, the result could be due to the fact that flood insurance only covers damage to a house when a flood occurs, and not damage caused by other extreme weather events or the permanent value-destruction to houses when land is permanently

[36] For instance, local officials in New Orleans lobbied FEMA to revise their map in 2016 such that more than half of the state's population is no longer in SFHAs, even though many of these residents live at or below sea level (Kailath, 2016).

inundated by rising sea levels. In any case, we do not find any evidence that the existence of flood insurance is a substitute for the SLR premium.

6.3 Heterogeneity Across Banks

Finally, we examine whether different banks price SLR risk differently. Because banks have different exposure and ability to incorporate SLR risk, we expect substantial heterogeneity across banks. Since our main McDash dataset does not report the lender that originates each mortgage, our analyses in this section use an alternative loan-level dataset collected under the Home Mortgage Disclosure Act (HMDA), which covers the near universe of U.S. mortgage applications. Each loan application in HMDA includes information on loan characteristics (e.g., the amount of loan applied for and its type and purpose), property type and location, the decision on the application (e.g., approved, denied, or withdrawn), year of origination, and importantly, lender identification.

Since 2018, HMDA has started recording additional variables, including the interest rate lenders charge on originated mortgages. Consequently, our sample is restricted to HMDA loans in 2018 and 2019. To ensure comparability with the McDash sample, our HMDA sample includes conventional, 30-year fixed-rate mortgages originated in 2018 and 2019. These mortgages are for properties located within 30 kilometers of the coast in the continental United States. There are two limitations of the HMDA dataset compared to McDash. First, HMDA does not report the borrower's *FICO* score and their documentation level required to construct our *Low Documentation* indicator variable. Second, the borrower's loan-to-value ratio has many missing values.[37] As a result, we use the borrower's income and their *Loan-to-Income* ratio to substitute for their *FICO* score and *Loan-to-Value* ratio, respectively. We run the following regression model:

[37] Given these data limitations, we use HMDA data for supplementary analyses and McDash as our main data source.

$$\{\text{Rate Spread}\}_{izt} = \alpha\{\text{SLR Exposure}\}_z + \mathbf{m}'_{it}\boldsymbol{\beta} + \gamma_t + \delta_{cdepvil2y} + \delta_{by} + \varepsilon_{it} \quad (2)$$

Similar to Equation (1), the dependent and independent variables are $\{\text{Rate Spread}\}_{izt}$ and $\{\text{SLR Exposure}\}_z$, respectively. The control variables $\mathbf{m}'_{it}$ are *Jumbo Loan*, *Has Prepayment Penalty*, *Applicant Income*, *Debt-to-income*, *Loan-to-Income*, and *Ln(Local Income)*. $\delta_{cydepvil2}$ comprises interacted fixed effects between county (C), year (Y), distance-to-coast bins (D), elevation above sea level decile bins (E), property type indicator variables (P),[38] property appraisal value decile bins (V), applicant income decile bins (I), and loan-to-income decile bins (L2). Further, because HMDA reports lender identification, we are able to additionally include interacted fixed effects δ_{by} between lender (B) and year (Y) fixed effects. The inclusion of lender × year fixed effects allows us to compare the interest rate spread among mortgages originated by the same bank in the same year, and the only variation comes from different locations' different SLR exposure.

The final HMDA sample includes 389,535 originated mortgages for properties located in 2,593 zip codes. The average loan amount is approximately \$504,360 and the average interest rate spread is 1.788%. The average SLR exposure of mortgages in the HMDA sample is 10.7%. These statistics are comparable to our main McDash dataset described in Section 2.2.

[Table IX around here]

Table IX displays the regression results using HMDA. Consistent with our results using McDash, Panel A shows that the coefficients on *SLR Exposure* are positive and statistically significant. Further, the magnitude of the effect remains stable as we progressively include more fixed effects into the model.

In Panels B-D of Table IX, we explore how the SLR premium varies across various bank characteristics, including bank size, profitability, risk, business model, balance sheet

[38] Property types include single family home, 2–4 family home, condo/townhouse, and others.

composition, and past exposure to SLR risk.[39] This analysis is especially important from a regulatory perspective because it would allow regulators to tailor monitoring efforts based on each individual bank's ability to recognize and incorporate climate risk.

We begin by examining how the SLR premium varies across bank size. While larger and national banks could have more sophisticated models to incorporate climate change risk (Stiroh, 2020), smaller and local banks tend to have superior local knowledge to better price this risk (Garmaise and Moskowitz, 2009; Lim and Nguyen, 2021). In Columns 1−4 of Panel B, we test this hypothesis by interacting *SLR Exposure* with four measures of bank size and localization: (i) *Ln(Bank Assets),* the natural logarithm of bank total book assets, (ii) *Ln(Branches)*, the natural logarithm of the number of branches a bank has, (iii) *Local branches*, the fraction of branches that are located in the same state as their banks' headquarters, and (iv) *Distance to branches*, the average physical distance between a bank's headquarters and its bank branches.

The positive interaction coefficients in Columns 1-4 of Panel B indicate that the SLR premium is stronger for smaller and local banks: banks with lower book assets, fewer branches, and those have more local and proximate branches. Thus the results suggest that smaller and local banks have an edge in understanding local market characteristics and incorporating long-run SLR exposure.

In Panel C of Table IX, we investigate whether the SLR premium depends on bank business models. We hypothesize that banks are better able to incorporate climate risk into their pricing decision if they are more experienced in traditional banking activities, such as accepting deposits and originating loans. To test this, we interact *SLR Exposure* with (i) *Interest Income/Total Income,* interest income divided by total income, (ii) *Loans/Assets,* total loans

[39] Because the regression model in Column 3 of Panel A is the most rigorous specification, we use it to perform the cross-sectional analyses in Panels B-D.

divided by total assets, and (iii) *Mortgage Loans/Assets,* mortgage loans divided by total assets. Consistent with our conjecture, the positive relation between SLR risk and loan spread is stronger for banks whose income mainly arises from traditional interest-bearing activities (Column 1) and banks having a greater proportion of loans and, more specifically, mortgage loans in their balance sheets (Columns 2 and 3, respectively). Overall, the results in Panel C suggest that relevant lending experience allows banks to better recognize and incorporate SLR risk.

Finally, we focus on banks' exposure to SLR risk. We expect that banks with more experience with SLR risk are more likely to understand and incorporate the information into the loan price. To test this hypothesis, we interact *SLR Exposure* with a bank's SLR risk experience, measured as the weighted average SLR exposure across all conventional, 30-year fixed-rate mortgages it originates in a given year. We construct our SLR risk experience measures using two different weighting variables: the number of mortgages in Column 1 and the loan amount in Column 2. The interaction coefficients in Panel D suggest that the SLR premium is stronger among banks with a greater experience of handling mortgage applications for properties exposed to SLR risk. Overall, our results in Panels B-D of Table IX suggest that experience and exposure to SLR risk is a key factor that determines a bank's ability to price this nonconventional risk.

7. Conclusion

Our paper asks whether and to what extent financial institutions price ex ante climate change risk. We find that they charge higher interest rate spreads on mortgages for properties exposed to greater sea level rise (SLR) risk. This effect is robust to a wide range of controls, including location and property characteristics, borrower creditworthiness, and flood insurance. The SLR premium is concentrated among long-term mortgages and is not driven by short-term flooding events or borrower creditworthiness at loan origination. This suggests that lenders view SLR risk as a long-run climate change risk.

We also evaluate the increase in implied default probability linked to the SLR premium, finding that this increase is modest compared to other benchmarks documented in recent studies. We further demonstrate that not all lenders are equally equipped to incorporate SLR risk. Specifically, the SLR premium is less salient in areas lacking exposure to climate-related events and news, and in areas where local residents are less likely to believe that climate change is happening. Taken together, our results highlight the challenges financial institutions face in incorporating long-run climate risks related to the sea level rising.

References

Agarwal, S., Duchin, R. and Sosyura, D. (2013) In the mood for a loan: The causal effect of sentiment on credit origination, unpublished working paper, National University of Singapore, Boston College, Arizona State University.

Baldauf, M., Garlappi, L. and Yannelis, C. (2020) Does climate change affect real estate prices? Only if you believe in it, *Review of Financial Studies* 33, 1256–1295.

Bansal, R., Ochoa, M. and Kiku, D. (2016) Climate change and growth risk, NBER working paper, National Bureau of Economic Research.

Barnett, M., Brock, W. and Hansen, L. P. (2020) Pricing uncertainty induced by climate change, *Review of Financial Studies* 33, 1024–1066.

Bartlett, R., Morse, A., Stanton, R. and Wallace, N. (2022) Consumer-lending discrimination in the FinTech era, *Journal of Financial Economics* 143, 30–56.

Bayer, P., Ferreira, F. and Ross, S. L. (2018) What drives racial and ethnic differences in high-cost mortgages? The role of high-risk lenders, *Review of Financial Studies* 31, 175–205.

Becketti, S. R. (2021) The impact of climate change on housing and housing finance, unpublished working paper, Elliott Bay Analytics.

Bernstein, A., Gustafson, M. T. and Lewis, R. (2019) Disaster on the horizon: The price effect of sea level rise, *Journal of Financial Economics* 134, 253–272.

Bin, O., Crawford, T. W., Kruse, J. B. and Landry, C. E. (2008) Viewscapes and flood hazard: Coastal housing market response to amenities and risk, *Land Economics* 84, 434–448.

Board of Governors of the Federal Reserve System (2020) *Financial Stability Report*. https://www.federalreserve.gov/publications/files/financial-stability-report-20201109.pdf.

Bolton, P. and Kacperczyk, M.T. (2021) Do investors care about carbon risk?, *Journal of Financial Economics* 142, 517–549.

Buchak, G., Matvos, G., Piskorski, T. and Seru, A. (2018) Fintech, regulatory arbitrage, and the rise of shadow banks, *Journal of Financial Economics* 130, 453–483.

Bhutta, N., Fuster, A. and Hizmo, A. (2020) Paying too much? Price dispersion in the US mortgage market, unpublished working paper, Board of Governors of the Federal Reserve System, Ecole Polytechnique Fédérale de Lausanne.

Cai, Y. and Lontzek, T. S. (2019) The social cost of carbon with economic and climate risks, *Journal of Political Economy* 127, 2684–2734.

Chen, D. L., Moskowitz, T. J. and Shue, K. (2016) Decision making under the gambler's fallacy: Evidence from asylum judges, loan officers, and baseball umpires, *Quarterly Journal of Economics* 131, 1181–1242.

Colman, Z. (2020) Fannie, Freddie take a close look at mortgage risks as climate events multiply, *Politico*, October 15, https://www.politico.com/news/2020/10/15/fannie-mae-freddie-mac-mortage-climate-risks-429641.

Cortés, K. R., Duchin, R. and Sosyura, D. (2016) Clouded judgement: The role of sentiment in credit origination, *Journal of Financial Economics* 121, 392–413.

Delis, M. D., de Greiff, K., M. Iosifidi and Ongena, S. (2021) Being stranded with fossil fuel reserves? Climate policy risk and the pricing of bank loans, SFI working paper, Swiss Finance Institute.

Dixon, L., Clancey, N., Seabury, S. A. and Overton, A. (2006) The National Flood Insurance Program's market penetration rate: Estimates and policy implications, RAND Corporation technical report series, RAND Corporation.

Edmans, A. (2010) The responsible homeowner reward: An incentive-based solution to strategic mortgage default, unpublished working paper, London Business School.

Engle, R. F., Giglio, S., Kelly, B., Lee, H. and Stroebel, J. (2020) Hedging climate change news, *Review of Financial Studies* 33, 1184–1216.

Epperson, J. F., Kau, J. B., Keenan, D. C. and Muller III, W. J. (1985) Pricing default risk in mortgages, *Real Estate Economics* 13, 261–272.

Foote, B. E., (2010) VA-home loan guaranty program: An overview, *Congressional Research Service.*

Foote, C. L. and Willen, P. S. (2018) Mortgage-default research and the recent foreclosure crisis, *Annual Review of Financial Economics* 10, 59–100.

Foote, C. L., Gerardi, K. and Willen, P. S. (2008) Negative equity and foreclosure: Theory and evidence. *Journal of Urban Economics*, 64, 234–245.

Garmaise, M. J. and Moskowitz, T. J. (2009) Catastrophic risk and credit markets, *Journal of Finance* 64, 657–707.

Goldsmith-Pinkham, P. S., Gustafson, M., Lewis, R. and Schwert, M. (2021) Sea level rise exposure and municipal bond yields, unpublished working paper, Yale School of Management, Pennsylvania State University, University of Colorado, Boulder, University of Pennsylvania.

Hong, H., Li, F. W. and Xu, J. (2019) Climate risk and market efficiency, *Journal of Econometrics* 208, 265–281.

Hong, H., Wang, N. and Yang, J. (2021) Mitigating disaster risks in the age of climate change, NBER working paper, National Bureau of Economic Research.

Howe, P. D., Mildenberger, M., Marlon, J. R. and Leiserowitz, A. (2015) Geographic variation in opinions on climate change at state and local scales in the USA, *Nature Climate Change* 5, 596–603.

Hurst, E., Keys, B. J., Seru, A. and Vavra, J. (2016) Regional redistribution through the US mortgage market, *American Economic Review* 106, 2982–3028.

Jiang, F., Li, C. W. and Qian, Y. (2020) Do costs of corporate loans rise with sea level?, unpublished working paper, University at Buffalo, University of Iowa, University of Connecticut.

Keene, D. E., Cowan, S. K. and Baker, A. C. (2015) “When you’re in a crisis like that, you don’t want people to know”: Mortgage strain, stigma, and mental health. *American Journal of Public Health* 105, 1008–1012.

Keys, B. J. and Mulder, P. (2020) Neglected no more: Housing markets, mortgage lending, and sea level rise, NBER working paper, National Bureau of Economic Research.

Kousky, C. (2017) Disasters as learning experiences or disasters as policy opportunities? Examining flood insurance purchases after hurricanes, *Risk Analysis* 37, 517–530.

Krueger, P., Sautner, Z. and Starks, L. T. (2020) The importance of climate risks for institutional investors, *Review of Financial Studies* 33, 1067–1111.

Kousky, C., Kunreuther, H., LaCour-Little, M. and Wachter, S. (2020) Flood risk and the US housing market, *Journal of Housing Research* 29, S3–S24.

Lim, I. and Nguyen, D.D. (2021) Hometown lending, *Journal of Financial and Quantitative Analysis* 56, 2894–2933.

Loutskina, E. (2011) The role of securitization in bank liquidity and funding management, *Journal of Financial Economics* 100, 663–684.

McGowan, D. and Nguyen, H. (2021) To securitize or to price credit risk?, *Journal of Financial and Quantitative Analysis,* forthcoming.

Merton, R. C. (1974) On the pricing of corporate debt: The risk structure of interest rates, *Journal of Finance* 29, 449–470.

Murfin, J. and Spiegel, M. (2020) Is the risk of sea level rise capitalized in residential real estate?, *Review of Financial Studies* 33, 1217–1255.

Montgomery, M. and Kunreuther, H. (2018) Pricing storm surge risks in Florida: Implications for determining flood insurance premiums and evaluating mitigation measures, *Risk Analysis* 38, 2275–2299.

Nyberg, D. and Wright, C. (2015) Performative and political: Corporate constructions of climate change risk, *Organization* 23, 617–638.

Ouazad, A. and Kahn, M. E. (2021) Mortgage finance and climate change: Securitization dynamics in the aftermath of natural disasters, NBER working paper, National Bureau of Economic Research.

Painter, M. (2020) An inconvenient cost: The effects of climate change on municipal bonds, *Journal of Financial Economics* 135, 468–482.

Pralle, S. (2019) Drawing lines: FEMA and the politics of mapping flood zones, *Climatic Change* 152, 227–237.

Ross, E.M. and Shibut, L. (2015) What drives loss given default? Evidence from commercial real estate loans at failed banks, unpublished working paper, Federal Deposit Insurance Corporation.

Stiroh, K. J. (2020) Climate change and risk management in bank supervision, *Speech*, March 4.

Sweet, W. W. V., Kopp, R., Weaver, C. P., Obeysekera, J. T. B., Horton, R. M., Thieler, E. R. and Zervas, C. E. (2017) Global and regional sea level rise scenarios for the United States, NOAA technical report, National Oceanic and Atmospheric Administration.

Tzioumis, K. and Gee, M. (2013) Nonlinear incentives and mortgage officers' decisions, *Journal of Financial Economic*s 107, 436–453.

Vandell, K. D. (1995) How ruthless is mortgage default? A review and synthesis of the evidence, *Journal of Housing Research* 6, 245–264.

Vitousek, S., Barnard, P. L., Fletcher, C. H., Frazer, N., Erikson, L. and Storlazzi, C. D. (2017) Doubling of coastal flooding frequency within decades due to sea-level rise, *Scientific Reports* 7, 1–9.

Table I. Summary Statistics

Panel A presents the summary statistics for the variables used in the main analysis. Panel B provides a detailed breakdown of the average SLR exposure and the interest rates on mortgages across states. The sample comprises 620,244 mortgages originated during 1992-2018 for properties located in 2,743 zip codes (238 counties). Appendix A provides descriptions of the variables.

Panel A: Summary statistics

	Mean	S.D.	25th	50th	75th	SLR Exposure = 0	SLR Exposure > 0
McDash sample							
SLR Exposure	0.094	0.193	0.000	0.000	0.087	0.000	0.199
Distance to Coast (km)	10.390	8.670	2.668	8.148	17.200	14.220	6.127
Elevation (m)	63.960	75.150	10.840	38.850	89.450	95.550	28.840
Interest Rate (%)	5.707	1.850	3.875	5.875	6.625	5.615	5.810
Risk-free rate (%)	3.585	1.176	2.320	4.130	4.570	3.540	3.636
Rate Spread (%)	2.122	1.137	1.515	1.815	2.280	2.074	2.174
FICO	737.800	51.410	704.000	748.000	779.000	740.400	735.000
Loan Amount ($ mil.)	0.507	0.415	0.206	0.450	0.672	0.517	0.495
Loan-to-Value	0.631	0.224	0.530	0.713	0.797	0.631	0.632
Debt-to-Income (%)	33.610	13.740	25.000	35.000	42.000	33.925	33.326
Jumbo Loan	0.464	0.499	0	0	1	0.484	0.442
Low Documentation	0.076	0.265	0	0	0	0.072	0.080
Has Prepayment Penalty	0.149	0.356	0	0	0	0.137	0.161
Ln(Local Income)	4.457	0.642	3.996	4.367	4.851	4.489	4.421
Property's Value ($mil.)	0.832	0.735	0.400	0.660	1.025	0.841	0.821
Observations					620,244	326,554	293,690
HMDA sample							
SLR Exposure	0.107	0.202	0.000	0.000	0.122	0.000	0.210
Rate Spread (%)	1.788	1.112	1.215	1.606	2.090	1.709	1.865
Loan Amount ($ mil.)	0.504	0.427	0.185	0.395	0.685	0.543	0.467
Applicant Income ($ mil.)	0.215	0.179	0.094	0.162	0.275	0.222	0.209
Loan-to-Income	2.616	1.406	1.505	2.550	3.593	2.709	2.527
Debt-to-Income	35.340	10.060	25.000	37.000	42.000	35.610	35.09
Jumbo Loan	0.287	0.452	0	0	1	0.311	0.264
Has Prepayment Penalty	0.140	0.347	0	0	0	0.146	0.134
Ln(Local Income)	5.091	0.762	4.554	5.094	5.620	5.172	5.014
Observations					389,535	190,846	198,689

Panel B: SLR risk by state

State	Observations	*SLR Exposure*	*Rate Spread*
Alabama	1,009	0.155	2.901
California	256,462	0.046	1.975
Connecticut	14,414	0.074	1.901
Delaware	2,894	0.224	2.391
District of Columbia	1,730	0.106	1.817
Florida	79,017	0.293	2.516
Georgia	913	0.402	2.435
Louisiana	1,269	0.146	2.480
Maine	1,274	0.053	2.418
Maryland	22,556	0.060	2.480
Massachusetts	32,479	0.077	2.216
Mississippi	178	0.214	2.754
New Hampshire	602	0.080	2.507
New Jersey	44,151	0.126	2.101
New York	89,816	0.071	1.974
North Carolina	2,670	0.311	2.093
Oregon	210	0.064	2.220
Pennsylvania	7,921	0.034	2.198
Rhode Island	3,173	0.046	2.405
South Carolina	5,554	0.442	2.114
Texas	3,283	0.094	2.208
Virginia	23,955	0.017	2.161
Washington	24,714	0.018	2.340

Table II. The Effects of Long-Run SLR Risk on Mortgage Pricing

This table reports loan-level regressions which estimate the effect of long-run SLR risk on mortgage loan pricing. The dependent variable is *Rate Spread*, which is the difference between the annual percentage rate first observed on the loan and the 10-year US treasury bond yield. The main independent variable of interest is *SLR Exposure*, which is the fraction of the zip code area that will be inundated if the sea level rises by 6 feet. The sample is restricted to mortgages located within 30 km of the coast between 1992 and 2018. Location × Mortgage × Year fixed effects refer to County × Distance-to-coast bins × Elevation bins × Property type dummies × Value of property bins × FICO bins × Loan-to-value bins × Year fixed effects. Refer to Appendix A for definitions of variables. *t*-statistics based on standard errors clustered at the zip code level are reported in brackets. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

Dependent variable: *Rate Spread*				
	(1)	(2)	(3)	(4)
SLR Exposure	0.103***	0.091***	0.054**	0.075***
	[6.321]	[5.902]	[2.539]	[3.026]
Low Documentation	0.483***	0.483***	0.326***	0.303***
	[45.217]	[44.823]	[40.893]	[32.337]
FICO	-0.006***	-0.006***	-0.003***	-0.003***
	[-128.317]	[-114.957]	[-47.718]	[-32.957]
Loan-to-Value	-2.188***	-2.143***	0.160***	0.281***
	[-91.257]	[-85.304]	[4.588]	[6.150]
Debt-to-Income	0.004***	0.004***	0.002***	0.002***
	[28.965]	[32.068]	[23.773]	[20.310]
Jumbo Loan	-0.095***	-0.076***	-0.007*	-0.044***
	[-27.305]	[-20.804]	[-1.925]	[-9.138]
Has Prepayment Penalty	0.349***	0.340***	0.189***	0.175***
	[44.191]	[40.612]	[33.326]	[21.793]
Ln(Local Income)	-0.214***	-0.207***	-0.064***	-0.059***
	[-35.518]	[-34.212]	[-13.372]	[-11.181]
Location × Mortgage × Year fixed effects	No	No	No	Yes
Location × Mortgage fixed effects	No	No	Yes	No
Year fixed effects	No	Yes	Yes	No
Observations	1,603,337	1,603,337	961,340	620,244
R^2	0.395	0.413	0.725	0.805

Table III. Robustness of Baseline Results

Panel A reports IV regression results which estimate the effect of long-run SLR risk on mortgage loan pricing. Column (1) reports the first-stage estimation results and Column (2) reports the second-stage results. The instrumental variable is *Beach Nourishment,* a dummy variable that equals 1 if there has been a beach nourishment project in a given zip code, and 0 otherwise. Panel B performs a placebo test by removing all loans in zip codes with a positive SLR risk (treatment zip codes) from the sample. We then construct *Placebo SLR Exposure* by assigning the positive *SLR Exposure* value of each treatment zip code to the nearest zip code that is not subject to SLR risk. Panel C balances the covariates of treatment and control observations using multivariate distance kernel matching. Specifically, we match loans in zip codes with a positive SLR risk (treatment zip codes) with loans in the zip codes with zero SLR risk (control zip codes) based on loan characteristics (FICO, loan-to-value, jumbo loan, low documentation, and the presence of prepayment penalty). We also require that treatment and control observations are for properties in the same county and were originated in the same year. Panel D reports other robustness tests. The dependent variable is *Rate Spread*, which is the difference between the annual percentage rate first observed on the loan and the 10-year US treasury bond yield. The main independent variable of interest is *SLR Exposure*, which is the fraction of the zip code area that will be inundated if the sea level rises by 6 feet. The sample is restricted to mortgages located within 30 km of the coast between 1992 and 2018. Location × Mortgage × Year fixed effects refer to County × Distance-to-coast bins × Elevation bins × Property type dummies × Value of property bins × FICO bins × Loan-to-value bins × Year fixed effects. Control variables are collapsed for brevity and are identical to those in Table II. Refer to Appendix A for definitions of variables. *t*-statistics based on standard errors clustered at the zip code level are reported in brackets. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

Panel A. Instrumental variable analysis

	First-stage	**Second-stage**
Dependent Variables	*SLR Exposure*	*Rate Spread*
	(1)	(2)
Beach Nourishment	0.134***	
	[5.688]	
SLR Exposure	-	0.195**
	-	[2.033]
Control variables	Yes	Yes
Location × Mortgage × Year fixed effects	Yes	Yes
Observations	627,418	620,244
R^2	0.926	0.034
Kleibergen-Paap F-statistics	32.076	

Panel B. Placebo test

Dependent Variable: *Rate Spread*	
	(1)
Placebo SLR Exposure	-0.010
	[-0.240]
Control variables	Yes
Location × Mortgage × Year fixed effects	Yes
Observations	318,927
R^2	0.789

Panel C. Covariate-Balanced Sample (Multivariate Distance Matching)

Dependent Variable: *Rate Spread*	
	(1)
SLR Exposure	0.075**
	[2.543]
Control variables	Yes
Location × Mortgage × Year fixed effects	Yes
Observations	574,514
R^2	0.814

Panel D. Other Robustness Tests

Dependent Variable: *Rate Spread*	Control for house price and house price growth	Control for local population and education levels	Control for other location and property characteristics	Year-Quarter FE instead of Year FE	Year-Month FE instead of Year FE	Include DTI bins FE	SLR>0 only	30-year Treasury rate
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
SLR Exposure	0.073***	0.070***	0.076***	0.084**	0.084**	0.098***	0.074***	0.094**
	[3.067]	[2.934]	[3.081]	[2.569]	[2.039]	[3.121]	[2.885]	[2.567]
Control variables	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Location × Mortgage × Year fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	605,163	620,244	619,561	382,851	219,040	361,340	285,639	436,838
R^2	0.803	0.805	0.806	0.855	0.878	0.852	0.824	0.819

Table IV. Implied change in default probability

This table reports the change in default probability implied by the Frictionless Option-theoretic Model. In this model, the value of default put option is equal to the difference between the value of the mortgage and the present value of monthly mortgage payment discounted at the risk-free interest rate. The implied change in default probability is estimated using 360-period binomial option pricing model, based on the difference in default probability of an average mortgage in the sample (5.707% mortgage interest rate, 3.585% risk-free rate, and 63.1% loan-to-value ratio), another otherwise identical mortgage with 5.782% interesting (including the SLR spread of 0.075%).

	Implied *change* in default probability
Lifetime of the mortgage	0.037%
First 15 years	0.000%
Last 15 years	0.049%
Last 10 years	0.055%
Last 5 years	0.076%

Table V. Short versus long-term mortgages

Panel A analyzes whether the SLR premium relates to loan maturity. Panel B examines whether the SLR premium is driven by ex-post flood events. The sample in Panel B excludes counties that experience a major river flood (Column (1)), coastal flood (Column (2)), or either river or coastal flood (Column (3)), and counties that receive a substantial FEMA assistance (Column (4)). Column (5) includes an additional control variable *Flood10,* which is the height of a flood that has a 10% chance of occurring in a given year. Panel C examines whether *SLR Exposure* is related to applicants' short-term credit risk. The dependent variable in Panels A and B is *Rate Spread,* which is the difference between the annual percentage rate first observed on the loan and the 10-year US treasury bond yield. The dependent variables in Panel C are the applicant's *FICO* score (Column (1)), *Loan-to-Value* ratio (Column (2)), and *Loan Delinquencies*, a dummy variable equals 1 if a loan becomes 90 days delinquent or enters foreclosure during the first five years of its life, and 0 otherwise (Column (3)). The main independent variable of interest is *SLR Exposure*, which is the fraction of zip code area that will be inundated if the sea level rises by 6 feet. The sample is restricted to mortgages located within 30 km of the coast between 1992 and 2018. Location × Mortgage × Year fixed effects refer to County × Distance-to-coast bins × Elevation bins × Property type dummies × Value of property bins × FICO bins × Loan-to-value bins × Year fixed effects. Location × Property × Year fixed effects refer to County × Distance-to-coast bins × Elevation bins × Property type dummies × Value of property bins × Year fixed effects. Control variables are collapsed for brevity and are identical to those in Table II. Refer to Appendix A for variable definition. *t-statistics* based on standard errors clustered at the zip code level are reported in brackets. ***, **, and * indicate significance at the 1, 5 and 10% level, respectively.

Panel A: Short-term versus long-term mortgages

Dependent variable: *Rate Spread*			
Sample includes:	Short-term mortgages (Duration=15 years) (1)	Short-term and long-term mortgages (2)	Short-term and long-term mortgages (3)
SLR Exposure	0.030	0.062**	0.064**
	[0.441]	[2.338]	[2.421]
*SLR Exposure*Short-term Mortgages*		-0.051*	-0.051*
		[-1.857]	[-1.956]
Short-term Mortgages		-0.426***	0.572***
		[-59.492]	[7.038]
Control variables	Yes	Yes	Yes
Short-term Mortgages × Control variables	No	No	Yes
Location × Mortgage × Year fixed effects	Yes	Yes	Yes
Quarter-year fixed effects	Yes	Yes	Yes
Observations	80,722	778,950	778,950
R^2	0.811	0.796	0.797

Panel B: Is the SLR premium driven by ex-post flood events?

Dependent variable: *Rate Spread*					
	No river flood (1)	No coastal flood (2)	No river or coastal flood (3)	No FEMA assistance (4)	Control for 10-year flood (5)
SLR Exposure	0.104***	0.076***	0.105***	0.071***	0.074***
	[2.686]	[3.027]	[2.669]	[2.669]	[2.896]
Flood10					0.026
					[0.754]
Control variables	Yes	Yes	Yes	Yes	Yes
Location × Mortgage × Year fixed effects	Yes	Yes	Yes	Yes	Yes
Observations	197,980	567,228	183,741	387,931	353,611
R^2	0.784	0.803	0.78	0.821	0.819

Panel C: SLR risk and applicants' quality at origination

Dependent variables:	*FICO*	*Loan-to-Value*	*Loan Delinquencies*
	(1)	(2)	(3)
SLR Exposure	0.963	-0.006	0.010
	[0.706]	[-0.996]	[0.732]
Low Documentation	-6.596***	-0.029***	0.032***
	[-24.916]	[-16.062]	[10.836]
FICO		-0.000***	-0.001***
		[-11.652]	[-24.812]
Loan-to-Value	-4.872***		0.201***
	[-11.634]		[10.072]
Debt-to-Income	-0.337***	0.002***	0.001***
	[-59.921]	[65.914]	[20.147]
Jumbo Loan	2.565***	0.286***	0.002
	[10.974]	[154.006]	[1.283]
Has Prepayment Penalty	-21.710***	-0.012***	0.063***
	[-61.199]	[-5.596]	[26.410]
Ln(Local Income)	6.645***	-0.029***	-0.047***
	[12.908]	[-10.429]	[-8.159]
Location × Mortgage × Year fixed effects	No	No	Yes
Location × Property × Year fixed effects	Yes	Yes	No
Observations	1,058,294	1,058,294	620,244
R^2	0.413	0.389	0.559

Table VI. Salience of climate risk

Panel A explores heterogeneity in the SLR premium over time. Panel B examines how the SLR premium changes immediately following a major hurricane event. *Hurricane (Q1), Hurricane (Q2), Hurricane (Q3),* and *Hurricane (Q4)* are indicator variables which equal 1 for the first, second, third, and fourth quarter following the hurricane respectively. We also exclude the states that are directly affected by the hurricane. Panel C examines whether the SLR premium is sensitive to the media attention on climate change risk. *CCNI Spike (Q1), CCNI Spike (Q2), CCNI Spike (Q3),* and *CCNI Spike (Q4)* are indicator variables which equal 1 for the first, second, third, and fourth quarter following the "spike" month, defined as a month in which the WSJ Climate Change News Index is in the top 10% of the sample. All indicator variables are centered at the sample average and are included in the regressions. The dependent variable is *Rate Spread*, which is the difference between the annual percentage rate first observed on the loan and the 10-year US treasury bond yield. The independent variable of interest is *SLR Exposure*, which is the fraction of the zip code area that will be inundated if the sea level rises by 6 feet. The sample is restricted to mortgages located within 30 km of the coast between 1992 and 2018. Location × Mortgage × Year fixed effects refer to County × Distance-to-coast bins × Elevation bins × Property type dummies × Value of property bins × FICO bins × Loan-to-value bins × Year fixed effects. Control variables are collapsed for brevity and are identical to those in Table II. Refer to Appendix A for variable definition. *t-statistics* based on standard errors clustered at the zip code level are reported in brackets. ***, **, and * indicate significance at the 1, 5 and 10% level, respectively.

Panel A: Time splits

Dependent Variables: *Rate Spread*	(1)	(2)
SLR Exposure * 1992-1999	-0.031	-0.031
	[-0.098]	[-0.098]
SLR Exposure * 2000-2018	0.075***	
	[3.032]	
SLR Exposure * 2000-2006		0.070***
		[3.002]
SLR Exposure * 2007-2018		0.082**
		[1.965]
Control variables	Yes	Yes
Location × Mortgage × Year fixed effects	Yes	Yes
Observations	620,244	620,244
R^2	0.805	0.805

Panel B: SLR premium after a major hurricane event

Dependent Variables: *Rate Spread*	(1)	(2)
*SLR Exposure * Hurricane (Q1)*	0.022	0.021
	[0.430]	[0.419]
*SLR Exposure * Hurricane (Q2)*	0.138**	0.129*
	[2.087]	[1.930]
*SLR Exposure * Hurricane (Q3)*		-0.029
		[-0.412]
*SLR Exposure * Hurricane (Q4)*		-0.026
		[-0.710]
SLR Exposure	0.082***	0.075***
	[2.984]	[2.831]
Control variables	Yes	Yes
Location × Mortgage × Year fixed effects	Yes	Yes
Observations	570,626	551,125
R^2	0.801	0.801

Panel C: SLR premium following climate attention

Dependent Variables: *Rate Spread*		
	(1)	(2)
*SLR Exposure * CCNI Spike (Q1)*	0.025	0.043
	[1.280]	[1.470]
*SLR Exposure * CCNI Spike (Q2)*	0.118***	0.145***
	[4.275]	[4.025]
*SLR Exposure * CCNI Spike (Q3)*		0.068*
		[1.774]
*SLR Exposure * CCNI Spike (Q4)*		0.022
		[0.652]
SLR Exposure	0.069***	0.067***
	[2.872]	[2.846]
Control variables	Yes	Yes
Location × Mortgage × Year fixed effects	Yes	Yes
Observations	618,966	618,966
R^2	0.805	0.807

Table VII. Mortgage change beliefs

This table examines how community beliefs regarding climate change risk affect the SLR premium. *Climate Believing County* is a dummy that equals 1 if the percentage of people in the county answering "yes" to the question asking whether they believe that climate change is happening is above the sample's median and 0 otherwise. Data on climate change beliefs come from the Yale Climate Opinion Maps 2014. We center this variable at the sample average. The sample is restricted to mortgages located within 30 km of the coast between 1992 and 2018. Location × Mortgage × Year fixed effects refer to County × Distance-to-coast bins × Elevation bins × Property type dummies × Value of property bins × FICO bins × Loan-to-value bins × Year fixed effects. Control variables are collapsed for brevity and are identical to those in Table II. Refer to Appendix A for variable definition. *t-statistics* based on standard errors clustered at the county level are reported in brackets. ***, **, and * indicate significance at the 1, 5 and 10% level, respectively.

Dependent Variables: *Rate Spread*	
	(1)
*SLR Exposure * Climate Believing County*	0.075***
	[3.289]
SLR Exposure	0.055***
	[3.894]
Control variables	Yes
Location × Mortgage × Year fixed effects	Yes
Observations	620,244
R^2	0.805

Table VIII. Additional results

Panel A examines whether the SLR premium depends on a loan's eligibility to be sold to GSEs—Fannie Mae and Freddie Mac. *GSE-ineligible loan* is an indicator variable which equals 1 if a loan is either a (1) jumbo loan, i.e., loans with an amount greater than the county conforming loan limit, or a (2) subprime loans, i.e., loans with above 45% debt-to-income ratio for manually underwritten loans, or above 50% debt-to-income ratio for non-manually underwritten loans, and those with a loan-to-value ratio above 97% for fixed rate mortgages and above 95% for adjustable rate mortgages. Panel B examines the role of flood insurance in explaining the SLR premium. *%SFHA* is the proportion of the zip code area that is designated by FEMA as a special flood hazard area. The sample is restricted to mortgages located within 30 km of the coast between 1992 and 2018. Location × Mortgage × Year fixed effects refer to County × Distance-to-coast bins × Elevation bins × Property type dummies × Value of property bins × FICO bins × Loan-to-value bins × Year fixed effects. Control variables are collapsed for brevity and are identical to those in Table II. Refer to Appendix A for the definition and construction of variables used in this study. *t-statistics* based on standard errors clustered at the zip code level are reported in brackets. ***, **, and * indicate significance at the 1, 5 and 10% level, respectively.

Panel A. Mortgage securitization

Dependent Variables: *Rate Spread*	
	(1)
*SLR Exposure * GSE-ineligible loan*	0.047**
	[1.999]
SLR Exposure	0.058**
	[2.063]
Control variables	Yes
Location × Mortgage × Year fixed effects	Yes
GSE-ineligible loan × FICO bins × LTV bins fixed effects	Yes
Observations	620,242
R^2	0.805

Panel B. Flood insurance

Dependent Variables: *Rate Spread*	
	(1)
*SLR Exposure * %SFHA*	0.015
	[0.017]
%SFHA	0.252
	[0.779]
SLR Exposure	0.074***
	[2.988]
Control variables	Yes
Location × Mortgage × Year fixed effects	Yes
Observations	620,242
R^2	0.805

Table IX. Evidence from HMDA data

Panel A estimates the effect of long-run SLR risk on mortgage loan pricing using HMDA data. Panel B examines how the SLR premium varies across bank size. *Ln(Bank Assets)* is the natural logarithm of bank total book assets. *Ln(Branches)* is the natural logarithm of the number of branches a bank has. *Local branches* is the fraction of branches that are located in the same state as their banks' headquarters. *Distance to branches* is the average physical distance between a bank's headquarters and its bank branches. Panel C examines how the SLR premium varies across bank business models. *Interest Income/Total Income* is interest income divided by total income. *Loans/Assets* is total loans divided by total assets. *Mortgage Loans/Assets* is mortgage loans divided by total assets. Panel D examines how the SLR premium varies across a bank's experience with SLR risk. *SLR Experience (# Loans)* is the weighted average SLR exposure (by the number of loans) across all first-lien, 30-year fixed-rate mortgages a bank originates in a given year. *SLR Experience (Loan Amount)* is the weighted average SLR exposure (by loan amount) across all first-lien, 30-year fixed-rate mortgages a bank originates in a given year. The sample is restricted to mortgages located within 30 km of the coast. Location × Mortgage × Year fixed effects refer to County x Distance-to-coast bins x Elevation bins x Property type dummies x Value of property bins x Income bins x Loan-to-income bins x Year. Control variables include *Jumbo Loan*, *Has Prepayment Penalty*, *Applicant Income*, *Debt-to-income*, *Loan-to-Income*, and *Ln(Local Income)*. Refer to Appendix A for variable definition. *t-statistics* based on standard errors clustered at the zip code level are reported in brackets. ***, **, and * indicate significance at the 1, 5 and 10% level, respectively.

Panel A: SLR Exposure and Interest Rate Spread using HMDA data

Dependent variable: *Rate Spread*		
	(1)	(2)
SLR Exposure	0.067**	0.065**
	[2.482]	[2.449]
Control variables	Yes	Yes
Location × Mortgage × Year fixed effects	Yes	Yes
Lender fixed effects	Yes	No
Lender × year fixed effects	No	Yes
Observations	389,551	389,535
R^2	0.718	0.722

Panel B: SLR Premium across bank size

Dependent variable: *Rate Spread*				
	(1)	(2)	(3)	(4)
SLR Exposure	0.072***	0.069**	0.074***	0.072***
	[2.642]	[2.559]	[2.741]	[2.655]
*SLR Exposure*Ln(Bank Assets)*	-0.025***			
	[-3.632]			
*SLR Exposure*Ln(Branches)*		-0.023***		
		[-3.024]		
*SLR Exposure*Local Branches*			0.144***	
			[3.871]	
*SLR Exposure*Distance to Branches*				-0.033**
				[-2.508]
Control variables	Yes	Yes	Yes	Yes
Location × Mortgage × Year fixed effects	Yes	Yes	Yes	Yes
Lender × year fixed effects	Yes	Yes	Yes	Yes
Observations	389,397	389,397	389,397	389,383
R^2	0.722	0.722	0.722	0.722

Panel C: SLR Premium across bank business models

Dependent variable: *Rate Spread*			
	(1)	(2)	(3)
SLR Exposure	0.073***	0.075***	0.078***
	[3.222]	[3.301]	[3.407]
*SLR Exposure*Interest Income/Total Income*	0.281**		
	[2.123]		
*SLR Exposure*Loans/Assets*		0.154*	
		[1.913]	
*SLR Exposure*Mortgage Loans/Assets*			0.249***
			[4.385]
Control variables	Yes	Yes	Yes
Location × Mortgage × Year fixed effects	Yes	Yes	Yes
Lender × year fixed effects	Yes	Yes	Yes
Observations	380,995	380,857	380,857
R^2	0.689	0.689	0.689

Panel D: SLR Premium across a bank's experience with SLR risk

Dependent variable: *Rate Spread*		
	(1)	(2)
SLR Exposure	0.053**	0.053**
	[1.986]	[1.971]
*SLR Exposure*SLR Experience (# Loans)*	0.889***	
	[4.912]	
*SLR Exposure*SLR Experience (Loan Amount)*		0.742***
		[4.295]
Control variables	Yes	Yes
Location × Mortgage × Year fixed effects	Yes	Yes
Lender × year fixed effects	Yes	Yes
Observations	389,535	389,535
R^2	0.722	0.722

Figure 1. Sample observations by zip code

This figure presents a zip code map representing the number of observations in our sample. In grey are zip codes with no observation in our sample.

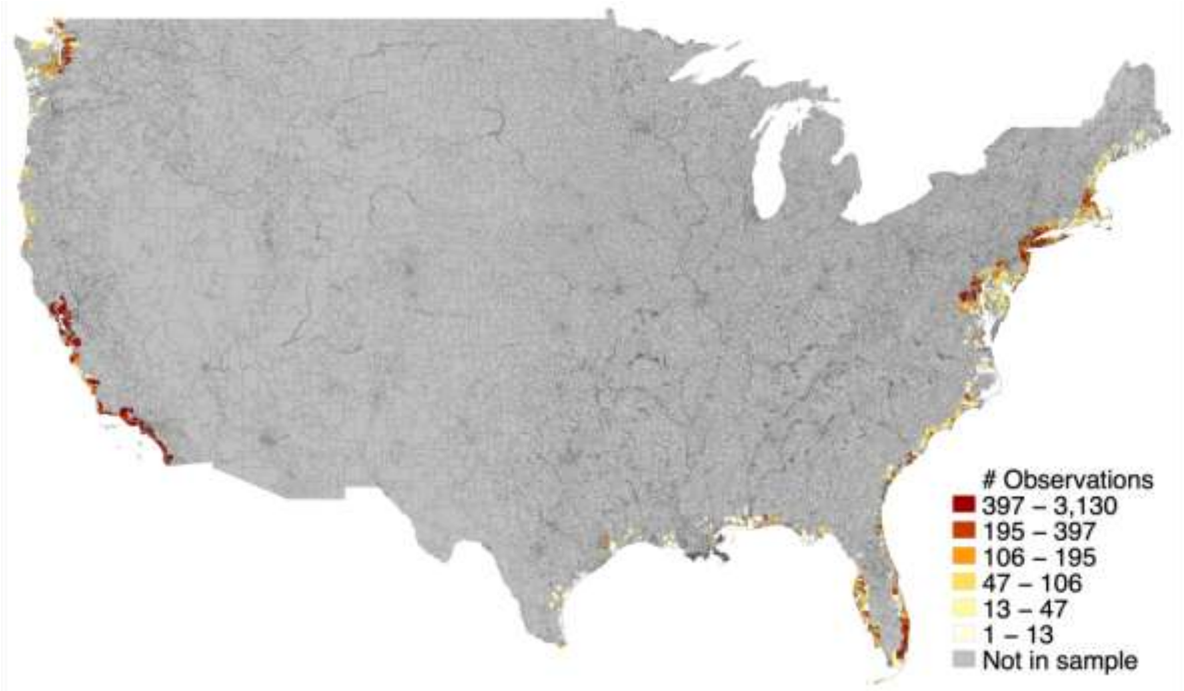
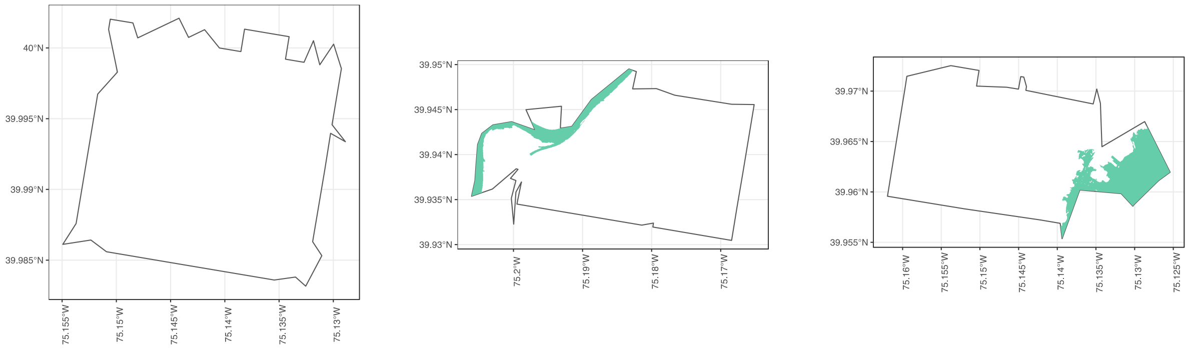


Figure 2. SLR exposure in Philadelphia, PA

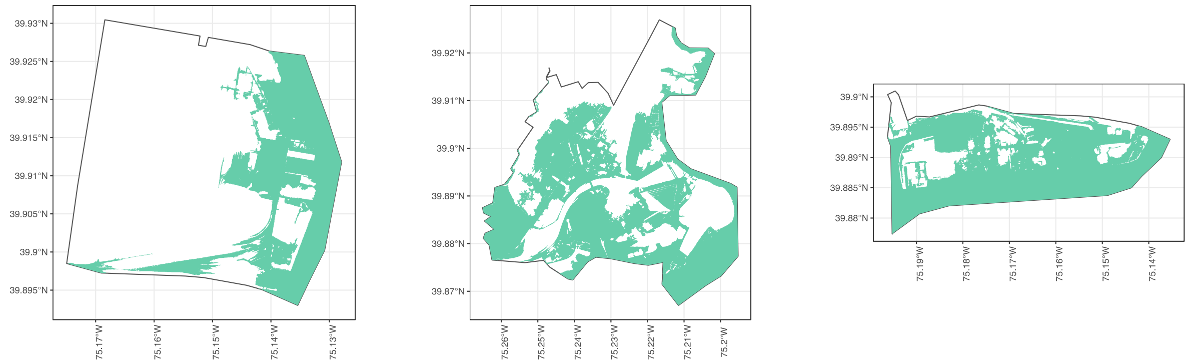
This figure illustrates the level of exposure to sea level rises of six ZIP code tabulation areas (ZCTAs) in Philadelphia, PA: 19133, 19146, 19123, 19148, 19153, and 19112. Each plot (A-F) shows the area that will be inundated if the sea level rises by 6 feet (highlighted). In parentheses are the numerical proportion of eac ZCTA that is exposed to 6-foot SLR.



(A)
19133 (0%)

(B)
19146 (6.07%)

(C)
19123 (12.65%)



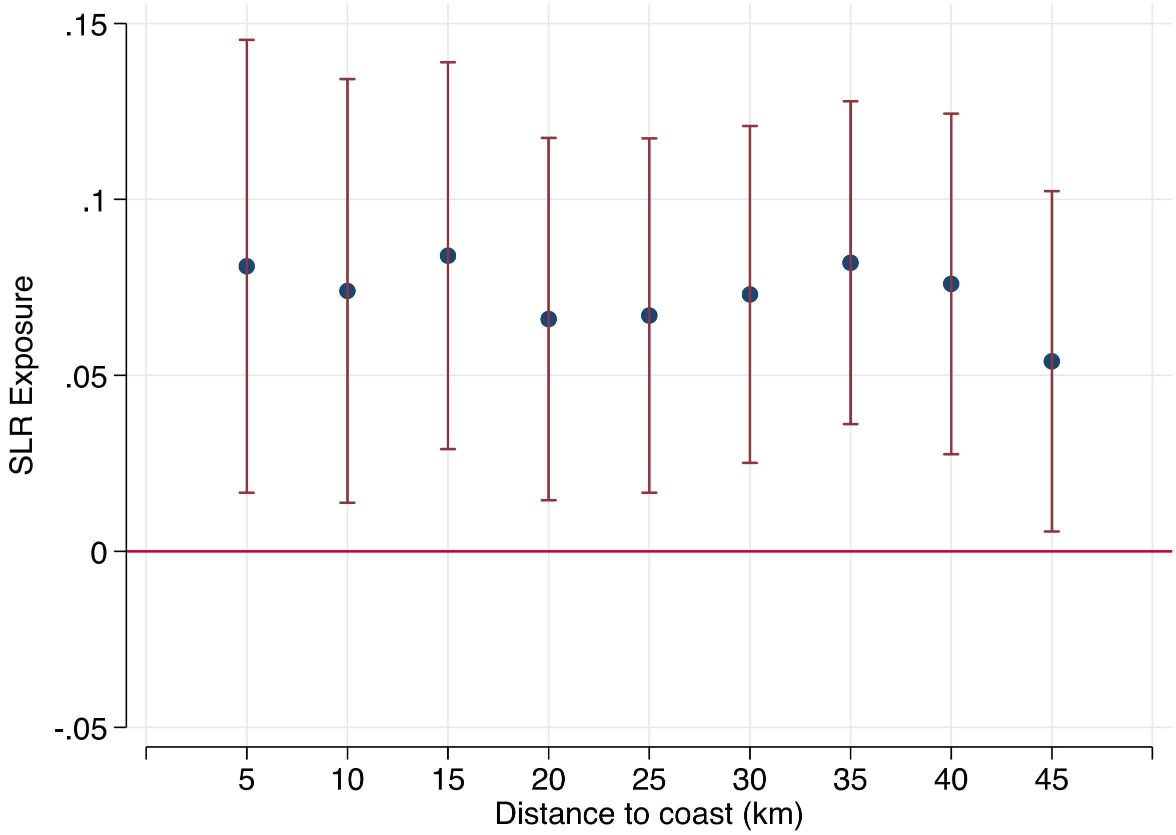
(D)
19148 (26.55%)

(E)
19153 (55.58%)

(F)
19112 (78.23%)

Figure 3. Alternative distance-to-coast restrictions

This figure reports the coefficient estimates on *SLR Exposure* using different sample restrictions.



Appendix A

This appendix defines each of the variables used throughout the paper.

Variable	Definition	Source
Main explanatory variable		
SLR Exposure	The fraction of a zip code area that will be inundated if the sea level rises by 6 feet.	NOAA
Loan-level characteristics		
Interest Rate	The annual percentage rate first observed on the loan.	McDash/HMDA
Rate Spread	The difference between the annual percentage rate first observed on the loan and the 10-year US treasury bond yield	McDash/HMDA
Low Documentation	= 1 if the applicant provides less than full documentation of household financials, and = 0 otherwise	McDash
FICO	The FICO score reported in the application divided by 100.	McDash
Loan-to-Value	The application's loan-to-value ratio.	McDash
Loan-to-Income	The application's loan-to-income ratio.	HMDA
Debt-to-Income	The application's debt-to-income ratio.	McDash/HMDA
Applicant Income	The applicant's reported income.	HMDA
Jumbo Loan	= 1 if the loan amount exceeds the conforming loan limit, and = 0 otherwise.	McDash/HMDA
Has Prepayment Penalty	= 1 if the mortgage contract stipulates charges for early payments, and = 0 otherwise.	McDash/HMDA
Loan Amount	Natural logarithm of loan amount (in thousands of dollars).	McDash/HMDA
Property Value	The property's appraisal value.	McDash/HMDA
Loan Delinquencies	= 1 if the mortgage becomes 90 days delinquent or enters foreclosure during the first five years of its life, and = 0 otherwise.	McDash
Short-term Mortgages	= 1 for short-term mortgages with a duration of 15 years.	McDash/HMDA
GSE-ineligible loan	=1 if a loan is either a jumbo loan, i.e., a loan with an amount greater than the county conforming loan limit, or a subprime loan, i.e., a loan with an above 45% debt-to-income ratio for manually underwritten loans, or an above 50% debt-to-income ratio for non-manually underwritten loans, and those with a loan-to-value ratio above 97% for fixed rate mortgages and above 95% for adjustable rate mortgages, and =0 otherwise.	HMDA/McDash
Location-level characteristics		
Distance to Coast	The distance from the centroid of the zip code to the nearest coast.	NASA's Ocean Biology Group
Elevation	The elevation of the land from the sea level. Measured at the centroid of the zip code.	US Geological Survey
Ln(Local Income)	The natural logarithm of the average income per capita in the zip code.	Internal Revenue Service
Flood10	The height of a flood that has a 10% of occurring in a given year.	Surging Seas: Risk Finder
Hurricane(Q1)	= 1 for the first quarter after a hurricane, and = 0 otherwise.	
Hurricane(Q2)	= 1 for the second quarter after a hurricane, and = 0 otherwise.	National Hurricane Center
Hurricane(Q3)	= 1 for the third quarter after a hurricane, and = 0 otherwise.	
Hurricane(Q4)	= 1 for the fourth quarter after a hurricane, and = 0 otherwise.	
CCNI Spike (Q1)	= 1 for the first quarter following a media spike, and = 0 otherwise.	
CCNI Spike (Q2)	= 1 for the second quarter following a media spike, and = 0 otherwise.	
CCNI Spike (Q3)	= 1 for the third quarter following a media spike, and = 0 otherwise.	Engle et al (2020)
CCNI Spike (Q4)	= 1 for the fourth quarter following a media spike, and = 0 otherwise.	

Climate Believing County	=1 if the percentage of people in the county answering "yes" to the question asking whether they believe that climate change is happening is above the sample's median, and = 0 otherwise.	2014 Yale Climate Opinion Maps
%SFHA	The fraction of a zip code area that is designated by FEMA as a special flood hazard area.	FEMA
Beach Nourishment	= 1 if there has been a beach nourishment project in the zip code, and =0 otherwise.	Program for the Study of Developed Shorelines
Bank-level characteristics		
Ln(Bank Assets)	The natural logarithm of bank total book assets.	Summary of Deposits
Ln(Branches)	The natural logarithm of the number of branches a bank has.	Summary of Deposits
Local Branches	The fraction of branches that are located in the same state as their banks' headquarters.	Summary of Deposits
Distance to Branches	The average physical distance between a bank's headquarters and its bank branches.	Summary of Deposits
Interest Income/Total Income	Interest income divided by total income.	Call Reports
Loans/Assets	Total loans divided by total assets.	Call Reports
Mortgage Loans/Assets	Mortgage loans divided by total assets	Call Reports
SLR Experience (# Loans)	The weighted average SLR exposure (by number of loans) across all first-lien, conventional, 30-year fixed-rate mortgages a bank originates in a given year.	HMDA/NOAA
SLR Experience (Loan Amount)	The weighted average SLR exposure (by loan amount) across all first-lien, conventional, 30-year fixed-rate mortgages a bank originates in a given year.	HMDA/NOAA

Internet Appendix

Climate change risk and the cost of mortgage credit

This internet appendix contains information on lenders' pricing of sea level rise risk.

Table IA-I. Sample construction

	# observations
All McDash mortgages originated between January 1992 and June 2018 with available SLR, 5-digit ZIP code, distance-to-coast, and Elevation data.	**32,650,000**
Less:	
Properties further than 30km from the coast	(18,198,267)
Non-conventional mortgages and mortgages that are not 30-year fixed rate	(11,095,572)
Mortgages with FICO scores below 300 and 900 and reported loan-to-value above 100%	(62,348)
Mortgages with exotic features	(93,453)
Missing FICO, loan-to-value ratio, interest rate, appraisal amount, and local income	(679,486)
Missing debt-to-income	(917,537)
Final sample:	**1,603,337**
Less: Singleton observations (as a result of interacted fixed effects)	(983,093)
Effective observations in Column 4, Table 2	**620,244**

Table IA-II. List of US hurricanes

This table lists name, date, and affected states of the hurricanes that cause at least $30 billion in damage as reported by the National Hurricane Center.

Name	Date	Affected states
Katrina	August 25, 2005	Alabama, Louisiana, Mississippi, Florida
Ike	September 12, 2008	Louisiana, Texas
Sandy	October 30, 2012	Connecticut, Delaware, Florida, Georgia, Maryland, New Jersey, Massachusetts, Maine, North Carolina, Philadelphia, Rhode Island, South Carolina, Virginia
Harvey	August 25, 2017	Louisiana, Texas
Irma	September 6, 2017	Florida, South Carolina
Maria	September 19, 2017	Puerto Rico

Figure IA-1. Relationship between distance to the coast and average interest rate spread

This figure displays the relationship between distance to coast (km) and average interest rate spread (%). The symbol (x) indicates 95% confidence interval.