Zixin Jiang
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Dear Organizing Committee,

I am writing to apply for the 2025 NBER PhD Student Workshop on Climate Finance. I am a fifth-year PhD candidate in Finance at the University of North Carolina at Charlotte, mentored by Dr. Yongqiang Chu, and I expect to graduate in May 2026. My primary research interests lie in real estate, corporate finance, and banking, with a growing focus on climate finance.

My current work explores the intersection of political ideology and climate risk pricing in mortgage markets. Specifically, I examine whether loan officers' political affiliations influence the pricing of sea level rise (SLR) risk in coastal residential mortgages. Using a novel dataset combining voter registration, mortgage, and climate risk data, I find that Democratic loan officers charge higher loan spreads for SLR-exposed properties than Republican officers, especially in areas outside FEMA flood zones, in coastal communities, and in regions with relatively low climate change belief. These findings highlight how individual-level ideology can shape financial decisions under climate uncertainty.

Looking forward, I plan to extend this research agenda to examine how individual-level ideology and climate risk interact in shaping credit allocation and pricing across other loan types, including commercial and syndicated lending. I believe the workshop would provide invaluable feedback from scholars active in this emerging area and help me refine both my empirical approach and theoretical framing.

My advisor, Dr. Yongqiang Chu, is willing to serve as a reference if needed. Thank you for your consideration, and I look forward to hearing from you soon.

Sincerely,



Zixin Jiang

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EDUCATION

University of North Carolina at Charlotte, Belk College of Business — **Charlotte, USA**
Ph.D in Finance — Expected May 2026
Dissertation: Essays on Mortgage Markets (ABD)

Kent State University, College of Business Administration — **Kent, USA**
M.A. in Economics, Concentration in Economic Analysis — May 2021

Wuhan University, Economics and Management School — **Wuhan, China**
Bachelor's degree in Economics, Major in Financial Engineering — June 2018

RESEARCH INTERESTS

Real Estate, Banking, Corporate Finance

WORKING PAPERS

Political Affiliation and the Pricing of Climate Risk in Mortgages (Job market paper)

Abstract: Using voter registration data of loan officers originating residential mortgages, I find that Democratic loan officers charge higher loan spreads for mortgages on properties exposed to sea level rise (SLR) than Republican loan officers. The results hold after controlling for loan officer fixed factors. The effect is more pronounced among loan officers in hurricane-prone states, living closer to the coast, and in communities with more climate change believers. These findings highlight how political ideology shapes the pricing of climate risks in mortgages.

Bank Mergers and Loan Officer Reallocation

Abstract: I find that mortgage loan officer turnover increases after bank mergers. The effect is more pronounced for officers working in areas where both target and acquiring banks have mortgage businesses. Officers staying in the merged banks originate more loans than those leaving for other banks. The findings suggest that merged banks trying to improve efficiency by reducing redundant employees. Focusing on officers in overlapping areas, I find that officers in merged banks originate fewer loans closer to their offices. I also find that officers in merged banks originate fewer small loans after mergers. These results suggest that bank mergers lead to the loss of soft information and limit the availability of small mortgages.

PROFESSIONAL ACTIVITIES

Conference & Seminar Presentations

Political Affiliation and the Pricing of Climate Risk in Mortgages

- Financial Management Association (FMA) Annual Meeting, 2025 (scheduled)
- Ba Li Tai Young Finance Scholar Forum (Nankai University), 2025
- UNC Charlotte Finance Seminar, 2025

Bank Mergers and Loan Officer Reallocation

- Financial Management Association (FMA) Annual Meeting, 2025 (scheduled)
- Southern Finance Association (SFA) Annual Meeting, 2025 (scheduled)
- American Real Estate and Urban Economics Association (AREUEA) National Conference, 2025
- UNC Charlotte Finance Seminar, 2024

Discussions

- Southern Finance Association (SFA) Annual Meeting, 2025 (scheduled)

TEACHING EXPERIENCE

Instructor

FINN 3120 Financial Management — Fall 2024

- Evaluation: 4.45/5.00**,** Response: 74/90 students

FINN 3120 Financial Management — Summer 2024

- Evaluation: 4.32/5.00**,** Response: 25/28 students

FINN 3120 Financial Management — Spring 2023

- Evaluation: 3.57/5.00**,** Response: 61/77 students

Teaching Assistant

MSRE 6160 Real Estate Capital Markets — Spring 2025
MSMG 6170 Financial Management — Spring 2024
MBAD 6155 Multinational Financial Management — Spring 2022
MBAD 6152 Financial Management — Fall 2021
FINN 6203 Financial Economic Theory — Fall 2021

HONORS, AWARDS, GRANTS

- Graduate Assistantship with Full Tuition Scholarship, UNC Charlotte — 2021-2026
- The Graduate School Summer Fellowship, UNC Charlotte — 2025
- Graduate and Professional Student Government Travel Funding, UNC Charlotte — 2024
- Graduate Assistantship with Full Tuition Scholarship, Kent State University — 2019-2021

- Second-Class Scholarship, Wuhan University 2017
- COMAP's Mathematical Contest in Modeling (Meritorious Winner) 2017

PROFESSIONAL MEMBERSHIP

- American Real Estate and Urban Economics Association (AREUEA)
- American Finance Association (AFA)
- Financial Management Association (FMA)
- Southern Finance Association (SFA)

SKILLS

- **Software**: SAS, STATA, Matlab, ArcGIS
- **Language**: Mandarin (Native), English (Fluent)

REFERENCES

Dr. Yongqiang Chu (Chair)
Childress Klein Distinguished Professor of Real Estate and Urban Economics
Director, Childress Klein Center for Real Estate
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Dr. Patrick Smith
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Political Affiliation and the Pricing of Climate Risk in Mortgages

Current Version: June 2025

Abstract

Using voter registration data of loan officers originating residential mortgages in coastal areas, I analyze whether climate change partisanship is reflected in mortgage lending. I find that Democratic loan officers charge higher loan spreads for mortgages on properties exposed to sea level rise (SLR) than Republican loan officers. The results hold after controlling for loan officer fixed factors. Partisan sorting is more pronounced for properties outside FEMA-designated flood zones, and for loan officers located nearer the coast or in communities with fewer climate change believers. These findings highlight how political ideology shapes the pricing of climate risks in mortgages.

Keywords: Political Affiliation, Sea Level Rise, Climate Change, Mortgage

JEL Code: D72, G14, G21, G23, Q54

1 Introduction

Political ideology shapes not only how people vote, but also how they perceive economic conditions and make financial decisions. A growing literature documents that partisanship colors individuals' economic expectations and behavior of market participants across multiple domains—including finance professionals (e.g.,Kempf and Tsoutsoura 2021), corporate executives (Rice, 2024; Fos et al., 2023), and households (e.g., Meeuwis et al. 2022; Chu et al. 2024). In this study, I examine how loan officers' political affiliation affects the pricing of climate risk in mortgage lending.

Political ideology also shapes individuals' perceptions of certain risk factors, including climate risk (Bernstein et al. 2022). Funk and Kennedy (2016) examine the political polarization in the U.S. regarding climate change, highlighting partisan differences in beliefs about its severity. Liberal Democrats are more likely to believe that climate change will cause severe environmental harms (e.g., extreme weather, rising sea levels, ecological damage). In contrast, conservative Republicans are generally more skeptical about the severity or inevitability of climate risks. In this paper, I focus on sea level rise (SLR) risk in coastal communities, which have a higher average exposure to SLR risk. Since inundation from SLR destroys the property value, rising sea levels may affect housing prices in residential real estate markets (Bernstein et al. 2019; Baldauf et al. 2020). Given that most residential housing is purchased with a mortgage, it is natural to explore the interaction of political ideology and climate risk pricing in mortgage markets.

In the mortgage underwriting process, loan officers play a key role in assessing borrower risk, evaluating financial backgrounds, and structuring suitable loan options. While lending decisions are guided by institutional policies and regulatory requirements, loan officers retain some discretion in influencing mortgage pricing (Ambrose et al. 2021; Bartlett et al. 2022; Chu 2024). Loan officers' judgments, shaped by their risk perception and personal beliefs, can ultimately impact how climate risks are factored into mortgage lending. Therefore, differences in officers' political ideology may lead to variations in mortgage pricing for properties exposed to climate risks.

I construct a sample by combining CoreLogic mortgage data, Home Mortgage Disclosure Act (HMDA) data, Nationwide Mortgage Licensing System (NMLS) loan officer data, L2 voter registration data, and National Oceanic and Atmospheric Administration (NOAA) data. L2 voter

registration data identifies loan officers' political affiliations, and NOAA data provides property-level exposure to SLR risk. I measure the SLR risk based on whether a property is projected to be inundated following an up to 6-foot increase in average global ocean level. CoreLogic mortgage data includes loan officers' unique NMLS ID numbers and names, which I use to merge with NMLS loan officer data and L2 voter registration records. Additionally, CoreLogic provides the exact property locations, allowing me to match them with NOAA data for SLR risk assessment.

First, I examine whether SLR risk is priced in residential mortgages. Properties closer to the coast differ from those that are farther away in terms of amenity values, such as scenic ocean views. To isolate the impact of SLR risk on mortgage rates, it is essential to compare properties with similar elevation and proximity to the coast. Following Bernstein et al. (2019) and Bernstein et al. (2022), I control for the property's zip code interacted with non-linear controls for its distance to the coast and elevation. On average, I do not find a statistically significant difference in mortgage spreads for properties with and without SLR risk. Similarly, when using interest rate, I still do not find a significant difference in mortgage interest rates for properties with and without exposure to SLR risk. This is consistent with the fact that the government-sponsored enterprises (GSEs) - Fannie Mae and Freddie Mac, don't factor climate change into rates.

Next, I examine whether loan officer's political affiliation affect how SLR risk is priced in residential mortgages. Democratic loan officers may work or reside farther from communities with higher SLR risk. To mitigate potential endogeneity arising from loan officer location, I include loan officer location (zip code) by year fixed effects. This approach allows me to compare loan officers with different political affiliations operating in the same location and issuing loans in the same year. I further use loan officer fixed effects to control for any potential loan officer characteristics that could affect their loan origination decisions. I find that Democratic loan officers charge higher rate spreads to mortgages on properties exposed to SLR risk than Republican loan officers. Specifically, the spread on loans for properties exposed to SLR by Democratic loan officers is about 2.5 basis points higher than those by Republican loan officers. However, I do not find that loan officers' political affiliation influences the pricing of SLR risk in mortgage interest rates. The results are not surprising. The GSEs determine credit-risk pricing adjustments via a fee that depends only on loan-to-value ratios (LTVs) and credit scores (Bartlett et al. 2022). If mortgages are sold to the GSEs, lenders are guaranteed against credit risk. Therefore, there is very little discretion for

loan officers to adjust mortgage interest rates. Instead, the rate spread is a measure of the overall mortgage cost that incorporates non-interest cost, such as origination fees and points. Thus, loan officers have relatively more discretion on it.

Furthermore, I explore the heterogeneity in the relationship of loan officer political ideology and the pricing of SLR risk. I first investigate whether the presence of mandated flood insurance mitigates the extent of partisan sorting in the pricing of SLR risk. The National Flood Insurance Reform Act of 1994 mandates that U.S. mortgage borrowers purchase flood insurance if the mortgaged property is located within a Special Flood Hazard Area (SFHA). The Federal Emergency Management Agency (FEMA) is responsible for defining SFHAs based on its flood hazard assessments and mapping. As a result, the collateral value of mortgages on properties within SFHAs is largely protected against flood risk through mandatory insurance coverage, while properties outside SFHAs remain exposed to uninsured flood losses. This institutional setting allows me to examine whether mandated flood insurance mitigates partisan differences in the pricing of SLR risk. If partisan heterogeneity primarily reflects differences in loan officers' subjective beliefs, the pricing gap should be more pronounced where flood risk remains uninsured. Consistent with this prediction, I find that the difference in SLR risk pricing between Republican and Democratic loan officers arises only for mortgages on properties located outside FEMA-designated flood zones. In contrast, there is no significant partisan difference for mortgages that are already protected against flood risk within SFHA areas. These results suggest that mandatory flood insurance partially substitutes for individual climate risk perceptions in mortgage pricing.

Moreover, loan officers' personal experience of coastal climate risks may also affect the partisan gap in mortgage pricing of SLR risk. SLR risk is a long-run risk of rising oceans eventually inundating coastal properties. While SLR is a gradual process, individuals can learn about it through their personal experience of coastal climate change. Officers located closer to the coast are more likely to have firsthand experience with coastal flooding, tidal surges, and other tangible signs of rising seas. If such exposure interacts with political ideology, Democrats and Republicans could respond very differently. Democrats may internalize climate risks more readily, whereas Republicans may remain skeptical, reinforcing partisan differences. Farther inland, where SLR risk is less salient, neither group may actively incorporate it into pricing decisions. I proxy for loan officers' personal experience of coastal climate risk using loan officers' home and work distance to

the coast and split the sample at the median. Indeed, I find that the political difference in the pricing of the SLR risk is more pronounced for officers living/working closer to the coast. The results suggest that direct experience with climate-related threats amplifies political disparities in risk perception and decision-making in mortgage lending.

Finally, to explore how local climate change beliefs shape partisan differences in pricing SLR risk, I match mortgage data with the Yale Climate Opinion Maps based on loan officers' home and work addresses. I find that the partisan gap in pricing SLR risk is more pronounced in communities with relatively low climate change belief, while there is no significant partisan gap in areas with stronger local climate concern. Pew Research Center finds that Republicans are more internally divided on climate change than Democrats. Republicans in Democratic-leaning, high-belief communities are more likely to be economically conservative and accept climate science, whereas those in Republican-dominated, low-belief communities tend to be socially conservative and skeptical of climate change. Moreover, Republicans may be more responsive than Democrats to local partisan norms, as shown in other contexts like prosocial behavior during COVID-19 (Baxter-King et al. 2022). Accordingly, Republican loan officers may be more responsive to prevailing community beliefs when pricing climate risk, particularly in regions with stronger public acceptance of climate change.

This paper contributes to the literature on political affiliation and finance, especially the economic outcomes in housing and loan markets. Bernstein et al. (2022) show that Republicans are more likely than Democrats to own homes exposed to SLR risk. Chu et al. (2024) find that individuals sharing the same political affiliation as the current U.S. President are more likely to engage in housing transactions as perceiving lower uncertainty in the economy. Chu (2024) show that Democratic loan officers originate more loans to minority borrowers by lowering the lending standard based on hard information. Dagostino et al. (2023) find that bankers whose party differs from that of the U.S. President charge higher loan spreads on syndicated loans than other bankers. This is the first paper to examine how the political ideology of mortgage officers interacts with climate change risk.

This paper contributes to the growing literature on climate finance. Recent studies have examined the pricing of climate risk in residential real estate markets (Bernstein et al. 2019; Murfin and Spiegel 2020; Baldauf et al. 2020), equity markets (Engle et al. 2020; Choi et al. 2020; Hsu et al. 2023; Sautner et al. 2023), and bond markets (Goldsmith-Pinkham et al. 2023). However,

relatively little is known about how climate risk is priced in the mortgage market. Nguyen et al. (2022) find that lenders charge higher interest rates on mortgages for properties exposed to greater SLR risk. Bakkensen et al. (2023) show that homebuyers with pessimistic beliefs about SLR risk are more likely to take on mortgage debt and prefer longer-maturity loans. Additionally, related studies have examined the impact of emperature anomalies on mortgage lending (Duan and Li 2024), and wildfires on housing and mortgage markets (Issler et al. 2024). This is the first paper to examine how the political ideology of economic agents interacts with climate change risk in mortgage markets.

Finally, this paper contributes to the literature on loan officers. The literature documents the role of loan officers on the racial gap in mortgage lending. Specifically, Frame et al. (2025) find that under-representation of minority loan officers contributes to the racial gap in mortgage lending; Ambrose et al. (2021) find that officer race affects the cost of mortgage credit to minorities; Chu (2024) finds that the political ideology of loan officers is another source of the racial gap in mortgage lending. Several other studies focus on syndicated loan officers. Dagostino et al. (2023) find that bankers whose political affiliation differs from that of the U.S. President apply higher loan spreads on syndicated loans than their peers. Herpfer (2021) and Bushman et al. (2021) find that loan officers can influence the loan contracting process of corporate lending. Drexler and Schoar (2014) find that loan officers play a crucial role in maintaining client relationships. This paper is the first to examine the impact of officers' political affiliation in the pricing of climate change risk.

The remainder of the paper is organized as follows. In Section 2, I describe the details of data sources and the sample construction process. Section 3 provides the results on the SLR risk and mortgage cost. Section 4 examines the relationship of officer political affiliation and the pricing of SLR risk in mortgage lending. Section 5 explores the heterogeneity in partisan sorting on SLR risk pricing, and Section 6 concludes.

2 Data and Sample Construction

2.1 Mortgage data

I obtain mortgage origination data from CoreLogic. The CoreLogic collects information from mortgage deed documents, including the exact location of the underlying property, loan amount,

mortgage origination date, mortgage type (FHA, VA, Conventional, fixed-rate, adjustable-rate), property type (single-family, multi-family, manufactured home), lien status (first lien, second lien, etc.), borrower name, lender name, and loan officer NMLSID. I geocode the location of each property and then determine the property's distance from the nearest coastline and elevation.

To obtain interest rate, underwriting criteria and borrower demographics, I merge the CoreLogic data with Home Mortgage Disclosure Act (HMDA) data. There is no common identifier between these two datasets. I match mortgages in these two datasets with variables that are common in these two datasets, including mortgage year, lender, census tract, loan amount, mortgage term, mortgage type, loan purpose, and whether the loan has a co-applicant. I only keep loans with a unique match in these two datasets. I restrict the sample to single-family, fixed-rate, first-lien, conventional mortgages with a 30-year term. I start the sample in 2018 because some key variables required in our analysis are only available in the post-2018 HMDA data.

2.2 Exposure to SLR risk

The property-level exposure assessment to SLR is derived from the publicly accessible SLR Viewer provided by the National Oceanic and Atmospheric Administration (NOAA). The NOAA provides detailed SLR shapefiles that describe the latitude and longitudes that will be inundated following an up to 6-foot increase in average global ocean level. Utilizing geographic information systems (GIS) software, I spatially intersect these NOAA inundation layers with property parcel data to accurately determine the exposure level of each individual property within the study area. I have 788,750 homes with exposure to SLR of up to 6 feet.

2.3 Loan officer data

Congress passed the Secure and Fair Enforcement for Mortgage Licensing Act in 2008 (SAFE Act). The SAFE Act requires all loan officer registrations and licenses to be included in the Nationwide Multistate Licensing System (NMLS). By 2012, all state and federal regulators had integrated into the NMLS and a nationwide mortgage licensing system and registry for the residential mortgage industry was established. This dataset contains officer information on registrations, licenses, employers, and office locations. The NMLS dataset assigns a unique and permanent ID number to each loan officer.

To identify political affiliation, I utilize voter registration data from L2. This dataset provides voters' names, demographic information, home addresses, and political affiliations. I keep voter records registered as "Democrat", Republican", and "Non-partisan." I match the L2 data based with the NMLS loan officer data on loan officers' names, and exclude matches with distance between voters' residential addresses and the location of loan officers' working addresses being greater than 100 miles.

2.4 Sample construction

I merge property-level exposure to SLR with mortgage data using exact street address, city, state, and zip code. Restricting the sample to properties within 2 miles of the coast, I have 741,167 mortgages originated between 2018 and 2022. After matching the mortgage data with the loan officer data using the officer NMLSID, the sample is reduced to about 241,090 mortgages with loan officer political affiliation information.

SLR exposure risk decreases with distance to the coast and elevation. Properties closer to the coast differ from those that are farther away due to the amenity values and market liquidity of being close to the coast. To isolate the impact of SLR risk on mortgage rates, it is essential to compare properties with similar elevation and proximity to the coast. Following Bernstein et al. (2019) and Bernstein et al. (2022), I control for the property's zip code interacted with flexible non-linear controls for its distance to the coast and its elevation. I assign continuous measures of elevation and distance to the coast for each property to intervals. Specifically, distance-to-the-coast is split up into intervals of 1/5th of a mile, while elevation is split into 2-meter intervals.

I present the summary statistics of the main variables in Table 1. Panel A is the summary statistics of the CoreLogic-HMDA sample. The average interest rate is 3.668%. The average rate spread, the difference between the annual percentage rate (APR) and the survey-based average prime offer rates, is 21.0 basis points. About 13.1% of mortgages are on properties with exposure to SLR risk. About 88.5% of loans are classified as conforming. About 60.3% of loans have co-applicants. The average combined loan-to-value (CLTV) ratio is 69.616%. About 9.0% of mortgages are issued to minority borrowers. The average loan amount is $450,544.

Panel B is the summary statistics of the CoreLogic-HMDA-L2 sample. The average interest rate is 3.680%. The average rate spread is 22.8 basis points. About 12.7% of mortgages are for

properties with exposure to SLR risk. About 41.5% of loans are originated by Republican loan officers, and 29.2% of loans are originated by Democratic loan officers. The average combined loan-to-value (CLTV) ratio is 70.305%. About 8.5% of mortgages are issued to minority borrowers. The average loan amount is $436,995.

3 SLR risk and mortgage cost

To examine whether SLR risk is priced in residential mortgages, I estimate the following specification,

$$Mortgage\ Cost_{ijzdet} = \beta_1 SLR_{izde} + X_{ijzdet}\phi + \alpha_{zde} + \alpha_{loan\,char} + \alpha_{borrower\,char} + \alpha_t + \epsilon_{ijzdet}, \tag{1}$$

where $Mortgage\ Cost_{ijzdet}$ is the rate spread (interest rate) of mortgage i to borrower j in year t, SLR_{izde} is a dummy variable that equals one if the property will experience chronic tidal flooding with up to 6 feet global average SLR and zero otherwise, X_{ijzdet} is a set of property, loan and borrower characteristics, including the age of the property (Property Age), the natural logarithm of the loan amount (Log Loan Amount), loan-to-income ratio (LTI), an indicator for conforming loans (Conforming), an indicator for the presence of a co-applicant (Co-applicant), an indicator for whether the borrower is over 62 (Age $>$ 62), and an indicator for whether the borrower is African American or Hispanic (Minority). α_{zde} is the set of zip, distance to coast, and elevation fixed effects. I also include a set of mortgage and borrower characteristics fixed effects, including debt-to-income ratio (DTI), loan purpose, loan-to-value ratio (LTV), borrower race, and borrower ethnicity fixed effects. I cluster the standard errors at the Zip code level.

I present the results of estimating Equation (1) in Table 2, with Panel A reporting results for the rate spread and Panel B for the interest rate. On average, I do not find a statistically significant difference in mortgage spreads for properties with and without SLR risk. Similarly, when using interest rate, I still do not find a significant difference in mortgage interest rates for properties with and without exposure to SLR risk. This is consistent with the fact that the government-sponsored enterprises (GSEs) - Fannie Mae and Freddie Mac, don't factor climate change into rates.

4 Partisan sorting on the pricing of SLR risk

To examine whether loan officer's political affiliation affects how SLR risk is priced in residential mortgages, I estimate the following specification,

$$\begin{aligned} Mortgage\ Cost_{ijkzdet} &= \beta_1 Rep\ LO_{kt} \times SLR_{izde} + \beta_2 Dem\ LO_{kt} \times SLR_{izde} + \beta_3 SLR_{izde} \\ &+ \beta_4 Rep\ LO_{kt} + \beta_5 Dem\ LO_{kt} + X_{ijkzdet}\phi + \alpha_{zde} + \alpha_{loan\ char} + \alpha_{borrower\ char} + \alpha_{k,s} + \alpha_{s,t} \\ &+ \alpha_{k,t} + \alpha_t + \epsilon_{ijkzdet}, \end{aligned} \tag{2}$$

where $Mortgage\ Cost_{ijkzdet}$ is the rate spread (interest rate) of mortgage i originated by officer k to borrower j in year t, $Rep\ LO_{kt}$ equals to one if loan officer k is registered as Republican in year t and zero otherwise, $Dem\ LO_{kt}$ equals to one if loan officer k is registered as Democratic in year t and zero otherwise. The other variables are the same as those in Equation (1). Under this specification, the reference group is unaffiliated loan officers. β_1 and β_2 capture the differences in mortgage cost to properties with SLR risk by Republican and Democratic officers, relative to unaffiliated loan officers. To satisfy the identifying assumption, I include loan officer-by-property state fixed effects. This specification absorbs all time-invariant factors at the individual loan officer level while simultaneously controlling for state-specific lending environments that may influence officer behavior. I further use loan officer-by-year fixed effects to control for loan officer characteristics that could impact their loan origination decisions in general. This approach allows me to compare mortgage lending for properties exposed to SLR risk versus those unexposed to SLR risk by the same loan officer in the same year. The standard errors are double clustered at the property Zip code and the loan officer level.

I put the results of estimating Equation (2) in Table 3, with Panel A reporting results for the rate spread and Panel B for the interest rate. Across all columns in panel A, the coefficient estimates on $Rep\,LO \times SLR$ are all insignificant and close to zero. In contrast, the coefficient estimates on $Dem\,LO \times SLR$ are all positive and statistically significant. In columns (1) and (2), I include loan officer-by-property state fixed effects, allowing me to compare mortgages originated by the same loan officers on properties within the same state. The differences between the two estimates are all statistically significant at 5% level, suggesting that Democratic loan officers charge higher rate

spreads to mortgages on properties exposed to SLR risk than Republican loan officers. Specifically, the spread on loans for properties exposed to SLR by Democratic loan officers is about 2.0 basis points higher than those by Republican loan officers. In columns (3)-(4), I include loan officer-by-year fixed effects to control for any potential loan officer characteristics that could affect their overall loan origination decisions in general in each year. The differences in the coefficient estimates remain qualitatively and quantitatively similar.

In panel B, however, I do not find that loan officers' political affiliation influences the pricing of SLR risk in mortgage interest rates. This is not surprising. In the U.S., GSEs determine credit-risk pricing adjustments through a fee structure based solely on loan-to-value (LTV) ratios and credit scores (Bartlett et al. 2022). Therefore, there is very little discretion for loan officers to adjust mortgage interest rates. Instead, the rate spread is a measure of the overall mortgage cost that incorporates non-interest cost, such as origination fees and points. Thus, loan officers have relatively more discretion on it.

5 Exploring heterogeneity in partisan sorting

To better understand the mechanisms through which officer partisanship influences the pricing of SLR risk in residential mortgages, I examine the heterogeneity in this relationship.

5.1 Flood insurance

The National Flood Insurance Reform Act of 1994 requires that U.S. mortgage borrowers buy flood insurance if the mortgaged property is located in a Special Flood Hazard Area (SFHA). The collateral value of mortgages on properties in SFHAs is protected against flood risk, whereas mortgages on properties outside SFHAs remain exposed to flood risk. Thus, it is interesting to examine whether the presence of mandated flood insurance mitigates the extent of partisan sorting in the pricing of SLR risk. If partisan heterogeneity in SLR risk pricing is primarily driven by officers' subjective assessments, I would expect it to be more pronounced outside SFHAs. I divide the sample based on whether the property is inside FEMA's identified flood zones and re-estimate the regression specified in Equation (2) separately for each group.

The results are presented in Table 4. In column (1) and (2), for mortgages on properties

located outside FEMA-identified flood zones, the difference between the coefficient estimates on $Dem\ LO \times SLR$ and $Rep\ LO \times SLR$ is positive and statistically significant. In contrast, in column (3) and (4), for mortgages on properties located inside FEMA-identified flood zones, the difference between the coefficient estimates is much smaller and statistically insignificant. These findings indicate that partisan differences in SLR risk pricing are more evident when flood risk is not covered by insurance, suggesting a greater reliance on individual beliefs in such contexts. In contrast, when flood risk is explicitly insured, the influence of officer partisanship on pricing is less pronounced. The results suggest that insurance requirements partially substitute for individual-level climate risk perception in shaping mortgage pricing.

5.2 Loan officers' experience of coastal climate risk

Next, I examine whether loan officers' own exposure to coastal climate risks affects the partisan gap in mortgage pricing of SLR risk. SLR risk is a long-run risk of rising oceans eventually inundating coastal properties. Although SLR is a slow-moving threat, individuals may internalize its significance through direct experience with coastal climate-related events. Intuitively, a loan officer located near the coast is more likely to have firsthand experience with coastal flooding, tidal surges, and other tangible signs of rising seas. Such personal exposure can make the long-term risk of SLR more concrete and salient. If individuals interpret such climate-related experience through a partisan lens, Democrats and Republicans may respond very differently. Democrats could respond by elevating the price of climate risk, but Republicans may still largely ignore or downplay it, making the partisan gap in pricing more pronounced there. In fact, Bernstein et al. (2022) find that Republicans are more likely than Democrats to own homes exposed to SLR risk. Conversely, farther inland, sea-level rise is a more abstract and distant concern. As a result, neither group may actively incorporates it into mortgage pricing. If that is the case, the partisan gap in the pricing of SLR risk may be reflected in officers near the coast only. I use the loan officers' home (work) distance to the coast as the measure of loan officers' personal experience of coastal climate risk and then split the sample based on whether their distance to the coast falls above or below the median.

I then re-estimate Equation (2) for more experienced and less experienced loan officers separately. I put the results in Table 5. Panel A is based on loan officers' residential distance to the coast. In column (1) and (2), for officers' live closer to the coast, the difference between the coeffi-

cient estimates on *Dem LO* × *SLR* and *Rep LO* × *SLR* is positive and statistically significant. In contrast, in column (3) and (4), for loan officers live farther from the coast, the difference between the coefficient estimates is much smaller and statistically insignificant. These findings suggest that direct experience with climate-related threats amplifies political disparities in risk perception and decision-making in mortgage lending. In panel B, I find similar results based on loan officers' work distance to the coast.

5.3 Local climate change beliefs

Finally, I examine how local community beliefs regarding climate change risk affect the relationship between officer partisanship and the pricing of SLR risk. Prior studies have shown evidence that local climate change beliefs affect how climate change risk is priced in real estate and mortgage markets (e.g., Bernstein et al. 2019, Baldauf et al. 2020, Nguyen et al. 2022). Whether local climate change beliefs exacerbate or mitigate the partisan disparity in pricing SLR risk is worth examining. I use data from the Yale Climate Opinion Maps, which provide county-level measures of public perceptions about climate change. Specifically, I construct my measure of local climate change belief using county-level responses to the survey item "Do you think that global warming is happening?" from the Yale Climate Opinion Maps. I merge the mortgage data with the Yale Climate Opinions map data from 2018 to 2022 based on loan officers' home and work addresses. I divide the sample into two groups based on the sample median and re-estimate the regression specified in Equation (2) separately for each group.

I present the results in Table 6. Based on loan officers' home address, in column (1) and (2) of panel A, for officers' live in communities with relatively low climate change belief, the difference between the coefficient estimates on *Dem LO*×*SLR* and *Rep LO*×*SLR* is positive and statistically significant. In contrast, in column (3) and (4), for loan officers live in areas with stronger local climate concern, the difference between the coefficient estimates is much smaller and statistically insignificant. In panel B, I find similar results using loan officers' work addresses. Geographic areas with stronger local beliefs in climate change exhibit a higher concentration of Democratic voters, whereas regions with weaker climate change convictions are predominantly Republican. Pew Research Center finds Republicans face greater internal divisions over climate change than do Democrats. Republicans in Democratic-leaning, high-belief communities are more likely to be

economically conservative and accept climate science, whereas those in Republican-dominated, low-belief communities tend to be socially conservative and skeptical of climate change. Therefore, a Republican loan officer in a high climate-belief area may also internalize SLR risk in loan pricing - unlike their counterparts in skeptical regions where SLR risk is usually ignored. Furthermore, it could also be that Republicans are more responsive than Democrats to social cues from their local partisan environment, as documented in other contexts such as prosocial behaviors during COVID-19 (Baxter-King et al. 2022). Republican loan officers' climate risk pricing is more sensitive to the prevailing beliefs in their local communities.

6 Conclusion

Using voter registration data of loan officers originating residential mortgages in coastal areas, I analyze whether climate change partisanship is reflected in mortgage lending. I find that Democratic loan officers charge higher loan spreads for mortgages on properties exposed to sea level rise (SLR) than Republican loan officers. The results hold after controlling for loan officer fixed factors. Partisan sorting is more pronounced for properties outside FEMA-designated flood zones, and for loan officers located nearer the coast or in communities with fewer climate change believers. These findings highlight how political ideology shapes the pricing of climate risks in mortgages.

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Table 1: Summary statistics of main variables

This table presents the summary statistics of the samples, with Panel A for the CoreLogic-HMDA matched sample and Panel B for the CoreLogic-HMDA-L2 matched sample. *Interest Rate* is the mortgage interest rate in percentage points; *Rate Spread* is the difference between mortgage APR and the average prime offering rate in percentage points; SLR is a dummy variable that equals one if the property will experience chronic tidal flooding with up to 6 feet global average SLR and zero otherwise; $Conforming$ is a dummy variable that equals one if the loan is sold to a GSE ; *Co Aplicant* is a dummy variable that equals one if the loan has a co-applicant; *Property Age* is the age of the house; $Age > 62$ is a dummy variable that equals one if the age of the borrower is over 62; $Mortgage\,Amount$ is the loan amount; $CLTV$ is the combined loan-to-income ratio; and $Minority$ is a dummy variable that equals one if the borrower is African American or Hispanic and zero otherwise.

Panel A: CoreLogic-HMDA matched sample

	N	Mean	SD	25th Perc.	Median	75th Perc.
Interest Rate	740,279	3.668	0.901	2.990	3.375	4.250
Rate Spread	708,577	0.210	0.441	-0.062	0.155	0.413
SLR	741,167	0.131	0.337	0	0	0
Conforming	741,167	0.885	0.319	1	1	1
Co Applicant	741,167	0.603	0.489	0	1	1
Property Age	678,277	52.023	30.532	28	50	70
Age > 62	740,633	0.199	0.400	0	0	0
Minority	740,930	0.090	0.286	0	0	0
CLTV	735,616	69.616	96.001	57.721	74.400	80.000
Mortgage Amount	741,167	450,544	391,835	245,000	366,700	537,200

Panel B: CoreLogic-HMDA-L2 matched sample

	N	Mean	SD	25th Perc.	Median	75th Perc.
Interest Rate	240,719	3.680	0.902	2.990	3.375	4.250
Rate Spread	230,899	0.228	0.433	-0.042	0.172	0.429
SLR	241,090	0.127	0.333	0	0	0
Republican	241,090	0.415	0.493	0	0	1
Democratic	241,090	0.292	0.455	0	0	1
Conforming	241,090	0.894	0.308	1	1	1
Co Applicant	241,090	0.604	0.489	0	1	1
Property Age	222,746	50.546	30.476	26	48	69
Age > 62	240,912	0.198	0.398	0	0	0
Minority	241,006	0.085	0.279	0	0	0
CLTV	239,678	70.305	18.865	58.659	75.000	80.000
Mortgage Amount	241,090	436,995	393,726	239,700	356,952	517,500

Table 2: SLR risk and mortgage cost

This table reports the results of estimating Equation (1). The dependent variable in Panel A is *Rate Spread* and the dependent variable in Panel B is *Interest Rate*. *Rate Spread* is the difference between mortgage APR and the average prime offering rate in percentage points. *Interest Rate* is the mortgage interest rate in percentage points. *SLR* is a dummy variable that equals one if the property will experience chronic tidal flooding with up to 6 feet global average SLR and zero otherwise. *DTI* is the debt-to-income ratio categorized as follows: $< 20\%$, 20%–30%, 30%–36%, 36%–40%, 40%–46%, 46%–50%, 50%–60%, and $> 60\%$. *LTV* is the combined loan-to-value ratio categorized as follows: $\leq 60\%$, $60\% - 70\%$, $70\% - 75\%$, $75\% - 80\%$, $80\% - 85\%$, $85\% - 90\%$, $90\% - 95\%$, and $> 95\%$. The definitions of other variables are in the note to Table 1. Standard errors double clustered by property zip and loan officer are reported in parentheses below the coefficient estimates. The significance at the levels of 1%, 5%, and 10% is indicated by ***, **, and *, respectively.

Panel A: Rate spread

	(1)	(2)	(3)	(4)	(5)	(6)
SLR	0.001	0.001	0.001	0.001	-0.001	-0.001
	(0.005)	(0.005)	(0.005)	(0.005)	(0.004)	(0.004)
Log Loan Amount	-0.171***	-0.173***	-0.171***	-0.172***	-0.170***	-0.172***
	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)
Conforming	0.014***	0.017***	0.014***	0.017***	-0.029***	-0.032***
	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)
Co Applicant	0.018***	0.018***	0.018***	0.019***	0.024***	0.024***
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
Property Age	0.001***	0.001***	0.001***	0.001***	0.000***	0.000***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Age > 62	-0.008***	-0.009***	-0.009***	-0.011***	-0.005***	-0.004***
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
Minority	0.060***	0.060***	0.072***	0.074***	0.049***	0.049***
	(0.003)	(0.003)	(0.020)	(0.020)	(0.019)	(0.019)
Observations	621,106	621,106	621,077	621,077	620,812	620,812
R-squared	0.342	0.351	0.343	0.352	0.431	0.434
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Zip-Dist-Elev FE	Yes	Yes	Yes	Yes	Yes	Yes
DTI FE	Yes	Yes	Yes	Yes	Yes	Yes
Loan Purpose FE	Yes	Yes	Yes	Yes	Yes	Yes
LTV-Year FE	Yes		Yes		Yes	Yes
LTV-Year-Month FE		Yes		Yes		
Borrower Race FE			Yes	Yes	Yes	Yes
Borrower Ethnicity FE			Yes	Yes	Yes	Yes
Lender FE					Yes	Yes
State-Year FE						Yes

Panel B: Interest rate

	(1)	(2)	(3)	(4)	(5)	(6)
SLR	-0.006	-0.001	-0.006	-0.001	-0.008	-0.008
	(0.007)	(0.005)	(0.007)	(0.005)	(0.006)	(0.006)
Log Loan Amount	-0.142***	-0.128***	-0.142***	-0.128***	-0.142***	-0.144***
	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)
Conforming	0.003	0.040***	0.003	0.040***	-0.028***	-0.030***
	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)
Co Applicant	0.018***	0.015***	0.019***	0.015***	0.025***	0.025***
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
Property Age	0.001***	0.001***	0.001***	0.001***	0.001***	0.001***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Age $>$ 62	-0.025***	-0.018***	-0.026***	-0.019***	-0.021***	-0.020***
	(0.003)	(0.002)	(0.003)	(0.002)	(0.002)	(0.002)
Minority	0.061***	0.054***	0.074***	0.075***	0.049**	0.047**
	(0.004)	(0.003)	(0.024)	(0.019)	(0.023)	(0.023)
Observations	648,432	648,432	648,403	648,403	648,140	648,140
R-squared	0.651	0.823	0.651	0.823	0.674	0.676
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Zip-Dist-Elev FE	Yes	Yes	Yes	Yes	Yes	Yes
DTI FE	Yes	Yes	Yes	Yes	Yes	Yes
Loan Purpose FE	Yes	Yes	Yes	Yes	Yes	Yes
LTV-Year FE	Yes		Yes		Yes	Yes
LTV-Year-Month FE		Yes		Yes		
Borrower Race FE			Yes	Yes	Yes	Yes
Borrower Ethnicity FE			Yes	Yes	Yes	Yes
Lender FE					Yes	Yes
State-Year FE						Yes

Table 3: Loan officer political affiliation and the pricing of SLR risk

This table reports the results of estimating Equation (2). The dependent variable in Panel A is *Rate Spread* and the dependent variable in Panel B is *Interest Rate*. *Rate Spread* is the difference between mortgage APR and the average prime offering rate in percentage points. *Interest Rate* is the mortgage interest rate in percentage points. *SLR* is a dummy variable that equals one if the property will experience chronic tidal flooding with up to 6 feet global average SLR and zero otherwise. *Rep LO* is a dummy variable that equals one if the loan officer is registered as Republican in the year and zero otherwise. *Dem LO* is a dummy variable that equals one if the loan officer is registered as Democratic in the year and zero otherwise. *DTI* is the debt-to-income ratio categorized as follows: $< 20\%$, 20%–30%, 30%–36%, 36%–40%, 40%–46%, 46%–50%, 50%–60%, and $> 60\%$. *LTV* is the combined loan-to-value ratio categorized as follows: $\leq 60\%$, $60\% - 70\%$, $70\% - 75\%$, $75\% - 80\%$, $80\% - 85\%$, $85\% - 90\%$, $90\% - 95\%$, and $> 95\%$. The definitions of other variables are in the note to Table 1. Standard errors double clustered by property zip and loan officer are reported in parentheses below the coefficient estimates. The significance at the levels of 1%, 5%, and 10% is indicated by ***, **, and *, respectively.

Panel A: Rate spread

	(1)	(2)	(3)	(4)
Rep LO $\times SLR$	-0.002	-0.002	0.008	0.008
	(0.008)	(0.008)	(0.009)	(0.009)
Dem LO $\times SLR$	0.020*	0.021**	0.028**	0.028**
	(0.010)	(0.010)	(0.011)	(0.012)
SLR	-0.006	-0.003	-0.009	-0.008
	(0.010)	(0.010)	(0.011)	(0.011)
Rep LO	-0.000	0.004		
	(0.052)	(0.052)		
Dem LO	0.031	0.032		
	(0.053)	(0.053)		
Minority $\times Rep\,LO$	-0.009	-0.009	-0.029**	-0.028**
	(0.011)	(0.011)	(0.013)	(0.013)
Minority $\times Dem\,LO$	-0.008	-0.009	-0.014	-0.014
	(0.012)	(0.012)	(0.014)	(0.014)
Log Loan Amount	-0.152***	-0.152***	-0.146***	-0.146***
	(0.006)	(0.006)	(0.006)	(0.006)
Conforming	-0.031***	-0.031***	-0.033***	-0.033***
	(0.007)	(0.007)	(0.007)	(0.007)
Co Applicant	0.027***	0.027***	0.025***	0.025***
	(0.003)	(0.003)	(0.003)	(0.003)
Property Age	0.000***	0.000***	0.000***	0.000***
	(0.000)	(0.000)	(0.000)	(0.000)
Age > 62	-0.010***	-0.011***	-0.006*	-0.006*
	(0.003)	(0.003)	(0.004)	(0.004)
Minority	0.085**	0.085**	0.072*	0.072*
	(0.038)	(0.038)	(0.041)	(0.041)
Dem LO$\times SLR - Rep\,LO \times SLR$	0.022**	0.023**	0.020**	0.020**
	(0.009)	(0.009)	(0.010)	(0.010)
Observations	163,009	162,328	144,960	144,960
R-squared	0.606	0.606	0.684	0.684
Year FE	Yes	Yes	Yes	Yes
Zip-Dist-Elev FE	Yes	Yes	Yes	Yes
DTI FE	Yes	Yes	Yes	Yes
Loan Purpose FE	Yes	Yes	Yes	Yes
Borrower Race FE	Yes	Yes	Yes	Yes
Borrower Ethnicity FE	Yes	Yes	Yes	Yes
LTV-Year FE	Yes	Yes	Yes	Yes
Officer-State FE	Yes	Yes	Yes	Yes
Lender FE	Yes	Yes	Yes	Yes
SFHA FE		Yes	Yes	Yes
Officer-Year FE			Yes	Yes
State-Year FE				Yes

Panel B: Interest rate

	(1)	(2)	(3)	(4)
Rep LO $\times SLR$	0.010	0.009	0.023	0.023
	(0.013)	(0.013)	(0.015)	(0.015)
Dem LO $\times SLR$	0.021	0.021	0.017	0.017
	(0.015)	(0.015)	(0.017)	(0.017)
SLR	-0.026*	-0.026	-0.028*	-0.027
	(0.016)	(0.016)	(0.017)	(0.017)
Rep LO	0.029	0.038		
	(0.081)	(0.082)		
Dem LO	-0.016	-0.012		
	(0.086)	(0.086)		
Minority $\times Rep\,LO$	-0.014	-0.014	-0.027	-0.027
	(0.018)	(0.018)	(0.019)	(0.019)
Minority $\times Dem\,LO$	-0.019	-0.019	-0.018	-0.017
	(0.020)	(0.020)	(0.022)	(0.022)
Log Loan Amount	-0.136***	-0.136***	-0.130***	-0.130***
	(0.007)	(0.007)	(0.008)	(0.008)
Conforming	-0.038***	-0.038***	-0.044***	-0.044***
	(0.009)	(0.009)	(0.009)	(0.009)
Co Applicant	0.034***	0.034***	0.031***	0.032***
	(0.004)	(0.004)	(0.004)	(0.004)
Property Age	0.000***	0.000***	0.000***	0.000***
	(0.000)	(0.000)	(0.000)	(0.000)
Age > 62	-0.021***	-0.022***	-0.016***	-0.016***
	(0.005)	(0.005)	(0.005)	(0.005)
Minority	0.023	0.023	0.100*	0.100*
	(0.057)	(0.057)	(0.054)	(0.054)
Dem LO$\times SLR - Rep\,LO \times SLR$	0.011	0.012	-0.006	-0.006
	(0.013)	(0.013)	(0.014)	(0.014)
Observations	171,008	170,316	152,607	152,607
R-squared	0.774	0.774	0.822	0.822
Year FE	Yes	Yes	Yes	Yes
Zip-Dist-Elev FE	Yes	Yes	Yes	Yes
DTI FE	Yes	Yes	Yes	Yes
Loan Purpose FE	Yes	Yes	Yes	Yes
Borrower Race FE	Yes	Yes	Yes	Yes
Borrower Ethnicity FE	Yes	Yes	Yes	Yes
LTV-Year FE	Yes	Yes	Yes	Yes
Officer-State FE	Yes	Yes	Yes	Yes
Lender FE	Yes	Yes	Yes	Yes
SFHA FE		Yes	Yes	Yes
Officer-Year FE			Yes	Yes
State-Year FE				Yes

Table 4: Loan officer political affiliation, SLR risk, and flood insurance

This table presents the results on how required flood insurance influences the relationship of political affiliation and the pricing of SLR risk. I divide the sample based on whether the property is inside FEMA's identified flood zones. The dependent variable is $Rate\,Spread$, the difference between mortgage APR and the average prime offering rate in percentage points. SLR is a dummy variable that equals one if the property will experience chronic tidal flooding with up to 6 feet global average SLR and zero otherwise. $Rep\,LO$ is a dummy variable that equals one if the loan officer is registered as Republican in the year and zero otherwise. $Dem\,LO$ is a dummy variable that equals one if the loan officer is registered as Democratic in the year and zero otherwise. DTI is the debt-to-income ratio categorized as follows: $< 20\%$, 20%–30%, 30%–36%, 36%–40%, 40%–46%, 46%–50%, 50%–60%, and $> 60\%$. LTV is the combined loan-to-value ratio categorized as follows: $\leq 60\%$, $60\%-70\%$, $70\%-75\%$, $75\%-80\%$, $80\%-85\%$, $85\%-90\%$, $90\%-95\%$, and $> 95\%$. The definitions of other variables are in the note to Table 1. Standard errors double clustered by property zip and loan officer are reported in parentheses below the coefficient estimates. The significance at the levels of 1%, 5%, and 10% is indicated by ***, **, and *, respectively.

	Mandatory flood insurance			
	No		Yes	
	(1)	(2)	(3)	(4)
Rep LO $\times SLR$	-0.008	0.007	0.020	0.031
	(0.017)	(0.019)	(0.018)	(0.025)
Dem LO $\times SLR$	0.033	0.054**	0.024	0.015
	(0.022)	(0.027)	(0.025)	(0.029)
SLR	0.008	-0.004	-0.014	0.002
	(0.017)	(0.018)	(0.019)	(0.024)
Rep LO	0.029		-0.033	
	(0.051)		(0.147)	
Dem LO	0.022		-0.066	
	(0.055)		(0.101)	
Minority $\times Rep\,LO$	-0.009	-0.023	-0.021	-0.061*
	(0.013)	(0.015)	(0.029)	(0.033)
Minority $\times Dem\,LO$	-0.012	-0.018	0.049	0.044
	(0.014)	(0.015)	(0.037)	(0.041)
Log Loan Amount	-0.149***	-0.138***	-0.146***	-0.141***
	(0.007)	(0.008)	(0.010)	(0.012)
Conforming	-0.016**	-0.019**	-0.056***	-0.061***
	(0.007)	(0.008)	(0.014)	(0.016)
Co Applicant	0.030***	0.027***	0.013*	0.010
	(0.003)	(0.003)	(0.007)	(0.008)
Property Age	0.000***	0.000***	0.001***	0.001***
	(0.000)	(0.000)	(0.000)	(0.000)
Age > 62	-0.008**	-0.003	-0.008	-0.022**
	(0.004)	(0.004)	(0.009)	(0.009)
Minority	0.093**	0.069	-0.062	0.046
	(0.043)	(0.047)	(0.097)	(0.154)
Dem LO$\times SLR - Rep\,LO \times SLR$	0.041*	0.046*	0.004	-0.015
	(0.021)	(0.025)	(0.022)	(0.027)
Observations	133,301	117,488	20,288	14,354
R-squared	0.622	0.699	0.631	0.722
Year FE	Yes	Yes	Yes	Yes
Zip-Dist-Elev FE	Yes	Yes	Yes	Yes
DTI FE	Yes	Yes	Yes	Yes
Loan Purpose FE	Yes	Yes	Yes	Yes
Borrower Race FE	Yes	Yes	Yes	Yes
Borrower Ethnicity FE	Yes	Yes	Yes	Yes
LTV-Year FE	Yes	Yes	Yes	Yes
Officer-State FE	Yes	Yes	Yes	Yes
Lender FE	Yes	Yes	Yes	Yes
Officer-Year FE		Yes		Yes
State-Year FE		Yes		Yes

Table 5: Loan officer political affiliation, SLR risk, and personal experience of coastal climate risk This table presents the results on how the loan officer's personal experience of coastal climate risk influences the relationship of political affiliation and the pricing of SLR risk. To measure loan officers' distance to the coast, Panel A uses officers' home address, and Panel B uses officers' work address. I divide the sample based on whether officers' distance to the coast falls above or below the median. The dependent variable is *Rate Spread*, the difference between mortgage APR and the average prime offering rate in percentage points. SLR is a dummy variable that equals one if the property will experience chronic tidal flooding with up to 6 feet global average SLR and zero otherwise. *Rep LO* is a dummy variable that equals one if the loan officer is registered as Republican in the year and zero otherwise. *Dem LO* is a dummy variable that equals one if the loan officer is registered as Democratic in the year and zero otherwise. DTI is the debt-to-income ratio categorized as follows: $< 20\%$, 20%–30%, 30%–36%, 36%–40%, 40%–46%, 46%–50%, 50%–60%, and $> 60\%$. LTV is the combined loan-to-value ratio categorized as follows: $\leq 60\%$, $60\% - 70\%$, $70\% - 75\%$, $75\% - 80\%$, $80\% - 85\%$, $85\% - 90\%$, $90\% - 95\%$, and $> 95\%$. The definitions of other variables are in the note to Table 1. Standard errors double clustered by property zip and loan officer are reported in parentheses below the coefficient estimates. The significance at the levels of 1%, 5%, and 10% is indicated by ***, **, and *, respectively.

Panel A: Based on Officer's Home Address

	Officer's Proximity to Coast			
	Near		Far	
	(1)	(2)	(3)	(4)
Rep LO $\times SLR$	0.007	0.016	-0.014	-0.005
	(0.014)	(0.014)	(0.016)	(0.017)
Dem LO $\times SLR$	0.043**	0.047**	-0.000	0.008
	(0.017)	(0.018)	(0.016)	(0.019)
SLR	-0.008	-0.013	0.001	0.010
	(0.016)	(0.016)	(0.018)	(0.021)
Rep LO	0.287***		0.063	
	(0.097)		(0.104)	
Dem LO	0.453		0.042	
	(0.317)		(0.096)	
Minority $\times Rep\,LO$	-0.019	-0.030	0.014	-0.011
	(0.017)	(0.018)	(0.020)	(0.024)
Minority $\times Dem\,LO$	0.004	-0.004	-0.008	-0.010
	(0.018)	(0.019)	(0.021)	(0.027)
Log Loan Amount	-0.140***	-0.137***	-0.173***	-0.165***
	(0.008)	(0.008)	(0.008)	(0.010)
Conforming	-0.028***	-0.031***	-0.039***	-0.047***
	(0.008)	(0.009)	(0.012)	(0.013)
Co Applicant	0.026***	0.024***	0.030***	0.028***
	(0.004)	(0.004)	(0.005)	(0.005)
Property Age	0.000***	0.000***	0.000***	0.000***
	(0.000)	(0.000)	(0.000)	(0.000)
Age > 62	-0.007	-0.007	-0.016***	-0.008
	(0.005)	(0.005)	(0.006)	(0.007)
Minority	0.125**	0.107*	0.085	0.054
	(0.059)	(0.063)	(0.061)	(0.057)
Dem LO$\times SLR - Rep\,LO \times SLR$	0.035**	0.031**	0.014	0.012
	(0.014)	(0.015)	(0.015)	(0.018)
Observations	83,466	78,308	62,765	49,506
R-squared	0.602	0.675	0.696	0.778
Year FE	Yes	Yes	Yes	Yes
Zip-Dist-Elev FE	Yes	Yes	Yes	Yes
DTI FE	Yes	Yes	Yes	Yes
Loan Purpose FE	Yes	Yes	Yes	Yes
Borrower Race FE	Yes	Yes	Yes	Yes
Borrower Ethnicity FE	Yes	Yes	Yes	Yes
LTV-Year FE	Yes	Yes	Yes	Yes
Officer-State FE	Yes	Yes	Yes	Yes
Lender FE	Yes	Yes	Yes	Yes
SFHA FE	Yes	Yes	Yes	Yes
State-Year FE	Yes	Yes	Yes	Yes
Officer-Year FE		Yes		Yes

Panel B: Based on Officer's Work Address

	Officer's Proximity to Coast			
	Near		Far	
	(1)	(2)	(3)	(4)
Rep LO $\times SLR$	0.003	0.019	0.003	0.020
	(0.013)	(0.013)	(0.015)	(0.018)
Dem LO $\times SLR$	0.036**	0.047***	0.009	0.019
	(0.016)	(0.017)	(0.018)	(0.022)
SLR	-0.008	-0.014	-0.005	-0.004
	(0.016)	(0.016)	(0.018)	(0.021)
Rep LO	0.233***		0.088	
	(0.077)		(0.102)	
Dem LO	0.399		0.073	
	(0.319)		(0.095)	
Minority $\times Rep\,LO$	0.003	-0.011	-0.026	-0.060**
	(0.017)	(0.018)	(0.019)	(0.024)
Minority $\times Dem\,LO$	0.000	0.004	-0.035	-0.046*
	(0.019)	(0.020)	(0.022)	(0.024)
Log Loan Amount	-0.142***	-0.136***	-0.169***	-0.160***
	(0.008)	(0.008)	(0.009)	(0.009)
Conforming	-0.025***	-0.029***	-0.044***	-0.039***
	(0.008)	(0.008)	(0.012)	(0.014)
Co Applicant	0.028***	0.024***	0.026***	0.028***
	(0.004)	(0.004)	(0.005)	(0.006)
Property Age	0.000***	0.000***	0.000***	0.000***
	(0.000)	(0.000)	(0.000)	(0.000)
Age > 62	-0.007	-0.004	-0.018***	-0.011
	(0.005)	(0.005)	(0.006)	(0.007)
Minority	0.114**	0.123**	0.054	0.009
	(0.057)	(0.059)	(0.065)	(0.078)
Dem LO$\times SLR - Rep\,LO \times SLR$	0.033**	0.027*	0.006	-0.001
	(0.014)	(0.014)	(0.015)	(0.018)
Observations	85,626	81,257	60,627	47,080
R-squared	0.603	0.672	0.694	0.777
Year FE	Yes	Yes	Yes	Yes
Zip-Dist-Elev FE	Yes	Yes	Yes	Yes
DTI FE	Yes	Yes	Yes	Yes
Loan Purpose FE	Yes	Yes	Yes	Yes
Borrower Race FE	Yes	Yes	Yes	Yes
Borrower Ethnicity FE	Yes	Yes	Yes	Yes
LTV-Year FE	Yes	Yes	Yes	Yes
Officer-State FE	Yes	Yes	Yes	Yes
Lender FE	Yes	Yes	Yes	Yes
SFHA FE	Yes	Yes	Yes	Yes
State-Year FE	Yes	Yes	Yes	Yes
Officer-Year FE		Yes		Yes

Table 6: Loan officer political affiliation, SLR risk, and local climate change beliefs

This table presents the results on how local climate change beliefs influence the relationship between political affiliation and the pricing of SLR risk. Panel A uses officers' home addresses, and Panel B uses work addresses. The sample is divided based on whether local belief in climate change is above or below the sample median. The dependent variable is *Rate Spread*, the difference between mortgage APR and the average prime offering rate in percentage points. SLR is a dummy variable that equals one if the property will experience chronic tidal flooding with up to 6 feet global average SLR and zero otherwise. *Rep LO* is a dummy variable that equals one if the loan officer is registered as Republican in the year and zero otherwise. *Dem LO* is a dummy variable that equals one if the loan officer is registered as Democratic in the year and zero otherwise. DTI is the debt-to-income ratio categorized as follows: $< 20\%$, 20%–30%, 30%–36%, 36%–40%, 40%–46%, 46%–50%, 50%–60%, and $> 60\%$. LTV is the combined loan-to-value ratio categorized as follows: $\leq 60\%$, $60\%-70\%$, $70\%-75\%$, $75\%-80\%$, $80\%-85\%$, $85\%-90\%$, $90\%-95\%$, and $> 95\%$. The definitions of other variables are in the note to Table 1. Standard errors double clustered by property zip and loan officer are reported in parentheses below the coefficient estimates. The significance at the levels of 1%, 5%, and 10% is indicated by ***, **, and *, respectively.

Panel A: Based on Officer's Home Address

	Local Climate Change Belief			
	Low		High	
	(1)	(2)	(3)	(4)
Rep LO $\times SLR$	-0.011	-0.007	0.004	0.018
	(0.011)	(0.013)	(0.016)	(0.017)
Dem LO $\times SLR$	0.023	0.022	0.014	0.036*
	(0.014)	(0.016)	(0.019)	(0.020)
SLR	0.004	0.004	-0.007	-0.015
	(0.014)	(0.016)	(0.020)	(0.021)
Rep LO	-0.011		0.153	
	(0.062)		(0.284)	
Dem LO	-0.017		0.274	
	(0.088)		(0.282)	
Minority $\times Rep\,LO$	-0.010	-0.030	-0.029*	-0.049**
	(0.019)	(0.021)	(0.018)	(0.019)
Minority $\times Dem\,LO$	-0.012	-0.017	0.005	-0.005
	(0.022)	(0.026)	(0.017)	(0.019)
Log Loan Amount	-0.194***	-0.186***	-0.104***	-0.096***
	(0.007)	(0.008)	(0.008)	(0.009)
Conforming	-0.068***	-0.067***	-0.003	-0.006
	(0.011)	(0.012)	(0.009)	(0.009)
Co Applicant	0.035***	0.033***	0.017***	0.016***
	(0.004)	(0.005)	(0.004)	(0.004)
Property Age	0.001***	0.001***	0.000***	0.000***
	(0.000)	(0.000)	(0.000)	(0.000)
Age > 62	-0.020***	-0.014***	0.002	0.005
	(0.005)	(0.005)	(0.006)	(0.006)
Minority	0.149*	0.104	0.036	0.044
	(0.082)	(0.088)	(0.049)	(0.054)
Dem LO$\times SLR - Rep\,LO \times SLR$	0.034***	0.030**	0.010	0.018
	(0.012)	(0.014)	(0.017)	(0.019)
Observations	70,259	61,584	72,325	65,105
R-squared	0.629	0.693	0.636	0.702
Year FE	Yes	Yes	Yes	Yes
Zip-Dist-Elev FE	Yes	Yes	Yes	Yes
DTI FE	Yes	Yes	Yes	Yes
Loan Purpose FE	Yes	Yes	Yes	Yes
Borrower Race FE	Yes	Yes	Yes	Yes
Borrower Ethnicity FE	Yes	Yes	Yes	Yes
LTV-Year FE	Yes	Yes	Yes	Yes
Officer-State FE	Yes	Yes	Yes	Yes
Lender FE	Yes	Yes	Yes	Yes
SFHA FE	Yes	Yes	Yes	Yes
State-Year FE	Yes	Yes	Yes	Yes
Officer-Year FE		Yes		Yes

Panel B: Based on Officer's Work Address

	Local Climate Change Belief			
	Low		High	
	(1)	(2)	(3)	(4)
Rep LO $\times SLR$	-0.012	-0.006	0.004	0.019
	(0.011)	(0.013)	(0.016)	(0.017)
Dem LO $\times SLR$	0.023	0.022	0.014	0.036*
	(0.014)	(0.016)	(0.019)	(0.020)
SLR	0.005	0.005	-0.008	-0.014
	(0.015)	(0.016)	(0.020)	(0.021)
Rep LO	-0.016		0.150	
	(0.063)		(0.284)	
Dem LO	-0.029		0.270	
	(0.092)		(0.282)	
Minority $\times Rep\,LO$	-0.011	-0.035	-0.029*	-0.049**
	(0.019)	(0.022)	(0.018)	(0.019)
Minority $\times Dem\,LO$	-0.014	-0.022	0.006	-0.005
	(0.023)	(0.027)	(0.017)	(0.019)
Log Loan Amount	-0.195***	-0.186***	-0.103***	-0.095***
	(0.007)	(0.008)	(0.008)	(0.009)
Conforming	-0.068***	-0.067***	-0.003	-0.006
	(0.011)	(0.012)	(0.009)	(0.009)
Co Applicant	0.036***	0.033***	0.016***	0.016***
	(0.004)	(0.005)	(0.004)	(0.004)
Property Age	0.001***	0.001***	0.000***	0.000***
	(0.000)	(0.000)	(0.000)	(0.000)
Age > 62	-0.020***	-0.015***	0.002	0.005
	(0.005)	(0.005)	(0.006)	(0.006)
Minority	0.153*	0.114	0.036	0.043
	(0.081)	(0.086)	(0.049)	(0.054)
Dem LO$\times SLR - Rep\,LO \times SLR$	0.034***	0.028**	0.010	0.017
	(0.013)	(0.014)	(0.017)	(0.019)
Observations	69,346	60,788	72,285	65,064
R-squared	0.629	0.693	0.636	0.702
Year FE	Yes	Yes	Yes	Yes
Zip-Dist-Elev FE	Yes	Yes	Yes	Yes
DTI FE	Yes	Yes	Yes	Yes
Loan Purpose FE	Yes	Yes	Yes	Yes
Borrower Race FE	Yes	Yes	Yes	Yes
Borrower Ethnicity FE	Yes	Yes	Yes	Yes
LTV-Year FE	Yes	Yes	Yes	Yes
Officer-State FE	Yes	Yes	Yes	Yes
Lender FE	Yes	Yes	Yes	Yes
SFHA FE	Yes	Yes	Yes	Yes
State-Year FE	Yes	Yes	Yes	Yes
Officer-Year FE		Yes		Yes