Leveraging the Disagreement on Climate Change: Theory and Evidence

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(Preliminary and incomplete; comments are welcome.
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Abstract

How do climate risks and heterogeneous climate beliefs impact financial markets? We present novel theoretical predictions and empirical evidence from the mortgage market for properties at risk from sea level rise (SLR). We first develop a competitive search model of defaultable debt contracts with heterogeneous beliefs over future SLR, where property price, loan amount, repayment, and maturity are endogenous. Unlike existing two-period heterogeneous beliefs models, our infinite-horizon model allows for heterogeneity in maturity choices. In equilibrium, climate pessimists are *more* likely to leverage and to use *longer* maturity debt relative to optimists, trading their climate risk exposure to banks via long-term defaultable debt contracts. An expansionary monetary policy can induce more leverage by pessimists and make the mortgage market more vulnerable to climate change. We test several of the model implications using a propriety comprehensive data set of single-family home sales and associated mortgage contracts across the U.S. Atlantic Coast from 2001 to 2016. In line with our theory, we find that purchases of houses more exposed to SLR risk are *more* likely to be leveraged and tend to use mortgage contracts with *longer* maturity, despite *lower* property prices. These results are driven by buyers from counties with more pessimistic climate beliefs, who are more likely aware of future climate risks. Our results highlight

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the importance of heterogeneous climate beliefs in understanding the effects of climate change on the financial system.

Keywords: climate change, sea level rise, belief disagreement, housing, mortgage, search and matching, monetary policy

1 Introduction

Given the magnitude of potential impacts,[1] understanding how climate change will affect financial markets is of primary importance to researchers, financial regulators, and policymakers around the world.[2] Hence, a rapidly growing climate finance literature has documented the extent to which climate risks affect asset markets, especially the effects of sea level rise (SLR) risks on housing prices (Bernstein et al. 2019; Baldauf et al. 2020; Bakkensen and Barrage 2022). However, much less is known about how climate risks affect debt markets, including the mortgage market, despite the critical role these markets play in the financial system. This is, in part, because understanding how credit markets allocate risks is nontrivial, including the agency problems that naturally arise in borrower-lender relationships (Tirole 1999; Allen and Gale 2000), a complication that is compounded when there is belief disagreement across economic agents about the fundamental values of the collateralized housing asset (Geanakoplos 2010; Simsek 2013; Bailey et al. 2019). In the presence of significantly heterogeneous beliefs about climate change (Howe et al. 2015; Ballew et al. 2019), a common hypothesis is that those who are less concerned about climate risks (the "optimists") are more likely to make a leveraged investment on a property that is exposed to climate risks, relative to those who are more concerned about climate risks (the "pessimists") (e.g., Litterman et al. 2020; Brunetti et al. 2021).[3] Whether this is the case in practice remains an open question of critical relevance to the future stability of financial markets.[4]

In this paper, we provide novel theoretical predictions and empirical evidence on how climate risks affect the mortgage market using the case of coastal inundation risk associated with SLR. We start by developing a novel competitive search model (Moen 1997) of defaultable collateralized loan contracts for properties at risk from SLR. Agents hold heterogeneous beliefs over a climate risk: they agree on the damage from SLR but

[1] For example, as highlighted in the 4th National Climate Assessment (Fleming et al. 2018), more than 40% of Americans live in coastal shoreline counties, which are subject to sea level rise inundation risk.

[2] See, e.g., the recent reports on climate change and financial stability by the NGFS (Network for Greening the Financial System 2019) and the Federal Reserve (Brunetti et al. 2021).

[3] For related arguments of how debt markets could amplify climate shocks via leveraged losses, with lessons from the recent Global Financial Crisis, see Phan (2021).

[4] There is also a practical challenge of data access: high quality propriety mortgage data is generally more difficult to obtain compared to high quality housing price data.

disagree on how soon it will likely happen. Borrowing-homebuyers direct their search for banks approving the loan contracts they want, depending on the borrower's belief of climate change, where property price and contract terms of loan amount, repayment amount, and maturity are endogenous. Importantly, unlike existing two-period heterogeneous beliefs models where maturity is fixed by construction (e.g., Geanakoplos 2010; Fostel and Geanakoplos 2015; Simsek 2013), our infinite-horizon model allows for heterogeneity in mortgage maturity choices. In equilibrium, we find that this matters as our model predicts that climate pessimists are *more* likely to leverage and to use *longer* maturity debt relative to optimists, trading their climate risk exposure to banks via long-term defaultable debt contracts. This finding stands despite the fact that pessimists are buying homes with lower prices due to climate risk exposure. In fact, both pessimists and optimists are satisfied with their respective contracts, as optimists would prefer shorter maturity since they believe SLR will occur later, whereas pessimists prefer a longer maturity to have less equity lost in the near term in case SLR induces them to default. The model also predicts that an expansionary monetary policy can induce more leverage by pessimists and make the mortgage market more vulnerable to climate change.

Next, we provide novel empirical evidence to evaluate our theoretical findings. In particular, we leverage an extensive proprietary database by Corelogic to examine the complete history of single-family home sales across the U.S. Atlantic Coast from 2001 to 2016, including property and sales characteristics and, if utilized, the associated mortgage contracts. Using the property's precise location, we match each property with its projected exposure to coastal inundation under various SLR scenarios, using a state-of-the-art high-resolution SLR mapping tool developed by the National Oceanic and Atmospheric Administration (NOAA) along with other geographic controls. The combination of Corelogic's rich transaction and mortgage data set with NOAA's high-resolution maps allows us to exploit the high levels of spatial variation in exposure to future SLR risk to identify the effects of climate change on the mortgage market. Conditioning on fixed effects for property zip code, distance to coast, elevation, number of bedrooms, year and month of sale, and mortgage lender, our identification strategy is to compare the observable mortgage outcomes for the transactions of two otherwise very similar properties, one exposed and one unexposed to SLR risk. Finally, to understand how belief disagreement affects the SLR-mortgage relationship, we obtain measures of beliefs about climate change from the Yale Climate Opinion Survey (Howe et al. 2015), which provides statistics of how residents in each county respond to various survey questions on their beliefs about global warming.

Our main empirical findings confirm the testable implications of our theoretical model. First, we re-estimate the classic hedonic price regression with our novel dataset.

We find that properties exposed to SLR sell at a discount relative to non-SLR exposed homes, but a rich set of fixed effects is necessary to disentangle the SLR capitalization effect from that of amenity values.

Second, we examine the impact of SLR exposure on mortgage characteristics. We find that a property's exposure to SLR risk is *positively* related with the likelihood that its purchase is leveraged. In particular, the transaction of a property exposed to SLR risk has an approximately 2% higher probability to be associated with a mortgage, indicating more leverage of riskier investments. The magnitude is economically significant: in our data, the rise of leveraged transactions from 2001 (the beginning of our sample) until 2007 (the peak of the housing boom before the 2008 financial crisis), measured by the fraction of property transactions associated with mortgages, was approximately 4%.

Third, we find that belief disagreement is a key moderator of the relationship between climate risk exposure and leverage. The positive correlation between exposure to SLR risk and leverage utilization is almost entirely driven by transactions with buyers from counties with strong climate beliefs. In other words, in contrast with existing logic, we find that buyers who are more likely to be pessimists are more likely to leverage. Among transactions with buyers from counties with above median climate beliefs, properties that are exposed to SLR risk are about 3.4% more likely to be leveraged.

We also find that beliefs matter on the intensive margin of maturity choice, as buyers from locations with more pessimistic climate beliefs are about 2.4% more likely to have a mortgage contract with a long maturity of thirty years. Note that these longer maturity contracts are naturally more exposed to future climate risks than contracts with the shorter maturity of fifteen years. These results are robust to alternative specifications for fixed effects, SLR definitions, and operationalizations of climate beliefs. In contrast with previous notions in the literature and policy circles, these findings affirm the novel conclusions of our theoretical model: among purchases of exposed properties, buyers who are more likely to have pessimistic beliefs about the damaging effects of SLR are more likely to shift their climate risk exposure to banks via long-term defaultable debt contracts.

A question may naturally arise as to why banks are potentially less pessimistic to climate risks in issuing mortgage contracts relative to certain borrowers. Recent work by Ouazad and Kahn (2021) provides evidence on a plausible mechanism, examining how banks can shift climate risks to government-sponsored enterprises (GSE) through securitization and sale of mortgages below the conforming loan limit. This is possible since GSE rules and fees tend to only reflect current official floodplain maps and not necessarily future SLR risks. We find that the leverage and maturity results are almost entirely driven by conforming loans as opposed to nonconforming loans, provid-

ing suggestive and complementary evidence that GSE policy may be facilitating these differential mortgage behaviors.

Our findings have relevant policy implications. Overall, they highlight the nontrivial ways that climate risk and climate beliefs affect the collateralized debt market (whose stability is key for the stability of the financial system, as evident in past financial crises Mian and Sufi 2015). Because of the option to transfer climate risks via the debt market, adaptation to climate change in the financial markets may have nuanced and nontrivial implications for the distribution of climate risks across the financial system. Our theoretical model also predicts that an expansionary monetary policy can induce more leverage by pessimists and inadvertently make the mortgage market more vulnerable to climate change. This is in fact consistent with our final empirical finding: a reduction in the nominal interest rate (as measured by the market yield on Treasury Securities) increases the leverage probability of purchases of exposed properties by buyers from counties with more pessimistic climate beliefs.

Related literature and contributions

To the best of our knowledge, our paper is the first to investigate the effects of the interaction between climate risks and heterogeneous climate beliefs on a collateralized debt market. Our paper is related to, and contributes to, several strands of the literature. First, our paper builds upon the nascent but rapidly growing literature on climate finance, which studies the ways in which climate risks interact with financial markets (for recent surveys of this literature, see Hong et al. 2020; Furukawa et al. 2020; Giglio et al. 2021). By exploiting the well-identified high-resolution spatial variation in the changes in inundation risk due to SLR to identify variation in climate risk exposure, our empirical analysis leverages very recent empirical advances in studying how SLR and increased flood risks affect the housing market (Bernstein et al. 2019; Baldauf et al. 2020; Murfin and Spiegel 2020; Hino and Burke 2021; Keys and Mulder 2020; Addoum et al. 2021; Bakkensen and Barrage 2022) and the municipal bond market (Painter 2020; Goldsmith-Pinkham et al. 2021).[5] Our paper also contributes to a growing but important set of papers investigating how the interaction between climate risks and existing government policies, including on securitization and insurance subsidies, affects the mortgage market (Issler et al. 2020; Liao and Mulder 2021; Ouazad and Kahn 2021; Sastry 2021). Complementary to our paper, the evidence in Liao and Mulder (2021) suggests that mortgage default could act as implicit insurance against climate-related disaster risks.

[5] Also related is an empirical literature that uses hedonic empirical analyses to study how flood risk affects property prices. See Hallstrom and Smith (2005); Bakkensen et al. (2019) and further references in Daniel et al. (2009) and Bakkensen and Barrage (2022).

Our theoretical model is related to the theoretical literature on equilibria with heterogeneous beliefs. In the model, search frictions and heterogeneous beliefs are essential to generate a dispersion of property prices and loan terms as seen in the data. If there is search friction but with homogeneous beliefs, then every borrower will search for the same loan contract, which leads to the same property price as the bargaining outcome. If beliefs are heterogeneous but without search friction, as in Fostel and Geanakoplos (2008, 2015), Geanakoplos (2010), and Simsek (2013), then the centralized market always features only one property price and one loan contract. Furthermore, in Geanakoplos (2010) and Simsek (2013), investors with strong climate beliefs are pessimists who neither borrow nor buy a house; in the equilibrium, only the climate deniers make the leverage home purchases. These results cannot fully explain the empirical finding we document.

Outside of the climate finance and economics literature, our paper is also related to Bailey et al. (2019), which develops a model of mortgage leverage choice with heterogeneous beliefs of future house prices. They find the model's predictions are consistent with the heterogeneous beliefs identified by their Facebook data. Our model design is different from Bailey et al. (2019) in order to explain the empirically-observed variation in property price, mortgage usage, and maturity. In particular, our model features bargaining, search frictions, and continuous time. Unlike any two-period model, continuous time allows agents to have heterogeneous beliefs on the likely arrival time of climate change. In addition, continuous time does not impose any restriction on the loan maturity nor the borrowers' timing to default. Moreover, the probability of mortgage usage is endogenous in our model due to search frictions. Lastly, we model property prices as the endogenous outcome of bargaining between borrowers of heterogeneous beliefs.

Our paper is related to the housing market search literature (Ngai and Tenreyro 2014; Head et al. 2014; Landvoigt et al. 2015; Garriga and Hedlund 2020). Unique to our setting, we incorporate climate risk and the associated heterogeneous belief in a competitive search model, which generates a dispersion of mortgage usage as well as prices and leverage as seen in the data. See Wright et al. (2021) for a survey of competitive search models and their applications.

Finally, our paper is also related to the growing theoretical and empirical literature on climate adaptation (e.g., for recent theoretical developments, see Desmet et al. 2021; Alvarez and Rossi-Hansberg 2021; Fried 2021; for empirical papers, see Hsiang and Narita 2012; Mendelsohn et al. 2012; Deschênes and Greenstone 2011; Annan and Schlenker 2015; Barreca et al. 2016; Bakkensen and Mendelsohn 2016), which mainly focuses on physical adaptation strategies, such as migration away from areas exposed to SLR, building houses on stilts, using more resilient crops, etc. However, our analysis shows that adaption strategies in the financial markets, which involve trading

of risky assets using incomplete contracts in markets that are known to be subject to agency problems (e.g., Tirole 1999; Allen and Gale 2000; Dubey and Geanakoplos 2002; Geanakoplos 2010; Bengui and Phan 2018), may have more nuanced implications due to the strategic transfers of climate risks (from certain borrowers to banks, as our evidence suggests, and from banks to GSEs, as the evidence in Ouazad and Kahn 2021 suggest).

The paper is organized as follows. Section 2 provides a theoretical model to help motivate the empirical analysis. Section 3 lays out the empirical framework and describes the data. Section 4 describes our empirical results. Section 5 provides robustness checks. Section 6 concludes.

2 Stylized model

To fix ideas, we develop a competitive search (partial equilibrium) model of defaultable mortgage debt contracts. The two key assumptions, which are particularly relevant to the context of mortgage markets under climate risks, are that the housing asset is exposed to the risk of a future disaster, and that investors disagree about the disaster's probability. Property prices, the probability of leverage, the loan amount, the repayment amount, and maturity will be endogenous. The preferences of a homebuyer are

$$-(1+\rho)(P-B)+\mathbb{E}\left\{\int_0^\tau re^{-rt}(H_t-m_t)\,dt+e^{-r\tau}\left[-F+\max(p_\tau-b_\tau,0)\right]\right\},$$

where P is the price of the house that delivers a use value H_t. Making a down payment is costly to homebuyers, captured by the funding cost $\rho \geq 0$. The homebuyer can reduce the down payment by borrowing B from a mortgage of maturity T. The mortgage is paid back continuously by payments $m_t = m$ for $t \leq T$ unless he chooses to default at time $\tau < T$, where he pays a default cost F to foreclose his house to some local liquidators for the fundamental price p_τ in order to settle the remaining mortgage balances b_τ, which leaves him the excess proceeds $\max(p_\tau - b_\tau, 0)$, if any. The remaining balances are given by $b_\tau = \int_\tau^T re^{-r(t-\tau)}mdt$. A homebuyer who never defaults chooses $\tau = \infty$. A homebuyer who does not take out a mortgage contract is captured by $B = m_t = 0$ (and $\tau = \infty$).

Climate risk. There is a climate shock that causes a permanent property damage. Denote t_C as the arrival time of the climate shock. The house's use value is normalized to $H_t = 1$ for $t < t_C$ and $H_t = 1 - D$ for $t \geq t_C$, where D measures the exposure to the climate damage. The arrival time t_C of the climate shock is uncertain. In our context, we can think of t_C as the time that SLR will be sufficient to cause permanent

inundation to a property.

Homebuyers have heterogeneous belief on how fast the climate shock will likely happen, captured by the arrival rate $r\lambda$ of the climate shock, where $\lambda \in \mathbb{R}_+$ varies across homebuyers. Banks believe that the arrival rate of the climate shocks is $r\bar{\lambda}$. For tractability, we assume that banks commonly share this belief.[6] The distribution of beliefs is common knowledge: the belief disagreement is known to everyone, and they agree to disagree with each other on λ.

Mortgage. A mortgage contract specifies the mortgage amount and the repayment schedule consisting of the mortgage payments and maturity. For sake of clear insights, we follow many others to model the stochastic maturity where the mortgage matures at the Poisson rate $r\mu$. The (expected) length of maturity is $1/(r\mu)$, thus a higher μ means the mortgage is paid back faster on average. A mortgage contract thus specifies $\{B, m, \mu\}$ for each homebuyer. Modeling the stochastic maturity is tractable because we can avoid exponents of maturity and do not need to keep track of the dynamics of the mortgage balances, which is always a constant as $b_\tau = \mathbb{E}\int_\tau^T re^{-r(t-\tau)}mdt = m/(1+\mu)$. In the appendix, we also solve an alternative model of deterministic maturity, and the results are qualitatively similar.

Homebuyer's value. There is a variety of mortgage contracts available where the homebuyers search for banks to approve. One way to model this is that the economy consists of "submarkets" of $\{B, m, \mu\}$ where banks offering the contract of $\{B, m, \mu\}$ and homebuyers looking for banks approving the contract of $\{B, m, \mu\}$ can match each other. The probability that the homebuyer can find an approving bank is α, which varies across submarkets. In the competitive-search equilibrium, submarkets of mortgage contracts with harsher terms (e.g., higher m or higher μ) are also easier to find approving banks (in terms of higher α). Homebuyers can direct their search in any submarkets (equivalently choosing their mortgage contract) and the problem is given by

$$U \equiv \max_{\{\alpha,B,m,\mu\}\in\Omega_\lambda} \left\{\alpha\left[-(1+\rho)(P-B)+V(m,\mu)\right]+(1-\alpha)\left[-(1+\rho)P+V(0,\infty)\right]\right\}, \tag{1}$$

where Ω_λ is the set of submarkets available to a homebuyer with belief λ, and $V(m,\mu)$

[6] Banks could have heterogeneous beliefs too. However, since banks could securitize and sell some of the loans to government-sponsored enterprises that tend to not incorporate climate risks into their policies (Ouazad and Kahn 2021), we think it is plausible to assume that there is more belief heterogeneity among homebuyers/borrowers than there are for banks. For simplicity, we assume banks have the same level of belief, but the model can be extended to relax this assumption.

is the value of buying a house with mortgage, given by:

$$V(m,\mu) \equiv \max_{\tau} \mathbb{E} \left\{ \begin{array}{l} \int_0^{\min(T,\tau)} re^{-rt}(H_t - m)\,dt \\ +e^{-r\tau} 1_{\tau \leq T} \left[-F + \max(p_\tau - b_\tau, 0)\right] \\ +e^{-rT} 1_{\tau > T} \int_0^{\infty} re^{-rt} H_t dt \end{array} \right\}. \tag{2}$$

The value of the homebuyer without mortgage is given by $V(0,\infty)$. If the mortgage is defaulted strictly before the mortgage maturity ($\tau \leq T$), then the homebuyer pays the default cost F and receives the excess proceeds of foreclosure $\max(p_\tau - b_\tau, 0)$. If there is no default ($\tau > T$), then homebuyer enjoys the house's remaining use value $\int_0^{\infty} re^{-rt} H_t dt$.

Bank's profit. Mortgages are provided by banks. Anticipating the homebuyer's default strategy, the expected present value of the mortgage payments before the climate shock is

$$\Pi(m,\mu) = \mathbb{E}\left\{ \int_0^{\min(T,\tau)} re^{-rt} m dt + 1_{\tau < T} e^{-r\tau} \min(p_\tau, b_\tau) \right\}. \tag{3}$$

Here, the expectation operator takes into account the bank's belief about the timing of the climate shock, as indexed by parameter $\bar{\lambda}$. The bank receives the mortgage payment m until the mortgage is either mature ($t \leq T$) or defaulted ($t \leq \tau$). If the mortgage is defaulted strictly before mature ($T > \tau$), then the bank receives the lesser of the foreclosed sale of the house p_τ and the remaining balances b_τ. Any excess proceeds will be returned to the homebuyer. The following lemma solves the expected present value of the mortgage payments.

Menu of mortgage contracts. Banks can create a mortgage contract of $\{B, m, \mu\}$ after paying a fixed cost κ. As standard in the competitive search environment, given the homebuyer's finding rate α, banks take as given the rate of matching a homebuyer is $\eta(\alpha)$, where $\eta(\alpha) : [0,1] \to \mathbb{R}_+$ is the aggregate matching function which we take as the primitive of economy, where $\eta'(\alpha) < 0$. The free-entry condition is given by

$$\kappa = \eta(\alpha)\left[-(1+i)B + \Pi(m,\mu) - K(\mu)\right], \tag{4}$$

where $i \in [0,\rho)$ is the funding cost of the banks, which is affected by the monetary policy. Banks have the advantage of funding the mortgage amount upfront over the homebuyer ($i < \rho$). However, there is a cost $K(\mu) : [0,\mu_0] \to \mathbb{R}_+$ to banks for lending and serving the mortgage contract, which is increasing in the maturity, i.e., $K'(\mu) < 0$. We assume that there is a minimal maturity associating with an upper bound $\mu_0 < \infty$: banks cannot underwrite a mortgage that matures immediately ($\mu = \infty$). In sum, after the contract is approved, the bank expects to collect the present value of the mortgage payments $\Pi(m,\mu)$ and incurs the cost of providing the amount upfront B and of the

mortgage contract $K(\mu)$. In the equilibrium, the collection of the mortgage contract available is given by Ω_λ, which is any $\{\alpha, B, m, \mu\}$ that satisfies the free-entry condition (4).

Substituting the mortgage amount B from the bank's problem (4), the homebuyer's problem (1) becomes

$$U = -(1+\rho)P + v(\lambda) + \max_{\substack{\alpha\in[0,1],\\ m\geq 0,\\ \mu\in[0,\mu_0]}} \left\{\alpha\left[S(m,\mu) - \frac{(1+\omega)\kappa}{\eta(\alpha)}\right]\right\}, \tag{5}$$

where

$$\begin{aligned} 1+\omega &\equiv \frac{1+\rho}{1+i}, \\ v(\lambda) &\equiv 1 - \frac{\lambda}{1+\lambda}D, \end{aligned}$$

$$S(m,\mu) \equiv V(m,\mu) - V(0,\infty) + (1+\omega)\left[\Pi(m,\mu) - K(\mu)\right].$$

The funding advantage of banks over homebuyer is measured by ω: when $\omega = 0$, the bank has no funding advantage. The expected house's use value is given by $v(\lambda)$. The joint surplus of the homebuyer and the bank is given by $S(m,\mu)$.

2.1 Competitive-search equilibrium

Lemma 1 solves the homebuyer's default strategy and the associated joint surplus.

Lemma 1. *The joint surplus is given by*

$$S(m,\mu) = \left\{\begin{array}{l} \omega\frac{m}{1+\mu},\ \textit{if}\ \frac{m}{1+\mu} \leq \underbrace{1-D+F}_{\textit{risk-free debt limit}}, \\ J(m,\mu),\ \textit{if}\ \frac{m}{1+\mu} \in (1-D+F, \underbrace{1-\frac{\mu}{1+\mu}\frac{\lambda}{1+\lambda}D+F}_{\textit{risky debt limit}}], \\ \omega v(\lambda) - F,\ \textit{otherwise} \end{array}\right\} \tag{6}$$

where

$$J(m,\mu) \equiv \underbrace{\left(\frac{1+\omega}{1+\bar{\lambda}+\mu} - \frac{1}{1+\lambda+\mu}\right)m}_{\textit{gain from maturity}} + \underbrace{\left[\frac{(1+\omega)\bar{\lambda}}{1+\bar{\lambda}+\mu} - \frac{\lambda}{1+\lambda+\mu}\right](1-D)}_{\textit{gain from posting collateral}} - \underbrace{\frac{\lambda}{1+\lambda+\mu}F}_{\textit{expected default cost}}. \tag{7}$$

The mortgage problem of the homebuyer is boiled down to three regions of (6). In

the first region, the mortgage balances are less than the risk-free debt limit such that the homebuyer never defaults. In this case, the joint surplus is simply the homebuyer's saving of funding the mortgage balances, which is $\omega m/(1+\mu)$. We assume that

$$\omega(1-D+F) > K(\mu_0) + \frac{\kappa}{\eta(0)}, \tag{8}$$

i.e., there is always positive social gain from lending to never-default homebuyers.

In the third region of (6), the mortgage balances are so large (above the *risky* debt limit) that the homebuyer defaults immediately – essentially the homebuyer sells the house to the bank. If the homebuyer does not take out a mortgage, she needs to pay the house price with the funding cost, so the joint surplus in this case is the homebuyer's saving of funding the house price minus the default cost, which is $\omega v(\lambda) - F$.

The key mechanism of this paper is the second region of (6). In this case, the mortgage balances are between the risk-free debt limit and the risky debt limit such that the homebuyer defaults only after the climate shock. The effects of heterogeneous belief go through the following channels:

Maturity channel. The first term of (7) captures the gain from trading defaultable mortgage payments. This gain comes from funding a mortgage to a pessimist who believes in the climate shock arriving soon (a high value of λ). From the homebuyer's point of view, the homebuyer expects to pay back the bank mT_λ in the present value, where $T_\lambda \equiv 1/(1+\lambda+\mu)$ is the homebuyer's risk-adjusted maturity. But from the bank's point of view, it expects to receive $m\bar{T}$ in the present value from the homebuyer, where $\bar{T} \equiv 1/\left(1+\bar{\lambda}+\mu\right)$ is the bank's risk-adjusted maturity. The gain is positive if the homebuyer is more pessimistic than the bank ($\lambda < \bar{\lambda}$), even if the bank does not have any funding advantage ($\omega = 0$). In this case, the homebuyer believes default due to the climate shock is likely, but the bank believes the opposite. The homebuyer believes she is going to pay shorter than the maturity the bank expects ($T_\lambda < \bar{T}$), hence the homebuyer and the bank are both better off from their own point of view, and there is a (subjective) gain of trade. This maturity channel increases the joint surplus $J(m,\mu)$ of lending to the pessimists, which is the key channel of this environment.

Collateral channel. The second term of (7) captures the transfer of the damaged house as a collateral from the homebuyer to the bank via defaulting the mortgage. This term tends to have the opposite sign of the first term. Again, consider the simple case without the bank's funding advantage ($\omega = 0$). Given its belief, the bank expects to receive the foreclosure value $1-D$ at the discount factor $\bar{\lambda}/\left(1+\bar{\lambda}+\mu\right)$. However, the homebuyer expects to lose the house with value $1-D$ at the discount factor $\lambda/(1+\lambda+\mu)$. If the bank lends to a homebuyer with a stronger climate belief than the bank's, the homebuyer believes he or she is more likely to lose the house than

the probability that the bank believes the loan will foreclose. The disagreement in the climate belief makes this term negative. This term is the standard element in the literature of heterogeneous belief. The last term is the expected default cost, which is higher to the pessimists as they believe default is more likely. In sum, the collateral channel reduces the joint surplus $J(m,\mu)$ of lending to the pessimists.

Debt-limit channel. If the risky debt limit of (6) is binding, then the mortgage payment and maturity are binded by the constraint, captured by a downward sloping curve of m and $\bar{T}$

$$\underbrace{m}_{\text{mortgage payment}} = \underbrace{\Delta(\lambda)}_{\text{disagreement}} - \underbrace{\bar{\lambda}(1-D)}_{\text{foreclosing the damaged house}} + \underbrace{\frac{1}{\bar{T}}\left[v(\lambda)+F\right]}_{\text{amortizing the subjective value}}, \tag{9}$$

where the disagreement payoff is defined as

$$\Delta(\lambda) \equiv \left(1+\bar{\lambda}\right)\left[v\left(\bar{\lambda}\right)-v(\lambda)\right]-\bar{\lambda}F. \tag{10}$$

From the point of view of the homebuyer, the disagreement payoff is the social value created from borrowing from the bank and defaulting after the climate shock. Obviously, we have $\Delta'(\lambda)>0$ and if the following condition is satisfied:

$$D > \bar{\lambda}F, \tag{11}$$

then $\Delta(\lambda)>0$ if and only if λ is sufficiently large. Otherwise, if (11) is not satisfied, then we have $\Delta(\lambda)\leq 0$ for all λ. Since pessimists have lower subjective value of keeping the house, lending to a pessimist tightens the risky debt limit by shifting the curve (9) inward.[7] This debt-limit channel reduces the joint surplus $J(m,\mu)$ of lending to the climate believers.

For the rest of this paper, we assume particular forms of $K(\mu)$ and $\eta(\alpha)$:

$$K(\mu) = \frac{k}{2}\left(1+\bar{\lambda}+\mu\right)^{-2} = \frac{k}{2}\bar{T}^2, \tag{12}$$

$$\eta(\alpha) = (1+1/\xi)\,\alpha^{-(1+1/\xi)}. \tag{13}$$

Notice that the above formulation assumes the lending cost is quadratic in the bank's risk-adjusted maturity $\bar{T}$. Denote the minimal maturity as $T_0 \equiv 1/\left(1+\bar{\lambda}+\mu_0\right)$. We

[7] Note that $\Delta'(\lambda)+v'(\lambda)/\bar{T} = \left[1/\bar{T}-\left(1+\bar{\lambda}\right)\right]v'(\lambda)<0$.

define two relevant belief thresholds $\lambda_a < \lambda_b$:

$$\begin{aligned}
\lambda_a &\equiv \frac{\bar{\lambda}(F+D) - \frac{\omega D}{(1+\omega)T_0}}{D - \bar{\lambda}F}, \\
\lambda_b &\equiv \left\{ \begin{array}{l} \bar{\lambda} + \left(1+\bar{\lambda}\right) \frac{(1+\omega)\bar{\lambda}F + kT_0}{(1+\omega)\left(D-\bar{\lambda}F\right) - kT_0}, \text{ if } D > \bar{\lambda}F + \frac{kT_0}{1+\omega} \\ \infty, \text{ otherwise} \end{array} \right\}.
\end{aligned}$$

Proposition 2. *Suppose that the climate damage is sufficiently large relative to the default cost that $D > \bar{\lambda}F$.*

i. The equilibrium mortgage contract of homebuyers with $\lambda > \lambda_b$ (the most "pessimistic" group) is given by:

$$\bar{T} = \underbrace{\Delta(\lambda)}_{disagreement} \frac{1}{k} > T_0, \tag{14}$$

$$\alpha = \{(1+\omega)\bar{T} \underbrace{\Delta(\lambda)}_{disagreement} + \omega \underbrace{[v(\lambda) + F]}_{subjective\ value} - \underbrace{\frac{k}{2}\bar{T}^2}_{lending\ cost} \}^{\xi}. \tag{15}$$

Given $\bar{T}$, the mortgage payment m is given by (9).

ii. The equilibrium mortgage contract of homebuyers with $\lambda \in [\lambda_a, \lambda_b]$ is the same as the case of $\lambda > \lambda_b$ but replacing $\bar{T} = T_0$.

iii. The equilibrium mortgage contract of homebuyers with $\lambda < \lambda_a$ (the most "optimistic" group) is a mortgage contract with no default probability and with minimal maturity:

$$\begin{aligned}
\bar{T} &= T_0, \\
m &= \frac{B}{T_0} = \frac{\overbrace{1 - D + F}^{risk\text{-}free\ debt\ limit}}{T_0}, \\
\alpha &= \left[\omega(1 - D + F) - \frac{k}{2}T_0^2\right]^{\xi}.
\end{aligned}$$

Proposition 2 states that, depending on her climate belief, homebuyers choose three kinds of mortgage contract, i.e., regions of $\lambda > \lambda_b$, $\lambda \in [\lambda_a, \lambda_b]$, and $\lambda < \lambda_a$. In all cases, the homebuyer's choice of mortgage terms $\{B, m, \mu\}$ can be summarized by her choice of maturity $\bar{T}$, as the key mechanism in this paper. If her belief of the climate shock is strong such that $\lambda > \lambda_b$, the homebuyer prefers defaulting after the climate shock (the second case of (7)). It is the case we are interested in, and we refer to it as the case of pessimists. In this case, the homebuyer chooses a longer maturity $\bar{T}$ than the minimal T_0. In the remaining two cases of $\lambda \in [\lambda_a, \lambda_b]$ and $\lambda < \lambda_a$, the maturity is at the lower

bound $\bar{T} = T_0$.

The intuition behind the mortgage choices of pessimists is as follows. In the case of pessimists ($\lambda > \lambda_b$), the maturity choice of $\bar{T}$ is driven by her belief disagreement with the bank, as captured by $\Delta(\lambda)$ in Proposition 2. Given her choice of $\bar{T}$, the pessimist maximizes his borrowing from the bank such that the mortgage payment is binding at the endogenous debt limit, as shown in (7). The longer the maturity $\bar{T}$, the lower the mortgage payments m satisfying the binding risky debt limit (9). The bank's expected present value of the mortgage payments is given by

$$\Pi\left(\lambda, \bar{T}\right) \equiv \Delta(\lambda)\bar{T} + v(\lambda) + F. \tag{16}$$

The joint surplus of lending to the pessimists with a binding risky debt limit is thus given by

$$J\left(\lambda, \bar{T}\right) \equiv (1+\omega)\Delta(\lambda)\bar{T} + \omega\left[v(\lambda) + F\right]. \tag{17}$$

Using this expression, we can see that the likelihood of taking out mortgage α is increasing in the joint surplus (the first two terms of (15)) net of the lending cost (the last term). The joint surplus is driven by the climate believer's disagreement with the bank $\Delta(\lambda)$ (multiplied by the maturity $\bar{T}$) and her subjective value of keeping the house $v(\lambda)$. The former is increasing in her belief, but the latter is decreasing. The following proposition summarizes the comparative statics.

Proposition 3. *For simplicity, suppose the minimum maturity T_0 is sufficiently large that $(1+\omega)\left(1+\bar{\lambda}\right)T_0 > \omega$. The comparative statics with respect to the climate belief λ are given by*

	climate belief				climate exposure				monetary policy			
	$\frac{d\bar{T}}{d\lambda}$	$\frac{d\alpha}{d\lambda}$	$\frac{dm}{d\lambda}$	$\frac{dB}{d\lambda}$	$\frac{d\bar{T}}{dD}$	$\frac{d\alpha}{dD}$	$\frac{dm}{dD}$	$\frac{dB}{dD}$	$\frac{d\bar{T}}{di}$	$\frac{d\alpha}{di}$	$\frac{dm}{di}$	$\frac{dB}{di}$
$\lambda > \lambda_b$	$+$	$+$	$+$	?	$+$	$+$	$-$	?	0	$-$	0	$-$
$\lambda \in [\lambda_a, \lambda_b]$	0	$+$	$+$	$+$	0	$+$	$-$	?	0	$-$	0	$-$
$\lambda < \lambda_a$	0	0	0	0	0	$-$	$-$	$-$	0	$-$	0	$-$

Mortgage maturity T is increasing in the belief λ and increasing in the expsoure D. From Proposition 2, a higher λ increases the belief disagreement with the bank $\Delta(\lambda)$ and hence increases the maturity choice of $\bar{T}$. Recall the joint surplus of lending to the pessimists with a binding endogenous debt limit, $J\left(\lambda, \bar{T}\right)$, is given by (17). As discussed, the belief λ has two opposite forces on $J\left(\lambda, \bar{T}\right)$: positively via the disagreement $\Delta(\lambda)$ and negatively via the subjective value $v(\lambda)$. It turns out the disagreement dominates, and $J\left(\lambda, \bar{T}\right)$ is increasing in λ (and indirectly via $\bar{T}$). In sum, the maturity channel dominates the collateral channel and the debt-limit channel.

2.2 House prices

Expecting the mortgage choice, the house price is determined by the bargaining between the homebuyer and seller:

$$\max_{P} U^{\theta} \left[P - v\left(\lambda\right) + \xi\right]^{1-\theta}, \tag{18}$$

where U is the homebuyer's utility as given by (1), θ is her bargaining power, and ξ is the seller's cost of maintaining the house relative to the homebuyer that motivates the seller to sell the house. Note that the housing valuate term $v(\lambda)$ in (18) implicitly assumes that the seller shares the same belief λ about the climate risk as the buyer. This assumption is for tractability and allows us to focus on the belief heterogeneity between buyers and lenders, but it is not essential for our result. The surplus of the seller is the price P minus the sum of her subjective value and her maintenance cost $(v\left(\lambda\right) - \zeta)$. We assume the maintenance cost is less than the foreclosure cost (i.e., $\zeta < F$) such that the seller does not sell the house to the liquidator. The bargaining solution is:

$$P = \underbrace{\frac{1+\theta\rho}{1+\rho} v\left(\lambda\right) - \theta\xi}_{\text{standard "hedonic" term}} + \underbrace{\left(1-\theta\right)\alpha \left[\frac{\overbrace{S\left(m,\mu\right)}^{\text{joint surplus}}}{1+\rho} - \frac{\overbrace{\kappa}^{\text{mortgage cost}}}{\eta\left(\alpha\right)}\right]}_{\text{mortgage term}}, \tag{19}$$

where α, m, μ are from the equilibrium mortgage contract. Substituting the above into the choice of α, the equilibrium mortgage likelihood is given by:

$$\alpha^{(1+\xi)/\xi} = \frac{1+\xi}{(1-\theta)\kappa} \overbrace{\left[P - \frac{1+\theta\rho}{1+\rho} v\left(\lambda\right) + \theta\xi\right]}^{\text{mortgage term}}. \tag{20}$$

The following proposition summarizes the impact of belief of the house price.

Proposition 4. *The house price, P, is decreasing in the climate belief, λ, decreasing in the climate exposure, D, and decreasing in the policy rate, i.*

Proposition 4 echoes most of the empirical findings about the climate belief and climate exposure on the house price. The mortgage part of the model is consistent with the empirical finding.

2.3 Financial stability

The effects of monetary policy on the economy are given by Proposition 3 and Proposition 4: given the homebuyer's belief λ, an expansionary monetary policy of lowering i will increase the likelihood of taking out a mortgage (higher α), increase the mortgage amount (higher B), and increase the house price (higher P). Monetary policy and climate exposure also have a composition effect (the extensive margin of risky leverage), which is summarized by the following proposition. Recall that λ_a is the threshold of belief below which borrowers will choose the risk-free mortgage contract.

Proposition 5. *λ_a is decreasing in D and i. As a consequence, an expansionary monetary policy that reduces i will expand the set of borrowers $[\lambda_a, \infty)$ who will choose risky mortgage contracts.*

Expansionary monetary policy induces more pessimists to increase their exposure and makes the mortgage market more vulnerable to climate change. What makes the climate risk special is that the climate shock will trigger the pessimists with $\lambda > \lambda_a$ to default, while there is no default after the other macro shocks as shown in Proposition 6. In particular, an expansionary monetary policy will increase the number of defaults after climate shock.

2.4 What makes climate risk special?

What distinguishes a climate shock from other macro shocks is that a climate shock tends to involve a large potential damage D in the future (low $\bar{\lambda}$) and agents in the economy have substantial heterogeneity in their beliefs about this shock. In our model, it is captured by the condition (11), which is crucial to Proposition 2. If the condition (11) is satisfied, then the disagreement on how soon the shock will happen (λ) can motivate the believers to take advantage of the disagreement by using more and longer mortgage (higher α and $\bar{T}$), via the maturity channel as we have highlighted. The following proposition illustrates that the comparative statics are overturned if the condition (11) is violated.

Proposition 6. *Suppose the damage from the shock is sufficiently small that $D \leq \bar{\lambda} F$.*

1. *The equilibrium mortgage contract of any homebuyer is risk-free, as given by part (iii) of Proposition 2.*

2. *Belief heterogeneity does not affect equilibrium outcomes.*

3. *Higher exposure (larger D) reduces the probability of leverage α and has no effect on maturity $\bar{T}$.*

If the shock does not qualify the condition (11), then the maturity channel is shut down, and the belief has no effect at all except the price. In sum, the nature of climate shock is special in the sense that it gives room for heterogeneous belief to have an impact on mortgage choices in this environment.

2.5 Taking stock.

Our model predicts that in a frictional market for defaultable mortgage contracts, the interaction between exposure to climate risk and heterogeneous beliefs over this risk plays an important role in determining the outcomes. Among others, the model predicts that relatively more pessimistic homebuyers – those with relatively stronger climate beliefs – are more likely to leverage and take out mortgage contracts with longer maturity when purchasing an exposed property, although their house prices are lower. The following corollary summarizes the testable implications of heterogeneous belief on the maturity, leverage, and house price from (14), (20), and (19), respectively, which forms the basis of our empirical investigation.

Corollary 7. *(Testable implications)*

	Believers exposed to climate risk $\lambda > \lambda_b$ and $D > 0$	Otherwise $\lambda \leq \lambda_b$ or $D = 0$
Maturity $\bar{T}$	long	short
Leverage α	high	low
Price P	low	high

3 Data and methodology

Motivated by our theoretical insights, we turn to examining empirical evidence. In particular, we first describe our econometric specifications and then detail our data sources.

3.1 Econometric specifications

Housing price. As an initial step to set the stage for our empirical analysis, we re-evaluate the literature's previous findings regarding the effects of SLR risk on property prices. Based on Bernstein et al. (2019), we adopt the following specification, which we estimate using the Ordinary Least Squares estimator:

$$\ln Price_{it} = \beta SLR_i + \lambda_{zdebm} + \phi' X_{ict} + \epsilon_{it}. \tag{P1}$$

Throughout, $Price_{it}$ denotes the transaction price of residential property i sold on date t. SLR_i denotes property i's exposure to inundation risk due to SLR. In our benchmark specification, we adopt the benchmark most often used in the climate finance literature and define SLR_i as one if property i is predicted to be underwater if the sea level is to rise by six feet, and zero otherwise. We will explore other more refined definitions of SLR risk in various robustness exercises. X_{ict} is a vector of property-level controls (age and square footage) and county-level controls (average income and population of the county where the buyer comes from).

Crucially, λ_{zdebm} denotes a rich set of fixed effects that allow us to compare transaction within the same zip code (z), distance to coast bin (d), elevation bin (e), number of bedrooms (b), and time (year and month; m) of sale.[8] Our identification assumption is that with these controls, β is uncorrelated with ϵ_{it} and therefore a plausible estimate of the effects of SLR exposure on house prices. In line with previous literature, we hypothesize that homes at risk of SLR sell at a discount ($\beta < 0$).

Going deeper, we re-investigate the literature's findings on the effect of heterogeneous climate beliefs in the pricing of SLR risk. In particular, we re-evaluate whether there is more SLR pricing in transactions involving buyers whose beliefs put higher probability on events where SLR risks realize. Ideally, we would like to have a direct measure of such climate belief for the buyer involved in each transaction but do not know of such a data set for the spatial and temporal scale of our analysis. Instead, following the climate finance literature (e.g., Bernstein et al. 2019; Baldauf et al. 2020; Goldsmith-Pinkham et al. 2021), we rely on the Yale Climate Opinion survey, which provides county-level averages of climate beliefs (as described in the data section). We adopt the following specification:

$$\begin{aligned}\ln Price_{it} = \beta SLR_i + \gamma SLR_i \times HighBelief_c \\ + \delta HighBelief_c + \lambda_{zdebm} + \phi' X_{ict} + \xi' SLR_i \times X_{ct} + \epsilon_{it}.\end{aligned} \tag{P2}$$

Here, $HighBelief_c$ is an indicator variable equal to one if the average climate belief in the county $c(i)$ of the buyer of property i at date t is above the sample median (i.e., the fraction of respondents stating that they believe global warming is happening is $\geq 66\%$) and zero otherwise (we explore other climate belief specifications in our robustness exercises.) For convenience, we will sometimes refer to transactions where $HighBelief_c = 1$ as transactions with more pessimistic buyers. To control for potentially confounding factors that could correlate with climate beliefs, we include the interaction terms be-

[8] Following Bernstein et al. (2019), we use nonlinear bins for the distance from coast: 0-.01 miles, .01-.02 miles, .02-.08 miles, .08-.16 miles, and more than .16+ miles, and we use two-meter elevation bins.

tween SLR and the buyer county controls (the population and average income of the county where the buyer comes from), as represented by the term $SLR_i \times X_{ct}$. Our hypothesis is that γ is negative, indicating that there is more pricing of climate risk in transactions with buyers who are more likely to have stronger beliefs in climate change.

Leverage and maturity. We now move on the paper's main empirical investigations of the potential effects of SLR risk on mortgage outcomes. First, we evaluate whether SLR risk affects the likelihood that transactions are leveraged:

$$Leveraged_{it} = \beta SLR_i + \alpha \ln Price_{it} + \lambda_{zdebm} + \phi' X_{ict} + \epsilon_{it}. \tag{L1}$$

Here, $Leveraged_{it}$ is an indicator variable that is equal to one if the transaction involves a mortgage and zero otherwise. We include price as a control variable and also consider a specification without price as a control variable in the robustness section. We estimate the above equation using the OLS estimator.

Importantly, we evaluate whether the interaction between SLR risk and climate beliefs affects the likelihood that transactions are leveraged:

$$\begin{aligned} Leveraged_{it} = \beta SLR_i + \gamma SLR_i \times HighBelief_{c(i)} + \delta HighBelief_c \\ + \alpha \ln Price_{it} + \lambda_{zdebm} + \phi' X_{ict} + \xi' SLR_i \times X_{ct} + \epsilon_{it}, \end{aligned} \tag{L2}$$

where $HighBelief$ is defined as in price regression (P2). Based on the prediction of our theoretical model, we hypothesize that γ is positive. Recall that this implies that in transactions of properties that are exposed to SLR risk, buyers who are more likely to have stronger climate beliefs, and therefore are relatively more likely to be pessimistic about the future of these properties, are more likely to take on a leveraged position.

Similarly, we consider the following regressions on the likelihood that leveraged transactions involve mortgages with longer maturity. For leveraged transactions, let $LongMaturity$ be an indicator for whether the maturity of the mortgage contract is thirty years.[9] We then run the following regressions on the sub-sample of leveraged transactions (i.e., transactions that have associated mortgage contracts):

$$LongMaturity_{it} = \beta SLR_i + \alpha \ln Price_{it} + \lambda_{zdebm} + \lambda_l + \phi' X_{ict} + \epsilon_{it}, \tag{M1}$$

[9]The distribution of mortgage maturity is bimodal: most of contracts either have a fifteen-year or a thirty-year term. In the main specification, we exclude the small sub-sample of transactions whose mortgages have maturity terms that are neither nor 30, which tend to be nonstandard mortgage contracts. Our results are robust to the inclusion of these nonstandard observations.

and

$$LongMaturity_{it} = \beta SLR_i + \gamma SLR_i \times HighBelief_{c(i)} + \delta HighBelief_c + \alpha \ln Price_{it} + \lambda_{zdebm} + \lambda_l + \phi' X_{ict} + \xi' SLR_i \times X_{ct} + \epsilon_{it}. \quad \text{(M2)}$$

Here, in addition to the set of fixed effects λ_{zdebm}, we also include a lender fixed effect to control for the possibility that different lenders may have varying tendencies to issue different types of mortgage contracts.[10] Based on the prediction of the model, our hypothesis is that buyers in counties with high climate belief are more likely to have a longer maturity ($\gamma > 0$). Specifications (L2) and (M2) are the main regression equations of our paper.

3.2 Data

To conduct our analysis, we leverage an extensive proprietary data set of real estate transactions data from Corelogic, a data vendor that compiles a comprehensive record of deed transactions and property tax roll information. The tax data set includes detailed information on property characteristics (including age, size, geographic location, and other information), and transaction prices. The deeds data set contains information on associated mortgage contracts (including the mortgage origination amount and maturity, the identity of the lender, and other characteristics). Using a property identifier and the sale date, we merge the tax and deeds data sets together.[11] The coverage period is between 2001 and 2016. We use the geographic location to match each property to a ZIP code, county, and to compute the distance to the coast. Since this is a very big data set, we filter it by restricting our attention to single-family homes that lie within 1km from the U.S. East Coast. We also exclude transactions with sale prices under \$50,000 or over \$10,000,000 and condos and keep the most recent tax year information. That leaves us with 2,250,995 transactions, 896,346 for which property characteristics are available. We combine our transaction and mortgage data with Fannie Mae and Freddie Mac conforming loan limit data from the Federal Housing Finance Agency, which provides county specific limits for each year between 2009 and 2016.

Note that the Corelogic data has a limitation: the data for the mortgage interest rates are often missing. We try to control for the missing interest rates with a rich set

[10] For transactions with more than one mortgages, we use the lender fixed effect for the first mortgage. In the robustness check section, we also exclude transactions with more than one mortgage and the results are unaffected.

[11] About 11% of leveraged transactions are associated with more than one mortgage. For each of those transactions, we obtain information for up to five mortgage contracts, and then take the average of the mortgage amounts. In our sample, for each property, the maturity terms are identical across these multiple mortgage contracts.

of fixed effects (including those for time, location, and the lender). However, we also note that the interest rate is a co-determined outcome of the mortgage choice, along with the maturity length and loan amount. Thus, it can be considered a bad control and is omitted from our main regression equations (Angrist and Pischke, 2008).

To exploit high-resolution spatial variation in each property's exposure to SLR risk, we utilize the NOAA SLR viewer,[12] which provides high-resolution maps showing community-level impacts at various levels of SLR. NOAA projects inundation threshold for each location based on its elevation, local and regional tidal variability, and hydrological connectivity. Then, based on each property's coordinates, we can determine whether the property will be inundated with x feet of SLR, where $x \in \{1, 2, \ldots, 6\}$. Figure 1 provides an example of the high-resolution spatial variation of exposure to inundation risk under the scenario of six feet of SLR for Miami, Florida. We also use First Street Foundation's Flood Factor data to obtain the minimum bare-earth elevation of each property as a control variable.

To obtain measures of beliefs about climate change, we employ the Yale Climate Opinion Survey 2014 (Howe et al. 2015).[13] This data set provides county-level averages of how respondents answer survey questions on climate change. Our main measure of beliefs in climate change is the percentage of people in each county who answered "yes" to whether they believe that climate change is happening. For robustness, we also use the percentage of people who answered "somewhat worried" or "very worried" to how worried they are about global warming.

Table A1 provides the summary statistics of our data.

4 Results

4.1 Price

Table 1 reports the results for price regressions. Recall that the aim of these regressions is to verify whether previous findings in the literature hold in our data set. To appreciate the importance of controlling for amenity values, column 1 shows the estimates from a "naive" regression that does not include fixed effects. It shows a positive and significant correlation between SLR exposure and price. This is not surprising, as properties that are exposed to SLR risk also tend to be close to the coast, and coastal properties tend to have higher values. Column 2 then includes our rich set of fixed effects, and the sign of the estimated coefficient flips to be negative. It shows that, all else equal, a property that is exposed to SLR risk is priced about 6% lower than an otherwise equivalent but

[12] Publicly available at https://coast.noaa.gov/digitalcoast/tools/slr.html.

[13] Publicly available at https://climatecommunication.yale.edu/visualizations-data/ycom/.

	Log Price		
SLR Risk	0.219***	-0.060***	-0.039*
	(0.028)	(0.022)	(0.021)
SLR Risk × High Belief			-0.059***
			(0.018)
Property & buyer county controls	Y	Y	Y
Z × D × E × B × M fe		Y	Y
Buyer county controls × SLR	Y	Y	Y
N	1583238	406601	406601
R2	0.335	0.866	0.867

Table 1: Effects of exposure to SLR risk and its interaction with climate belief on housing prices. *SLR Risk* indicates whether a property's location will be inundated with six feet of SLR. *High Belief* indicates whether the buyer is from a county where the fraction of respondents in Yale Climate Opinion Survey stating that they believe global warming is happening is above the sample median ($\geq 66\%$). Z×D×E×B×M indicates ZIP code × distance to coast × elevation × number of bedrooms × time (transaction month-year) fixed effects. Property controls include age and square footage. Buyer county controls include average county income and county population. Sample includes all transactions of single-family homes that lie within 1km from the U.S. East Coast between 2001 and 2016. See Section 3.2 for more data descriptions. Standard errors in parentheses are clustered at the zip code level; * ($p < 0.1$), ** ($p < 0.05$), *** ($p < 0.01$).

unexposed property (the "SLR discount" is around 6%). The estimate is statistically significant ($p < 1\%$), and the magnitude is similar to that in Bernstein et al. (2019). Thus, column 2 replicates the recent finding in the climate finance literature that the coastal property market is pricing in future SLR risk.

Furthermore, column 3 shows that the extent of the pricing of SLR risk varies: much of the discounting of SLR risk is driven by transactions with more pessimistic buyers. The SLR discount is nearly 10% ($3.9 + 5.9$) among transactions with buyers from counties whose average climate beliefs are above the sample median, while the discount is only 3.9% among transactions with the other group of buyers. This result of the variation in the pricing of SLR risk based on buyers' climate beliefs is consistent with that in Baldauf et al. (2020).

Having replicated the literature's findings on the SLR discount in housing prices, we now move on to our main results on mortgage outcomes.

4.2 Leverage

Table 2 reports the results for leverage regressions. Again, column 1 shows a "naive" regression that excludes the set of fixed effects. The result there shows a negative

	Leveraged				
SLR Risk	-0.093***	0.021***	-0.004	-0.003	
	(0.008)	(0.007)	(0.007)	(0.014)	
SLR Risk × High Belief			0.047***	0.034***	
			(0.009)	(0.011)	
Moderate SLR Risk					0.003
					(0.014)
High SLR Risk					-0.035
					(0.031)
Moderate SLR × High Belief					0.026**
					(0.011)
High SLR × High Belief					0.083***
					(0.023)
Log Sale Price	0.064***	0.161***	0.161***	0.161***	0.162***
	(0.006)	(0.010)	(0.010)	(0.010)	(0.010)
Property & buyer county controls	Y	Y	Y	Y	Y
Z × D × E × B × M fe		Y	Y	Y	Y
Buyer county controls × SLR				Y	Y
N	1580756	405893	405893	405893	405893
R2	0.019	0.473	0.473	0.473	0.473

Table 2: Effects of exposure to SLR risk and its interaction with climate belief on *Leveraged*, an indicator for whether the transaction is associated with a mortgage. *SLR Risk* indicates whether a property's location will be inundated with six feet of SLR. *Moderate SLR Risk* (*High SLR Risk*) indicates whether a property's location will be inundated with > 3 to ≤ 6 feet of SLR (≤ 3 feet of SLR, respectively). *High Belief* indicates whether the buyer is from a county where the fraction of respondents in Yale Climate Opinion Survey stating that they believe global warming is happening is above the sample median ($\geq 66\%$). Z×D×E×B×M indicates ZIP code × distance to coast × elevation × number of bedrooms × time (transaction month-year) fixed effects. Property controls include age and square footage. Buyer county controls include average county income and county population. Sample includes all transactions of single-family homes that lie within 1km from the U.S. East Coast between 2001 and 2016. See Section 3.2 for more data descriptions. Standard errors in parentheses are clustered at the zip code level; * ($p < 0.1$), ** ($p < 0.05$), *** ($p < 0.01$). Regressions are estimated using OLS

correlation between SLR risk exposure and leveraged, suggesting that transactions of exposed properties on average are less likely to be financed with mortgage.

However, the result flips in column 2, where we include the rich set of fixed effects. The estimate in column 2 shows that, rather surprisingly, transactions of properties that are exposed to SLR risk are about 2% more likely to be leveraged (i.e., there is an associated mortgage contract). The estimate is not only very statistically significant but also economically meaningful. To get a sense of relative magnitude, note that the rise of leveraged transactions from 2001 to the peak of the 2008 financial crisis, measured

by the fraction of property transactions associated with mortgages in our data, was 4.65%.

Crucially, column 3 shows that the SLR-leverage association is *driven by transactions with more pessimistic buyers*. The estimate for the interaction term between *SLR Risk* and *High Belief* indicates that, among transactions with buyers from counties with above median climate beliefs, properties that are exposed to SLR risk are about 4.7% more likely to be leveraged. The estimate for the uninteracted *SLR Risk* term indicates that, among transactions with buyers from counties with below median climate beliefs, the association between SLR risk and the leveraged dummy is negative but not statistically significant.

A potential concern is that climate belief is correlated with other factors that predict leverage outcomes. Ideally, we would like to control for buyer-specific characteristics such as income, wealth, or credit score. However, as mentioned in the data description, the only information that we have about buyers is where they come from. Hence, the best proxy for buyer-specific characteristics would be the aggregate statistics from where buyers come from. Column 4 repeats the benchmark regression in column 3 but includes the interaction terms between SLR and buyer county controls, namely the population and average income of the county where the buyer comes from. The estimate of *SLR Risk*×*High Belief* remains very statistically significant. The magnitude of the coefficient reduces slightly to about 3.4%.

Another potential concern is that the measure of SLR exposure there is too coarse. In particular, it is very unlikely that the sea level will rise by six feet in the next thirty years.[14] Column 5 aims to address this concern. It repeats the exercises in column 4 but replaces the benchmark *SLR Risk* dummy (for whether a property is inundated with six feet of SLR) with a more refined measure of risk exposure. *Moderate SLR Risk* indicates whether a property will be inundated with > 3 but ≤ 6 feet of SLR. Similarly, *High SLR Risk* indicates whether a property will be inundated even with ≤ 3 feet of SLR. The comparison group is *Low SLR Risk*, indicating properties that will not be inundated even with six feet of SLR. As the label suggests, properties lying in the high risk group is the most exposed to inundation risk, compared to properties lying in the medium risk group. Those in the low risk group are the least likely to experience inundation.

As in columns 3 and 4, column 5 shows that the estimates for the interaction between the SLR terms and the high belief dummy are both positive and statistically significant, while the estimates for the uninteracted SLR terms are not significant. Furthermore,

[14] However, it is plausible that properties inundated with six feet of SLR face higher climate-related risks, such as flood risk from storm surges (Zhang et al. 2013), which are relevant for the thirty-year term.

the estimate of 8.3% for *High SLR Risk* $\times$ $HighBelief$ is larger than the estimate of 2.6% for *Moderate SLR Risk* $\times$ $HighBelief$. This monotonic ordering is consistent with our model's prediction: the more exposed a property is, the higher the likelihood that its transaction with a buyer from a county with strong climate belief is going to be leveraged.

Overall, our findings on the relationship between SLR exposure and leverage are consistent with our theoretical model's prediction on the extensive margin of leverage: in purchases of properties that are exposed to climate risks, buyers with more pessimistic climate beliefs are more likely to make a leveraged investment.

4.3 Maturity

With a similar structure to Table 2, Table 3 reports the estimates for regressions of the long maturity dummy. As in previous tables, the first column shows a "naive" regression that excludes the set of fixed effects. There, the coefficient of SLR risk is negative and significant.

However, once the fixed effects are introduced in column 2, the sign of the estimated coefficient flips and becomes statistically insignificant. Column 2 thus indicates that on average there does not seem to be a significant relationship between SLR risk exposure and maturity.

However, a pattern emerges when we break this relationship down by category of buyers. Column 3 shows that among leveraged transactions with buyers from counties with above median climate beliefs, properties that are exposed to SLR risk are about 1.8% more likely to be associated with mortgage contracts that have longer maturity. This finding is also consistent with our model's prediction on the intensive margin of the choice of mortgage maturity.

Column 4 repeats the exercise in column 3 but includes the interaction terms between SLR and buyer county controls. The estimate for the interaction term remains very statistically significant, and the magnitude increases slightly to 2.4%.

Column 5 repeats the exercise in column 4 but replaces the benchmark *SLR Risk* indicator with the *Moderate SLR Risk* and *High SLR Risk* indicators. The pattern in columns 3 and 4 continues to hold with the more refined measure of SLR risk. The correlation between SLR exposure and the long maturity dummy is not statistically significant. However, the relationship becomes statistically significant when this relationship is broken down by category of buyers. Among leveraged transactions with buyers from counties with above median climate beliefs, mortgage contracts of properties with moderate SLR risk is 2.3% more likely to have long maturity, and those with high SLR risk is 3.1% more likely.

	Long Maturity				
SLR Risk	-0.019***	0.005	-0.004	0.002	
	(0.002)	(0.005)	(0.007)	(0.014)	
SLR Risk × High Belief			0.018***	0.024***	
			(0.007)	(0.007)	
Moderate SLR Risk					0.006
					(0.014)
High SLR Risk					-0.028
					(0.024)
Moderate SLR × High Belief					0.023***
					(0.008)
High SLR × High Belief					0.031*
					(0.019)
Log Sale Price	0.001	-0.003	-0.003	-0.003	-0.003
	(0.001)	(0.004)	(0.004)	(0.004)	(0.004)
Property & buyer county controls	Y	Y	Y	Y	Y
Z × D × E × B × M fe		Y	Y	Y	Y
Lender fe		Y	Y	Y	Y
Buyer county controls × SLR				Y	Y
N	822890	150746	150746	150746	150746
R2	0.002	0.441	0.441	0.441	0.441

Table 3: Effects of exposure to SLR risk and its interaction with climate belief on *Long Maturity*, an indicator for whether the mortgage term is 30 years (as opposed to 15 years). *SLR Risk* indicates whether a property's location will be inundated with six feet of SLR. *Moderate SLR Risk* (*High SLR Risk*) indicates whether a property's location will be inundated with > 3 to ≤ 6 feet of SLR (≤ 3 feet of SLR, respectively). *High Belief* indicates whether the buyer is from a county where the fraction of respondents in Yale Climate Opinion Survey stating that they believe global warming is happening is above the sample median ($\geq 66\%$). Z×D×E×B×M indicates ZIP code × distance to coast × elevation × number of bedrooms × time (transaction month-year) fixed effects. *Lender fe* indicates lender fixed effects. Property controls include age and square footage. Buyer county controls include average county income and county population. Sample includes all transactions of single-family homes that lie within 1km from the U.S. East Coast between 2001 and 2016 (see Section 3.2 for more data descriptions); exclude transactions that do not have an associated mortgage contract (for which the dependent variable is not well defined); exclude nonstandard mortgage observations where term is not 15 nor 30 years. Standard errors in parentheses are clustered at the zip code level; * ($p < 0.1$), ** ($p < 0.05$), *** ($p < 0.01$). Regressions are estimated using OLS.

Overall, our findings are consistent with the model's predictions on the relationship between climate risk exposure and the intensive margin of maturity choice: in leveraged purchases of properties that are exposed to climate risks, buyers with more pessimistic climate beliefs are more likely to use debt contracts with a longer maturity.

4.4 Further results

4.4.1 Conforming loan limits

Recently, Ouazad and Kahn (2021) have highlighted a mechanism through which banks can potentially shift climate risks to government-sponsored enterprises (GSEs): by securitizing and selling off mortgages that are below the conforming loan limit (and thus are eligible to be sold to the GSEs). This mechanism is potentially relevant and complementary to our story. Suppose it is true that banks can securitize and sell off conforming mortgage contracts to the GSEs, whose rules and fees tend to only reflect current official flood-plain maps and do not necessarily reflect future SLR risks.[15] Then, we may expect that the effects of SLR exposure interacted with the climate belief of buyers on leverage and maturity outcomes to strengthen in the segment of conforming loans. Furthermore, suppose banks cannot as easily sell off and thus are more likely to hold on to nonconforming mortgages on their balance sheets. Then, we may expect the effects of SLR exposure interacted with climate belief to weaken in the segment of nonconforming loans.

We investigate this potential story in Table 4. In column 1, we repeat leverage regression (L2), but replace the dependent variable with a dummy for whether a transaction is leveraged *and* the mortgage is conforming. In column 2, we do the same thing as in column 1, but replace conforming with nonconforming. Confirming our intuition above, the estimates for SLR $\times$ High Belief is positive and significant for the conforming leveraged dummy (column 1). It is negative but not statistically significant for the nonconforming leveraged dummy (column 2).

Similarly, columns 3 and 4 repeat the long maturity regression (M2), but replace the dependent variable with a dummy for whether the leveraged transaction is associated with a long maturity mortgage *and* the mortgage is conforming/nonconforming (column 3/4, respectively). Again, the estimates for SLR $\times$ High Belief is positive and significant for the conforming leveraged dummy (column 1), but is negative and significant for the nonconforming leveraged dummy (column 2).

Overall, the results in Table 4 confirm our intuition that the effects of SLR exposure interacted with climate belief to be stronger for conforming loans (which banks can securitize and sell to the GSEs) than for nonconforming loans.

4.4.2 Monetary policies

We now test the model's main policy implication: that a reduction (or equivalently, an increase) in the interest rate i increases (decreases) the probability that a purchase of

[15] It has been argued that, e.g., by Hurst et al. (2016), that the GSEs do not price predictable regional variations in default risk, which could be driven by the variations in SLR risk.

	Leveraged &		Long Maturity &	
	Conforming	Nonconform	Conforming	Nonconform
SLR	-0.016	0.013*	-0.009	0.007
	(0.015)	(0.007)	(0.021)	(0.013)
SLR × High Belief	0.033***	-0.001	0.033***	-0.015**
	(0.012)	(0.004)	(0.012)	(0.007)
Property & buyer county controls	Y	Y	Y	Y
Buyer county controls × SLR	Y	Y	Y	Y
Z × D × E × B × M fe	Y	Y	Y	Y
Lender fe			Y	Y
N	406601	406601	182771	182771
R2	0.478	0.566	0.569	0.669

Table 4: Role of conforming loans. Column 1: dependent variable is whether a transaction is leveraged *and* the mortgage is conforming. Column 3: restricting to leveraged sample, dependent variable is whether the mortgage has long maturity (≥30 years) and is conforming. Column 2 and 4 repeat columns 1 and 3, respectively, but replace conforming with nonconforming. *SLR Risk* indicates whether a property's location will be inundated with six feet of SLR. *High Belief* indicates whether the buyer is from a county where the fraction of respondents in Yale Climate Opinion Survey stating that they believe global warming is happening is above the sample median (≥ 66%). Z×D×E×B×M indicates ZIP code × distance to coast × elevation × number of bedrooms × time (transaction month-year) fixed effects. *Lender fe* indicates lender fixed effects. Property controls include age and square footage. Buyer county controls include average county income and county population. Sample includes all transactions of single-family homes that lie within 1km from the U.S. East Coast between 2001 and 2016 (see Section 3.2 for more data descriptions); exclude transactions that do not have an associated mortgage contract (for which the dependent variable is not well defined); exclude nonstandard mortgage observations where term is not 15 nor 30 years. Standard errors in parentheses are clustered at the zip code level; * ($p < 0.1$), ** ($p < 0.05$), *** ($p < 0.01$). Regressions are estimated using OLS.

an exposed property by a pessimist is leveraged. To do so, we augment specification (L2) by including interactions with a variable that captures the interest rate i_t:

$$\begin{aligned} Leveraged_{it} = {} & \beta SLR_i + \gamma SLR_i \times \delta HighBelief_{c(i)} \\ & + \zeta SLR_i \times HighBelief_{c(i)} \times i_t \\ & + \delta_0 i_t + \delta_1 HighBelief_c + \delta_2 SLR_i \times i_t + \delta_3 HighBelief_{c(i)} \times i_t \\ & + \alpha \ln Price_{it} + \lambda_{zdebq} + \phi' X_{ict} + \xi' SLR_i \times X_{ct} + \epsilon_{it}, \end{aligned} \tag{L3}$$

The main coefficient of interest is ζ. The model predicts that ζ is negative, as increase in i_t should reduce the pessimists' incentive to make a leveraged investment on exposed properties. For an empirical measure of i_t, we use the market yield on Treasury securities

at 2-year maturity, a standard proxy for the nominal interest rate set by the monetary authority in the U.S., provided by the St. Louis Fed.[16]

Column 1 of Table 5 reports the estimates for β, γ and ζ from equation (L3). As before, the coefficient γ for the double interaction term between SLR risk and High Buyer Belief remains significant and positive. However, as the model predicted, the estimate for the coefficient ζ for the triple interaction term is negative and statistically significant. Column 2 repeats the exercise but replaces the left-hand-side variable with the Long Maturity dummy. As the model predicted, the triple interaction term is not significant.

Overall, our empirical results give some moderate support for the model's implication on the effect of monetary policy on the leverage probability of property transactions that are subject to SLR risk.

5 Robustness checks

5.1 Other levels of SLR

To further provide a more nuanced measure of SLR exposure, we define a monotonically increasing exposure variable *SLR Risk*, which is zero if a property is not going to be inundated even with the high level of six feet of SLR, one if it is going to be inundated with six feet, two if inundated with five feet, three if inundated with four feet, and four if inundated with three or fewer feet. Thus, the higher the value, the higher the exposure to inundation risk.

Table 6 repeats the benchmark mortgage regressions (L2) and (M2) using this measure of SLR. The table shows that our results continue to hold with this more refined measure of exposure. The estimates for the interaction terms between *SLR Risk* and *High Belief* are positive and significant for higher values of the *SLR Risk* variables. Also, generally speaking, the higher the exposure value, the larger the estimated coefficients, though the differences are not necessarily statistically significant.

5.2 Other fixed effect specifications

Table 7 checks whether our main results are robust to alternative specifications. The top panel reports checks for leveraged regression (L2) and the bottom panel reports those for long maturity regression (M2).

Column 1 uses a more flexible fixed effect specification relative to the benchmark specification by dropping the time dimension: zip code $\times$ distance to coast bin $\times$

[16] Downloaded from https://fred.stlouisfed.org/series/DGS2.

	Leveraged	Long Maturity
SLR Risk	-0.022	0.008
	(0.017)	(0.012)
SLR Risk x High Belief	0.051***	0.002
	(0.015)	(0.009)
SLR Risk x High Belief x i	-0.010**	0.002
	(0.005)	(0.003)
Z × D × E × B × M fe	Y	Y
Property & buyer county controls	Y	Y
Buyer county controls x SLR	Y	Y
Lender fe		Y
N	405908	182269
R2	0.473	0.527

Table 5: Effects of monetary policy. Dependent variable in Column 1 is *Leveraged* (whether the transaction is associated with a mortgage) and in Column 2 is *Long Maturity* (whether the mortgage term is 30 years). i denotes the market yield on Treasury securities at 2-year maturity. *SLR Risk* indicates whether a property's location will be inundated with six feet of SLR. *High Belief* indicates whether the buyer is from a county where the fraction of respondents in Yale Climate Opinion Survey stating that they believe global warming is happening is above the sample median ($\geq$ 66%). Z×D×E×B×T indicates ZIP code × distance to coast × elevation × number of bedrooms × time (transaction month-year) fixed effects; similarly for Z×D×E×B×Q, except that Q indicates quarter-year. Property controls include age and square footage. Buyer county controls include average county income and county population. Sample includes all transactions of single-family homes that lie within 1km from the U.S. East Coast between 2001 and 2016 (see Section 3.2 for more data descriptions); exclude transactions that do not have an associated mortgage contract (for which the dependent variable is not well defined); exclude nonstandard mortgage observations where term is not 15 nor 30 years. Standard errors in parentheses are clustered at the zip code level; * ($p < 0.1$), ** ($p < 0.05$), *** ($p < 0.01$). Regressions are estimated using OLS.

elevation bin × number of bedrooms (Z×D×E×B). The estimate for the coefficient of the interaction term between SLR risk and High Buyer Belief remains positive and significant for the leveraged regression. It remains positive but is no longer significant for the maturity regression.

Column 2 reintroduces a time dimension to the fixed effects by incorporating the quarter and year of the transaction (Z×D×E×B×Q). The estimate for the interaction term between SLR risk and High Buyer Belief is now both positive and statistically significant, as in our benchmark specification.

A potential concern for our benchmark regressions (L2) and (M2) is that they pool together owner-occupied (OO) transactions and non-owner-occupied (NOO) ones. It is possible that NOO buyers have different incentives than OO buyers, as the former could

	Leveraged	Long Maturity
1.SLR (6ft)	0.0180	0.0169
	(0.014)	(0.017)
2.SLR (5ft)	0.0140	-0.0042
	(0.020)	(0.026)
3.SLR (4ft)	-0.0343	-0.0038
	(0.027)	(0.020)
4.SLR (≤3ft)	-0.0362	-0.0305
	(0.031)	(0.024)
1.SLR x High Belief	0.0154	0.0140
	(0.012)	(0.009)
2.SLR x High Belief	0.0246*	0.0321**
	(0.015)	(0.014)
3.SLR x High Belief	0.0455**	0.0323**
	(0.018)	(0.014)
4.SLR x High Belief	0.0856***	0.0322*
	(0.023)	(0.018)
Property & buyer county controls	Y	Y
Buyer county controls x SLR	Y	Y
Z × D × E × B × M fe	Y	Y
Lender fe		Y
N	405893	150746
R2	0.473	0.441

Table 6: Robustness with more refined measure of SLR risk. $i.SLR\ Risk$ where $i \in \{1, \ldots, 4\}$ indicates whether a property will be inundated with 6, 5, 4, or less than equal to 3 feet of SLR, respectively. Comparison group: properties that will not be inundated even with six feet of SLR. The rest is the same as in Tables 2 and 3.

be using their property more as an investment vehicle, or they could be more "sophisticated" in processing future SLR risk (Bernstein et al. 2019). For this reason, column augments the specification in column 2 with a dummy O, which is one if the transion is OO and zero otherwise, leading to a specification denoted by Z×D×E×B×Q$times$O. Hence, we are comparing two transactions that are not only in the same zip code, distance to coast bin, elevation bin, having the same number of bedrooms, the same quarter and year of transaction, but *also* having the same owner occupied status (i.e., both OO or both NOO). Our main results hold: the coefficient for the interaction term is positive and significant in both the leveraged and in the long maturity regression.

Column 4 repeats the exercise in column 3, but replaces the quarter-year variable for the transaction time Q with the benchmark month-year variable M. Again, our main results hold.

In summary, our main results are robust to various alternative fixed effect specifications.

	Leveraged			
SLR Risk	0.007	-0.005	0.010	0.012
	(0.016)	(0.012)	(0.010)	(0.013)
SLR Risk × High Belief	0.032***	0.031***	0.019**	0.021**
	(0.010)	(0.011)	(0.008)	(0.010)
F.e.	Z×D×E×B	Z×D×E×B×Q	Z×D×E×B×Q×O	Z×D×E×B×M×O
Property & buyer county controls	Y	Y	Y	Y
Buyer county controls × SLR	Y	Y	Y	Y
N	852817	568636	490546	322484
R2	0.188	0.404	0.461	0.526

	Long Maturity			
SLR Risk	-0.011*	-0.003	-0.005	-0.010
	(0.006)	(0.011)	(0.012)	(0.019)
SLR Risk × High Belief	0.007	0.017***	0.012*	0.022**
	(0.005)	(0.006)	(0.007)	(0.009)
F.e.	Z×D×E×B	Z×D×E×B×Q	Z×D×E×B×Q×O	Z×D×E×B×M×O
Property & buyer county controls	Y	Y	Y	Y
Buyer county controls × SLR	Y	Y	Y	Y
Lender fe	Y	Y	Y	Y
N	852817	568636	490546	322484
R2	0.188	0.404	0.461	0.526

Table 7: Robustness with alternative fixed effects. Top table: dependent variable in Column 1 is *Leveraged* (whether the transaction is associated with a mortgage). Bottom table: dependent variable is *Long Maturity* (whether the mortgage term is 30 years). Fixed effect abbreviations: Z – zip code, D – distance to coast bin, E – elevation bin, B – number of bedrooms, Q – quarter and year of transaction, M – month and year of transaction. The rest is the same as in Tables 2 and 3.

5.3 Other belief specifications

Table 8 provides a series of robustness checks for our benchmark regressions (L2) and (M2) with alternative specification for the buyer county climate belief variable. For brevity, we will only report the estimates for the relevant coefficients of the interaction term between SLR Risk and the corresponding belief variable. The set of controls and fixed effects remain as in the benchmark regressions and are reported at the bottom of the table.

Columns 1 and 4 (*Happening*) use the benchmark 2014 Yale Climate Opinion survey data for the percentage of people in each county who say they believe climate change is happening. Columns 2 and 5 (*Worried*) instead use the percentage who say they are worried about climate change. Similarly, columns 3 and 6 (*Timing*) use the percentage who think global warming will start to harm people in the U.S. within 10 years.

Row 1 uses the *High Belief* dummy for whether the buyer is from a county where the corresponding climate belief variable is above the sample median. Rows 2 to 4 rank counties into quartiles of the climate belief variable, and *nth Quartile Belief* is one if the buyer is from a county in that nth quartile of belief and zero otherwise (the comparison group is the first quartile, those with the most optimistic beliefs). Finally,

row 5 uses the continuous measure of the belief variable (i.e., respectively, the fraction of the buyer's county saying that they belief climate change is happening, or that they are worried about climate change, or that they think that global warming will harm the U.S. within 10 years).

Row 1 shows that our main results continue to hold – the estimates of the interaction term *SLR Risk* × *High Belief* are positive and significant, regardless of the survey question (*Happening*, *Worried*, or *Timing*). In rows 2 to 4 (belief quartile specifications), the estimates continue to show that the estimates for the interaction between SLR and the belief variable are positive and generally statistically significant (especially for the top 4th belief quartile). Note that the estimates of the interaction terms also generally tend to be larger in magnitude for the 4th (top) belief quartile, especially when compared with the interaction terms for the 2nd quartile. This is qualitatively consistent with the model's prediction that the effect of SLR risk on the leverage and the long maturity probabilities should be stronger for buyers with more pessimistic climate beliefs. This can also be seen in the final row, which shows the estimates for the interaction terms between SLR risk and the continuous measure of belief being positive throughout and statistically significant in 4 of the 6 columns.

6 Conclusion

What makes climate risks special? Two outstanding characteristics are that (i) climate risks could have potentially large damages, and (ii) there is substantial belief disagreement over climate risks, especially in the United States. Our paper finds that the combination of these two features is key in understanding the effects of climate risks on the financial system. In particular, we theoretically argue and empirically document that the interaction between the exposure to future SLR risk and climate belief disagreement is an important predictor of leverage and maturity outcomes in the coastal mortgage market.

Our analysis has some limitations. As mentioned, the data for the mortgage interest rates are largely missing from our Corelogic sample. While we try to control for the missing interest rates with a rich set of fixed effects (including those for time, location, and the lender), we acknowledge that this missing data could affect the interpretation of our estimates. As future work, we are investigating incorporating other data sets that could examine how interest rates factor into the mortgage decision. Second, our measure of climate beliefs is relatively coarse: the Yale Climate Opinion Survey only provides averages at the county level, which were computed from individual responses that we do not have access to. Ideally, we would like to collect individual beliefs about SLR (as done in Bakkensen and Barrage 2022 for Rhode Island), at least for a representative

	Leveraged			Long Maturity		
	Happening	Worried	Timing	Happening	Worried	Timing
SLR Risk × High Belief (above median)	0.034***	0.049***	0.031**	0.024***	0.026***	0.023***
	(0.011)	(0.012)	(0.013)	(0.007)	(0.007)	(0.007)
SLR × 2nd Quartile Belief	0.023**	0.006	0.001	0.030***	0.008	0.025**
	(0.011)	(0.012)	(0.011)	(0.008)	(0.010)	(0.010)
SLR × 3rd Quartile Belief	0.011	0.058***	0.022	0.034***	0.033***	0.017
	(0.017)	(0.013)	(0.015)	(0.011)	(0.009)	(0.010)
SLR × 4th Quartile (highest) Belief	0.045**	0.047*	0.051***	0.034***	0.023	0.038***
	(0.018)	(0.027)	(0.015)	(0.010)	(0.017)	(0.010)
SLR Risk × Belief (continuous)	0.002	0.003***	0.002*	0.002*	0.002**	0.000
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.000)
Z × D × E × B × M fe	Y	Y	Y	Y	Y	Y
Property & buyer county controls	Y	Y	Y	Y	Y	Y
Buyer county controls × SLR	Y	Y	Y	Y	Y	Y
Lender fe				Y	Y	Y

Table 8: Robustness with alternate specification for the buyer county belief measure. Columns 1-3 report results for variations of leveraged regression (L2) and columns 4-6 for long maturity regressions (M2). For brevity, only estimates of the coefficients of the interaction term SLR Risk × belief are reported. Columns 1 and 4 (*Happening*) use 2014 Yale Climate Opinion survey data for the percentage of people in each county who say they believe climate change is happening; Columns 2 and 5 (*Worried*) – the percentage who say they are worried about climate change; Columns 3 and 6 (*Timing*) – the percentage who think global warming will start to harm people in the U.S. within 10 years. *High Belief* in row 1 indicates whether the buyer is from a county where the climate belief variable is above the sample median. Rows 2-4 rank counties into quartiles of the climate belief variable, and *nth Quartile Belief* is one if the buyer is from a county in that nth quartile of belief and zero otherwise. Row 5 uses the continuous measure of the belief variable (i.e., respectively, the fraction of the buyer's county saying that they belief climate change is happening, or that they are worried about climate change, or that they think that global warming will harm the U.S. within 10 years). The rest is the same as in Tables 2 and 3.

sample of homebuyers living along the East Coast, along with information from their housing and mortgage transactions. We leave this potentially important undertaking for a future project. Another fruitful area for future work is examining delinquency and default data to examine these additional mechanisms.

Finally, our analysis implies that adaptation strategies in financial markets, which are known to be subject to agency problems, may have nontrivial implications, specifically due to the strategic transfers of climate risks. Whether this could lead to concentration of climate risks and whether it could affect financial stability or general welfare remain open questions. Future research on the potential effects of climate change on financial stability (such as climate stress testing exercises, as recently developed in Jung et al. 2021) should take the strategic transferring of climate-related risks into account.

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A Appendix

A.1 Further data descriptions

	Mean	Std
Sale price ($)	419,358.90	631,877.10
Leveraged dummy	0.60	0.49
Mortgage amount ($)	181,407.00	290,976.90
Mortgage term (y)	27.90	6.19
Distance to coast (m)	386.42	294.66
Elevation (m)	7.03	12.43
Climate belief (happening, county level,%)	66.01	4.80
Inundated with 1ft SLR	0.01	0.07
Inundated with 2ft SLR	0.01	0.11
Inundated with 3ft SLR	0.04	0.19
Inundated with 4ft SLR	0.09	0.29
Inundated with 5ft SLR	0.16	0.37
Inundated with 6ft SLR	0.24	0.43

Table A1: Summary statistics

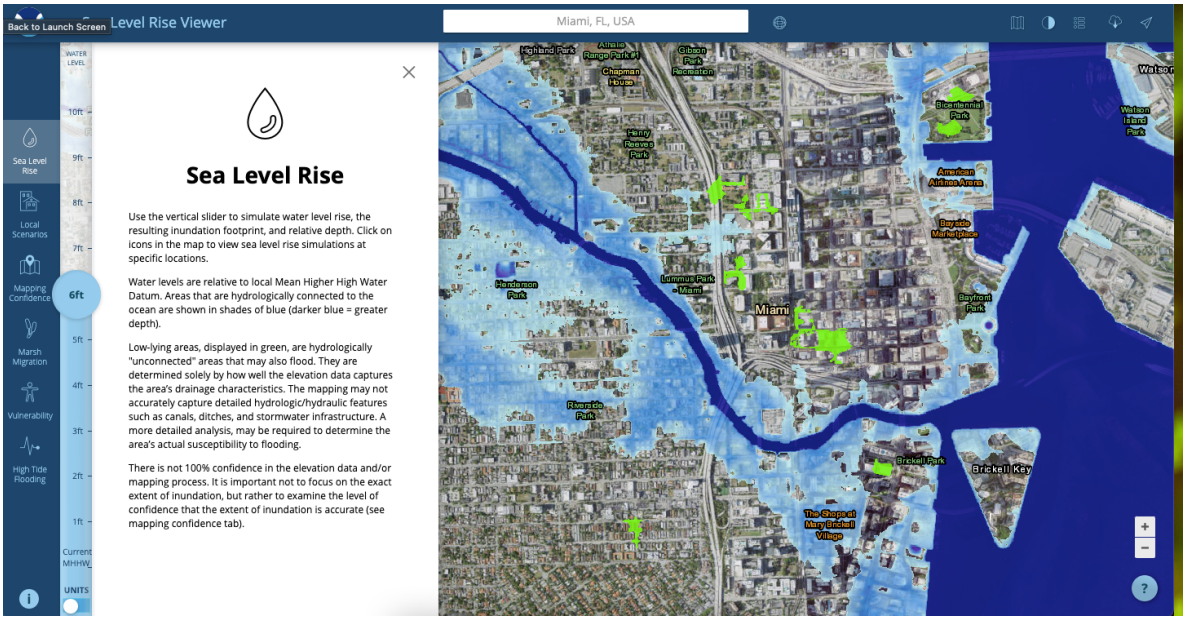

Figure 1: Screenshot of NOAA SLR Viewer for Miami under the scenario of six feet of SLR. Coordinates that lie in the shaded light blue areas are predicted to be inundated under this scenario.