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Leveraging the Disagreement on Climate Change: Theory and Evidence

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Leveraging the Disagreement on Climate Change: Theory and Evidence

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Abstract

We theoretically and empirically investigate how climate risks affect collateralized debt markets. First, we develop a debt model where agents have different beliefs over a long-run risk. In contrast with existing two-period competitive-equilibrium models, our infinite-horizon competitive-search model predicts more pessimistic agents are *more* likely to make leveraged investments on risky collateral assets. They also tend to use *longer* maturity debt contracts, which are more exposed to the long-run risk. Second, employing large data on real estate *and* mortgage transactions, combined with high resolution sea-level-rise maps, we find robust evidence for these findings. We also show how monetary and securitization policies affect mortgage climate risk exposure. Our results highlight the importance of heterogeneous beliefs in understanding the effects of climate change on the financial system.

Keywords: climate finance, sea level rise, heterogeneous beliefs, real estate, mortgage, search and matching, monetary policy.

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1 Introduction

Understanding how climate change may affect financial markets is a question of primary importance to researchers, financial regulators, and policymakers around the world.[1] A rapidly growing "climate finance" literature is investigating the extent to which climate risks affect asset markets, especially how sea level rise risks affect 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, especially the mortgage market, despite the critical role these markets play in the financial system and in past financial crises (Phan 2021). This is likely because theoretically and empirically understanding how credit markets allocate an emerging source of risk is nontrivial, in part due to the agency problems that naturally arise in borrower-lender relationships (Tirole 1999; Allen and Gale 2000). These complications compound when there is belief disagreement across economic agents about future risks (Geanakoplos 2010; Simsek 2013), and belief disagreement is especially pronounced for climate change (Howe et al. 2015; Ballew et al. 2019). A hypothesis common in policy discussions is that those who are less concerned about climate risks (the "optimists") are more likely to make leveraged investment on assets exposed to climate risks – such as coastal real estate properties – relative to those who are more concerned about climate risks (the "pessimists") (e.g., Litterman et al. 2020; Brunetti et al. 2021). In fact, this hypothesis is consistent with the benchmark prediction in standard models of leveraged investments under belief disagreement (e.g., Geanakoplos 2010; Simsek 2013; Fostel and Geanakoplos 2015).

In this paper, we provide novel theoretical predictions and empirical evidence on how climate risks affect the mortgage market. We start by developing a parsimonious model of a competitive collateralized credit market under belief disagreement, building upon the literature that follows the pioneering work of Geanakoplos (2010). We introduce two empirically-relevant elements: endogenous maturity choice and search frictions. The maturity dimension is especially relevant for the context of climate change for two reasons: (i) most of the damages from climate change will occur in the future, and hence (ii) a contract with a longer maturity is naturally more exposed to climate risks than a shorter contract. By allowing debt contracts to have different maturity lengths, the model allows for a new channel where pessimistic borrowers can gain by trading their exposure to the long-run risks with relatively more optimistic lenders.[2] We show that this new gain from trade can "overturn" the conventional prediction in standard

[1] See, e.g., the recent reports on climate change and financial stability by the NGFS (Network for Greening the Financial System 2019), by the Financial Stability Oversight Council (Council 2021), by the U.S. Commodity Futures Trading Commission (Litterman et al. 2020), by the Federal Reserve (Brunetti et al. 2021), and the Executive Order on Tackling the Climate Crisis by the White House.

[2] We refer to this phenomenon as "leveraging the belief disagreement" in the title of the paper.

models of belief disagreement.

More specifically, we consider an infinite-horizon environment where the collateral assets (e.g., coastal real estate properties) are exposed to a potentially damaging disaster risk in the long run (e.g., inundation due to sea level rise). We assume belief heterogeneity in a simple way: borrowers (e.g., homebuyers) and lenders (e.g., banks and buyers of mortgage-backed securities) disagree on the rate at which the disaster arrives. More optimistic agents believe that the disaster will happen far into the future, while more pessimistic ones believe that the it will happen sooner. Everyone's belief is common knowledge and agents agree to disagree.

A collateralized long-term loan (e.g., mortgage) is a contract where a lender loans an amount to a borrower in exchange for a promise of a repayment stream by the borrower until a maturity date. The borrower chooses the loan amount, repayment stream, *and* the maturity of the contract. The borrower can always default before the contract matures, but in doing so she will lose the collateral asset and face an exogenous default cost. There is a competitive search process that matches the borrower with a lender with an endogenous probability, which we call the *leverage probability*. The equilibrium leverage probability depends on the loan amount, promised payment stream, and maturity. This probability is a key moment from the model that maps to the probability that a housing transaction is associated with a mortgage contract in the data. Note that if the collateral asset is sufficiently exposed, then when the disaster shock eventually hits, it will be optimal for the borrower to default and surrender the damaged collateral to the lender. This linkage between the disaster risk and the default risk will be important in determining equilibrium outcomes.

The model yields clear analytical results. If the underlying collateral asset is sufficiently exposed, then the equilibrium leverage probability and the equilibrium maturity are both increasing in the degree of borrower pessimism (relative to the beliefs of lenders). At the extensive margin, purchases of exposed properties by pessimists are *more* likely to be financed with debt. At the intensive margin, these debt contracts tend to have *longer* maturity. These are two key implications of the model that we will test in the data. Note that these predictions are in contrast to those of the standard models of belief disagreement (e.g., Geanakoplos 2010; Simsek 2013), which assume exogenous debt maturity and predict that pessimists are less likely to leverage and have no prediction on the maturity dimension.[3]

Figure 1 illustrates the intuition.[4] In the absence of long-term insurance contracts, a defaultable long-term debt contract provides implicit insurance against the long-run

[3]Most existing models of credit markets with belief disagreement shut down the endogeneity of debt maturity, either explicitly or implicitly, by assuming a two-period environment, where the maturity is automatically fixed to be the duration between the two periods. See the related literature section.

[4]We thank Asaf Bernstein for suggesting this illustration.

climate risk. And this insurance service is more valuable for more pessimistic agents. Hence, there is a gain from trading a long-term debt contract, collateralized by the risky asset, between a relatively optimistic lender and a relatively pessimistic borrower. The pessimistic borrower believes that the disaster will happen soon, and when it does, she knows that it will be optimal for her to default. All else equal, given that she expects an early default, she would like to back-load the repayment *promises*. She could do so by choosing a long-maturity debt contract, which stretches the payment stream over a long horizon. On the other hand, the relatively more optimistic lender believes that the disaster will happen later and thus does not assign a high default risk to the debt contract. In sum, the belief disagreement gives rise to a gain from trading a defaultable debt contract with long maturity.

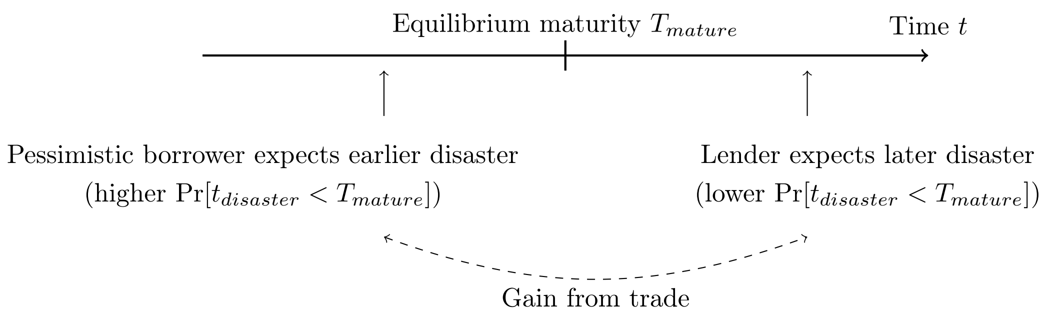

Figure 1: Illustration of the model's main intuition.

We further show that the leveraging of the belief disagreement depends on macroeconomic factors that affect general credit conditions. One factor of particular relevance is monetary policy. We provide an extension of the model where borrowers and lenders have different funding costs, which depend on the interest rate sets by a monetary authority. We show that an expansionary monetary policy (e.g., a decrease in the Fed's interest rate) increases the equilibrium leverage probability by pessimists (effect at the extensive margin). However, the policy does not affect the equilibrium maturity (no effect at the intensive margin). These are two additional testable implications that we can empirically evaluate.

Finally, we extend the model to endogenize the asset prices by allowing for a Nash bargaining between buyers and a set of sellers. The extension implies rather intuitively that, all else equal, the pricing of the long-run risk increases with the buyer's pessimism. This is another natural implication that we test in the data.

Next, we evaluate the testable implications of the model by analyzing the effects of long-run sea level rise (SLR) risks on the mortgage market. We focus on SLR not only because it is one of the most salient dimensions of climate change projected to affect millions of households in the U.S.,[5] but also because it is one type of climate risk that

[5]For example, as highlighted in the Fourth National Climate Assessment (Fleming et al. 2018),

has been well documented with high-resolution spatial variation (see Figure 4 for an illustration). We employ an extensive proprietary data set of real estate *and* mortgage transactions provided by CoreLogic, a large data vendor, to examine the complete sales history of single-family homes along the U.S. Atlantic Coast from 2001 to 2016.

We match each property's coordinates with its projected exposure to permanent coastal inundation under various long-run SLR scenarios, using the National Oceanic and Atmospheric Administration's (NOAA) state-of-the-art SLR mapping tool as well as a series of additional control variables. Employing this large-scale yet highly granular data and additionally conditioning on a rich set of fixed effects, our identification strategy is to compare the observable mortgage outcomes between the transactions of properties that have different SLR risk exposure but are otherwise very similar in other dimensions: having the same ZIP code, distance to coast, elevation, number of bedrooms, year and month of sale, and mortgage lender.

To assign whether the buyer in a transaction is a (likely) pessimist or (likely) optimist regarding the underlying exposure of the house to future SLR risks, we follow the most recent development in the climate finance literature (e.g., Bernstein et al. 2019 and Baldauf et al. 2020 – henceforth BGL and BGY, respectively) and rely on Yale Climate Opinion Survey (Howe et al. 2015)'s national survey of public perception on global warming. This database provides information on the fractions of adults in each county who believe that global warming is happening, are worried about it, or believe that it will harm them in the near future. For each property transaction, we match the geographic location of where the buyer comes from to the respective county's climate belief measure. The key assumption in this matching is that a buyer who comes from a county with a more pessimistic belief measure is more likely to have a pessimistic belief herself.[6]

Our empirical results are as follows. First, in re-estimating the classic hedonic housing price regression, after our rich set of fixed effects disentangles the SLR risk capitalization from the effects of coastal amenity values, we find that at-risk properties (those projected to be permanently inundated at six feet of SLR) sell at a 6% discount on average, relative to similar but less-at-risk properties. The sign and magnitude of our estimates align closely with the previous literature's findings on the capitalization of SLR risks in the coastal real estate market (e.g., BGL and BGY) and are robust to various alternative measures of SLR risks and econometric specifications.

more than 40% of Americans live in coastal shoreline counties subject to SLR inundation risk.

[6] In a related paper outside of the climate context, Meeuwis et al. (2021) exploit a large proprietary household financial data set to evaluate the implications of the belief disagreement between (likely) Republicans and (likely) Democrats for equity investment decisions after the 2016 presidential election. Due to a data limitation similar to ours, the authors cannot observe households' equity belief or political affiliation. Instead, they devise ways to assign whether a household is a (likely) Democrat or (likely) Republican.

Second, we find robust evidence for the model's main implication on the relationship between risk exposure and the extensive margin of the leverage probability. The transaction of an at-risk property has an approximately two percentage points higher probability of being associated with a mortgage (relative to that of a similar but less-at-risk property), indicating higher leverage probabilities for riskier investments. The magnitude is economically significant – two percentage points is about a half of the rise in the share of property transactions that are leveraged in our data between 2001 (the beginning of our sample) and 2007 (the peak of the housing boom before the Great Recession).

Importantly, consistent with our theory, we find that belief disagreement is a key moderator of the relationship between climate risk exposure and leverage at the extensive margin. Buyers who are more likely to be pessimists are *more* likely to use a mortgage contract to finance the purchase of exposed properties. Among transactions with such buyers, at-risk properties are about 3.4% more likely to be leveraged, while the relationship between SLR risks and leverage is not statistically significant among likely optimistic buyers.

Consistent with the theory, we also find that beliefs matter for the intensive margin of maturity choice. Among transactions of at-risk properties, likely pessimistic buyers are more likely to have a mortgage contract with a long maturity of thirty years. All of the results above are robust to alternative specifications including fixed effects, SLR risk definitions, operationalizations of climate beliefs, and a suite of additional control variables. The findings affirm the novel implications of our theory – more pessimistic buyers are more likely to shift their long-run risk exposure to lenders via long-term defaultable debt contracts.

In response to potential concerns about our measurement of climate beliefs based on the Yale survey, including the potential selection bias due to residential sorting over climate risks (Bakkensen and Ma, 2020; Bakkensen and Barrage, 2022), we provide several additional ways to measure homebuyers' climate beliefs in Section 6.1. In one approach, we obtain two decades of a nationally-representative proprietary survey data set from Gallup to construct our own panel measure of climate beliefs that varies at the county-by-year level. In another approach, instead of relying on surveys, we develop a novel belief imputation strategy to estimate transaction-specific beliefs from our micro data. Specifically, we recover individual homebuyer beliefs from the residuals of a hedonic regression of the housing price on observable housing, neighborhood, and buyer neighborhood characteristics. Intuitively, the extent to which a transaction price capitalizes the SLR risk should reveal the extent to which the homebuyer is concerned about the risk. We then use the transaction-level imputed beliefs in our mortgage regressions. All our results are robust to these alternative measures of climate beliefs.

Diving deeper, we find evidence supporting the model's two additional predictions on the effects of monetary policies. A reduction in the interest rate – as measured by the market yield on Treasury securities – increases the leverage probability (the extensive margin) of purchases of at-risk properties by likely pessimistic buyers, but does not affect the maturity of the associated mortgage contracts (the intensive margin).

A question may naturally arise as to why mortgage lenders are potentially (acting as if they are) less pessimistic about climate risks than certain borrowers. Recent papers in the literature have argued that mortgage lenders tend to shift climate risks to government-sponsored enterprises (GSE) through the process of securitization and the sale of mortgages below the conforming loan limits to such institutions. This is possible since GSE securitization rules and fees tend to only reflect current official floodplain maps and not necessarily future SLR risks (e.g., Liao and Mulder 2021; Ouazad and Kahn 2022; Panjwani 2022). If this is indeed the case, then we should expect our empirical results to hold more for the conforming loan segment than for the jumbo segment. In fact, this is exactly what we find: our leverage and maturity results are almost entirely driven by conforming loans as opposed to nonconforming loans.

Our findings have relevant policy implications. 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 evidenced in past financial crises (e.g., Mian and Sufi 2015). The results also suggest the role of monetary and regulatory policies in dampening or exacerbating the influence of climate risk in the financial system. 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.

The rest of the paper is organized as follows. Section 2 discusses the related literature. Section 3 provides the theoretical model. Section 4 describes the data and empirical framework. Section 5 describes our main empirical results. Section 6 provides a battery of robustness checks and our transaction-level belief imputation exercise. Section 7 provides further evidence of the roles of securitization and monetary policies. Section 8 concludes. The Appendix provides proofs and further details of the empirical analysis.

2 Related literature

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. In doing so, it relates and contributes to several bodies of research.

The first is a rapidly growing (empirical) literature on climate finance, which studies how 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). Our paper contributes to the understanding of how SLR and increased flood risks affect the housing market (BGL; BGY; Murfin and Spiegel 2020; Hino and Burke 2021; Keys and Mulder 2020; Addoum et al. 2021; Bakkensen and Barrage 2022).[7] Our paper also contributes to a growing but important set of papers investigating how the interaction between climate risks and existing government policies, including policies on securitization and insurance subsidies, affects the mortgage market (Issler et al. 2020; Liao and Mulder 2021; Sastry 2021; Ouazad and Kahn 2022). 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. In investigating climate risks as a source of long-run risks that could affect the prices of long-term financial assets/liabilities such as stocks and long-term municipal or sovereign bonds, our analysis is related to those in Bansal et al. (2021), Painter (2020), Goldsmith-Pinkham et al. (2021), and Barnett and Yannelis (2021). In developing a method to infer investors' climate beliefs from detailed financial market data (residential housing transactions in our case), our paper is also related to Alekseev et al. (2021) (changes in the portfolios of mutual funds) and Ouazad (2022) (firm-level option prices).

On the theoretical side, our paper is related to the literature on modeling credit markets with heterogeneous beliefs, as pioneered by Geanakoplos (1997, 2003, 2010). To the best of our knowledge, ours is the first to apply such a theory to the context of climate change. In doing so, we make two contributions. On the empirical side, we are the first to exploit the well-documented heterogeneity in the beliefs about climate change to evaluate theories of investment under belief disagreement.[8] On the theoretical side, we add a new insight on how the time dimension of endogenous maturity choice can change the theoretical predictions. As mentioned previously, most existing models – including those in Geanakoplos (2010), Simsek (2013), Fostel and Geanakoplos (2008, 2015), Geerolf (2015), Cao (2018), and Dong et al. (2022) – predict that optimists, rather than pessimists, are more likely to make leveraged investments and thus cannot explain the empirical finding that we document. In "overturning" this standard prediction, the closest paper to ours is Bailey et al. (2019), which develops a two-period model of mortgage leverage choice with heterogeneous beliefs over future house prices, where agents have an additional choice at the intensive margin to either purchase a cheaper

[7] 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).

[8] Also related is an empirical literature that studies the role of heterogeneous information (on land/structure/neighborhood characteristics) in housing and mortgage markets. See Kurlat and Stroebel (2015), Stroebel (2016), and references therein.

home or to rent, and evaluates the model's predictions using Facebook data. Our model provides a different yet complementary channel to that of Bailey et al. (2019): the choice at the intensive margin of debt maturity. The endogenous maturity is key in explaining the empirical patterns on the relationship we find between climate risks and mortgage maturity. Our infinite-horizon long-run-risk model is also arguably more appropriate to study the implications of future climate risks. Moreover, our model also features search frictions, which allow us to endogenize and characterize the probability of mortgage usage, which is a critical moment in mapping our model to data.

Our model also builds upon the housing market search literature (e.g., Ngai and Tenreyro 2014; Head et al. 2014; Landvoigt et al. 2015; Garriga and Hedlund 2020) and the credit market search literature (e.g., Bethune et al. 2022; Rocheteau et al. 2018). Our contribution to this literature is to incorporate long-run (climate) risks and heterogeneous beliefs in a competitive search model, which generates a dispersion of mortgage usage as well as prices and leverage as seen in the data.[9] See Wright et al. (2021) for a survey of competitive search models and their other applications. Our model also relates to models of risk shifting in the markets for debt collateralized by bubbly assets such as housing (Allen and Gale 2000; Barlevy 2014; Bengui and Phan 2018; Allen et al. 2022).

Finally, our paper adds to the growing literature on climate adaptation (e.g., Hsiang and Narita 2012; Mendelsohn et al. 2012; Barreca et al. 2016; Desmet et al. 2021; Alvarez and Rossi-Hansberg 2021; Fried 2021; Phan and Schwartzman 2021). While this literature has mainly focused on physical adaptation (e.g., migration away from areas exposed to SLR, building houses on stilts, adoption of air conditioning), we provide a novel analysis of financial adaptation, in particular the leveraged investment strategies we document.

3 Stylized model

3.1 Environment

Agents. Time is continuous and infinite. There is unit measure of atomistic buyers, and there are competitive lenders with free entry. For simplicity, assume all agents are

[9] Alternatively, Allen et al. (2014) and Allen et al. (2019) formulate a model of random search and negotiation (à la English auction) with mortgage lenders. The key difference is that lenders in their model compete for the borrower post-match a la English auction, while our competitive search environment features the lenders' pre-match competition in the loan approval probability (on top of the terms like the loan amount and interest rate), which is particularly attractive to pessimistic borrowers via the directed search and we find evidence of this mechanism.

risk neutral, discount future payoffs at a common rate $r > 0$, and have deep pockets.[10]

Assets. At the beginning of time, each buyer is matched exogenously with a seller of an indivisible asset. If buyers desire to finance the asset purchase, buyers will search for lenders for a loan contract in the competitive-search markets that we will describe in details later. For now, we take the price P of the asset as given (we will endogenize P in Section 3.3.3).

Disaster. Assets are exposed to a common disaster risk, which follows a Poisson process. For analytical tractability, we assume that the disaster arrives only once at a random period T_d and causes a deterministic permanent damage to the asset's returns. The flow of returns of an asset is:

$$H_t = \begin{cases} h & \text{for } t < T_d \\ h - d & \text{for } t \geq T_d \end{cases},$$

where d is the measure of risk exposure (which may vary across assets).

Beliefs. Buyers have different beliefs about the unobserved true Poisson arrival rate of T_d. Each buyer believes that the arrival rate is $r\lambda$, where the belief parameter λ is distributed over a bounded support $[\lambda_{\min}, \lambda_{\max}]$ with a probability distribution ϕ. A higher value of λ indicates more pessimism: the agent believes that the disaster will arrive sooner. Similarly, a very low value of λ indicates optimism: the agent believes that the shock will arrive very far into the future. For example, we can think of each asset as a coastal property, and homebuyers disagree on how soon each house will be permanently inundated due to sea level rise. We assume for simplicity that lenders share a common belief, denoted by $\bar{\lambda} \in [\lambda_{\min}, \lambda_{\max}]$.[11] Each agent's belief is common knowledge; agents agree to disagree with each other (and hence there is no learning or signaling).

Loan contracts. Buyers/borrowers and lenders trade via loan contracts, collateralized by the assets. A contract specifies the amount L a lender loans to a buyer at $t = 0$,

[10] The assumption of deep-pocketed buyers (whose budget constraints are nonbinding) is also arguably reasonable for our empirical context. As explained in Section 4.1, we will be focusing on transactions of relatively expensive coastal properties, 40% of which are bought with cash.

[11] This assumption is without loss of generality in our environment, where lenders have deep pockets. Alternatively, suppose lenders' beliefs about the arrival probability have a support $[\bar{\lambda}, \bar{\bar{\lambda}}]$. Since lenders have deep pockets, in equilibrium, the supply of credit from the most optimistic lenders (those with belief parameter $\bar{\lambda}$) will crowd out that of other lenders. Hence, equilibrium outcomes are not affected by the presence of other lenders in $(\bar{\lambda}, \bar{\bar{\lambda}}]$.

and the amount M that the buyer promises to repay the lender continuously until the loan matures at T_m (e.g., the monthly mortgage payment). As is usual in models of long-term debt, we assume for convenience that the maturity date T_m is a random variable that arrives at a Poisson rate $r(\frac{1}{\Gamma}-1)$, where the *discounted maturity* parameter $\Gamma \in [\Gamma_0, 1]$ is an endogenous choice.[12] The expected length of maturity is $\mathbb{E}T_m = \frac{\Gamma}{r(1-\Gamma)}$, and thus a higher Γ means a longer loan contract. The random maturity assumption allows us to exploit the memory-less property of the Poisson process without keeping track of the remaining loan balance. For example, the loan balance B_t at any period $t < T_m$ is always constant:

$$B_t \equiv \mathbb{E}\int_t^{T_m} re^{-r(\tau-t)}M d\tau = \Gamma M.$$

In sum, a loan contract is characterized by three attributes $\mathbf{a} \equiv (L, M, \Gamma)$, specifying the loan amount, repayment flow, and discounted maturity, respectively.

Default option. Borrowers could default on their promise to repay at any time before the contract matures. Defaulting, however, comes with a punishment: she will have to surrender the collateral asset and will face an exogenous deterministic default cost $f \geq 0$ (e.g., legal costs and recourse due to foreclosure).

The period $t = 0$ expected utility for a buyer using the loan contract $\mathbf{a} = (L, M, \Gamma)$ to finance the asset purchase and never defaulting (a risk-free leveraged buyer) is:

$$-(P-L) + \mathbb{E}_\lambda\left\{\int_0^{T_m} re^{-rt}(H_t - M)dt + \int_{T_m}^{\infty} re^{-rt}H_t dt\right\},$$

where the first term $P - L$ is the down payment, and the second term is the total expected utility from the asset return H_t, minus the debt repayment stream M until the loan matures at T_m. Note that the entire term in the curly brackets can be rewritten as $v_\lambda - \Gamma M$, where the subjective value of the asset, v_λ, is:

$$v_\lambda \equiv \mathbb{E}_\lambda \int_0^\infty re^{-rt}H_t dt = h - \frac{\lambda}{1+\lambda}d. \tag{1}$$

For unleveraged buyers ($L = M = 0$), their expected utility is simply $-P + v_\lambda$. We assume

$$P < v_\lambda, \tag{2}$$

so that buyers always want to purchase the asset.

The period $t = 0$ expected utility for a buyer choosing to default at some date

[12] The lower bound $\Gamma_0 > 0$ means that lenders cannot underwrite contracts that mature immediately.

$T_f < T_m$ (a risky leveraged buyer) is instead given by:

$$-(P-L)+\mathbb{E}_\lambda\left\{\int_0^{T_f} re^{-rt}(H_t-M)dt+e^{-rT_f}\left[\max\{p_{T_f}-B_{T_f},0\}-f\right]\right\},$$

where the last term in the square brackets indicates that the defaulting buyer will surrender the collateral, walk away from any loan balance B_{T_f} in excess of liquidation price of the asset p_{T_f}, and face the default cost f. Buyers and lenders take the liquidation price p_{T_f} of the asset as given. Without loss of generality, we set the liquidation price at $p_t = h-d$ if $t \geq T_d$ (as all uncertainly will be resolved after the disaster date T_d). If $t < T_d$, we set $p_t = \bar{p}_\lambda$, where $\bar{p}_\lambda$ is an exogenous parameter that can depend on λ. For tractability, we assume

$$\bar{p}_\lambda - f < v_\lambda, \tag{3}$$

so that defaulting before the disaster is never optimal.

Combining the above cases, a buyer's optimal default time for a given loan contract $\mathbf{a}$, denoted by $T_f(\lambda, \mathbf{a})$, solves:

$$V_\lambda(\mathbf{a}) \equiv \max_{T_f} \mathbb{E}_\lambda \left\{ \begin{array}{l} \int_0^{\min(T_m,T_f)} re^{-rt}(H_t-M)dt \\ +1_{T_f\geq T_m}\int_{T_m}^{\infty} re^{-rt}H_t dt \\ +1_{T_f<T_m}e^{-rT_f}\left[\max\{p_{T_f}-B_{T_f},0\}-f\right] \end{array} \right\}. \tag{4}$$

Finally, the buyer's choice of the loan contract solves:

$$U_\lambda \equiv \max_{\mathbf{a}\in\mathcal{A}_\lambda}\left\{\alpha_\lambda(\mathbf{a})\left[-(P-L)+V_\lambda(\mathbf{a})\right]+\left[1-\alpha_\lambda(\mathbf{a})\right](-P+v_\lambda)\right\}, \tag{5}$$

where $\mathcal{A}_\lambda$ is the menu of loan contracts and $\alpha_\lambda(\mathbf{a})$ is the buyer's probability of finding a lender approving the loan contract $\mathbf{a}$. Both $\mathcal{A}_\lambda$ and α_λ will be specified in equilibrium.

Lender's profit. Anticipating the buyer's default strategy, a lender's period $t=0$ expected profit of offering loan contract $\mathbf{a}=(L,M,\Gamma)$ to a buyer of belief type λ is:

$$\Pi_\lambda(\mathbf{a}) \equiv -L + R_\lambda(\mathbf{a}) - \kappa_0(\Gamma). \tag{6}$$

The term $R_\lambda(\mathbf{a})$ is the lender's expected present value of the loan repayment, given lender belief $\bar{\lambda}$ and the borrower's optimal default time $T_f = T_f(\lambda, \mathbf{a})$:

$$R_\lambda(\mathbf{a}) \equiv \mathbb{E}_{\bar{\lambda}}\left\{\int_0^{\min\{T_m,T_f\}} re^{-rt}Mdt + 1_{T_f<T_m}e^{-rT_f}\min\{p_{T_f},B_{T_f}\}|T_f=T_f(\lambda,\mathbf{a})\right\}, \tag{7}$$

Since a borrower can walk away from any loan balance in excess of the liquidation price of the collateral asset, the lender collects $\min\{p_{T_f}, B_{T_f}\}$ at the default date T_f. Finally, the term $\kappa_0(\Gamma)$ in (6) is the operational cost of servicing a loan contract of maturity Γ. We assume that longer maturity loans are costlier to service ($\kappa_0' > 0$) and that the cost is convex ($\kappa_0'' > 0$), and we normalize $\kappa_0(\Gamma_0) = 0$. This cost term will help yield an interior solution to the optimal maturity choice.

Competitive search. Buyers search for lenders via a competitive search process. We choose the search environment not only because we think it captures the essence of credit search in practice (e.g., homebuyers searching for a mortgage lender), but more importantly also because it will allow us to endogenize *and* characterize the probability that an asset purchase is leveraged – a quantity at the extensive margin that is key in our empirical analysis.[13]

As there are many types of borrowers, it will be convenient to define the concept of a submarket. For each type-λ buyer/borrower and for each loan contract $\mathbf{a}$, a *submarket* consists of an (endogenous) measure n_b of type-λ buyers for whom contract $\mathbf{a}$ solves their optimization problem and an (endogenous) measure n_l of lenders for whom approving contract $\mathbf{a}$ to type-λ buyers satisfies their free-entry condition (to be described below).

Within each submarket, given the borrower mass n_b and the lender mass n_l, the number of matches produced is given by $N(n_b, n_l)$, where N is a constant-returns-to-scale matching technology function. A convenient implication of this specification is that the implied probability that a borrower in the submarket finds a match – which we will refer to as the *leverage (or approval) probability* – is given by:

$$\alpha_\lambda \equiv \frac{N(n_b, n_l)}{n_b} = N(1, n), \tag{8}$$

and the probability that a lender finds a match is:

$$\eta_\lambda \equiv \frac{N(n_b, n_l)}{n_l} = N(1/n, 1), \tag{9}$$

where $n \equiv n_l/n_b$ is the loan market thickness. As usual, we assume that $N(1, n)$ is increasing and concave in n.

To pin down the equilibrium mass of lenders n_l, we assume that lenders can freely enter a submarket after paying a fixed entry cost $\psi > 0$. For each submarket, given the probability $\eta_\lambda(\mathbf{a})$ that a lender finds a type-λ borrower and given the expected profit

[13]Without search frictions, our model would have a bang-bang solution: the leverage probability is either zero or one, as in most existing models of belief disagreement (e.g., Geanakoplos 2010; Simsek 2013).

$\Pi_\lambda(\mathbf{a})$, the free-entry condition is given by:

$$\eta_\lambda(\mathbf{a})\Pi_\lambda(\mathbf{a}) - \psi \leq 0, \text{ where strict inequality implies } n_l = 0. \tag{10}$$

In other words, competitive lenders in any active submarket (with $n_l > 0$) must be indifferent between entering or not. We can now define our equilibrium concept.

Definition 1. *A* competitive search equilibrium *consists of, for each buyer's type λ, (i) a menu of all available loan contracts $\mathcal{A}_\lambda$, (ii) measures (n_b, n_l) of borrowers and lenders, and (iii) their matching probabilities α_λ and η_λ such that:*

1. *Given $\alpha_\lambda(\boldsymbol{a})$ and $\mathcal{A}_\lambda$, $n_b(\lambda, \boldsymbol{a})$ is the measure of type-λ borrowers choosing loan contract $\boldsymbol{a}$ in their optimization problem (5);*

2. *Given $\eta_\lambda(\boldsymbol{a})$, $n_l(\lambda, \boldsymbol{a})$ is the measure of lenders offering loan contract $\boldsymbol{a}$ to type-λ borrowers to satisfy the free-entry condition (10);*

3. *Given $n_b(\lambda, \boldsymbol{a})$ and $n_l(\lambda, \boldsymbol{a})$, $\alpha_\lambda(\boldsymbol{a})$ and $\eta_\lambda(\boldsymbol{a})$ are given by the matching functions (8) and (9);*[14] *$\mathcal{A}_\lambda$ is the set of $\boldsymbol{a}$ such that (10) holds with equality;*

4. *The total measure of borrowers over submarkets clears the market:*

$$\int_{\boldsymbol{a}\in\mathcal{A}_\lambda} n_b(\lambda, \boldsymbol{a}) d\boldsymbol{a} = \phi(\lambda),$$

where ϕ is the density function of the borrower's type distribution.

Figure 2 summarizes the timeline of the model.

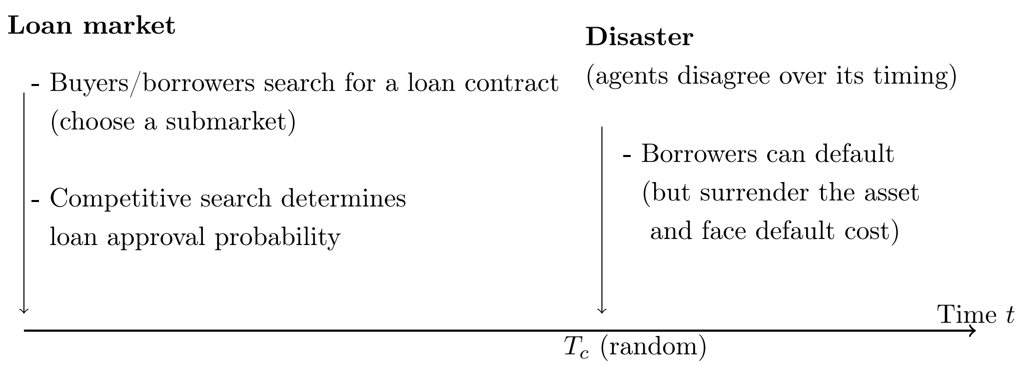

Figure 2: Illustration of the timing of events in the model.

[14]For the submarkets with $n_b(\lambda, \mathbf{a}) = n_l(\lambda, \mathbf{a}) = 0$ (i.e., off-equilibrium contracts in $\mathcal{A}_\lambda$ not chosen by any borrower nor lender), the market thickness $n = n_l/n_b$ involves taking the limit of zero dividing zero. We set $\eta_\lambda(\mathbf{a})$ according to the free-entry condition (10) with equality and set $\alpha_\lambda(\mathbf{a})$ by the corresponding n according to (8) and (9).

Some brief remarks on our modeling choices are warranted. To focus on modeling the choice of loan contract, we have assumed that agents do not resell the asset. Adding other motivations to resell would significantly complicate the model. We could have rewritten the model with a discrete deterministic maturity choice, but the continuous-time Poisson model is much more analytically tractable (e.g. we can compute $\partial T_{\bar{\lambda}}/\partial \lambda$; no need to keep track of remaining mortgage balances), while the implications are qualitatively similar in both environments. Although agents are risk-neutral with deep pockets, we can introduce concave consumption utility and convex cost of labor supply in the search model a la Wong (2016) without changing much of the findings qualitatively. It is straightforward to extend the model to allow for richer specifications of the disaster shock process (e.g., as in Barro 2009; Gourio 2012). However, the current specification will give us very tractable solutions, including the solution to the default decision, which we describe below. Finally, as in the belief disagreement literature, we assume for clarity that the belief of a buyer is common knowledge; however, we can extend our model to allow for the possibility that a buyer's belief is private information and the main results will be qualitatively similar.[15]

3.2 Equilibrium

We now characterize the equilibrium loan contracts and formalize the overall intuition described in the introduction.

Step 1. We first solve the borrower's optimal default problem given a contract:

Proposition 1. *Given a loan contract $\boldsymbol{a} = (L, M, \Gamma)$, the optimal default time T_f that solves problem (4) is:*

$$T_f(\lambda, \boldsymbol{a}) = \begin{cases} 0, & \textit{if } B > b^{risky}; \\ T_d, & \textit{if } B \in (b^{safe}, b_{\lambda}^{risky}] \textit{ and } T_d < T_m; \\ \infty, & \textit{otherwise,} \end{cases}$$

[15]Specifically, we can follow Guerrieri et al. (2010) to specify the menu $\mathcal{A}$ (without indexing on λ) under private information. Here, we sketch the heuristic argument. Note that, from the perspective of the revelation principle, pessimists always want to mimic the optimist to obtain a larger loan and then default immediately. Thus, in the separating equilibrium, every buyer now is offered the same menu of $\lambda_{\max}$ in our benchmark economy. For the safe loans, buyers never default. For the risky loans under the risky debt limit of type-$\lambda_{\max}$ buyers, which is also the tightest, lenders always anticipate buyers to default when the disaster hits, no matter the buyer's belief. So the lender's profit will not depend on the type of buyer and the contract on the menu of $\lambda_{\max}$ chosen. Thus, offering any buyers the menu of $\lambda_{\max}$ in our benchmark economy always satisfies the free-entry condition. We thank Pablo Kurlat for raising this point to us.

where $B = \Gamma M$ is again the loan balance, and the safe and risky debt limits, $b^{safe} < b_\lambda^{risky}$, are given by:

$$b^{safe} \equiv h - d + f, \quad b_\lambda^{risky} \equiv h - (1-\Gamma)\frac{\lambda}{1+\lambda}d + f. \tag{11}$$

Analyzing high-dimensional loan contracts and arbitrary price process may look intractable, but our Poisson environment implies that the default problem of the buyer can be described by three regions of Proposition 1. In the first region $B > b_\lambda^{\text{risky}}$, the loan balances are so large that the buyer defaults immediately. In the second region $B \in (b^{\text{safe}}, b_\lambda^{\text{risky}}]$, the loan balances are between the safe debt limit and the risky debt limit, and the buyer defaults only when the disaster hits. In the third remaining region, the loan balances are less than the safe debt limit and the buyer never defaults. Since rational lenders will not accept a loan contract with 100% default probability, any equilibrium contract must satisfy $B \leq b_\lambda^{\text{risky}}$.

Step 2. We now solve for the optimal loan contract. For any contract $\mathbf{a}$ in the menu $\mathcal{A}_\lambda$, the loan amount L must satisfy lenders' free-entry condition (10):

$$L = R_\lambda(\mathbf{a}) - \underbrace{\left[\kappa_0(\Gamma) + \frac{\psi}{\eta(\alpha)}\right]}_{\text{loan markup}}, \tag{12}$$

where, by conveniently rewriting $\eta_\lambda(\mathbf{a})$ as $\eta(\alpha)$, we have made use of the fact that (8) and (9) implies η can be written as function of α. Borrowers pay a positive loan markup, $\kappa_0(\Gamma) + \psi/\eta(\alpha)$, which is increasing in the discounted maturity Γ and the approval rate α. The markup compensates the lenders for the fixed cost and service cost.

By substituting L from (12) into borrowers' optimization problem (5), we get that the optimal loan contract solves the following joint surplus maximization:[16]

$$J_\lambda \equiv \max_{\alpha\in[0,1]} \underbrace{\alpha \left[\max_{\Gamma\in[\Gamma_0,1]} [S_\lambda(\Gamma) - \kappa_0(\Gamma)] - \frac{\psi}{\eta(\alpha)}\right]}_{\text{expected joint surplus (after deducting costs)}}, \tag{13}$$

where

$$S_\lambda(\Gamma) \equiv \max_{M\geq 0} \underbrace{[V_\lambda(\mathbf{a}) - v_\lambda + R_\lambda(\mathbf{a})]}_{\text{joint surplus (before deducting costs)}}.$$

The term $V_\lambda(\mathbf{a}) - v_\lambda$ captures the buyer's surplus from using loan contract $\mathbf{a}$ (relative to

[16] The fact that the equilibrium contract maximizes the *joint* surplus (rather than just the buyers' surplus) is a typical property of the competitive search environment, where the First Welfare Theorem holds (see, e.g., Wright et al. 2021). This is because the menu $\mathcal{A}_\lambda$ of all contracts satisfying the lender's free-entry condition (as specified in the equilibrium definition) is rich enough to include all Pareto optimal contracts.

not using any loan). In return, the buyer repays the lender $R_\lambda(\mathbf{a})$, which is the lender's surplus. Thus, $V_\lambda(\mathbf{a}) - v_\lambda + R_\lambda(\mathbf{a})$ is the joint surplus of the buyer and lender (before deducting the service cost and fixed cost) from the loan contract $\mathbf{a}$.

Using the optimal default time from Proposition 1, the joint surplus can be categorized in two regions: $B \leq b^{\text{safe}}$ and $B \in (b^{\text{safe}}, b_\lambda^{\text{risky}}]$.[17]

Safe loans. For loan contracts in the region $B \leq b^{\text{safe}}$, the borrower never defaults. In this case, we have shown that the buyer's continuation value (4) is $V_\lambda(\mathbf{a}) = v_\lambda - \Gamma M$. The lender's present value of the loan repayment (7) is simply $R_\lambda(\mathbf{a}) = \Gamma M$. Thus, the joint surplus is zero. Intuitively, without default, the buyer and lender just exchange cash flows without changing the present value of owning an asset. As borrowers and lenders have the same preferences, a safe loan contract will not be used, given the service and fixed costs.[18]

Risky loans. For loan contracts in the region $B \in (b^{\text{safe}}, b_\lambda^{\text{risky}}]$, the buyer defaults when the disaster hits before maturity, i.e., $T_f = T_d < T_m$. Her continuation value (4) can be written as:[19]

$$V_\lambda(\mathbf{a}) = v_\lambda - Q_\lambda(h - d) - T_\lambda M - Q_\lambda f,$$

and the lender's present value of the loan repayment (7) can be written as:

$$R_\lambda(\mathbf{a}) = T_{\bar{\lambda}} M + Q_{\bar{\lambda}}(h - d).$$

Here, $T_{\bar{\lambda}}$ and T_λ are the *expected effective maturity*, which take into account the expectation of the borrower's optimal default time $T_f = T_d$, under the respective beliefs of the lender and borrower:

$$T_x \equiv \mathbb{E}_x \int_0^{T_m \wedge T_f} r e^{-rt} dt = \frac{\Gamma}{1 + x\Gamma}, \quad x \in \{\bar{\lambda}, \lambda\}. \tag{14}$$

Similarly, $Q_{\bar{\lambda}}$ and Q_λ are the *discounted probability of default*, defined as:

$$Q_x \equiv \mathbb{E}_x \left\{ 1_{T_f < T_m} e^{-rT_f} \right\} = \frac{x\Gamma}{1 + x\Gamma}, \quad x \in \{\bar{\lambda}, \lambda\}.$$

[17] Recall that we can ignore the region $B > b_\lambda^{\text{risky}}$, which will never occur in equilibrium.

[18] When lenders have a funding advantage compared to borrowers, safe loan contracts can be featured in equilibrium – see the extension in Section 3.3.2.

[19] We have made use of the fact that $B > b^{\text{safe}}$ implies $\max\{p_{T_d} - B_{T_d}, 0\} = 0$ following assumption (3). Note that the liquidation price at the time of disaster is $p_{T_d} = h - d$.

Hence, unlike safe loans, the joint surplus of risky loans is non-zero and is given by:

$$V_\lambda(\mathbf{a}) - v_\lambda + R_\lambda(\mathbf{a}) = \underbrace{(T_{\bar{\lambda}} - T_\lambda)M}_{\text{gain from maturity}} - \underbrace{(Q_\lambda - Q_{\bar{\lambda}})(h-d)}_{\text{loss of collateral}} - \underbrace{Q_\lambda f}_{\text{default cost}} . \tag{15}$$

Equation (15) highlights two opposite channels behind the potential gain from trading a risky loan:

Maturity channel (new). The first term on the right-hand side of (15) captures the gain from trading defaultable loans at long maturity. $T_{\bar{\lambda}}M$ and $T_\lambda M$ captures the lender's and borrower's expected present values of the *actual* repayment stream, under their respective beliefs about the timing of the climate shock. Since the borrower defaults on the risky loan when the disaster hits before maturity (Proposition 1), a borrower who is more pessimistic than the lender ($\lambda > \bar{\lambda}$) believes that the default time will arrive sooner and hence the expected actual repayment stream to be smaller than what the lender believes. As a result, $(T_{\bar{\lambda}} - T_\lambda)M > 0$ when $\lambda > \bar{\lambda}$. In other words, there is a gain from trade when a relatively more pessimistic buyer borrows from a relatively more optimistic lender.[20] This maturity channel is missing from existing static models of credit markets with heterogeneous beliefs.

Note that $(T_{\bar{\lambda}} - T_\lambda)M$ is increasing in both the repayment flow M and the loan maturity parameter Γ. Intuitively, a higher repayment promise or a longer maturity increases the probability that the loan contract will end in default instead of maturing, hence increasing the gain from disagreement.

Collateral channel (conventional). The second term of (15) captures the expected losses due to the surrender of the collateral from the borrower to the lender after default. This term has the opposite sign compared to the previous gain-from-maturity term. A borrower who is more pessimistic than a lender ($\lambda > \bar{\lambda}$) will have a higher discounted probability of default ($Q_\lambda > Q_{\bar{\lambda}}$), leading to an expected loss of $(Q_\lambda - Q_{\bar{\lambda}})(h-d) > 0$ from surrendering the collateral asset. This collateral channel is standard in static models of heterogeneous beliefs (e.g., Geanakoplos 2010), where *optimistic* buyers choose to borrow in equilibrium. The last term of (15) is the expected discounted default cost, which is also higher for a more pessimistic borrower and strengthens the collateral channel.

[20] This intuition was illustrated in Figure 1 in the introduction.

Step 3. Finally, we establish the existence and uniqueness of a competitive search equilibrium. For convenience, we define the following functions:

$$\begin{aligned} k(x) &\equiv \kappa'^{-1}(x), \text{ where } \kappa(T_{\bar{\lambda}}) \equiv \kappa_0 \left(\frac{1}{\frac{1}{T_{\bar{\lambda}}} - \bar{\lambda}} \right), \\ g(x) &\equiv N\left(1, G^{-1}\left(\frac{\psi}{x}\right)\right), \text{ where } G(n) \equiv \frac{\partial N(1,n)}{\partial n}. \end{aligned}$$

Note that $g(x) = 0$ for all $x \leq 0$. Also, let $T_0 \equiv (\bar{\lambda} + \frac{1}{\Gamma_0})^{-1}$ denote the minimum expected effective maturity, and Δ_λ denote the following *belief disagreement term*:

$$\Delta_\lambda \equiv (1 + \bar{\lambda})(v_{\bar{\lambda}} - v_\lambda) - \bar{\lambda} f. \tag{16}$$

The following proposition characterizes the equilibrium in closed forms:

Proposition 2 (Equilibrium loan contracts)**.** *A competitive search equilibrium exists and is unique. In equilibrium, there are two belief cutoff thresholds:*

$$\lambda_a \equiv \begin{cases} \frac{\bar{\lambda}(f+d)}{d-\bar{\lambda}f}, & \text{if } d > \bar{\lambda}f \\ \infty, & \text{otherwise} \end{cases}, \quad \lambda_b \equiv \begin{cases} \frac{\bar{\lambda}(f+d)+\kappa'(T_0)}{d-\bar{\lambda}f-\kappa'(T_0)} & \text{if } d > \bar{\lambda}f + \kappa'(T_0) \\ \infty, & \text{otherwise} \end{cases}, \tag{17}$$

such that:

(i) Sufficiently optimistic buyers with $\lambda \leq \lambda_a$ choose not to borrow: $\alpha = L = M = 0$.

(ii) Sufficiently pessimistic buyers with $\lambda > \lambda_a$ search for a risky loan contract where risky debt limit (11) binds at $M = b_\lambda^{risky}/\Gamma$, the loan amount L is determined by lenders' free-entry condition as in (12), and the parameter for the maturity rate is $\Gamma = \frac{T_{\bar{\lambda}}}{1-\bar{\lambda}T_{\bar{\lambda}}}$, where the expected effective maturity $T_{\bar{\lambda}}$ is given by:

$$T_{\bar{\lambda}} = \begin{cases} k(\Delta_\lambda) > T_0 & \text{if } \lambda > \lambda_b \\ T_0 & \text{if } \lambda \in (\lambda_a, \lambda_b] \end{cases}. \tag{18}$$

The equilibrium probability of loan approval (or leverage probability) is:

$$\alpha = g\left(\Delta_\lambda T_{\bar{\lambda}} - \kappa(T_{\bar{\lambda}})\right). \tag{19}$$

Figure 3 illustrates the solutions over the regions of Proposition 2. The solid line plots the equilibrium leverage probability α. The dashed line plots the equilibrium expected effective maturity $T_{\bar{\lambda}}$. Since the payoff difference due to belief disagreement Δ_λ is increasing in λ, both α and $T_{\bar{\lambda}}$ are increasing in λ (and strictly increasing when

$\lambda > \lambda_b$). In words, we find that the maturity channel dominates the collateral channel, and, hence, both the extensive margin of the leverage probability and the intensive margin of the maturity are increasing in the degree of the buyer's pessimism. These are two key implications of the model that we will test in the data.

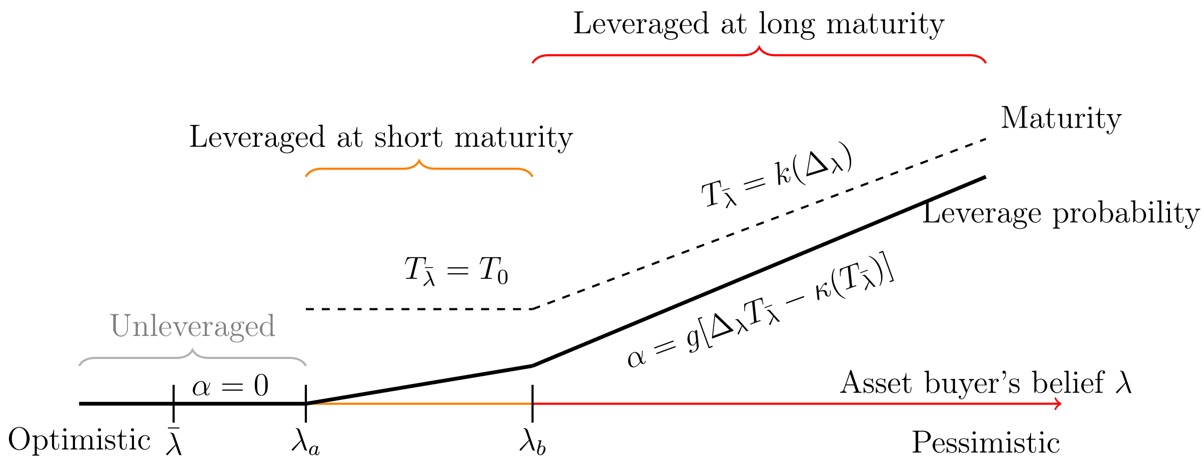

Figure 3: Equilibrium loan contracts.

Note that an important condition for pessimists to leverage in equilibrium is that the asset is sufficiently exposed to the disaster risk (i.e., the disaster damage d sufficiently exceeds the default cost $\bar\lambda f$: $d > \bar\lambda f + \kappa'(T_0)$). If instead the asset is not very exposed ($d \leq \bar\lambda f$), then Proposition 2 implies $\lambda_a = \lambda_b = \infty$. In that case, the gain from a risky loan contract is not enough to justify the service and fixed costs. As a result, buyers would not leverage and belief disagreement would not affect the equilibrium outcomes.

In summary, our model predicts that in a frictional market for defaultable loan contracts, the *interaction* between the exposure to disaster (sufficiently high d) and the belief disagreement (sufficiently high λ relative to $\bar\lambda$) plays an important role in determining the outcomes in the loan market. The model predicts that relatively more pessimistic buyers are more likely to take out loans with longer maturity when purchasing an exposed asset. Table 1 summarizes the testable implications, which forms the basis of our empirical investigation.

	Pessimistic buyers ($\lambda > \lambda_b$) & exposed asset ($d > \bar\lambda f + \kappa'(T_0)$)	Otherwise
Leverage probability α	high	low
Maturity $T_{\bar\lambda}$	long	short

Table 1: Main testable implications of the model.

3.3 Further results and extensions

3.3.1 Comparative statics

Given the tractability of the model, we could further characterize how equilibrium outcomes depend on the primitives. The following corollary summarizes the comparative statics for the equilibrium maturity $T_{\bar{\lambda}}$, loan approval probability α, loan repayment M, loan amount L, and implied loan rate r^m, defined as $1 + r^m \equiv R(\mathbf{a})/L$.

Proposition 3. *The comparative statics with respect to λ and d are given in Table 2.*

	climate belief					climate exposure				
	$\frac{\partial T_{\bar{\lambda}}}{\partial \lambda}$	$\frac{\partial \alpha}{\partial \lambda}$	$\frac{M}{\partial \lambda}$	$\frac{\partial L}{\partial \lambda}$	$\frac{\partial r^m}{\partial \lambda}$	$\frac{\partial T_{\bar{\lambda}}}{\partial d}$	$\frac{\partial \alpha}{\partial d}$	$\frac{\partial M}{\partial d}$	$\frac{\partial L}{\partial d}$	$\frac{\partial r^m}{\partial d}$
PessBuyer ($\lambda > \lambda_b$)	+	+	−	?	?	+	+	−	?	?
Somewhat PessBuyer ($\lambda \in [\lambda_a, \lambda_b]$)	0	+	−	−	+	0	+	−	−	+
Optimistic Buyer ($\lambda < \lambda_a$)	0	0	0	0	0	0	0	0	0	0

Table 2: Comparative statics. Note: + means ≥ 0, − means ≤ 0, ? means ambiguous.

The comparative statics for the expected effective maturity $T_{\bar{\lambda}}$ and the leverage probability α follow immediately from their closed-form solutions. The comparative statics for the repayment flow $M = b^{risky}/\Gamma$ is also straightforward: it is weakly decreasing in the buyer's belief parameter λ and the disaster exposure parameter d.

However, the comparative statics for the loan amount L with respect to λ is ambiguous for a sufficient pessimistic buyer ($\lambda > \lambda_b$), due to two opposite forces. On the loan demand side, more pessimism (a higher λ relative to a fixed $\bar{\lambda}$) implies more gain from trade and hence more incentive for the buyer to borrow. On the loan supply side, a higher λ implies a lower buyer's valuation of the asset v_λ, which in turn lowers her willingness to repay and lenders' willingness to lend. Similarly, a change in the disaster exposure d would have two opposite effects on the loan amount. And finally, since the implied loan rate r^m is directly related to L, it follows that the comparative statics for r^m is ambiguous.

3.3.2 Extension: Monetary policy

Monetary policies are relevant in our context, as they are a powerful instrument affecting the supply of credit in the market, and a large literature has studied their role in shaping credit market outcomes (e.g., Bernanke et al. 1999; Khan et al. 2003; Bethune et al. 2022). We now extend the benchmark model to study the effects of monetary policies on the loan market under belief disagreement. To do so, we introduce asymmetric costs of funds. Specifically, we assume that at $t = 0$, buyers and lenders face exogenous funding costs, denoted by ρ and ι respectively, so that the buyer's problem (5) becomes:

$$U_\lambda \equiv \max_{\mathbf{a}\in\mathcal{A}_\lambda} \{\alpha(\mathbf{a})\left[-(1+\rho)(P-L)+V_\lambda(\mathbf{a})\right]+[1-\alpha(\mathbf{a})][-(1+\rho)P+v_\lambda]\}, \qquad (20)$$

and equation (6) for lenders' expected profit from loan contract $\mathbf{a}$ becomes:

$$\Pi_\lambda(\mathbf{a}) \equiv -(1+\iota)L + R_\lambda(\mathbf{a}) - \kappa_0(\Gamma). \qquad (21)$$

We assume that $\iota < \rho$. This is a natural assumption, given that banks have access to cheaper wholesale funding (such as the Fed funds market or commercial papers), while individual buyers (such as homebuyers) do not. This asymmetry implies two interacting sources of potential gain from trade: belief disagreement and different funding costs.

To study policies, we assume that lenders' funding cost ι depends on the policies of a monetary authority. We will interpret an expansionary (contractionary) monetary policy is a policy that reduces (increases) in ι. This captures the idea that a central bank reduces the funding costs of banks to induce an expansion in the credit supply.

By substituting L into the buyer's problem (20) using free-entry condition (10) and the lender's profit (21), the optimal loan contract still solves (13), but S_λ (the joint surplus) becomes

$$S_\lambda(\Gamma) \equiv \max_M \left[\frac{V_\lambda(\mathbf{a})-v_\lambda}{1+\omega}+R_\lambda(\mathbf{a})\right], \text{ where } \omega \equiv \frac{1+\rho}{1+\iota}-1. \qquad (22)$$

A larger parameter ω indicates a larger difference in funding costs.

The equilibrium still features three regions. As shown in Appendix A.1.4, the belief threshold λ_b is the same, but λ_a now becomes:

$$\lambda_a = \begin{cases} \frac{\bar{\lambda}(d+f)-\frac{\omega f}{(1+\omega)T_0}}{d-\bar{\lambda}f}, \text{ if } d > \bar{\lambda}f, \\ \infty, \text{ otherwise.} \end{cases} \qquad (23)$$

The following proposition summarizes the equilibrium given a monetary policy.

Proposition 4 (Monetary policy)**.** *A competitive search equilibrium exists and is unique.*

(i) In equilibrium, buyers with $\lambda \leq \lambda_a$ search for a safe loan, and buyers with $\lambda > \lambda_a$ search for a risky loan. The expected effective maturity is given by:

$$T_{\bar{\lambda}} = \begin{cases} k(\Delta_\lambda) > T_0, & \textit{if } \lambda > \lambda_b, \\ T_0, & \textit{if } \lambda \leq \lambda_b, \end{cases}$$

where $\lambda_a < \lambda_b$; the equilibrium probability of loan approval is given by:

$$\alpha = \begin{cases} g[\frac{\omega}{1+\omega}(v_\lambda + f) + \Delta_\lambda T_{\bar{\lambda}} - \kappa(T_{\bar{\lambda}})], & \text{if } \lambda > \lambda_a, \\ g[\frac{\omega}{1+\omega}(h - d + f) - \kappa(T_{\bar{\lambda}})] & \text{if } \lambda \le \lambda_a. \end{cases}$$

(ii) An expansionary monetary policy (a reduction in ι) will increase the equilibrium leverage probability α but does not affect the equilibrium maturity $T_{\bar{\lambda}}$.

Unlike part i of Proposition 2, part i of Proposition 4 states that optimistic buyers with $\lambda \le \lambda_a$ now choose safe loans at the minimum maturity (equivalently, $T_{\bar{\lambda}} = T_0$) and never default. In the benchmark, these optimistic buyers prefer no borrowing at all. The buyer's contract choices in the other two regions are the same as Proposition 2. Given (23), it is immediate that an expansionary monetary policy that reduces ι will also decrease λ_a.

Given the closed-form solution, it is straightforward to show that an expansionary policy (lower ι) will increase the likelihood that a buyer takes out a loan (higher α), as stated in part ii of Proposition 4.[21] However, the policy has no effect on the equilibrium maturity. This is intuitive, as a change in ι only changes the funding cost of lenders in period 0 (and hence affects the extensive margin of the leverage probability), but does not affect the incentives of borrowers once the funding costs have been paid (and hence does not affect the intensive margin). The proposition thus generates two further testable implications: changes in the short-term monetary policy rates will affect the leverage probability (the extensive margin) but not the maturity (the intensive margin).

Altogether, an expansionary policy will induce more buyers to search for risky loans (lower λ_a), and each of them will have a higher chance of being approved (higher α). Consequently, such a policy would increase the number of defaults after the disaster. The result implies that changes in monetary policies can (unintentionally) induce buyers to behave more like pessimists and increase the extent to which the "leveraging the belief disagreement" takes place in the debt market.

3.3.3 Extension: Endogenous asset price

So far, we have taken the asset price P as given. We now extend the model to endogenize P as an equilibrium object. Like in the literature of search models, assume that at $t = 0$ (before the loan market search takes place), a buyer is matched with a seller, and the asset price is determined by Nash bargaining:

$$\max_P U_\lambda^\theta (P - v_s)^{1-\theta}, \tag{24}$$

[21] It is straightforward to show that a reduction in ι will also raise the loan amount L.

where $U_\lambda = v_\lambda - (1+\rho)P + (1+\omega)J_\lambda$ is the buyer's utility as given by (22), $\theta \in (0,1)$ is her bargaining power, and v_s is the seller's value of the asset (which could be the same as the buyer). The Nash bargaining problem solves the price that splits their surpluses according to their bargaining powers. The bargaining solution is:

$$P = \underbrace{\frac{1-\theta}{1+\rho}v_\lambda + \theta v_s}_{\text{standard "hedonic" term}} + \underbrace{\frac{1-\theta}{1+\iota}J_\lambda}_{\text{loan term}}. \tag{25}$$

Proposition 5. *Suppose $d > \bar{\lambda} f + \kappa'(T_0)$. The asset price P is decreasing in the buyer's disaster belief λ, decreasing in the disaster exposure d, and decreasing in the policy rate ι.*

Proposition 5 states that, although pessimists have a higher loan surplus J_λ, the effect of a lower subjective value v_λ still dominates for asset pricing. Consequently, the asset price decreases in the degree of pessimism and disaster exposure (and is consistent with most of the existing literature's empirical findings about how climate belief and climate risk exposure affects housing prices). It is also intuitive that an expansionary monetary policy that reduces lenders' funding cost ι would also raise the loan's joint surplus and hence the asset price.

3.3.4 Comparison with the prediction in the literature

Our prediction that pessimists leverage more contrasts with the standard prediction in the theoretical literature of heterogeneous beliefs, where optimists leverage more (Fostel and Geanakoplos 2008, 2015; Geanakoplos 2010; Simsek 2013). Our key mechanism is the maturity channel, which is absent in the standard two-period framework. To see more clearly the role of the maturity channel, consider a modified case of our generalized model in Section 3.3.2, where maturity is exogenously fixed at $T_{\bar{\lambda}} = T_0$ and the minimum maturity T_0 is sufficiently short such that:

$$T_0 < \frac{\omega}{(1+\omega)\left(1+\bar{\lambda}\right)}.$$

Buyers can still choose the loan amount L and repayment flow M. We focus on buyers who are sufficiently pessimistic ($\lambda > \lambda_a$) such that they choose a risky loan. There, the equilibrium probability of loan approval is:

$$\alpha = g\left[\frac{\omega}{1+\omega}(v_\lambda + f) + \Delta_\lambda T_0\right].$$

A notable implication is that now the leverage probability is decreasing in λ, i.e., more pessimistic buyers are less likely to leverage.[22] Intuitively, the gain from trading a risky loan due to the belief disagreement is now weaker under a shorter loan such that the collateral channel dominates the maturity channel. In summary, in this special case without the possibility of choosing long-term loan contracts, our model would imply that optimists would borrow more (both at the extensive and intensive margin), consistent with the standard finding in the literature.

4 Data and methodology

Motivated by our theoretical insights, we now turn to an empirical analysis of how climate risk and heterogeneous beliefs affect the mortgage market.

4.1 Data

We develop a new large-scale data set of coastal property sales along the U.S. Atlantic Coast from 2001 to 2016, along with the associated mortgage information for each transaction, and the exposure to sea level rise (SLR) risk for each property. We first leverage an extensive proprietary set of real estate transactions data from CoreLogic, a data vendor that compiles a thorough record of property tax roll information and deed transactions. The tax roll information includes transaction prices and property characteristics, including square feet of the lot, number of bedrooms, building age, and address. The deeds data contain comprehensive information on any mortgage contract associated with a transaction, including the mortgage origination amount and maturity, the identity of the lender, and other characteristics. We use each property's coordinates to compute its distance to the nearest coast. Since this is a large data set and the relevant variation comes from homes near the coast, we restrict our attention to properties that lie within 1km of the coast. We focus on single-unit single-family homes, and thus exclude condos and duplexes, which may have different exposure to flood risks depending on the floors they are on. We also exclude outlier transactions with sale prices under \$50,000 or over \$10,000,000, and exclude transactions with unavailable property characteristics.

To exploit the spatial variation in exposure to SLR risk and define our key independent variable SLR_i, we utilize state-of-the-art high-resolution maps from NOAA's SLR Viewer.[23] These maps allow us to extract property-specific inundation readings across various heights of SLR. NOAA utilizes a bathtub-style model to project future inundation based on local land elevation, local and regional tidal variability, topographical

[22] Recall that $g'(x) > 0$ and v_λ is decreasing in λ.

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

variation, and hydrological connectivity. Note that this SLR product is not based on potentially endogenous factors such as land subsidence or future mitigation efforts that could be impacted by local management decisions. Based on each property's latitude and longitude, we determine whether the property will be inundated with x feet of SLR, where $x \in \{1, 2, \ldots, 6\}$. We also use First Street Foundation's data to obtain the minimum bare-earth elevation of each property as a control variable.

To operationalize climate beliefs including the likely pessimistic buyers in our sample, we employ three approaches. First, we utilize data from the 2014 Yale Climate Opinion Survey (Howe et al. 2015).[24] This innovative data set, based on >13,000 individual responses to their national survey across multiple waves since 2008, provides estimates of the average beliefs about climate change among the adult population in each county. Given its novel scope and availability, the Yale Climate Opinion data has been widely used in the climate finance literature to estimate climate beliefs (e.g., BGL, BGY, Keys and Mulder 2020; Goldsmith-Pinkham et al. 2021; Bakkensen and Barrage 2022). Our benchmark proxy measure of the climate belief of a buyer in a transaction is the percentage of people in the buyer's county who answered "yes" to whether they believe that climate change is happening. For robustness checks in Section 6.1.1, we will use two additional variables: the percentage of people who answered "somewhat worried" or "very worried" to how worried they are about global warming, and the percentage of people who answered "yes" to whether they believe that global warming will start to harm people in the U.S. within 10 years. We refer to these three measures as *Belief: happening*, *Belief: worried*, and *Belief: timing* in summary statistics Table 3. Second, we employ a proprietary data set containing almost two decades of annual climate beliefs survey from the Gallup Environmental Poll, allowing us to estimate a secondary proxy for climate beliefs that varies at the county-by-year level. Finally, instead of relying on survey data, we develop a novel empirical approach to recover homebuyer-specific climate beliefs from the capitalization of SLR risk in housing prices. We use this as a transaction-level proxy for climate beliefs at the time of property purchase. See Section 6.1 for a complete explanation of the Gallup and homebuyer-specific beliefs approaches.

Finally, we include a suite of county-by-year level socioeconomic and neighborhood variables as additional controls. Our baseline specifications include controls for average personal income and county population, using the data from the Bureau of Economic Analysis' (BEA) Regional Economic Accounts, which is available for all of the years in our sample. In additional sensitivity analyses, we also gather data at the county-by-year

[24] Publicly available at https://climatecommunication.yale.edu/visualizations-data/ycom/. The Yale data set has more recent updates, but the 2014 vintage has the best overlap with our CoreLogic sample period, which ends in 2016.

level on the demographic and ideological composition of the buyer's county (gender, age, race/ethnicity, voting behavior, and education) as well as local economic data from the property's location (unemployment rate, test scores, arrests, new building permits, and previous flood events). Data for most of these additional control variables are available since 2010. We use the annual county-level population files from the National Cancer Institute's Surveillance, Epidemiology, and End Results Program to calculate the share of each county that is female, nonwhite, age 65 and older, and age 5 and younger. We gather data from the MIT Election Lab on the percentage of Republican or Democratic votes in the previous presidential election. As a proxy for education, we use annual test scores data from the Stanford Education Data Archive (SEDA). SEDA provides average academic achievement for grades 3-8 at the county level, as measured by standardized tests in reading and math. We download annual county unemployment rates from the Bureau of Labor Statistics. For data on the yearly total number of arrests at the county level, we use the Uniform Crime Reporting (UCR) Program Data. We use the Building Permits Survey from the Census Bureau to calculate the yearly number of new housing units authorized by building permits in each county. Lastly, we use NOAA's Storm Events Database to calculate the number of flood events each year. We then lag this measure by one year to control for the previous year's flood events.

	Mean	Std	p10	p90	N
Sale Price	\$419,337	\$631,804	\$95,000	\$779,000	2,250,995
Leveraged (dummy)	0.60	0.49	0	1	2,247,670
Mortgage amount	\$300,517	\$337,469	\$90,000	\$537,500	1,349,817
Long Maturity (dummy)	0.87	0.34	0	1	1,196,639
Mortgage term (years)	27.90	6.19	15	30	1,196,639
Distance to coast (meters)	386.42	294.66	42.24	841.53	2,250,995
Elevation (meters)	7.03	12.43	1.30	14.35	916,170
Belief: happening (buyer county, %)	66.32	5.21	61	73	2,219,924
Belief: worried (buyer county, %)	56.33	6.29	49	66	2,219,924
Belief: timing (buyer county, %)	44.81	4.67	40	52	2,219,892
Inundated at 6ft SLR (dummy)	0.24	0.43	0	1	2,250,995
Moderate SLR Risk (dummy)	0.20	0.40	0	1	2,250,995
High SLR Risk (dummy)	0.04	0.19	0	0	2,250,995

Table 3: Summary statistics of key variables. Leveraged is a dummy for whether a transaction is associated with a mortgage or not. Long Maturity is a dummy for whether the mortgage term is at least 30 years. Mortgage amount and term statistics are reported conditional on having a mortgage. Inundated at 6ft of SLR is a dummy for whether the property is predicted to be inundated at 6ft of SLR according to NOAA. Moderate SLR Risk (High SLR Risk) indicates whether a property will be inundated with >3 but ≤ 6 feet of SLR (≤ 3 feet of SLR). Main data sources: CoreLogic, NOAA SLR Viewer, and Yale Climate Opinion Survey.

Table 3 provides the summary statistics of selected key variables. The final sample in which main property and county control variables are available contains 1,582,525 transactions. It is worth noting that the houses in our sample are relatively expensive, with an average sale price of \$419,337, nearly 45% higher than the national average over the same period (\$288,742). Also nearly 40% of the transactions are purchased without a mortgage (i.e., "bought with cash"). This is consistent with the well-known stylized fact that buyers of coastal properties on average tend to come from the higher end of the wealth distribution (Kahn and Smith 2017; Bakkensen and Ma 2020).

4.2 Econometric specifications

Housing price. To set the stage for our main empirical analysis, we begin by revisiting the literature's previous findings regarding the effects of SLR risk on property prices. Based on BGL (Bernstein et al. 2019), we adopt the following specification:

$$\ln Price_{it} = \beta_P SLR_i + \phi'_P X_i + \theta'_P Z_{ct} + \Lambda^P_{ZDEBM} + \varrho_P + \epsilon^P_{it}. \qquad \text{(P0)}$$

Throughout, $\ln Price_{it}$ denotes the natural log of the transaction price of residential property i sold in month-year t. SLR_i denotes property i's exposure to inundation risk due to SLR. In our benchmark specification for housing price, we adopt the operationalization most often used in the existing literature (including BGL and BGY) and define SLR_i as equal to one if property i is predicted to be underwater if the sea level rises by six feet and equal to zero otherwise. We explore more refined definitions of SLR risk in various robustness exercises. X_i is a vector of property-level controls (age and square footage), and Z_{ct} is a vector of controls at the county-by-year level of the buyer's previous residence (average income and population of the buyer's county).[25] Finally, ϱ_P is a constant, and ϵ^P_{it} is the error term, which we cluster at the ZIP code level.

Crucial for our identification, Λ^P_{ZDEBM} denotes a rich set of fixed effects that allow us to compare transactions 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.[26] Our identification assumption is that with these controls, SLR_i is uncorrelated with ϵ^P_{it} and therefore β_P is a plausible estimate of the effects of SLR exposure on house prices. Figure 4 provides an example the high-resolution spatial variation of exposure to inundation risk under a scenario of six feet of SLR for Chesapeake, Virginia. We compare the transaction outcomes of properties that are very similar but with one

[25]In our sensitivity analysis in Section 6, we include the aforementioned host of additional control variables, which are available for later years in our sample.

[26]Following BGL, we use nonlinear bins for the distance from the East 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.

more exposed to future climate-related risks than the other. In this illustration, all five properties are within the same ZIP code, same distance bin to the coast, same elevation bin, have the same number of bedrooms, and the same month and year of transaction corresponding to the level of variation of our Z × D × E × B × M fixed effects. However, the properties located at points B, C, and E (which lie inside the predicted inundation area) are more exposed to future climate-related risks than the properties located at points A and D.

In line with our model and the previous literature, we hypothesize that:

Hypothesis 1 ($\beta_P < 0$)**.** *All else equal, properties with more exposure to SLR risks sell at a discount relative to less exposed ones.*

Going deeper, we re-investigate the literature's findings on the effect of heterogeneous climate beliefs in the pricing of SLR risk. In the following specification, we evaluate whether there is a larger SLR price discount in transactions with (likely) more pessimistic buyers:

$$\begin{aligned} \ln Price_{it} &= \beta_P SLR_i + \delta_P PessBuyer_c + \gamma_P SLR_i \times PessBuyer_c \\ &\quad + \phi'_P X_i + \theta'_P Z_{ct} + \xi'_P SLR_i \times Z_{ct} + \Lambda^P_{ZDEBM} + \varrho_P + \epsilon^P_{it}. \end{aligned} \tag{P1}$$

Here, $PessBuyer_c$ is an indicator variable equal to one if the average climate belief in the county $c = c(it)$ from which the buyer of property i at date t comes is above the sample median and zero otherwise.[27] We interpret $PessBuyer = 1$ as an indicator of a likely more pessimistic homebuyer. Based on our model and the previous literature, we further hypothesize that:

Hypothesis 2 ($\gamma_P < 0$)**.** *There is more discount of SLR risk in transactions with more pessimistic homebuyers.*

To control for potentially confounding factors that could correlate with climate beliefs, we include the interaction terms between SLR and the buyer county-by-year level controls (the population and average income of the county where the buyer comes from), as represented by the term $SLR_i \times Z_{ct}$. We provide a battery of robustness exercises with alternative specifications of different cutoff thresholds and control variables, as well as alternative proxies for climate belief in Section 6.

Leverage dummy (extensive margin). We now move to our main analysis of the effects of SLR risks on mortgage outcomes. First, we evaluate whether SLR risk and

[27] Specifically, in the benchmark spefication, we define $PessBuyer_c = 1$ if $> 65\%$ of respondents in county c state that they believe that global warming is happening, according to the Yale survey.

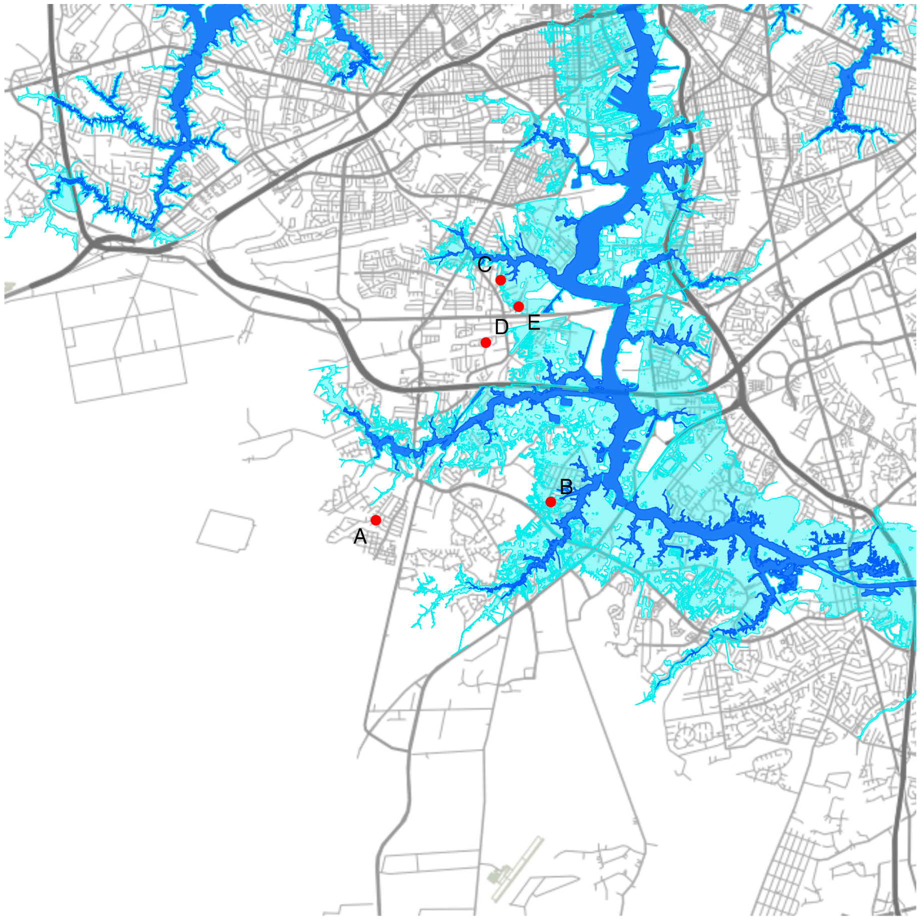

Figure 4: Illustration of our empirical identification strategy in Chesapeake, Virginia. Five properties (points A through E) that are within the same ZIP code, same distance bin to the coast, same elevation bin, having the same number of bedrooms, and having the same month and year of transaction. Properties B, C, and E are expected to be inundated under six feet of SLR rise whereas properties A and D are not. Light blue shaded areas correspond to areas that are predicted to be inundated with six feet of SLR. Dark blue shaded areas are currently inundated waterways. (Sources: authors' calculations based on NOAA SLR Viewer and CoreLogic data; property locations are adjusted for illustration purposes and do not reflect locations of actual observations).

climate beliefs affect the likelihood that transactions are leveraged:

$$\begin{aligned} Leveraged_{it} &= \beta_L SLR_i + \delta_L PessBuyer_c + \gamma_L SLR_i \times PessBuyer_c \\ &\quad + \rho_L \ln Price_{it} + \phi_L' X_i + \theta_L' Z_{ct} + \xi_L' SLR_i \times Z_{ct} + \Lambda^L_{ZDEBM} + \varrho_L + \epsilon^L_{it}, \end{aligned} \tag{L1}$$

Here, $Leveraged_{it}$ is an indicator variable that is equal to one if the transaction on property i at time t involves a mortgage and zero otherwise. As a benchmark, we include housing price as a control variable, but our results are robust to omitting it (see

Section 6.2.4).[28] The dummy $PessBuyer_c$ is defined as in price regression (P1). Based on our model (recall Table 1), we hypothesize that:

Hypothesis 3 ($\gamma_L > 0$). *In transactions of exposed properties, more pessimistic buyers are more likely to take on a leveraged position.*

Maturity (intensive margin). Next, we analyze the effects of SLR risks on the maturity of mortgage contracts. For leveraged transactions (i.e., those associated with a mortgage contract), we define $LongMaturity_{it}$ as an indicator equal to one if the maturity of the mortgage contract for property i transacted at t is at least 30 years and zero otherwise.[29] We then run the following regression on the sub-sample of leveraged transactions:

$$\begin{aligned} LongMaturity_{it} = {} & \beta_M SLR_i + \delta_M PessBuyer_c + \gamma_M SLR_i \times PessBuyer_c \\ & + \rho_M \ln Price_{it} + \phi'_M X_i + \theta'_M Z_{ct} + \xi'_M SLR_i \times Z_{ct} \\ & + \Lambda^M_{ZDEBM} + \Lambda_L + \varrho_M + \epsilon^M_{it}. \end{aligned} \tag{M1}$$

Here, in addition to the set of fixed effects Λ_{ZDEBM}, we also include a lender fixed effect, Λ_L, to control for the possibility that different lenders may have varying tendencies to issue different types of mortgage contracts.[30] Based on our model, we hypothesize that:

Hypothesis 4 ($\gamma_M > 0$). *When choosing a mortgage contract to finance the purchase of an exposed property, more pessimistic buyers are more likely to pick a contract with long maturity.*

Specifications (L1) and (M1) are our main regression equations. We estimate them using the ordinary least squares (OLS) estimator.[31]

[28] The inclusion of the housing price is also consistent with our model, where buyers choose a debt contract given the housing price.

[29] The distribution of mortgage maturity is bimodal: most contracts either have a fifteen-year or a thirty-year term. In the main specification for (M1), we exclude the small sub-sample of transactions whose mortgages have maturity terms that are neither 15 nor 30 years (less than 4% of our sample), which tend to be nonstandard mortgage contracts. Our results are robust to the inclusion of these nonstandard observations.

[30] For transactions with more than one mortgage, we use the lender fixed effect for the first mortgage. In our sample, all mortgage contracts associated with the same contract have the same maturity, hence our $LongMaturity$ dummy is well defined for these observations. As a robustness check, we also exclude transactions with more than one mortgage and the results are unaffected.

[31] We utilize the OLS estimator given concerns over implementation and bias of fixed effects in nonlinear models, including the probit and logit models (Greene et al., 2002).

5 Results

5.1 Setting the stage: Housing price

Table 4 reports the results for housing price regressions (P0) and (P1). To appreciate the importance of controlling for amenity values, column 1 shows the estimates from a naïve regression that does not include our rich set of fixed effects. It shows a positive and significant correlation between SLR exposure and price. This is not surprising, as properties exposed to SLR risk also tend to be close to the coast, and coastal properties tend to have higher amenity values.

	log(Housing Price)		
SLR Risk	0.219***	-0.060***	-0.039*
	(0.028)	(0.022)	(0.021)
SLR Risk × PessBuyer			-0.059***
			(0.018)
Property & buyer county controls	Y	Y	Y
Z × D × E × B × M fe		Y	Y
Buyer county controls × SLR			Y
N	1,583,238	406,601	406,601
R^2	0.335	0.866	0.867

Table 4: 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. *PessBuyer* 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. Z×D×E×B×M indicates ZIP code × distance to coast bin × elevation bin × 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 4.1 for more data descriptions. Standard errors in parentheses are clustered at the ZIP code level; * ($p < 0.1$), ** ($p < 0.05$), *** ($p < 0.01$).

Column 2, which corresponds to specification (P0), 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 expected to be inundated with six feet of SLR is priced about 6% lower than an otherwise equivalent but unexposed property. In other words, the "SLR discount" is around 6%. The estimate is statistically significant ($p < 0.01$), and the magnitude is very similar to the benchmark estimates of 5 to 6.6% in BGL. Thus, column 2 replicates the recent finding in the climate finance literature that the coastal property market is pricing in future SLR risks.

Furthermore, column 3, which corresponds to specification (P1), shows that the extent of the pricing of SLR risk varies: much of the discounting of SLR risk is driven by transactions with pessimistic homebuyers. The SLR discount is nearly 10% ($\approx 3.9 + 5.9$) among transactions with likely pessimistic buyers, 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 BGY.

Having replicated the literature's findings on the SLR discount in housing prices, providing reassuring evidence on the validity of our data set and identification strategy, we now move on to our main results on mortgage outcomes.

5.2 Extensive margin: Leverage probability

	Leveraged				
SLR Risk	-0.093***	0.021***	-0.004	-0.003	
	(0.008)	(0.007)	(0.007)	(0.014)	
SLR Risk × PessBuyer			0.047***	0.034***	
			(0.009)	(0.011)	
Moderate SLR Risk					0.003
					(0.014)
High SLR Risk					-0.035
					(0.031)
Moderate SLR × PessBuyer					0.026**
					(0.011)
High SLR × PessBuyer					0.083***
					(0.023)
Log Housing 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	1,580,756	405,893	405,893	405,893	405,893
R^2	0.019	0.473	0.473	0.473	0.473

Table 5: 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. *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). See Table 4 for the definitions of the remaining variables.

Moving to the main results, Table 5 reports estimates from regressions where the dependent variable is *Leveraged* – the indicator variable equal to 1 if a transaction is financed with a mortgage contract and 0 otherwise. Again, column 1 shows a naïve regression that excludes the set of fixed effects. The result shows a negative correlation between SLR risk exposure and leverage, suggesting that transactions of exposed properties on average are less likely to be financed with debt, consistent with existing conventional views (e.g., Litterman et al. 2020; Brunetti et al. 2021).

However, the result reverses in column 2, where we include the rich set of fixed effects. The estimate in column 2 shows that, in contrast to conventional wisdom, transactions of properties exposed to SLR risk are about two percentage points more likely to be leveraged. The estimate is not only statistically significant ($p < 0.01$) but also economically meaningful. To get a sense of relative magnitude, note that the rise of leveraged transactions – measured by the fraction of property transactions associated with mortgages in our data – from 2001 (the beginning of our sample) to 2007 (the peak of the housing boom before the 2008 financial crisis) is about four percentage points, or twice our estimated coefficient.

Crucially, column 3, which corresponds to specification (L1), shows that the SLR-leverage association is *driven by transactions with pessimistic homebuyers*. The estimate for the interaction term indicates that, among transactions with likely pessimistic buyers, properties exposed to SLR risk are about 4.7% more likely to be leveraged. The estimate for the uninteracted *SLR Risk* term indicates that the association between SLR risk and the leveraged dummy is negative but not statistically significant for the other group of homebuyers.

A potential concern for the specification in column 3 is that climate beliefs are correlated with other factors that predict leverage outcomes.[32] 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*$\times$*PessBuyer* remains strongly statistically significant. The magnitude of the coefficient reduces slightly to about 3.4%, but is not statically different from before. In Section 6, we show that the results are also robust to the inclusion of a wider variety of county-level socioeconomic variables that become available for later years in our sample, including political ideology, education, race and ethnicity, age, and gender as well as unemployment, new building permits, crime statistics, and flood events from the property's neighborhood.

Another potential concern is that the measure of SLR exposure is too coarse. In particular, despite being a commonly used benchmark definition in the empirical climate literature, it is very unlikely that the sea level will rise by six feet in the next thirty years.[33] Column 5 aims to address this concern. It repeats the exercises in column 4

[32]Ideally, we would like to control for buyer-specific characteristics such as income, wealth, or credit score. However, as described in Section 4.1, the only individual-level information we observe is the location that buyers comes from. Thus, we also include aggregated statistics from the buyer's origin.

[33]However, it is plausible that properties inundated with six feet of SLR face higher climate-related risks that will likely realize in thirty years, e.g., increased flooding from storm surges (Zhang et al.

but replaces the benchmark *SLR Risk* indicator 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 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.

Using the same base specification as columns 3 and 4, column 5 shows that the estimates for the interaction between the SLR terms and the pessimistic buyer dummy are both positive and statistically significant, while the estimates for the uninteracted SLR terms are not significant, highlighting the importance of climate beliefs in this setting. Furthermore, the estimate of 8.3% for *High SLR Risk* $\times$ $PessBuyer$ is larger and statistically different than the estimate of 2.6% for *Moderate SLR Risk* $\times$ $PessBuyer$. 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. See section Section 6.2 for additional robustness surrounding our SLR risk measure. 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 exposed to climate risks, buyers with more pessimistic climate beliefs are more likely to make a leveraged investment.

5.3 Intensive margin: Maturity

With a similar structure to Table 5, Table 6 reports the estimates for regressions of the long maturity dummy. Recall that these are results at the intensive margin of the mortgage choice, as the dependent variable $LongMaturity$ is only defined for transactions that have an associated mortgage contract. As in previous tables, the first column shows a naïve 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 changes sign 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.

A pattern emerges when we examine this relationship by category of buyers. Column 3, consistent with empirical model (M1), shows that among leveraged transactions with likely pessimistic buyers, properties exposed to SLR risk are about 1.8 percentage points more likely to be associated with long maturity mortgage contracts (relative to leveraged transactions with likely optimistic buyers). Column 4 repeats the exercise in column 3 but includes the interaction terms between SLR and buyer county controls.

2013).

	Long Maturity				
SLR Risk	-0.019***	0.005	-0.004	0.002	
	(0.002)	(0.005)	(0.007)	(0.014)	
SLR Risk × PessBuyer			0.018***	0.024***	
			(0.007)	(0.007)	
Moderate SLR Risk					0.006
					(0.014)
High SLR Risk					-0.028
					(0.024)
Moderate SLR × PessBuyer					0.023***
					(0.008)
High SLR × PessBuyer					0.031*
					(0.019)
Log Housing 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	822,890	150,746	150,746	150,746	150,746
R^2	0.002	0.441	0.441	0.441	0.441

Table 6: 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). *Lender fe* indicates lender fixed effects. Sample excludes transactions that do not have an associated mortgage contract (for which the dependent variable is not well defined) and excludes nonstandard mortgage observations where term is not 15 nor 30 years. The rest is the same as in Table 5.

The estimate for the interaction term remains highly statistically significant, and the magnitude increases slightly to 2.4%.

Finally, 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 relationship between SLR exposure and the long maturity dummy is not statistically significant. However, the relationship becomes statistically significant when the SLR exposure is interacted with beliefs. Among leveraged transactions with pessimistic buyers, mortgage contracts of properties with moderate SLR risk are 2.3% more likely to have long maturity ($p < 0.01$), and those with high SLR risk are 3.1% more likely ($p < 0.1$), relative to similar transactions optimistic buyers.

Overall, our findings are consistent with the model's predictions: in purchases of properties exposed to climate risks, buyers with more pessimistic climate beliefs are more likely to leverage and use debt contracts with longer maturities.

6 Robustness and sensitivity

6.1 Climate beliefs

A classic concern for empirical analyses are unobservable confounders. In this case, a concern can arise from potential sorting across SLR risk based on climate beliefs, which has been documented in the coastal housing literature (Bakkensen and Barrage, 2022). If climate optimists are more likely to move into coastal properties, then our county-level beliefs measure could be a biased proxy for individual-level buyer beliefs, as the county-level measure would overestimate the level of climate pessimism in our coastal buyers.

While we cannot definitively rule out sorting over climate beliefs in this setting, to the extent that it may be occurring, we do not believe it to be a large biasing force on our lending results. First, Bakkensen and Barrage (2022) find that the county-level Yale Climate Opinion data are strongly correlated ($\bar{R}^2 = .999$) with individual-level beliefs data collected through door-to-door surveys in coastal Rhode Island.[34] Second, if sorting was strong enough to confound our results, we should find the SLR coefficient in our house sales price regressions to be attenuated towards zero, given that climate optimists would pay more for a home at high SLR risk relative to its value based on market fundamentals. Recall from Table 4 that we find a strong and robust negative capitalization of SLR risk into home prices, in line with, e.g., BGL. Third, if sorting was dominant in our data, then we would expect to find a strong negative correlation between the frequency of coastal buyers in a county and the county's beliefs. In other words, we might expect fewer buyers of coastal homes coming from pessimistic counties. However, as shown in Appendix Table A1, when controlling for income, population, education, age, and racial composition of the buyer's county, the fraction of buyers from a county choosing a coastal home is actually positively related to county beliefs ($p < 0.1$).[35]

Nonetheless, since climate beliefs play a central role in our analysis, in this subsection, we evaluate how robust our results are to alternative definitions of the pessimistic buyer variable. In particular, while Sections 6.1.1 and 6.1.2 provide sensitivity analyses surrounding the cross-sectional Yale Climate Opinion data commonly utilized by the climate finance literature, Sections 6.1.3 and 6.1.4 provide two additional (novel) estimates of climate beliefs. Reassuringly, our results persist across the different operationalizations of climate beliefs. All together, these additional results reassure us to

[34] This is from a small sample of 187 individual-level respondents across three counties.

[35] This correlation may not occur if the supply of coastal homes is so small relative to the housing market that no climate optimists buy along the coast. However, Bakkensen and Barrage (2022) estimate that even in the highly optimistic settings across the U.S. coast that they consider, optimists do not exceed 48% of the share of coastal residents.

the persistence of our main findings across a variety of belief specifications and operationalizations.

6.1.1 Alternative specifications using Yale Climate Opinion data

Table A2 provides a series of robustness checks for our benchmark regressions (L1) and (M1) with alternative specifications for the buyer county climate belief variable from the Yale Climate Opinion data. For brevity, we only report the estimates for the relevant coefficients of the interaction term between SLR Risk and the corresponding belief variable. However, 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 (cross-sectional) 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 *PessBuyer* variable for whether the buyer is from a county where the corresponding climate belief variable is above the sample median, thus repeating our benchmark specification. Rows 2 to 4 rank counties into quartiles of the climate belief variable, and *nth Quartile Belief* is equal to one if the buyer is from a county in that nth quartile of belief and zero otherwise. Here, the comparison group is the first quartile, namely those with the most optimistic beliefs. Finally, row 5 uses the continuous measures of the belief variables: the fractions of the buyer's county saying that they believe climate change is happening, that they are worried about climate change, or that they think that global warming will harm the U.S. within 10 years. Overall, we find our main results to be consistent across this variety of climate beliefs specifications and operationalizations, and as motivated by our theory, our results generally increase monotonically in magnitude with the level of climate pessimism.

6.1.2 Omitted belief covariates

A related concern about climate beliefs is that this beliefs variable could be correlated with other individual-level unobservable characteristics that could confound the analysis. Hornsey et al. (2016) perform a meta-analysis on the determinants of climate beliefs, finding political affiliation to be most strongly related to climate beliefs relative other sociodemographic variables such as education, gender, and income. To address these concerns, we include a variety of additional control variables in our main specifications. In Table A3, in addition to income and population, we also include an expanded suite of county-level control variables including data at the county-by-year level on the demographic composition of the buyer's county (gender, age, race/ethnicity, and education) as well as local economic data from the property's location (unemployment rate, test scores, arrests, new building permits, and the count of previous flood events).[36] In Table A4, in addition to income and population, we include data on political affiliation (percent of Republican or Democrat vote shares in the previous presidential election at the county level). As shown in both tables, our main results are robust.

6.1.3 Beliefs using Gallup data

While the Yale Climate Opinions survey remains a frontier data source for climate belief surveys across the U.S., a limitation is that it is a cross-sectional estimate at the county level.[37] As additional robustness, we replicate the Yale Climate Opinions estimation approach using survey data from Gallup's annual Environment poll to estimate a panel of climate opinions at the county-by-year level. In particular, we utilize annual waves of Gallup survey data from 2000 to 2020, totalling 10,339 observations where climate beliefs are elicited.[38] In parallel with the Yale climate beliefs estimation methodology described in Howe et al. (2015), we model beliefs based on respondent age (<30, 30-49, 50-64, >64), race and ethnicity (White, Black, Hispanic, Asian, Other), education (no college, some college, college graduate only, post-graduate), gender (male, female), as well as location (state) and time (year) fixed effects. We then use the model results to predict climate beliefs at the county-by-year level utilizing data on age, race/ethnicity, and gender from the National Cancer Institute's Surveillance, Epidemiology, and End Results Program's U.S. County Population Data. We use county by 5 year average estimates for educational attainment from the U.S. Census' American Community Survey.

Finally, we define $PessBuyer$ to be equal to one if the buyer in a transaction i in year y is from a county where the predicted belief is greater than or equal to the median sample belief level in that year y, and zero otherwise. Table 7 displays the Gallup beliefs model replicating our leverage and maturity results, which remaining strikingly similar to our main results.

[36] Since test score data and other data are only available for a subset of years, our sample for this robustness check covers years 2009 to 2016.

[37] Cross-sectional county-level estimates from the Yale Climate Opinions survey have been released across several years, but the Yale data set is not designed to be used as a panel, due to changes in the survey methodologies over time (Howe et al. 2015; Ballew et al. 2019).

[38] We utilize the question on the timing of climate beliefs that asks "Which of the following statements reflects your view of when the effects of global warming will begin to happen: they have already begun to happen, they will start happening within a few years, they will start happening within your lifetime, they will not happen within your lifetime, but they will affect future generations, (or) they will never happen]?" For an additional sensitivity check, we also estimate beliefs based on how worried the respondent is regarding climate change.

	Leveraged	Long Maturity
SLR Risk	-0.031	0.007
	(0.021)	(0.021)
SLR Risk × PessBuyer	0.033**	0.026*
	(0.015)	(0.015)
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	210,764	62,926
R^2	0.439	0.442

Table 7: Robustness with *PessBuyer* derived from county-by-year climate beliefs interpolated from Gallup survey data according to the procedure in Section 6.1.3. Column 1 reports results for leveraged regression (L1) and column 2 for long maturity regression (M1). The rest is the same as in Tables 5 and 6.

6.1.4 Inferring individual-level climate beliefs from home prices

Finally, rather than relying on county-level averages based on survey data, we present a novel method to impute the climate beliefs of the homebuyer in *each* transaction. The underlying idea is that the housing price should reflect the homebuyer's climate belief (recall the theoretical model in Section 3.3.3). Hence, the extent to which the housing price capitalizes the SLR risk should reveal the extent to which the homebuyer is concerned about the future climate risk.

For a transaction of property i at time t, we impute the homebuyer's relative degree of climate pessimism λ_{it} as follows. Suppose that there is a true but unobserved distribution of climate beliefs in the population of homebuyers in our transaction data. Let λ_{it} denote the (unobserved) climate belief of the homebuyer in transaction it, where a higher value of λ_{it} represents a higher level of climate pessimism. Based on specification (P1) in Section 4.2, suppose that housing price is given by:

$$\ln Price_{it} = \beta_P SLR_i + \gamma_P SLR_i \times \lambda_{it} + \delta_P \lambda_{it} + \text{controls}_{it} + \epsilon_{it}^{\lambda} \tag{26}$$

where the impact of the SLR risk on the house price contains the general SLR discount β_P (< 0), as well as the belief-moderated discount γ_P (< 0) for the interaction between the SLR risk and the (unobserved) transaction-specific buyer belief term λ_{it}. The set of control variables are the same as in (P1).[39]

[39]In particular, $\text{controls}_{it} = \phi'_P X_i + \theta'_P Z_{ct} + \xi'_P SLR_i \times Z_{ct} + \Lambda^P_{ZDEBM} + \varrho_P$.

To impute the unobserved λ_{it}, we first estimate the housing price without beliefs:

$$\ln Price_{it} = \beta_P SLR_i + \text{controls}_{it} + \zeta_{it}. \tag{27}$$

We then predict the residual from equation (27) as $\hat{\zeta}_{it}$. Note that moments of ζ_{it} are informative about the unobserved belief λ_{it}, because $\zeta_{it} = \gamma_P SLR_i \times \lambda_{it} + \delta_P \lambda_{it} + \epsilon_{it}^{\lambda}$ according to equation (26).[40] Intuitively, if we observe a buyer paying a lower price for an identical property in a location exposed to SLR risk, ceteris paribus, then she must be more SLR-pessimistic. Define our imputed (cardinal) climate belief parameter as:

$$\hat{\lambda}_{it} \equiv -\hat{\zeta}_{it}. \tag{28}$$

Under the assumptions above, the imputed $\hat{\lambda}_{it}$ is positively correlated with the unobserved climate pessimism λ_{it} of the homebuyer in each transaction it. Finally, to incorporate the imputed beliefs into mortgage regressions, we define the (ordinal) dummy $\widehat{PessBuyer}_{it}$ to be equal to one if $\hat{\lambda}_{it}$ is above the median predicted sample value and $SLR_i = 1$, and equal to zero otherwise.[41]

Appendix tables A5 and A6 provide the pairwise correlation between the continuous and binary versions of our imputed $\hat{\lambda}_{it}$ beliefs data and other beliefs operationalizations in this paper. Despite the large differences in how $\hat{\lambda}_{it}$ is imputed from real estate transactions relative to how the Yale and Gallup beliefs are constructed from surveys, the pairwise correlations are significantly and positively correlated (p<0.000) with almost all other beliefs operationalizations.

Replacing the county-level $PessBuyer_c$ with the transaction-level $\widehat{PessBuyer}_{it}$, we re-estimate the main mortgage regressions in (L1) and (M1). As reported in Table 8, our result for the leveraged regression continues to hold: largely consistent with our previous estimates in Table 5, pessimistic buyers are 3.8% more likely to take out a mortgage ($p < 0.01$). Our long maturity result also holds, with pessimistic buyers 1.3% more likely to have a 30 year mortgage ($p < 0.1$). Overall, our main results are robust to using imputed climate beliefs at the transaction level. This gives us additional confidence that our main empirical findings are not purely driven by the selection bias due to residential sorting.

[40] Note that SLR_i is a binary variable and γ_P and δ_P are scalar transformations of λ_{it}. Following previous literature and our own empirical findings in Section 5.1, we assume that climate pessimists will pay less for a property relative to climate optimists ($\gamma_p + \delta_p < 0$). Assuming $E(\lambda_{it}\epsilon_{it}^{\lambda}) = 0$, then $\hat{\zeta}_{it}$ can recovery individual climate beliefs.

[41] Note that for transactions of properties with $SLR_i = 0$, the interaction of SLR_i with individual-level belief λ_{it} does not matter for the choice of leverage and maturity, so without loss of generality we can assign $\widehat{PessBuyer}_{it} = 0$.

	Leveraged	Long maturity
SLR Risk	-0.031	0.130**
	(0.044)	(0.059)
SLR Risk $\times \widehat{PessBuyer}$	0.038***	0.013*
	(0.009)	(0.008)
Z x D x E x B x T fe	Y	Y
Property & buyer county controls	Y	Y
Buyer county controls $\times$ SLR	Y	Y
Lender fe		Y
N	210,764	62,926
R^2	0.440	0.442

Table 8: Robustness with alternative specifications for the belief measure using transaction-level imputed beliefs. Beliefs are imputed following the procedure in Section 6.1.4. Column 1 reports results for leveraged regression (L1) and column 2 for long maturity regression (M1). The rest of the table is the same as in Tables 5 and 6.

6.2 Additional robustness

6.2.1 SLR measures

We further examine the sensitivity of our results to alternative operationalizations of SLR risk measurement. To provide a more nuanced measure of SLR exposure, we define a monotonically increasing exposure variable *SLR Risk*, which is equal to zero if a property is not expected to be inundated with six feet of SLR, one if it is expected 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 A7 repeats the benchmark mortgage regressions (L1) and (M1) using this more nuanced 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 *PessBuyer* are positive and significant for higher values of the *SLR Risk* variables. Also, generally, the higher the exposure value, the larger the estimated coefficients – though the differences are not always statistically significant from each other – highlighting that our results are robust to different SLR definitions and individuals are attentive to the magnitude of SLR inundation risk consistent with our theory.

6.2.2 Fixed effect specifications

Recall that our main results include ZIP code $\times$ distance to coast bin $\times$ elevation bin $\times$ number of bedrooms $\times$ time (transaction month-year) fixed effects (Z$\times$D$\times$E$\times$B$\times$M), in addition to lender fixed effects in our long maturity results. Table A8 tests whether our main results are robust to alternative fixed effects specifications. The top panel reports results for the leveraged regression (L1) and the bottom panel reports those for long maturity regression (M1).

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 $\times$ elevation bin $\times$ number of bedrooms (Z$\times$D$\times$E$\times$B). The estimate for the coefficient of the interaction term between *SLR risk* and *PessBuyer* 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$\times$D$\times$E$\times$B$\times$Q). The estimate for the interaction term between *SLR risk* and *PessBuyer* is now both positive and statistically significant, in line with our benchmark specification.

6.2.3 Owner occupied vs. non-owner occupied

A potential concern for our benchmark regressions (L1) and (M1) is that they pool together owner-occupied (OO) transactions and non-owner-occupied (NOO) ones. It is possible that NOO buyers have different incentives or constraints compared to OO buyers, as the former could be using their property as an investment vehicle and therefore could be more "sophisticated" in processing future SLR risk (see BGL) or more "deep-pocketed." For this reason, column 3 of Table A8 augments the specification in column 2 with a dummy O, which is equal to one if the transaction is OO and zero otherwise, leading to a specification denoted by Z$\times$D$\times$E$\times$B$\times$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. Thus, we find that our main results are robust to a variety of alternative fixed effect specifications.

In addition to the inclusion of a fixed effect for OO interacted with our other fixed effects, we also directly examine how the main results differ for OO versus NOO buyers. In particular, we re-estimate the main house price regression results from BGL using our data. We replicate their findings that NOO buyers are more attentive to SLR and, on average, pay a lower price for a home exposed to SLR relative to one not exposed. However, when we re-estimate our main mortgage regressions instead interacting SLR exposure with a variable for NOO buyer, we find that NOO buyers are not more strategic or sophisticated in the probability that they take out a mortgage or the terms of a mortgage, relative to OO buyers of high SLR risk properties.

6.2.4 Bad controls

In examining the effects of climate beliefs on mortgage decisions, and as highlighted in our theoretical model, we note that multiple mortgage characteristics (e.g., lending decision, maturity length, interest rate, loan amount) are endogenously co-determined in the lending process. Since these endogenous mortgage characteristics are outcomes, themselves, we do not include them in our main specifications, as we consider them to be "bad controls." Conditioning on them would change the characteristics of our treatment and control comparisons, leading to results that do not represent the average effect on our sample as a whole (Angrist and Pischke, 2008). However, as a robustness check, we also include the interest rate as a control variable in the analysis and find the results to be robust.[42]

We note that we include house price as a control variable in our main regression results. However, while less directly negotiated in the lending decision, house price may also arguably be a bad control if buyers include expectations about mortgage lending in their purchase offers. Thus, Table A9 performs a further robustness check where we repeat the leverage and maturity regressions (L1) and (M1) but omit the housing price as a control variable. As the table shows, our results are qualitatively unaffected: the interaction term between SLR and climate belief is positive and significant in both columns.

6.2.5 Floods, insurance, and other natural disasters

Another potential concern is the role of flood events, current flood risk, and flood insurance in this setting. To examine, first recall that in Table A3, we include the count of flood events in the previous year in the property's county, finding that its inclusion does not alter the main results. In addition, we matched each property with its flood risk zone using National Flood Insurance Program (NFIP) Flood Insurance Rate Maps, which provide digitized maps for flood risk zones across the U.S. The NFIP defines high flood risk as a probability of >1 in 100 of inundation by flooding in a given year. Thus, we define the variable FEMA Zone equal to one if a property is in a high risk flood zone and zero otherwise.[43] In Table A10, we include this as an

[42] The interest rate is only available for ≈30,000 observations in our sample. Results available by request.

[43] Specifically, FEMA Zone is equal to one if the property is in an A- or V-type zone, which comprise the Special Flood Hazard Area. Note that location in an NFIP high risk flood zone implies both high

additional variable in our main regressions and also interact the variable FEMA Zone with our climate beliefs variable. Our main results remain robust in sign, magnitude, and significance. Interestingly, the interaction between climate beliefs and FEMA flood zone does not significantly impact the leverage decision, further reassuring us that our results are being driven by beliefs over SLR and not current flood risk or insurance. This finding is logical when considering that NFIP insurance contracts are only written for one year without the possibility of multi-year or longer-term contracts. Thus, there are missing markets for longer-term coverage as the long-run risk cannot be hedged through insurance.[44] Defaultable long-term debt contracts could plausibly fill this gap orthogonal to short term insurance.

When examining flood risk separate from SLR, a natural question arises regarding other types of natural disasters as potential confounders of the analysis. Given our use of high-dimension fixed effects (ZIP code × distance to coast × elevation × number of bedrooms × transaction month-year), confounding variation in underlying disaster risk would need to vary across properties at this fine of a spatial scale and be correlated with SLR risk. Many types of disaster risk are arguably constant across this fine of a spatial scale, including risk from earthquakes, hurricane winds, wildfires, tornadoes, extreme precipitation, and heat. Outside of current flood risk, which we do not find to be confounding our regressions, storm surge is a potential candidate. While we do not have data on future storm surge estimates, we are less concerned about the potential for this confounding our results for several reasons. First, while it is well agreed that a changing climate will increase storm surge risk for coastal communities in the U.S. (Wuebbles et al., 2017), the impacts of climate change on storm surge is a frontier of climate science. Unlike for SLR, where data products such as the NOAA projections are readily available, there is a dearth of high-resolution, national-scale estimates of storm surge under a changing climate. Thus, unlike for SLR, there is no easily available viewer for the public to find the specific risk of their properties or communities, casting doubt on the public's ability to find their future storm surge risk.[45] Second, NOAA does not include storm surge risk in their SLR model, which is based on a calm-water bathtub-style inundation model. Thus, to the extent that storm surge matters, it is separate from our SLR definition. Since FEMA's flood risk maps are created to include the

flood risk and the mandate to hold flood insurance, although uptake of flood insurance remains low even in high risk zones (Kousky and Michel-Kerjan, 2017; Kousky et al., 2017).

[44]Most flood insurance contracts in the U.S. have a one-year maturity, and the maximum maturity is three years. However, immediately following a disaster, some households are eligible to buy Group Flood Insurance for a three-year policy period, but this temporary insurance is not renewable and thus would not cover longer-run risk.

[45]Property-specific SLR risk can easily be found through NOAA's SLR Viewer site: https://coast.noaa.gov/slr/ .

impacts of current storm surge,[46] it is also reassuring that our results are robust to the inclusion of flood risk information. Further, as discussed above, climate beliefs do not significantly modify the mortgage decision of buyers in high-flood-risk zones relative to low-risk zones. While we leave to future work the interesting question of the impact of climate beliefs on mortgage decisions in other types of natural disaster risk zones, we are reassured that our results are likely not confounded by them.

7 Diving deeper

7.1 Securitization

Thus far we have focused on testing the main implication of the model regarding the belief heterogeneity across homebuyers (the λ's in our model). However, the main driving force in the model is the disagreement between lenders and borrowers (the difference between $\bar{\lambda}$ and λ captured by Δ_λ). To further check this mechanism, we consider an important institutional detail that could lead banks to behave as if they are more optimistic about future climate risks. In particular, Ouazad and Kahn (2022) have highlighted a mechanism through which mortgage lenders can potentially shift climate risks to government-sponsored enterprises (GSEs): by approving and securitizing mortgages that are below the conforming loan limit, which are eligible to be sold to the GSEs. Doing so would be profitable to mortgage lenders if mortgage securities exposed to the SLR risks are mispriced, as the GSEs' rules and fees tend to only reflect current official flood-plain maps and do not necessarily reflect future SLR risks.[47] Via this mechanism, mortgage lenders are more SLR-optimistic because they can shift the SLR risks favorably to the GSEs.

This securitization mechanism is potentially relevant and complementary to our theoretical and empirical findings. Suppose it is true that mortgage lenders can securitize and sell conforming mortgage contracts to the GSEs. 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. Based on this mechanism, we hypothesize that:

Hypothesis 5. *The leverage and maturity channels should be stronger in the sample of conforming loans than the non-conforming loans ($\gamma_L^{conforming\ loans} > \gamma_L^{nonconforming\ loans}$, $\gamma_M^{conforming\ loans} > \gamma_M^{nonconforming\ loans}$).*

[46] FEMA Zone V, a type of high risk flood zone, designates locations at risk from high coastal velocity flooding.

[47] It has been argued that GSE policies generally tend to be rigid and do not reflect relevant spatial variations, including predictable regional variations in default risks (Hurst et al. 2016).

We investigate this securitization mechanism in Table 9. We collect data on Fannie Mae and Freddie Mac conforming loan limits for single-unit single family homes across our data sample from 2001 to 2016.[48] Between 2001 and 2007, when the conforming loan limit was constant across our data sample each year, we collect loan limit information from data replication files from LaCour-Little et al. (2022). From 2008 onward, we collect county-by-year loan limit information from the Federal Housing Finance Agency (FHFA).[49] We then match each property with the conforming loan limit in the county and year of purchase. In column 1, we repeat our main empirical leverage regression (L1), 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 $SLR \times PessBuyer$ 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, we repeat the long maturity regression (M1) 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) in column 3 (column 4). Again, the estimates for $SLR \times PessBuyer$ is positive and significant for the conforming long-maturity outcome (column 3), but is negative and significant for the nonconforming long-maturity outcome (column 4).

Overall, the results in Table 9 confirm our hypothesis: the effects of SLR exposure interacted with climate belief are stronger for the conforming loan segment – which banks can securitize loans and sell to the GSEs – than for the nonconforming loan segment.[50]

[48]Recall that we keep only single-unit single family homes and exclude duplexes, triplexes, and quadruplexes.

[49]Available online at https://www.fhfa.gov/DataTools/Downloads/Pages/Conforming-Loan-Limit.aspx

[50]We note three potential concerns about the conforming loan results. First, prior work has highlighted concerns about mismeasurement of the conforming loan limit in empirical analyses (LaCour-Little et al., 2022). In particular, the conforming loan limit could be misassigned if using the national annual average loan limit or using loan values rounded to the nearest $1,000. We note that we utilize county-by-year specific conforming loan limits from the FHFA, and our data on the mortgage loan amount at origination from CoreLogic are not rounded, therefore alleviating these concerns. Second, there is a potential concern that since conforming loan limits are based on average housing prices within a county, the loan limit could be endogenous to the underlying SLR risk. We note that in our sample from 2001 to 2007, this would not be a concern since the FHFA sets uniform limits across our data sample during this time period. In addition, our rich set of fixed effects will compare the leverage behavior of similar houses within the same zip code, which should control for this concern. A final concern is that conformity is defined by the origination loan amount relative to the loan limit at the year of acquisition by the GSE, not the limit in the year of the mortgage origination, which we observe in our data. As additional robustness, we re-estimate our conforming loan results using only years 2009 to 2016, when the conforming loan limits remained unchanged for nearly all counties in the U.S., and therefore should be immune to measurement concerns regarding origination versus acquisition year.

	Leveraged &		Long Maturity &	
	Conforming	Nonconform	Conforming	Nonconform
SLR Risk	-0.016	0.013*	-0.009	0.007
	(0.015)	(0.007)	(0.021)	(0.013)
SLR Risk × PessBuyer	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	406,601	406,601	182,771	182,771
R^2	0.478	0.566	0.569	0.669

Table 9: 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. For brevity, only estimates of the coefficients of SLR Risk and the interaction term SLR Risk × Pessimistic Buyer are reported. The rest is the same as in Tables 5 and 6.

7.2 Monetary policy implications

We now test the model's monetary policy implications. We augment specification (L1) by including a triple interaction of our SLR and beliefs variables with the policy interest rate ι_t:

$$\begin{aligned} Leveraged_{it} = {} & \beta_L SLR_i + \gamma_L SLR_i \times PessBuyer_c + \zeta_L SLR_i \times PessBuyer_c \times \iota_t \\ & + \varpi_L^0 \iota_t + \varpi_L^1 SLR_i \times \iota_t + \varpi_L^2 PessBuyer_c \times \iota_t + \delta_L PessBuyer_c \\ & + \rho_L \ln Price_{it} + \phi_L' X_i + \theta_L' Z_{ct} + \xi_L' SLR_i \times Z_{ct} + \Lambda_{ZDEBM}^L + \epsilon_{it}^L. \end{aligned} \tag{L2}$$

The key coefficient of interest is ζ_L. For an empirical measure of ι_t, we use the market yield on Treasury securities at two-year maturity, a standard proxy for lenders' funding cost affected by the nominal interest rate set by the monetary authority in the U.S.[51] Similarly, we set up a maturity regression (M2) with all the interaction terms with ι_t. Based on Proposition 4, we hypothesize that:

Hypothesis 6. *In transactions of properties exposed to SLR risk, a decrease (increase) in the interest rate ι increases (decreases) the probability that a purchase of an exposed property by a pessimist is leveraged, but it does not impact the maturity choice ($\zeta_L >$*

Table A11 presents the results. Our leverage results remain robust. Our long maturity results on the interaction term remain robust in magnitude although lose significant under the reduced sample size.

[51] Retrieved from https://fred.stlouisfed.org/series/DGS2.

$0, \zeta_M = 0$).

	Leveraged	Long Maturity
SLR Risk	-0.022	0.003
	(0.017)	(0.016)
SLR Risk × PessBuyer	0.049***	0.035***
	(0.015)	(0.012)
SLR Risk × PessBuyer × Policy Rate	-0.009**	-0.005
	(0.005)	(0.004)
Property & buyer county controls	Y	Y
Buyer county controls × SLR	Y	Y
Z × D × E × B × M fe	Y	Y
Lender fe		Y
N	405,893	150,746
R^2	0.473	0.441

Table 10: 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; sample restricted to transactions with an associated mortgage contract). Policy Rate denotes the market yield on Treasury securities at two-year maturity. For brevity, only estimates of the coefficients of SLR Risk and its interaction terms are reported. The rest is the same as in Tables 5 and 6.

Column 1 of Table 10 reports the estimates for β_L, γ_L and ζ_L from equation (L2). As before, the coefficient γ_L 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_L 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. There, the triple interaction term is not significant. This is consistent with the model's prediction that the interest rate ι_t does not have any significant effect on maturity choice. Overall, our empirical results suggest support for the model's implication on the effect of monetary policies on the leverage probability of property transactions that are subject to SLR risk. The results highlight the potential impact of monetary policies on climate risk in the financial system.

7.3 Results over time

Since both the attention to global warming and the disagreement in public opinion about climate change have become more salient in the past decade (Engle et al. 2020; Bernstein et al. 2022), it is natural to ask whether our results change over time. Table A12 investigates this question. Columns 1, 3, and 5 repeat regressions (P1), (L1), and (M1), respectively, for the subsample of transactions that took place before 2010, while columns 2, 4, and 6 repeat them for transactions during or after 2010.

Consistent with the earlier literature (e.g., BGL and Goldsmith-Pinkham et al. 2021), columns 1 and 2 show that the pricing of SLR risk is more pronounced after 2010, as the estimates for the SLR variable are more significant and negative in the recent sample. More importantly, the estimates of the interaction terms *SLR Risk*× *PessBuyer* in columns 3 to 6 show that our main results on the effects of SLR and climate beliefs on mortgage outcomes are more significant (statistically and economically) in the more recent sample. Thus, these results are consistent with climate risk in financial systems becoming more pronounced over time as heterogeneous climate beliefs, and climate risk salience among pessimists, has increased.

7.4 Other intensive margins

A natural question arises as to how climate beliefs affect other intensive margin outcomes such as the loan amount and interest rate mortgage characteristics.[52] Thus, we re-estimate our main regression specifications using the loan amount and interest rates as outcome variables. Table A13 reports these results. Consistent with our theoretical model, which produce ambiguous comparative statics with respect to the equilibrium loan amount B, column 1 shows that the interaction between the SLR risk and the pessimistic buyer dummy does not have a significant impact on the mortgage amount: the estimated coefficient is positive but not statistically significant. Similarly, in column 2, where the dependent variable is the mortgage interest rate, the estimate of the interaction term is positive but not statistically significant.[53]

8 Conclusion

What makes climate risks special? Three outstanding characteristics are that (i) climate risks could have potentially large damages, (ii) the risks are back-loaded (i.e., most damages are expected to occur in the future), and (iii) there is substantial belief disagreement over climate risks, especially in the U.S. Our paper theoretically and empirically argues that the combination of these features is key in understanding the effects of climate risks on the financial market. In particular, we find that despite paying less for an at-risk property, climate pessimists are more likely to take out a mortgage and for a longer maturity relative to climate optimists.

[52] Recall from Section 6.2.4 that we do not include these in endogenous mortgage characteristics in our main regression models as they are bad controls.

[53] Note that in column 2, we also include a fixed effect for whether a mortgage has a 30-year maturity, so that we are only comparing the mortgage interest rates of loans that have similar maturity. Also note that the sample size shrinks to approximately 30,000 observations in this exercise. It is possible that the interaction term becomes statistically significant if we had a larger sample.

We believe that the exploration of the implications of climate risks for debt markets is an exciting area for future research, both theoretically and empirically. For instance, 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 among a small set of systemically important financial institutions and whether it could affect financial stability or general welfare remain open questions (Phan 2021, 2022). While we have focused entirely on a positive analysis, future work could explore a normative analysis of prudential policies vis-a-vis the strategic transferring of climate risks we documented. For example, it could be interesting to introduce belief heterogeneity into a quantitative macro model with climate risk (e.g., à la Panjwani 2022) and study optimal prudential policies (e.g., à la Bianchi and Mendoza 2018). Moreover, future research on the potential effects of climate change on financial stability (such as climate stress testing exercises à la Jung et al. 2021) should take the strategic transferring of climate-related risks into account.

Finally, future work could explore the roles of several important margins we have not considered in this paper. For instance, one could extend our theoretical model to allow agents to resell the house, and one could expand our empirical analysis to study whether climate risks and climate beliefs affect how resalable a property is. One could extend our analysis to theoretically and empirically study potential interactions between mortgage choice and residential sorting (à la Bakkensen and Ma 2020; Bakkensen and Barrage 2022). These are some open questions that are exciting for future research.

References

Addoum, J. M., Eichholtz, P., Steiner, E., and Yönder, E. (2021). Climate change and commercial real estate: Evidence from Hurricane Sandy. *Working paper*.

Alekseev, G., Giglio, S., Maingi, Q., Selgrad, J., and Stroebel, J. (2021). A quantity-based approach to constructing climate risk hedge portfolios. *NBER Working Paper*.

Allen, F., Barlevy, G., and Gale, D. (2022). Asset price booms and macroeconomic policy: A risk-shifting approach. *American Economic Journal: Macroeconomics*, 14(2):243–80.

Allen, F. and Gale, D. (2000). Bubbles and crises. *The Economic Journal*, 110(460):236–255.

Allen, J., Clark, R., and Houde, J.-F. (2014). The effect of mergers in search markets: Evidence from the canadian mortgage industry. *American Economic Review*, 104(10):3365–96.

Allen, J., Clark, R., and Houde, J.-F. (2019). Search frictions and market power in negotiated-price markets. *Journal of Political Economy*, 127(4):1550–1598.

Alvarez, J. L. C. and Rossi-Hansberg, E. (2021). The economic geography of global warming. Technical report, National Bureau of Economic Research.

Angrist, J. D. and Pischke, J.-S. (2008). *Mostly harmless econometrics*. Princeton university press.

Bailey, M., Dávila, E., Kuchler, T., and Stroebel, J. (2019). House price beliefs and mortgage leverage choice. *The Review of Economic Studies*, 86(6):2403–2452.

Bakkensen, L. A. and Barrage, L. (2022). Going underwater? Flood risk belief heterogeneity and coastal home price dynamics. *The Review of Financial Studies*, 35(8):3666–3709.

Bakkensen, L. A., Ding, X., and Ma, L. (2019). Flood risk and salience: New evidence from the Sunshine State. *Southern Economic Journal*, 85(4):1132–1158.

Bakkensen, L. A. and Ma, L. (2020). Sorting over flood risk and implications for policy reform. *Journal of Environmental Economics and Management*, 104:102362.

Baldauf, M., Garlappi, L., and Yannelis, C. (2020). Does climate change affect real estate prices? only if you believe in it. *The Review of Financial Studies*, 33(3):1256–1295.

Ballew, M. T., Leiserowitz, A., Roser-Renouf, C., Rosenthal, S. A., Kotcher, J. E., Marlon, J. R., Lyon, E., Goldberg, M. H., and Maibach, E. W. (2019). Climate change in the American mind: Data, tools, and trends. *Environment: Science and Policy for Sustainable Development*, 61(3):4–18.

Bansal, R., Kiku, D., and Ochoa, M. (2021). Climate change risk. *Working Paper*.

Barlevy, G. (2014). A leverage-based model of speculative bubbles. *Journal of Economic Theory*, 153:459–505.

Barnett, M. and Yannelis, C. (2021). Does climate change impact sovereign bond yields? *Working Paper*.

Barreca, A., Clay, K., Deschenes, O., Greenstone, M., and Shapiro, J. S. (2016). Adapting to climate change: The remarkable decline in the us temperature-mortality relationship over the twentieth century. *Journal of Political Economy*, 124(1):105–159.

Barro, R. J. (2009). Rare disasters, asset prices, and welfare costs. *American Economic Review*, 99(1):243–64.

Bengui, J. and Phan, T. (2018). Asset pledgeability and endogenously leveraged bubbles. *Journal of Economic Theory*, 177:280–314.

Bernanke, B. S., Gertler, M., and Gilchrist, S. (1999). The financial accelerator in a quantitative business cycle framework. *Handbook of macroeconomics*, 1:1341–1393.

Bernstein, A., Billings, S. B., Gustafson, M. T., and Lewis, R. (2022). Partisan residential sorting on climate change risk. *Journal of Financial Economics*.

Bernstein, A., Gustafson, M. T., and Lewis, R. (2019). Disaster on the horizon: The price effect of sea level rise. *Journal of Financial Economics*, 134(2):253–272.

Bethune, Z., Rocheteau, G., Wong, T.-N., and Zhang, C. (2022). Lending relationships and optimal monetary policy. *The Review of Economic Studies*, 89(4):1833–1872.

Bianchi, J. and Mendoza, E. G. (2018). Optimal time-consistent macroprudential policy. *Journal of Political Economy*, 126(2):588–634.

Brunetti, C., Dennis, B., Gates, D., Hancock, D., Ignell, D., Kiser, E. K., Kotta, G., Kovner, A., Rosen, R. J., and Tabor, N. K. (2021). Climate change and financial stability. *FEDS Notes*, (2021-03):19–3.

Cao, D. (2018). Speculation and financial wealth distribution under belief heterogeneity. *The Economic Journal*, 128(614):2258–2281.

Council, F. S. O. (2021). Fsoc report on climate-related financial risk. Technical report, Financial Stability Oversight Council.

Daniel, V. E., Florax, R. J., and Rietveld, P. (2009). Flooding risk and housing values: An economic assessment of environmental hazard. *Ecological Economics*, 69(2):355–365.

Desmet, K., Kopp, R. E., Kulp, S. A., Nagy, D. K., Oppenheimer, M., Rossi-Hansberg, E., and Strauss, B. H. (2021). Evaluating the economic cost of coastal flooding. *American Economic Journal: Macroeconomics*, 13(2).

Dong, D., Liu, Z., Wang, P., and Zha, T. (2022). A theory of housing demand shocks. *Journal of Economic Theory*, page 105484.

Engle, R. F., Giglio, S., Kelly, B., Lee, H., and Stroebel, J. (2020). Hedging climate change news. *The Review of Financial Studies*, 33(3):1184–1216.

Fleming, E., Payne, J., Sweet, W. V., Craghan, M., Haines, J. W., Hart, J. F., Stiller, H., and Sutton-Grier, A. (2018). Coastal effects. Technical report, US Global Change Research Program.

Fostel, A. and Geanakoplos, J. (2008). Leverage cycles and the anxious economy. *American Economic Review*, 98(4):1211–44.

Fostel, A. and Geanakoplos, J. (2015). Leverage and default in binomial economies: a complete characterization. *Econometrica*, 83(6):2191–2229.

Fried, S. (2021). Seawalls and Stilts: A Quantitative Macro Study of Climate Adaptation. *The Review of Economic Studies*.

Furukawa, K., Ichiue, H., Shiraki, N., et al. (2020). How does climate change interact with the financial system? a survey. Technical report, Bank of Japan.

Garriga, C. and Hedlund, A. (2020). Mortgage debt, consumption, and illiquid housing markets in the great recession. *American Economic Review*, 110(6):1603–34.

Geanakoplos, J. (1997). Promises promises. In *The Economy as an Evolving Complex System II*, pages 285–320. CRC Press.

Geanakoplos, J. (2003). Liquidity, default, and crashes. In *Advances in economics and econometrics: Theory and applications: 8th World Congress*.

Geanakoplos, J. (2010). The leverage cycle. *NBER macroeconomics annual*, 24(1):1–66.

Geerolf, F. (2015). Leverage and disagreement. *Working Paper, UCLA*.

Giglio, S., Kelly, B., and Stroebel, J. (2021). Climate finance. *Annual Review of Financial Economics*, 13(1):15–36.

Goldsmith-Pinkham, P. S., Gustafson, M., Lewis, R., and Schwert, M. (2021). Sea level rise exposure and municipal bond yields. *Jacobs Levy Equity Management Center for Quantitative Financial Research Paper*.

Gourio, F. (2012). Disaster risk and business cycles. *American Economic Review*, 102(6):2734–66.

Greene, W., Han, C., and Schmidt, P. (2002). The bias of the fixed effects estimator in nonlinear models. *Unpublished Manuscript, Stern School of Business, NYU*, 29.

Guerrieri, V., Shimer, R., and Wright, R. (2010). Adverse selection in competitive search equilibrium. *Econometrica*, 78(6):1823–1862.

Hallstrom, D. G. and Smith, V. K. (2005). Market responses to hurricanes. *Journal of Environmental Economics and Management*, 50(3):541–561.

Head, A., Lloyd-Ellis, H., and Sun, H. (2014). Search, liquidity, and the dynamics of house prices and construction. *American Economic Review*, 104(4):1172–1210.

Hino, M. and Burke, M. (2021). The effect of information about climate risk on property values. *Proceedings of the National Academy of Sciences*, 118(17).

Hong, H., Karolyi, G. A., and Scheinkman, J. A. (2020). Climate finance. *The Review of Financial Studies*, 33(3):1011–1023.

Hornsey, M. J., Harris, E. A., Bain, P. G., and Fielding, K. S. (2016). Meta-analyses of the determinants and outcomes of belief in climate change. *Nature climate change*, 6(6):622–626.

Howe, P. D., Mildenberger, M., Marlon, J. R., and Leiserowitz, A. (2015). Geographic variation in opinions on climate change at state and local scales in the USA. *Nature climate change*, 5(6):596–603.

Hsiang, S. M. and Narita, D. (2012). Adaptation to cyclone risk: Evidence from the global cross-section. *Climate Change Economics*, 3(02):1250011.

Hurst, E., Keys, B. J., Seru, A., and Vavra, J. (2016). Regional redistribution through the US mortgage market. *American Economic Review*, 106(10):2982–3028.

Issler, P., Stanton, R., Vergara-Alert, C., and Wallace, N. (2020). Mortgage markets with climate-change risk: Evidence from wildfires in california. *Available at SSRN 3511843*.

Jung, H., Engle, R. F., and Berner, R. (2021). Climate stress testing. *FRB of New York Staff Report*, (977).

Kahn, M. E. and Smith, V. K. (2017). The affordability goal and prices in the national flood insurance program. Technical report, National Bureau of Economic Research.

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

Khan, A., King, R. G., and Wolman, A. L. (2003). Optimal monetary policy. *The Review of Economic Studies*, 70(4):825–860.

Kousky, C., Lingle, B., and Shabman, L. (2017). The pricing of flood insurance. *Journal of Extreme Events*, 4(02):1750001.

Kousky, C. and Michel-Kerjan, E. (2017). Examining flood insurance claims in the United States: Six key findings. *Journal of Risk and Insurance*, 84(3):819–850.

Kurlat, P. and Stroebel, J. (2015). Testing for information asymmetries in real estate markets. *The Review of Financial Studies*, 28(8):2429–2461.

LaCour-Little, M., Pavlov, A. D., and Wachter, S. M. (2022). Adverse selection and climate risk: A response to Ouazad and Khan (2021). *Available at SSRN*.

Landvoigt, T., Piazzesi, M., and Schneider, M. (2015). The housing market(s) of San Diego. *American Economic Review*, 105(4):1371–1407.

Liao, Y. and Mulder, P. (2021). What's at stake? understanding the role of home equity in flood insurance demand. *Working paper*.

Litterman, R., Anderson, C. E., Bullard, N., Caldecott, B., Cheung, M. L., Colas, J. T., Coviello, R., Davidson, P. W., Dukes, J., Duteil, H. P., et al. (2020). Managing climate risk in the U.S. financial system: Report of the Climate-Related Market Risk Subcommittee, Market Risk Advisory Committee of the U.S. Commodity Futures Trading Commission. Technical report.

Meeuwis, M., Parker, J. A., Schoar, A., and Simester, D. (2021). Belief disagreement and portfolio choice. *Journal of Finance, Forthcoming*.

Mendelsohn, R., Emanuel, K., Chonabayashi, S., and Bakkensen, L. (2012). The impact of climate change on global tropical cyclone damage. *Nature Climate Change*, 2(3):205–209.

Mian, A. and Sufi, A. (2015). *House of debt: How they (and you) caused the Great Recession, and how we can prevent it from happening again*. University of Chicago Press.

Murfin, J. and Spiegel, M. (2020). Is the risk of sea level rise capitalized in residential real estate? *The Review of Financial Studies*, 33(3):1217–1255.

Network for Greening the Financial System (2019). Macroeconomic and financial stability: Implications of climate change. *Technical supplement to the First comprehensive report*.

Ngai, L. R. and Tenreyro, S. (2014). Hot and cold seasons in the housing market. *American Economic Review*, 104(12):3991–4026.

Ouazad, A. (2022). Do investors hedge against green swans? option-implied risk aversion to wildfires. *SSRN Working Paper*.

Ouazad, A. and Kahn, M. E. (2022). Mortgage finance and climate change: Securitization dynamics in the aftermath of natural disasters. *The Review of Financial Studies*, 35(8):3617–3665.

Painter, M. (2020). An inconvenient cost: The effects of climate change on municipal bonds. *Journal of Financial Economics*, 135(2):468–482.

Panjwani, A. (2022). Underwater: The effect of federal policies on households' exposure to climate change risk. *Working paper*.

Phan, T. (2021). Climate change and financial stability? Recalling lessons from the Great Recession. *Richmond Fed Economic Brief*, 21(27).

Phan, T. (2022). Are some homebuyers strategically transferring climate risks to lenders? *Richmond Fed Economic Brief*, 22(14).

Phan, T. and Schwartzman, F. (2021). Climate defaults and financial adaptation. *Richmond Fed Working Paper*.

Rocheteau, G., Wright, R., and Zhang, C. (2018). Corporate finance and monetary policy. *American Economic Review*, 108(4-5):1147–86.

Sastry, P. (2021). Who bears flood risk? Evidence from mortgage markets in Florida. *Working paper*.

Simsek, A. (2013). Belief disagreements and collateral constraints. *Econometrica*, 81(1):1–53.

Stroebel, J. (2016). Asymmetric information about collateral values. *The Journal of Finance*, 71(3):1071–1112.

Tirole, J. (1999). Incomplete contracts: Where do we stand? *Econometrica*, 67(4):741–781.

Wong, T.-N. (2016). A tractable monetary model under general preferences. *The Review of Economic Studies*, 83(1):402–420.

Wright, R., Kircher, P., Julien, B., and Guerrieri, V. (2021). Directed search and competitive search equilibrium: A guided tour. *Journal of Economic Literature*, 59(1):90–148.

Wuebbles, D. J., Fahey, D. W., and Hibbard, K. A. (2017). Climate science special report: Fourth National Climate Assessment, volume 1.

Zhang, K., Li, Y., Liu, H., Xu, H., and Shen, J. (2013). Comparison of three methods for estimating the sea level rise effect on storm surge flooding. *Climatic Change*, 118(2):487–500.

A Appendix

A.1 Omitted proofs

A.1.1 Proof of Proposition 1

Given the Poisson nature of the disaster and loan maturity, there is no new information nor change in the individual state before the arrival of the disaster or loan maturity. Thus, the optimal default time is time-independent and will take the following form, which is contingent on the timing of the disaster and loan maturity:

$$T_f = \begin{cases} \tau_0 & \text{before the disaster and loan maturity} \\ T_d + \tau_d & \text{after the disaster but before loan maturity} \\ \infty & \text{after loan maturity} \end{cases} .$$

We solve the buyer's default decision using backward induction. Consider the subgame after the disaster has happened at $t = T_d$ but before the loan maturity. Denote $T_m = T_d + \tau_m$ as the loan maturity date, where τ_m follows an exponential distribution with parameter $r\mu$, where

$$\mu = \frac{1}{\Gamma} - 1 \leq \mu_0 = \frac{1}{\Gamma_0} - 1.$$

The buyer's continuation value at $t = T_d$ of defaulting at $T_f = T_d + \tau_d$ is given by:

$$W(\tau_d) \equiv \int r\mu e^{-r\mu\tau_m} \left\{ \begin{array}{l} \int_0^{\min(\tau_m,\tau_d)} re^{-rt}(h-d-M)\,dt \\ +e^{-r\tau_d} 1_{\tau_d \leq \tau_m} \left[-f + \{h-d-B\}_+\right] \\ +e^{-r\tau_m} 1_{\tau_d > \tau_m} (h-d) \end{array} \right\} d\tau_m$$

where we have made use of the fact that $p_t = h - d$ and $B_t = B = \Gamma M$. Note that the value function satisfies the following Hamilton–Jacobi–Bellman (HJB) equation:

$$\frac{d}{d\tau} W(\tau) = r(h-d-M) + r\mu\left[h-d-W(\tau)\right] - rW(\tau). \tag{29}$$

The HJB states that the marginal value of postponing default (the left-hand side) is equal to the sum of the flow of asset return (post-disaster) net of the loan repayment,

$r(h-d-M)$, and the expected gain of paying off the loan, $r\mu[h-d-W(\tau)]$, minus the cost of discounting, $rW(\tau)$. The case $\tau=0$ represents that the buyer defaults immediately, which gives the following boundary condition to (29):

$$W(0)=-f+\{h-d-B\}_+.$$

Using the boundary condition, the HJB equation has the following solution:

$$W(\tau)=\left[1-e^{-r(1+\mu)\tau}\right](h-d-B)+e^{-r(1+\mu)\tau}\left[-f+\{h-d-B\}_+\right]. \tag{30}$$

The first term is the present value of never default, and the second term is the value of immediate default. Thus, $W(\tau)$ is the average weighing the latter by the factor $\exp[-r(1+\mu)\tau]$. The optimal stopping time to default is $\tau_d=\infty$ if the first term is weakly larger and $\tau_d=0$ if the second term is strictly larger, imposing a tie-breaking rule that a borrower chooses to never default when he is indifferent. The first term is a downward-sloping curve in B; the second term is downward-sloping curve in B with the same slope for all $B<h-d$ but then flat at $-f$ for all $B\geq h-d$. Thus, the first term cuts the second term from above in the flat region of the second term at the single crossing point $B=b^{\text{safe}}$, where

$$b^{\text{safe}}=h-d+f. \tag{31}$$

Denote $W^*(b)\equiv\max_\tau W(\tau)$ as the continuation value under the optimal stopping time of default τ_d, which is given by:

$$W^*(B)\equiv W(\tau_d)=\begin{cases} h-d-B, \text{ if } B\leq b^{\text{safe}} \\ -f, \text{ if } B>b^{\text{safe}} \end{cases} \tag{32}$$

which is given by:

$$\tau_d\equiv\arg\max_\tau W(\tau)=\begin{cases} \infty, \text{ if } B\leq b^{\text{safe}} \\ 0, \text{ if } B>b^{\text{safe}} \end{cases}. \tag{33}$$

Now, consider the subgame at $t=0$ before the disaster and loan maturity. Denote T_m as the loan maturity date in this case, where T_m follows an exponential distribution with parameter $r\mu$. Recall the disaster arrives at T_d, which follows the Poisson rate $r\lambda$.

At $t=0$, the buyer's continuation value of defaulting at τ_0, where $\tau_0 \leq T_d$, is given by:

$$V(\tau_0) \equiv \int r\lambda e^{-r\lambda T_d} \int r\mu e^{-r\mu T_m} \left\{ \begin{array}{l} \int_0^{\min(T_m,\tau_0,T_d)} re^{-rt}(h-M)\,dt \\ +e^{-rT_d} 1_{T_d \leq \min(T_m,\tau_0)} W^*(B_{T_d}) \\ +e^{-r\tau_0} 1_{\tau_0 \leq T_m, \tau_0 < T_d} \left[-f + \{\bar{p}_\lambda - B_{\tau_0}\}_+\right] \\ +e^{-rT} 1_{T_m < \tau_0, T_m < T_d} v_\lambda \end{array} \right\} dT_m dT_d \tag{34}$$

Note that the value function satisfies the following HJB equation:

$$\frac{d}{d\tau} V(\tau) = r(h-M) + r\mu[v_\lambda - V(\tau)] - r\lambda[V(\tau) - W^*(B)] - rV(\tau). \tag{35}$$

The HJB states that the marginal value of postponing default is equal to the sum of the flow of asset return (pre-disaster) net of the loan repayment, $r(h-M)$, and the expected gain of paying off the loan, $r\mu[v_\lambda - V(\tau)]$, minus the expected loss from the exposure to the disaster, $r\lambda[V(\tau) - W^*(B)]$, and the cost of discounting, $rV(\tau)$. At $\tau = 0$, the buyer defaults immediately, which gives the boundary condition to (35):

$$V(0) = -f + \{\bar{p}_\lambda - B\}_+.$$

Using the boundary condition, the HJB equation has the following solution:

$$\begin{aligned} V(\tau) \quad = \quad & \left[1 - e^{-r(1+\lambda+\mu)\tau}\right] \underbrace{\frac{h - (1+\mu)B + \lambda W^*(B) + \mu v_\lambda}{1+\lambda+\mu}}_{V_1(B)} \\ & + e^{-r(1+\lambda+\mu)\tau} \underbrace{\left[-f + \{\bar{p}_\lambda - B\}_+\right]}_{V_2(B)}. \end{aligned} \tag{36}$$

The first term is the present value of never default before the disaster, and the second term is the value of immediate default. Define the first term as $V_1(B)$ and the second term as $V_2(B)$. Thus, we have $\tau_0 = 0$ if $V_1(B) < V_2(B)$ and $\tau_0 = \infty$ if $V_1(B) \geq V_2(B)$, imposing a tie-breaking rule that a borrower chooses to never default when he is indifferent. We want to solve the region of B such that $V_1(B) < V_2(B)$.

Using $W^*(B)$ from (32), $V_1(B)$ is given by:

$$V_1(B) = \left\{ \begin{array}{l} v_\lambda - B, \text{ if } B \leq b^{\text{safe}} \\ \frac{h-\lambda f+\mu v_\lambda}{1+\lambda+\mu} - \frac{1+\mu}{1+\lambda+\mu} B, \text{ if } B > b^{\text{safe}} \end{array} \right. .$$

$V_1(B)$ features the values for two default strategies: in the first region $B \leq b^{\text{safe}}$, the buyer never defaults; in the second region $B > b^{\text{safe}}$, the buyer defaults immediately after the disaster (which is also optimal in that subgame, shown above) but does not default beforehand. Thus, $V_1(B)$ is descreasing in B with slope equal to -1 in the first region and with slope equal to $-\frac{1+\mu}{1+1+\lambda+\mu} \in (-1,0)$ in the second region.

On the other hand, $V_2(B)$ is decreasing in B, with the slope equal to -1 when $B \leq \bar{p}_\lambda$; otherwise the slope equals 0. Also, notice that we have $V_1(0) = v_\lambda > \bar{p}_\lambda - f = V_2(0)$ following the assumption (3). Thus, we must have $V_2(B)$ intersecting $V_1(B)$ from below at the flat region of $V_2(B)$ – see the illustration in Figure A1. Denote the intersection as $B = b_\lambda^{\text{risky}}$, i.e., $V_1\left(b_\lambda^{\text{risky}}\right) = V_2\left(b_\lambda^{\text{risky}}\right) = -f$, where $V_1(b) > V_2(b)$ if $B < b_\lambda^{\text{risky}}$ and vice versa. Notice that since $V_1\left(b^{\text{safe}}\right) = v_\lambda - (h - d + f) > -f = V_1\left(b_\lambda^{\text{risky}}\right)$, we must have $b_\lambda^{\text{risky}} > b^{\text{safe}}$. In sum, b_λ^{risky} is given by setting the second region of $V_1\left(b_\lambda^{\text{risky}}\right)$ to $-f$:

$$b_\lambda^{\text{risky}} = h - (1-\Gamma)\frac{\lambda}{1+\lambda}d + f. \tag{37}$$

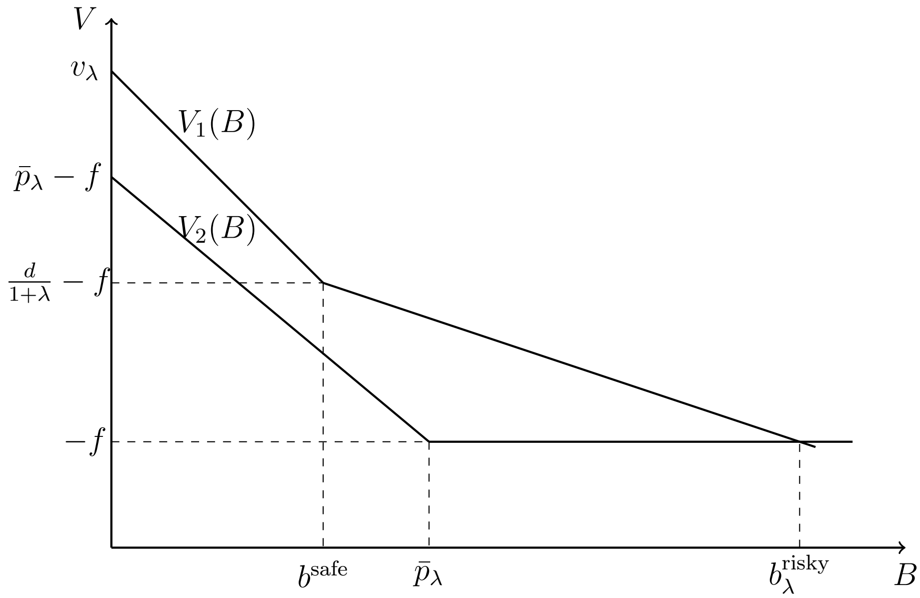

Figure A1: Illustration of value functions $V_1(B)$ and $V_2(B)$ from equation (36) and the determination of the risky debt limit b_λ^{risky} in (37).

Summarizing the above cases, the optimal stopping time of default before the disaster is given as:

$$T_f = \begin{cases} \infty & \text{if } B \leq b^{\text{safe}}, \\ T_d & \text{if } B \in (b^{\text{safe}}, b_\lambda^{\text{risky}}] \text{ and } T_d < T_m, \\ 0 & \text{otherwise.} \end{cases} .$$

QED

A.1.2 Proof of Proposition 2

In this section, we solve for the optimal contract $\mathbf{a} = (L, M, \Gamma)$ in the general case with the difference in funding costs $\omega \geq 0$ (as described in Section 3.3.2); Proposition 2 is the special case with $\omega = 0$. Using Proposition 1, the borrower's surplus of buying an asset with the loan contract $\mathbf{a}$ is given by:

$$V_\lambda(\mathbf{a}) = v_\lambda + \begin{cases} -B & \text{if } B \leq b^{\text{safe}}, \\ -T_\lambda M - Q_\lambda (h - d + f) & \text{if } B \in (b^{\text{safe}}, b_\lambda^{\text{risky}}], \\ -v_\lambda - f & \text{otherwise} \end{cases} \tag{38}$$

where

$$\begin{aligned} T_\lambda &\equiv \mathbb{E}_\lambda \int_0^{T_m \wedge T_f(\lambda, \mathbf{a})} r e^{-rt} dt = \frac{1}{1 + \lambda + \mu}, \\ Q_\lambda &\equiv \mathbb{E}_\lambda \left\{ 1_{T_f(\lambda,\mathbf{a}) < T_m} e^{-rT_f(\lambda,\mathbf{a})} \right\} = \frac{\lambda}{1 + \lambda + \mu}. \end{aligned}$$

Given the buyer's default strategy $T_f(\lambda, \mathbf{a})$ from Proposition 1, the expected present value of the loan repayments before the disaster is

$$R_\lambda(\mathbf{a}) = \begin{cases} B & \text{if } B \leq b^{\text{safe}} \\ T_{\bar{\lambda}} M + Q_{\bar{\lambda}} (h - d) & \text{if } B \in (b^{\text{safe}}, b_\lambda^{\text{risky}}], \\ \bar{p}_\lambda & \text{otherwise} \end{cases} \tag{39}$$

where

$$\begin{aligned} T_{\bar{\lambda}} &\equiv \mathbb{E}_{\bar{\lambda}} \int_0^{T_m \wedge T_f(\lambda, \mathbf{a})} r e^{-rt} dt = \frac{1}{1 + \bar{\lambda} + \mu}, \\ Q_{\bar{\lambda}} &\equiv \mathbb{E}_{\bar{\lambda}} \left\{ 1_{T_f(\lambda,\mathbf{a}) < T_m} e^{-rT_f(\lambda,\mathbf{a})} \right\} = \frac{\bar{\lambda}}{1 + \bar{\lambda} + \mu} = \bar{\lambda} T_{\bar{\lambda}}, \\ \Gamma &= \frac{T_{\bar{\lambda}}}{1 - \bar{\lambda} T_{\bar{\lambda}}}. \end{aligned}$$

The joint surplus is thus given by

$$\frac{V_\lambda(\mathbf{a}) - v_\lambda}{1 + \omega} + R_\lambda(\mathbf{a}) = \begin{cases} \frac{\omega}{1+\omega} B & \text{if } B \leq b^{\text{safe}} \\ \left(T_{\bar{\lambda}} - \frac{T_\lambda}{1+\omega}\right) \frac{B}{\Gamma} + \left(Q_{\bar{\lambda}} - \frac{Q_\lambda}{1+\omega}\right)(h - d) - Q_\lambda f & \text{if } B \in (b^{\text{safe}}, b_\lambda^{\text{risky}}]. \\ \bar{p}_\lambda - \frac{v_\lambda + f}{1+\omega} & \text{otherwise} \end{cases} \tag{40}$$

The equilibrium contract solves

$$\max_{\mathbf{a}} \left\{ \frac{V(\mathbf{a}) - v_\lambda}{1+\omega} + R_\lambda(\mathbf{a}) - \kappa_0(\Gamma) \right\} = \max_{T_{\bar{\lambda}} \geq T_0} \left\{ S_\lambda(T_{\bar{\lambda}}) - \kappa(T_{\bar{\lambda}}) \right\},$$

with

$$S_\lambda(T_{\bar{\lambda}}) = \max\left\{ S^{\text{safe}}, S_\lambda^{\text{risky}}(T_{\bar{\lambda}}), S_\lambda^0 \right\},$$

where the optimal joint surpluses in three regions are given by:

$$\begin{aligned} S^{\text{safe}} &\equiv \frac{\omega}{1+\omega} b^{\text{safe}}, \\ S_\lambda^{\text{risky}}(T_{\bar{\lambda}}) &\equiv \max_{B \in (b^{\text{safe}}, b^{\text{risky}}]} \left\{ \left(T_{\bar{\lambda}} - \frac{T_\lambda}{1+\omega} \right) \frac{B}{\Gamma} + \left(Q_{\bar{\lambda}} - \frac{Q_\lambda}{1+\omega} \right)(h-d) - Q_\lambda f \right\}, \\ S_\lambda^0 &\equiv \bar{p}_\lambda - \frac{v_\lambda + f}{1+\omega}. \end{aligned}$$

Assume that ω is sufficiently small such that

$$v_\lambda + f - \bar{p}_\lambda > \omega\left(\bar{p}_\lambda - b^{\text{safe}}\right) \text{ for all } \lambda. \tag{41}$$

Thus, we have $S^{\text{safe}} > S_\lambda^0$. In other words, the borrower prefers never default over immediate default. That is, the optimal S in the first region of (40) always dominates any S in the third region, and so we can ignore the third region. The condition is automatically satisfied when $\omega = 0$.

Notice that the optimal B for S_λ^{risky} is given by

$$B = \begin{cases} b_\lambda^{\text{risky}}, \text{ if } \left(\lambda - \bar{\lambda}\right) T_{\bar{\lambda}} \geq \frac{-\omega}{1+\omega}, \\ b^{\text{safe}}, \text{ otherwise}, \end{cases}$$

where we have made use of the fact that $T_{\bar{\lambda}} - \frac{T_\lambda}{1+\omega} \geq 0$ is equivalent to $\left(\lambda - \bar{\lambda}\right) T_{\bar{\lambda}} \geq \frac{-\omega}{1+\omega}$. Substituting the optimal B, we have

$$S_\lambda^{\text{risky}}(T_{\bar{\lambda}}) \equiv \begin{cases} \frac{\omega}{1+\omega}(v_\lambda + f) + \Delta_\lambda T_{\bar{\lambda}}, \text{ if } \left(\lambda - \bar{\lambda}\right) T_{\bar{\lambda}} \geq \frac{-\omega}{1+\omega}, \\ S^{\text{safe}} - \bar{\lambda} f T_{\bar{\lambda}}, \text{ otherwise.} \end{cases}$$

We define the following constants (the version in Proposition 2 is the special case

$\omega = 0$):

$$\lambda_a \equiv \begin{cases} \frac{\bar{\lambda}(f+d) - \frac{\omega d}{(1+\omega) T_0}}{d - \bar{\lambda} f}, \text{ if } d > \bar{\lambda} f, \\ \infty, \text{ otherwise}, \end{cases},$$
$$\lambda_b \equiv \begin{cases} \frac{\bar{\lambda}(f+d) + \kappa'(T_0)}{d - \bar{\lambda} f - \kappa'(T_0)}, \text{ if } d > \bar{\lambda} f + \kappa'(T_0), \\ \infty, \text{ otherwise}, \end{cases}$$

We note the following results. First,

$$T_{\bar{\lambda}} > T_0 \Leftrightarrow S_{\lambda}^{\text{risky}\prime}(T_0) > \kappa'(T_0) \Leftrightarrow \lambda > \lambda_b. \tag{42}$$

Second, the condition that a binding risky loan with $B = b_{\lambda}^{\text{risky}}$ and $T_{\bar{\lambda}} = T_0$ dominates a binding safe loan $B = b^{\text{safe}}$ and $T_{\bar{\lambda}} = T_0$ is given by

$$S_{\lambda}^{\text{risky}}(T_0) > S^{\text{safe}} \Leftrightarrow \lambda > \lambda_a. \tag{43}$$

Third, rearranging terms, we have that

$$\lambda > \lambda_a \Rightarrow \left(\lambda - \bar{\lambda}\right) T_{\bar{\lambda}} > \frac{-\omega}{1+\omega}. \tag{44}$$

We want to verify the three cases in Proposition 2. First, if $\lambda > \lambda_b$, then the equilibrium contract is the risky loans with $B = b_{\lambda}^{\text{risky}}$ and $T_{\bar{\lambda}} > T_0$. Second, if $\lambda \in (\lambda_a, \lambda_b]$, then the equilibrium contract is also the risky loans with $B = b_{\lambda}^{\text{risky}}$ but $T_{\bar{\lambda}} = T_0$. Third, if $\lambda \leq \lambda_a$, then the equilibrium contract is in the safe loans with $B = b^{\text{safe}}$ and $T_{\bar{\lambda}} = T_0$ if $\omega > 0$, and no borrowing at all if $\omega = 0$. Notice that $\lambda_b > \lambda_a$, so these regions are well-defined.

Consider the case $\lambda > \lambda_b$. Notice that $S_{\lambda}^{\text{risky}}(T_{\bar{\lambda}}) \geq S_{\lambda}^{\text{risky}}(T_0)$ and $\lambda_b > \lambda_a$, so the buyer always searches for a risky loan with $T_{\bar{\lambda}}$, following (43). Following $\lambda > \lambda_b$, we have $T_{\bar{\lambda}} > T_0$ from (42). The first-order condition of $T_{\bar{\lambda}}$ is

$$\kappa'(T_{\bar{\lambda}}) = S_{\lambda}^{\text{risky}\prime}(T_{\bar{\lambda}}) = \Delta_{\lambda},$$

and hence we have $T_{\bar{\lambda}} = k(\Delta_{\lambda})$ stated in Proposition 2. Using the fact that $\lambda > \lambda_b > \lambda_a$, we have $\left(\lambda - \bar{\lambda}\right) T_{\bar{\lambda}} > \frac{-\omega}{1+\omega}$ from (44), so the optimal risky loan features $B = b_{\lambda}^{\text{risky}}$.

Consider the case $\lambda \in (\lambda_a, \lambda_b]$. Notice that $\lambda > \lambda_a$, so the buyer always searches for a risky loan with $T_{\bar{\lambda}}$, following (43). Since $\lambda \leq \lambda_b$, we have $T_{\bar{\lambda}} = T_0$ from (42), Since $\lambda > \lambda_a$, we have $\left(\lambda - \bar{\lambda}\right) T_{\bar{\lambda}} > \frac{-\omega}{1+\omega}$ from (44), so the optimal risky loan features $B = b_{\lambda}^{\text{risky}}$.

Consider the case $\lambda \leq \lambda_a$. Notice that $\lambda \leq \lambda_a$, so the buyer does not search for a risky loan, following (43). She searches for a safe loan with $B = b^{\text{safe}}$ and $T_{\bar{\lambda}} = T_0$ if $S^{\text{safe}} > 0$, which is equivalent to $\omega > 0$. Otherwise, if $\omega = 0$, then she prefers not searching for any loan at all. In sum, we have established the three regions of Proposition 2.

Finally, given the optimal loan contract $\mathbf{a}$, the buyer's problem w.r.t. α is

$$J_\lambda = \max_{\alpha\in[0,1]} \alpha \left[\max_{T_{\bar{\lambda}}\geq T_0} \{S_\lambda (T_{\bar{\lambda}}) - \kappa (T_{\bar{\lambda}})\} - \frac{\psi}{\eta(\alpha)} \right] = \max_{n\geq 0} \left\{ N(1,n) \max_{T_{\bar{\lambda}}\geq T_0} \{S_\lambda (T_{\bar{\lambda}}) - \kappa (T_{\bar{\lambda}})\} - \psi n \right\},$$

where we have made use of the matching function identities from (8) and (9) that $\alpha = N(1,n)$ and $\alpha/\eta(\alpha) = n$. The first-order conditions with respect to n is

$$\psi \geq \frac{\partial}{\partial n} N(1,n) \max_{T_{\bar{\lambda}}\geq T_0} \{S_\lambda (T_{\bar{\lambda}}) - \kappa (T_{\bar{\lambda}})\}, \tag{45}$$

with equality if $\alpha > 0$ and otherwise $\alpha = 0$ if $S_\lambda (T_{\bar{\lambda}}) - \kappa (T_{\bar{\lambda}}) \leq 0$. Substituting the functional form of $g(x)$, we have the formula of α stated in Proposition 2.

The competitive-search equilibrium exists and is uniquely constructed by setting

$$\begin{aligned}
\mathcal{A}_\lambda &= \left\{ \mathbf{a} \,\middle|\, \frac{\psi}{\frac{V_\lambda(\mathbf{a})-v_\lambda}{1+\omega} + R_\lambda(\mathbf{a}) - \kappa_0(\Gamma)} \in [0,1] \right\}; \\
\eta_\lambda(\mathbf{a}) &= \frac{\psi}{\frac{V_\lambda(\mathbf{a})-v_\lambda}{1+\omega} + R_\lambda(\mathbf{a}) - \kappa_0(\Gamma)}; \\
\alpha_\lambda(\mathbf{a}) &= \eta^{-1}[\eta_\lambda(\mathbf{a})]; \\
n_b(\lambda,\mathbf{a}) &= \begin{cases} \phi(\lambda) & \text{if type-}\lambda \text{ buyers choose } \mathbf{a}, \\ 0 & \text{otherwise,} \end{cases} \\
n_l(\lambda,\mathbf{a}) &= n_b(\lambda,\mathbf{a}) \frac{\alpha_\lambda(\mathbf{a})}{\eta_\lambda(\mathbf{a})}.
\end{aligned}$$

QED

A.1.3 Proof of Proposition 3

Notice that

$$\begin{aligned}
\kappa'(T_{\bar{\lambda}}) &= \kappa_0'\left(\frac{1}{\frac{1}{T_{\bar{\lambda}}} - \bar{\lambda}}\right) \frac{1}{(1-\bar{\lambda}T_{\bar{\lambda}})^2} > 0, \\
\kappa''(T_{\bar{\lambda}}) &= \kappa_0''\left(\frac{1}{\frac{1}{T_{\bar{\lambda}}} - \bar{\lambda}}\right) \frac{1}{(1-\bar{\lambda}T_{\bar{\lambda}})^4} + \kappa_0'\left(\frac{1}{\frac{1}{T_{\bar{\lambda}}} - \bar{\lambda}}\right) \frac{2\bar{\lambda}}{(1-\bar{\lambda}T_{\bar{\lambda}})^3} > 0,
\end{aligned}$$

Thus, $k(x)$ is increasing in x as we have $k'(x) = 1/\kappa''(T_{\bar{\lambda}}) > 0$. Similarly, notice that $G(n) \equiv \partial N(1,n)/\partial n$ is decreasing in n following the concavity of $N(1,n)$ and hence $g(x) \equiv N\left[1, G^{-1}(\psi/x)\right]$ is increasing in x. Using these results, the comparative statics of $T_{\bar{\lambda}}$ and α are straightforward following the closed forms provided in Proposition 2. We will focus on the comparative statics of m, B and r^m.

Using Proposition 2, for any $\lambda > \lambda_a$, M is given by

$$M = \frac{b_{\lambda}^{\text{risky}}}{\Gamma} = (1+\mu)(h-d+f) + \left(1 + \frac{\mu}{1+\lambda}\right)d = (1+\mu)(h+f) - \frac{\lambda\mu}{1+\lambda}d \tag{46}$$

Recall that $T_{\bar{\lambda}} = 1/\left(1+\bar{\lambda}+\mu\right)$. Since $\partial\mu/\partial\lambda < 0$ for any $\lambda > \lambda_a$ following $\partial T_{\bar{\lambda}}/\partial\lambda > 0$, differentiating the sides of the first equality above, we have $\partial M/\partial\lambda < 0$. Similarly, since $\partial\mu/\partial d < 0$ for any $\lambda > \lambda_a$ following $\partial T_{\bar{\lambda}}/\partial d > 0$, differentiating the sides of the second equality above, $\partial M/\partial d < 0$ as stated in Proposition 3.

For the comparative statics of B, notice that the free-entry condition implies that

$$L = \frac{M}{1+\mu+\bar{\lambda}} + \frac{\bar{\lambda}}{1+\mu+\bar{\lambda}}(h-d) - \kappa(T_{\bar{\lambda}}) - \frac{k}{\eta(\alpha)}. \tag{47}$$

Since μ is constant in the region of $\lambda \in (\lambda_a, \lambda_b]$, using the above result that $\partial M/\partial\lambda < 0$ and $\partial\alpha/\partial\lambda > 0$ (hence $-\psi/\eta(\alpha)$ is decreasing in λ), we have $\partial L/\partial\lambda < 0$ in the region of $\lambda \in (\lambda_a, \lambda_b]$. Similarly, we can show $\partial L/\partial d < 0$. In region of $\lambda > \lambda_b$, we have $\partial\mu/\partial\lambda < 0$ so, via μ, λ additionally increases the first two terms of (47) but decreases the third term. The overall sign of $\partial L/d\lambda$ becomes ambiguous for $\lambda > \lambda_b$. The same is true for $\partial L/\partial d$ for $\lambda > \lambda_b$.

For the comparative statics of r^m, notice that r^m is defined as the lender's yield of mortgage payments such that:

$$r^m \equiv \frac{R_{\lambda}(\mathbf{a})}{L} - 1 = \frac{\kappa(T_{\bar{\lambda}}) + \frac{\psi}{\eta(\alpha)}}{L}. \tag{48}$$

In the region of $\lambda \in (\lambda_a, \lambda_b]$, since $T_{\bar{\lambda}}$ is constant, using the result that $\partial L/\partial\lambda < 0$ and $\partial\alpha/\partial\lambda > 0$ (hence $\psi/\eta(\alpha)$ is increasing in λ), we have $\partial r^m/\partial\lambda > 0$ in the region of $\lambda \in (\lambda_a, \lambda_b]$. Similarly, we can show $\partial r^m/\partial d < 0$. In region of $\lambda > \lambda_b$, we have $\partial T_{\bar{\lambda}}/\partial\lambda > 0$ so, via $T_{\bar{\lambda}}$, λ additionally increases the term $\kappa(T_{\bar{\lambda}})$ of (48), but the sign of $\partial L/\partial\lambda$ is ambiguous. The overall sign of $\partial r^m/\partial\lambda$ becomes ambiguous for $\lambda > \lambda_b$. The same is true for $\partial r^m/\partial d$ for $\lambda > \lambda_b$. **QED**

A.1.4 Proof of Proposition 4

The first part was already proved in Section A.1.2. For the second part, note that an expansionary monetary policy means a higher ω. The comparative statics of $T_{\bar{\lambda}}$ with respect to ω is straightforward, so we focus on α. The derivative of (45) is

$$\frac{-G'(n)}{G(n)}\partial n = \frac{d}{d\omega}\max_{T_{\bar{\lambda}}\geq T_0}\left\{S_\lambda\left(T_{\bar{\lambda}}\right)-\kappa\left(T_{\bar{\lambda}}\right)\right\}\frac{\partial\lambda}{\max_{T_{\bar{\lambda}}\geq T_0}\left\{S_\lambda\left(T_{\bar{\lambda}}\right)-\kappa\left(T_{\bar{\lambda}}\right)\right\}},$$

where the envelope theorem implies that

$$\frac{d}{d\omega}\max_{T_{\bar{\lambda}}\geq T_0}\left\{S_\lambda\left(T_{\bar{\lambda}}\right)-\kappa\left(T_{\bar{\lambda}}\right)\right\} = \frac{1}{(1+\omega)^2}\begin{cases} b^{\text{safe}}, \text{ if } \lambda\leq\lambda_a; \\ v_\lambda+f, \text{ if } \lambda>\lambda_a. \end{cases} > 0 \tag{49}$$

Notice that $\partial\alpha = G(n)\,\partial n$ and $G'(n)<0$, so combining the above we have $\partial\alpha/\partial\omega>0$. **QED**

A.1.5 Proof of Proposition 5

Notice that

$$\begin{aligned} J_\lambda &= \max_{\alpha\in[0,1]}\alpha\left[\max_{T_{\bar{\lambda}}\geq T_0}\left\{S_\lambda\left(T_{\bar{\lambda}}\right)-\kappa\left(T_{\bar{\lambda}}\right)\right\}-\frac{\psi}{\eta(\alpha)}\right], \\ &= \max_{\alpha\in[0,1]}\alpha\left[\max_{T_{\bar{\lambda}}\geq T_0}\left\{\frac{\omega\left(v_\lambda+f\right)}{1+\omega}+\left[\left(1+\bar{\lambda}\right)\left(v_{\bar{\lambda}}-v_\lambda\right)+\bar{\lambda}f\right]T_{\bar{\lambda}}-\kappa\left(T_{\bar{\lambda}}\right)\right\}-\frac{\psi}{\eta(\alpha)}\right]. \end{aligned}$$

The envelope theorem implies that

$$\frac{\partial J_\lambda}{\partial\lambda} = \alpha\left(\frac{\omega}{1+\omega}-\frac{1+\bar{\lambda}}{1+\mu+\bar{\lambda}}\right)\frac{\partial v_\lambda}{\partial\lambda}$$

Recall that the bargaining solution of the house price is

$$P = \frac{1-\theta}{1+\rho}\left[v_\lambda+(1+\omega)J_\lambda\right]+\theta v_{\lambda_s},$$

Thus we have

$$\begin{aligned} \frac{\partial P}{\partial\lambda} &= \frac{1-\theta}{1+\rho}\left[\frac{\partial v_\lambda}{\partial\lambda}+(1+\omega)\frac{\partial J_\lambda}{\partial\lambda}\right] = \frac{1-\theta}{1+\rho}\left[1+\alpha\left(\omega-\frac{1+\bar{\lambda}}{1+\mu+\bar{\lambda}}(1+\omega)\right)\right]\frac{\partial v_\lambda}{\partial\lambda} \\ &= \frac{1-\theta}{1+\rho}\underbrace{\left[1-\alpha\overbrace{\frac{1+\bar{\lambda}}{1+\mu+\bar{\lambda}}}^{<1}+\frac{\alpha\omega\mu}{1+\mu+\bar{\lambda}}\right]}_{>0}\underbrace{\frac{\partial v_\lambda}{\partial\lambda}}_{<0}<0. \end{aligned}$$

Similarly, we have

$$\frac{\partial J_\lambda}{\partial d} = \alpha \left(\frac{\omega}{1+\omega} - \frac{1-\frac{\bar{\lambda}}{\lambda}}{1+\mu+\bar{\lambda}} \right) \frac{\partial v_\lambda}{\partial d},$$

where we have made use of the fact that

$$\left(1+\bar{\lambda}\right) \frac{\partial v_{\bar{\lambda}}}{\partial d} = (1+\lambda) \frac{\bar{\lambda}}{\lambda} \frac{\partial v_\lambda}{\partial d}.$$

Thus we have

$$\begin{aligned} \frac{\partial P}{\partial d} &= \frac{1-\theta}{1+\rho} \left[1 + \alpha \left(\omega - \frac{(1+\omega)\left(1-\frac{\bar{\lambda}}{\lambda}\right)}{1+\mu+\bar{\lambda}} \right) \right] \frac{\partial v_\lambda}{\partial d} \\ &= \frac{1-\theta}{1+\rho} \underbrace{\left[1 - \overbrace{\frac{\alpha\left(1-\frac{\bar{\lambda}}{\lambda}\right)}{1+\mu+\bar{\lambda}}}^{<1} + \frac{\alpha\omega\left(\mu+\bar{\lambda}+\frac{\bar{\lambda}}{\lambda}\right)}{1+\mu+\bar{\lambda}} \right]}_{>0} \underbrace{\frac{\partial v_\lambda}{\partial d}}_{<0} < 0. \end{aligned}$$

Finally, we have

$$\frac{\partial P}{\partial \iota} = (1-\theta) \left[-\frac{J_\lambda}{(1+\iota)^2} + \underbrace{\frac{\partial \omega}{\partial \iota}}_{<0} \underbrace{\frac{\partial J_\lambda}{\partial \omega}}_{>0} \right] < 0.$$

QED

A.2 Omitted tables

	Fraction of buyers from county choosing a coastal home
Buyer county belief	0.001*
	(0.001)
Buyer county income	0.003***
	(0.000)
Buyer county population	-0.000***
	(0.000)
Buyer county share with bachelor's degree	-0.006
	(0.072)
Buyer county share 18-29 age	-0.089
	(0.056)
Buyer county share of white	-0.067***
	(0.019)
Time F.E.	Y
State F.E.	Y
N	14921
R2	0.174

Table A1: Coastal buyers and buyer beliefs. This figure models the fraction of buyers in a county that select a coastal home. If sorting were a concern, one would expect a negative correlation between the fraction of buyers purchasing a coastal home and the climate beliefs of where the buyer is from (a proxy for the buyer's climate belief). Instead, after controlling for sociodemographic factors from the buyer's county of origin as well as time and state fixed effects, we find a positive correlation between the buyer's county beliefs and the fraction of buyers purchasing a coastal home.

	Leveraged			Long Maturity		
	Happening	Worried	Timing	Happening	Worried	Timing
SLR Risk × Pess Buyer (above median)	0.034***	0.046***	0.031**	0.024***	0.027***	0.023***
	(0.011)	(0.012)	(0.013)	(0.007)	(0.007)	(0.007)
SLR × 2nd Quartile Belief	0.023**	0.006	0.002	0.030***	0.008	0.025**
	(0.011)	(0.012)	(0.011)	(0.008)	(0.010)	(0.010)
SLR × 3rd Quartile Belief	0.010	0.058***	0.021	0.034***	0.033***	0.016
	(0.017)	(0.013)	(0.015)	(0.011)	(0.009)	(0.010)
SLR × 4th Quartile (highest) Belief	0.046**	0.047*	0.051***	0.035***	0.023	0.038***
	(0.018)	(0.027)	(0.015)	(0.010)	(0.017)	(0.010)
SLR Risk × Belief (continuous)	0.002	0.003***	0.003**	0.002**	0.002**	0.003***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
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 A2: Robustness with alternative specifications for the buyer county belief measure. Columns 1-3 report results for variations of leveraged regression (L1) and columns 4-6 for long maturity regressions (M1). 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. *PessBuyer* 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). For brevity, only estimates of the coefficients of the interaction term SLR Risk × belief are reported. The rest is the same as in Tables 5 and 6.

	Leveraged	Long Maturity
SLR	0.425	0.514**
	(0.347)	(0.249)
SLR × PessBuyer	0.036**	0.033**
	(0.014)	(0.014)
Additional Controls	Y	Y
Property & Buyer County Controls	Y	Y
Z × D × E × B × M fe	Y	Y
Buyer County Controls × SLR	Y	Y
Lender fe		Y
N	222,920	67,299
R2	0.444	0.447

Table A3: Robustness to the inclusion of a variety of additional control variables, including buyer's county average test scores, race, age, and gender as well as crime, unemployment, new building permits and previous flood events from the property's county. The sample is 2010 to 2016. The rest is the same as in Tables 5 and 6.

	Leveraged	Long Maturity	Leveraged	Long Maturity
SLR	-0.013	0.016	0.006	0.005
	(0.04)	(0.025)	(.025)	(0.023)
SLR × PessBuyer	0.036***	0.022***	0.036***	0.025***
	(0.013)	(0.008)	(0.014)	(0.009)
Political Control	Repub. share	Repub. share	Dem. share	Dem. share
Z × D × E × B × M fe	Y	Y	Y	Y
Buyer county controls × SLR	Y	Y	Y	Y
Lender fe		Y		Y
N	405,893	150,746	405,825	150,734
R^2	0.473	0.441	0.473	0.441

Table A4: Robustness to the inclusion of political affiliation data (percent of Republican or Democrat vote shares in the previous presidential election at the county level). The rest is the same as in Tables 5 and 6.

Continuous	Yale happening	Yale worried	Yale timing	Gallup when	Gallup worry	Individual $\widehat{\lambda}$	County average $\widehat{\lambda}$
	1						
	(0.0000)						
Yale worried	0.9020***	1					
	(0.0000)	(0.0000)					
Yale timing	0.8526***	0.9187***	1				
	(0.0000)	(0.0000)	(0.0000)				
Gallup when	0.5685***	0.6414***	0.5133***	1			
	(0.0000)	(0.0000)	(0.0000)	(0.0000)			
Gallup worried	0.6759***	0.7742***	0.6843***	0.8083***	1		
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)		
Individual $\hat{\lambda}$	0.0046**	0.0021	0.0005	0.0029	0.0001	1	
	(0.0339)	(0.346)	(0.8041)	(0.1777)	(0.9465)	(0.0000)	
County mean $\hat{\lambda}$	0.1391***	0.1267***	0.1216***	0.0627***	0.0919***	0.1165***	1
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)

Table A5: Pairwise correlation of continuous belief variables. Yale beliefs data are from the Yale Climate Opinions survey operationalized as the average county-level climate belief. Beliefs from the Gallup data are imputed by the authors as described in the main text at the county-by-year level. Individual $\widehat{\lambda}$ is the transaction-level beliefs imputed by the authors as described in the main text. County mean $\widehat{\lambda}$ represents a county-level mean value of the continuous $\widehat{\lambda}$ variable averaged across buyers from that county. Pairwise correlation p-values are shown in parentheses.

Above median	Yale happening	Yale worried	Yale timing	Gallup when	Gallup worry	Individual $\widehat{\lambda}$	County average $\widehat{\lambda}$
Yale happening	1						
	(0.0000)						
Yale worried	0.6458***	1					
	(0.0000)	(0.0000)					
Yale timing	0.5898***	0.6868***	1				
	(0.0000)	(0.0000)	(0.0000)				
Gallup when	0.4631***	0.6794***	0.4574***	1			
	(0.0000)	(0.0000)	(0.0000)	(0.0000)			
Gallup worried	0.4697***	0.7178***	0.5075***	0.7425***	1		
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)		
$\widehat{PessBuyer}$	0.0464***	0.0299***	0.0302***	0.0058***	0.0419***	1	
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	
County above med. $\hat{\lambda}$	0.0909***	0.0493***	0.1106***	-0.0382***	0.0166***	0.0491***	1
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)

Table A6: Pairwise correlation of dichotomous (above median) belief variables, which are defined to be one if the corresponding belief variable from Table A5 is above the sample median and zero otherwise.

	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 ($\leq$3ft)	-0.0362	-0.0305
	(0.031)	(0.024)
1.SLR $\times$ PessBuyer	0.0154	0.0140
	(0.012)	(0.009)
2.SLR $\times$ PessBuyer	0.0246*	0.0321**
	(0.015)	(0.014)
3.SLR $\times$ PessBuyer	0.0455**	0.0323**
	(0.018)	(0.014)
4.SLR $\times$ PessBuyer	0.0856***	0.0322*
	(0.023)	(0.018)
Property & buyer county controls	Y	Y
Buyer county controls x SLR	Y	Y
Z $\times$ D $\times$ E $\times$ B $\times$ M fe	Y	Y
Lender fe		Y
N	405,893	150,746
R^2	0.473	0.441

Table A7: 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 or 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 5 and 6.

	Leveraged			
SLR Risk	0.007	-0.005	0.010	0.012
	(0.016)	(0.012)	(0.010)	(0.013)
SLR Risk × PessBuyer	0.032***	0.031***	0.019**	0.021**
	(0.010)	(0.011)	(0.008)	(0.010)
Fixed effects	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	852,817	568,636	490,546	322,484
R^2	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 × PessBuyer	0.007	0.017***	0.012*	0.022**
	(0.005)	(0.006)	(0.007)	(0.009)
Fixed effects	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	852,817	568,636	490,546	322,484
R^2	0.188	0.404	0.461	0.526

Table A8: 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, O – owner-occupied status. The rest is the same as in Tables 5 and 6.

	Leveraged	Long Maturity
SLR Risk	-0.009	0.002
	(0.014)	(0.014)
SLR Risk × PessBuyer	0.025**	0.024***
	(0.010)	(0.007)
Log Housing Price	–	–
Property & buyer county controls	Y	Y
Z × D × E × B × M fe	Y	Y
Buyer county controls × SLR	Y	Y
Lender fe		Y
N	405,893	150,746
R^2	0.465	0.441

Table A9: Robustness where housing price is *not* included as a control variable. The rest is the same as in Tables 5 and 6.

	Leveraged	Long Maturity
SLR	0.006	0.002
	(0.014)	(0.014)
SLR × PessBuyer	0.026**	0.024***
	(0.011)	(0.008)
FEMA Zone	-0.024***	-0.002
	(0.008)	(0.004)
FEMA Zone × PessBuyer	0.014	0.000
	(0.011)	(0.007)
Z × D × E × B × M fe	Y	Y
Buyer county controls × SLR	Y	Y
Lender FE		Y
N	405,893	150,746
R^2	0.473	0.441

Table A10: The main results are robust to the inclusion of current National Flood Insurance Program flood zone information. The rest is the same as in Tables 5 and 6.

	Leveraged &		Long Maturity &	
	Conforming	Nonconform	Conforming	Nonconform
SLR Risk	-0.058***	0.024***	0.005	0.003
	(0.019)	(0.008)	(0.027)	(0.018)
SLR Risk × PessBuyer	0.030**	0.006	0.027	-0.001
	(0.015)	(0.005)	(0.016)	(0.011)
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	229,294	229,294	87,623	87,623
R^2	0.437	0.540	0.539	0.652

Table A11: Role of conforming loans in years $\geq$ 2009. 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 ($\geq$30 years) and is conforming. Column 2 and 4 repeat columns 1 and 3, respectively, but replace conforming with nonconforming. Only mortgages from 2009 to 2016 are included in these results. For brevity, only estimates of the coefficients of SLR Risk and the interaction term SLR Risk × Pessimistic Buyer are reported. The rest is the same as in Tables 5 and 6.

	log(Housing Price)		Leveraged		Long Maturity	
	<2010	≥2010	<2010	≥2010	<2010	≥2010
SLR	-0.018	-0.060**	0.022	-0.033	0.002	0.009
	(0.023)	(0.027)	(0.016)	(0.021)	(0.017)	(0.020)
SLR x PessBuyer	-0.056***	-0.066***	0.025*	0.037**	0.015*	0.038**
	(0.018)	(0.022)	(0.013)	(0.014)	(0.009)	(0.015)
Property & buyer county controls	Y	Y	Y	Y	Y	Y
Buyer county controls × SLR	Y	Y	Y	Y	Y	Y
Z × D × E × B × M fe	Y	Y	Y	Y	Y	Y
Lender fe					Y	Y
N	195,521	211,080	195,096	210,797	86,992	62,927
R^2	0.883	0.854	0.474	0.439	0.448	0.442

Table A12: Results over time. Columns 1, 3, and 5 use only the sample of property transactions that take place up to December 2009. Columns 2, 4, and 6 use only those that take place from January 2010 onward. The rest is the same as in Tables 4, 5, and 6.

	log(Loan amount)	Mortgage interest rate
SLR Risk	0.001	-0.095
	(0.011)	(0.160)
SLR Risk × PessBuyer	0.008	0.037
	(0.009)	(0.088)
Property & buyer county controls	Y	Y
Buyer county controls × SLR	Y	Y
Z × D × E × B × M fe	Y	Y
Lender fe	Y	Y
30 year f.e.		Y
N	168,409	28,873
R^2	0.920	0.725

Table A13: Other intensive margins: Effects of exposure to SLR risk and its interaction with climate belief on mortgage loan amount (column 1) and mortgage interest rate (column 2). Sample restricted to transactions associated with a mortgage contract. In order to compare the mortgage interest rates across only loans with similar maturity, column 2 also includes a fixed effect equal to one if a mortgage has a 30-year maturity (and zero if it has a 15-year maturity). The rest is the same as in Tables 5 and 6.