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Leveraging the Disagreement on Climate Change: Theory and Evidence

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Abstract

We develop a credit model where agents disagree on when long-run disaster risk, such as flooding from sea level rise (SLR), will damage collateral assets. Unlike existing models, ours predicts that pessimistic agents are *more* likely to leverage risky asset purchases, and prefer debt contracts with *longer* maturities. Intuitively, anticipating high risk of collateral damage, pessimists value the implicit insurance in the option to default. Using high-resolution SLR projections and comprehensive coastal real estate and mortgage data, we find robust evidence of these predictions. We also analyze how securitization and other policies affect the mortgage market's SLR exposure.

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

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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 (SLR) affects housing prices (Bernstein et al. 2019; Baldauf et al. 2020; Bakkensen and Barrage 2022). However, much less is known about how SLR risk affects the mortgage market, despite the critical role this market plays in the financial system and financial stability. 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). 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 investments on at-risk assets than those who are more concerned (the "pessimists") (e.g., Litterman et al. 2020; Brunetti et al. 2021), as predicted by 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, specifically the increased risks of coastal flooding due to SLR, affect the mortgage market. We start with a parsimonious model of collateralized credit under belief disagreement, building upon the literature that follows the pioneering work of Geanakoplos (2010). We introduce two empirically relevant elements: maturity choice and search frictions. The maturity dimension is realistic for mortgage contracts and especially relevant for the SLR context because (i) most of the damages from SLR will occur in the future, and hence (ii) a contract with a longer maturity is naturally more exposed to SLR risks than one with a shorter maturity. By allowing for different maturity lengths, the model uncovers a new channel where pessimistic borrowers can trade their exposure to the long-run risks with relatively more optimistic lenders.[2] We show that this new gain from trade is larger for more pessimistic borrowers, "overturning" the conventional prediction in standard models of belief disagreement.

Specifically, we consider a model of defaultable long-term debt (a mortgage contract) where the collateral asset (a coastal real estate property) is exposed to a potentially damaging disaster risk in the long run (flooding risk due to SLR). We assume belief heterogeneity in a simple way: a borrower (homebuyer) and lenders (mortgage-originating banks and mortgage-purchasing financial institutions) 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 it will happen sooner.

The model yields clear analytical results. For a given default cost, if the underlying col-

[1] See, e.g., Network for Greening the Financial System (2019); Financial Stability Oversight Council (2021); Board of Governors of the Federal Reserve System (2024), and the White House's Executive Order on Tackling the Climate Crisis.

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

lateral asset is sufficiently exposed to the disaster risk, then the optimal leverage probability and optimal maturity are *both increasing* in the degree of borrower pessimism (relative to lenders' beliefs). These are two key predictions of the model that we will test in the data. Furthermore, we show that these predictions robustly hold in a series of model extensions under plausible assumptions, including (mandatory or voluntary) disaster insurance, government disaster assistance, endogenous housing prices, belief convergence, rental, and securitization.

Figure 1 illustrates the intuition.[3] A defaultable long-term mortgage provides implicit insurance against the long-run climate risk. The borrower has the option to default on the loan when the disaster eventually damages the collateral asset. This implicit insurance is more valuable for more pessimistic borrowers. The pessimistic borrower believes that the disaster will happen soon, and when it does, it will be optimal to default. Expecting an early default, the borrower would like to back load the repayment *promises* by choosing a long-maturity debt contract, which stretches the payment stream over a long horizon. In contrast, the relatively more optimistic lender believes that the collateral is safe, as according to their belief the disaster will happen later. Thus, the lender is willing to offer a long-maturity debt contract. As a result, 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.

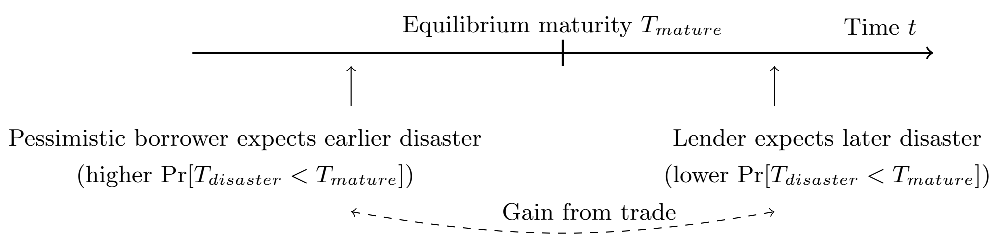

Figure 1: Illustration of the model's main intuition.

Next, we evaluate the testable implications of the model by analyzing the effects of long-run SLR risk on the mortgage market. We focus on coastal flooding associated with SLR not only because it is one of the most salient dimensions of climate change, projected to affect millions of households (Fleming et al., 2018; May et al., 2023), but also because SLR risk exposures have been well documented with high-resolution spatial variations (see Figure 3 for an illustration). SLR poses significant risks to the mortgage market due to increased and more severe flooding or even permanent inundation. These events can damage housing assets and reduce the value of the underlying land, unlike other climate change effects like heat or drought, which primarily affect local productivity and amenities but do not directly harm the value of the collateral asset.[4]

We employ an extensive proprietary dataset of real estate *and* mortgage transactions (provided by CoreLogic) to examine the complete sales history of single-family homes along the U.S. East Coast from 2001 to 2016. We match each property's exact coordinates with its exposure to permanent coastal inundation projected under various SLR levels, using the Na-

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

[4]Moreover, as public trust doctrine typically defines public ownership of coastal land and waters below mean high-tide levels, SLR will also pose unique legal issues including for private property rights (Hiatt, 2007).

tional Oceanic and Atmospheric Administration's (NOAA) state-of-the-art SLR mapping tool. Exploiting the highly granular spatial variations in the SLR maps, 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, same number of bedrooms, same year and month of sale, same mortgage lender, similar distance to the coast and similar elevation.

To assign whether the homebuyer in a transaction is a (likely) pessimist or optimist regarding 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 the Yale Climate Opinion Survey (Howe et al. 2015)'s of public perceptions on global warming across the U.S. 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 homebuyer comes from to the respective county's climate belief measure. The assumption is that a homebuyer from a county with a more pessimistic belief measure is more likely to have a pessimistic belief themselves.[5]

Our empirical results are as follows. First, in re-estimating the classic hedonic housing price regression, equipped with the rich set of fixed effects disentangling the SLR risks from 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 SLR discount is significantly stronger (at about 10%) when the homebuyer is a likely pessimist. 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 alternative measures of SLR risks and econometric specifications.

Second, we find robust evidence for the model's implication on the extensive margin of the leverage probability. All else equal, the transaction of an at-risk property has an approximately two percentage points higher probability of being associated with a mortgage, 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).

Further consistent with our theory, we find that belief disagreement is a key moderator of the relationship between SLR risks and leverage. Buyers who are more likely to be pessimists are *more* likely to use mortgage debt to finance the purchase of at-risk properties. Among transactions with such homebuyers, 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 homebuyers.

[5] In a related paper outside of the climate context, Meeuwis et al. (2022) 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, and they devise ways to assign whether a household is (likely) Democrat or (likely) Republican based on publicly available political data aggregated at the local ZIP code level.

Third, we also find robust evidence for the model's implication on the intensive margin of maturity choice. Among transactions of at-risk properties, likely pessimistic homebuyers are more likely to borrow with a mortgage contract with a long maturity of thirty years. Note that these contracts are naturally more exposed to future SLR risks than contracts with a shorter maturity of fifteen years. All of the results above are robust to alternative specifications of climate beliefs, fixed effects, SLR risk definitions, and a suite of additional control variables.

In response to potential concerns about climate belief variables 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 one 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 homebuyer 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 the mortgage regressions, and our results robustly hold.

It is natural to ask 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 guarantee fees do not incorporate future SLR risks (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 largely driven by conforming loans.

Finally, we use the model to explore relevant policy implications related to financial stability, including phasing out the GSEs' guarantee subsidy, the roles of flood insurance mandates, and disaster forbearance policies. We further provide an accounting exercise on the flood risk exposure of more than 100 million single-family mortgages on GSE balance sheets, and an event study of how a climate-related disaster increases the default rates in this sample. Overall, our paper highlights the nontrivial ways that climate-related risks and beliefs affect the mortgage market, whose stability is key to the stability of the financial system.

The rest of the paper is organized as follows. Section 2 discusses the related literature. Section 3 provides the theoretical model, while Section 4 provides a series of extensions. Section 5 describes the data, empirical framework, and empirical results. Section 6 provides a battery of robustness checks. Section 7 discusses potential policy implications. Section 8 concludes. The Appendix provides proofs and further details of the extensions and empirical analysis.

2 Related literature

To the best of our knowledge, our paper is the first to investigate the effects of 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 (Hong et al. 2020; Furukawa et al. 2020; Giglio et al. 2021; Hsiang et al. 2023). 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).[6] Our paper also contributes to a growing but important set of papers investigating how the interaction between climate risks and policies (on securitization and insurance subsidies) affects the mortgage market (Issler et al. 2020; Liao and Mulder 2021; Sastry 2021; Ouazad and Kahn 2022; Nguyen et al. 2022). 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).

Our paper also 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; Fried 2021; Phan and Schwartzman 2021; Cruz and Rossi-Hansberg 2024). 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 strategy via the mortgage market.

On the theoretical side, our paper is related to the literature on modeling credit markets with heterogeneous beliefs 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. Empirically, we are the first to exploit the well-documented heterogeneity in the beliefs about climate change to evaluate these theories.[7] Theoretically, we add a new insight into how the time dimension of endogenous maturity choice can change the theoretical predictions. As mentioned previously, most existing models (e.g., 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

[6] 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).

[7] Also related is 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.

two-period model of mortgage leverage choice with heterogeneous beliefs over future house prices (and default probability), where agents have an additional choice at the intensive margin to either purchase a cheaper home or to rent, and evaluates the model's predictions using Facebook data. Our model provides a different yet complementary channel: the choice at the intensive margin of debt maturity. In particular, while the maturity is automatically fixed in existing two-period environments, including Bailey et al. (2019), our model features endogenous maturity choice for the debt contract. The endogenous maturity is key in explaining the empirical patterns on the relationship we find between climate risks and mortgage maturity.[8] 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 (Ngai and Tenreyro 2014; Head et al. 2014; Landvoigt et al. 2015; Garriga and Hedlund 2020) and the credit market search literature (Bethune et al. 2022; Rocheteau et al. 2018). Our contribution to this literature is to incorporate long-run risks and heterogeneous beliefs in a competitive search model, which generates a dispersion of housing prices and mortgage outcomes as seen in the data.[9] Our model also relates to models of risk shifting in collateralized debt markets (Allen and Gale 2000; Barlevy 2014; Bengui and Phan 2018; Allen et al. 2022).

3 Model

3.1 Environment

We develop a theoretical framework to analyze how belief disagreement about long-run risk affects debt outcomes. The baseline is a parsimonious model of a single borrower, with the timing summarized in Figure 2. Section 4 will provide a series of extensions and generalizations.

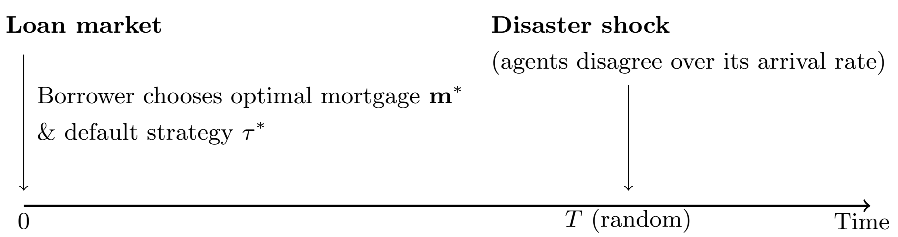

Figure 2: Illustration of the timing of events in the model.

Asset Time is continuous and infinite. There is an indivisible housing unit, which yields a constant flow of housing utility $h > 0$, until a disaster strikes and permanently lowers the utility flow to $h - d$, where $d > 0$ denotes the house's disaster exposure. For simplicity, we

[8]Where Bailey et al. (2019) assume homebuyer beliefs are not known to the lenders and only focus on the borrower's decision, we assume agents agree to disagree over beliefs—arguably fitting for our climate risk setting—and formally model both the borrower and lender decisions. Thus, our model generates insight for the puzzling question of why lenders lend to known pessimists who anticipate a higher probability of default.

[9]See also Allen et al. (2014, 2019) for a random search model of mortgage, Lagos and Zhang (2020) for a monetary search model with heterogeneous belief and Wright et al. (2021) for a survey of competitive search.

assume d is a known constant, but the arrival time of the disaster T is a random variable (the only source of uncertainty in the baseline model). The flow of housing utility thus given by:

$$h_t = \begin{cases} h & \text{for } t < T \\ h - d & \text{for } t \geq T \end{cases}.$$

For now, we take as given the housing price p (endogenized in Section 4.5), and assume agents cannot insure against the disaster (relaxed in Section 4.1).

Agents At $t = 0$, the house is matched with a homebuyer/borrower. The homebuyer has an option to finance the house purchase with a mortgage loan, which is collateralized by the housing asset. Lenders are competitive and free to enter the mortgage market with an entry fee and search frictions (to be described below). We assume that all agents are risk-neutral and discount future utility at a common rate $r > 0$ (generalized in Section 4.6), i.e., their preferences for the accumulated cash flow process C_t are given by $\mathbb{E}\int_0^\infty re^{-rt}\mathrm{d}C_t$.

Belief disagreement The borrower believes that the disaster date T will arrive at a rate $r\lambda$, i.e., T has an exponential distribution: $\mathbb{P}^\lambda[T \leq t] = 1 - e^{-r\lambda t}$.[10] The lenders believe that it will arrive at the rate $r\bar{\lambda}$, which can be different from $r\lambda$. A higher value of λ or $\bar{\lambda}$ indicates more pessimism: the agent believes that the disaster will arrive sooner. For example, when $\lambda \to \infty$, the agent (very pessimistically) believes that the disaster will happen immediately, while when $\lambda \to 0$, the agent (very optimistically) believes that the disaster will never arrive. Each agent's belief is common knowledge and they agree to disagree with each other (we allow for learning and belief convergence in Section 4.8).

Mortgage contract A mortgage $\mathbf{m} = (l, b, \mu)$ is a loan contract collateralized by the house. It specifies the amount $l \geq 0$ that the lender loans to the borrower at $t = 0$, the fixed amount $b \geq 0$ that the borrower promises to repay the lender continuously at every $t \in [0, T_\mu]$ until the loan matures at date T_μ, which arrives at rate $r\mu \geq 0$ (i.e., $\mathbb{P}[T_\mu \leq t] = 1 - e^{r\mu t}$). A higher μ implies that the loan will mature faster, and hence has a shorter average maturity.[11] The corresponding (normalized) loan balance at t is $B_t \equiv \mathbb{E}\int_t^{T_\mu} re^{-r(s-t)}b\mathrm{d}s$.

The borrower can default at any time τ before the loan matures. After doing so, she surrenders the house and additionally faces a one-time exogenous default cost $f/r \geq 0$ (representing monetary and nonmonetary costs in the foreclosure process). The lender then forecloses and sells the house at *liquidation price* $\bar{p}_\tau$. If the foreclosure takes place on or after the disaster ($\tau \geq T$), then we naturally set $\bar{p}_\tau = (h - d)/r$, which is the present value of the post-disaster housing utility stream (since all uncertainty will be resolved after the disaster). However, if the foreclosure occurs before T, then we set the liquidation price at a general value $\bar{p}_\tau = \underline{p}$.

[10] Since only the ratio between the arrival rate and the discount rate (rather than their values) that matters, we normalize all the arrival rates (e.g., the disaster arrival rate or the mortgage maturity rate) with r.

[11] We can think of a long-term (30-year) fixed-rate mortgage in practice as a contract with low μ in our model. Also, the fact that the loan repayment b is noncontingent (fixed at $t = 0$) maps to the fixed interest rate at the time of loan origination.

Borrower's value functions At $t = 0$, the borrower's amortized present value (PV) of the stream of housing utility from the house is given by:

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

An increase in λ (more pessimism) leads to a lower valuation. We focus on the relevant case where the homebuyer's PV of purchasing the house without leverage $v_\lambda - rp$ is positive, and foreclosing the house before the disaster always involves a loss, i.e., $r\underline{p} - f - v_\lambda < 0$.

The PV of fully repaying the mortgage is:

$$-r \underbrace{(p-l)}_{\text{down payment}} + \underbrace{\mathbb{E}_\lambda \left[\int_0^{T_\mu} re^{-rt}(h_t - b)\mathrm{d}t \right]}_{\text{PV of owning minus debt repayment}} + \underbrace{\mathbb{E}_\lambda \left[\int_{T_\mu}^\infty re^{-rt} h_t \mathrm{d}t \right]}_{\text{PV after loan has matured}}.$$

In contrast, if the borrower defaults before the loan matures ($\tau \le T_\mu$), then the valuation is:

$$-r(p-l) + \mathbb{E}_\lambda \left[\int_0^\tau re^{-rt}(h_t - b)\mathrm{d}t \right] + \underbrace{\mathbb{E}_\lambda \left[e^{-r\tau} (r \max\{\bar{p}_\tau - B_\tau/r, 0\} - f) \right]}_{\text{PV of default cost}}$$

where the last term represents the fact that the defaulting borrower can walk away from any remaining loan balance B_τ/r in excess of the house's liquidation price $\bar{p}_\tau$.

The optimal default time $\tau^*_{\mathbf{m}}$ solves the following:

$$V_\lambda(\mathbf{m}) \equiv \max_\tau \mathbb{E}_\lambda \left[\underbrace{\int_0^{\tau \wedge T_\mu} re^{-rt}(h_t - b)\mathrm{d}t}_{\text{value of repaying until } \tau \wedge T_\mu} + e^{-r(\tau \wedge T_\mu)} \left(\begin{array}{c} \underbrace{\mathbf{1}_{\tau > T_\mu} \int_0^\infty re^{-rt} h_{t+T_\mu} \mathrm{d}t}_{\text{value of full repayment}} \\ + \underbrace{\mathbf{1}_{\tau \le T_\mu} (\max\{r\bar{p}_\tau - B_\tau, 0\} - f)}_{\text{value of defaulting at } \tau} \end{array} \right) \right], \tag{2}$$

where τ is chosen from the set of related stopping times (i.e., τ can be contingent on the realizations of events like disaster and maturity), and $\tau \wedge T_\mu$ denotes $\min\{\tau, T_\mu\}$.[12]

Remark 1 (Random maturity). As is standard in models of long-term debt (e.g., Leland and Toft, 1996; Cochrane, 2001; Elenev et al., 2016), we assume that the maturity date T_μ is random. This assumption is not essential for our results (see a model with deterministic maturity in Appendix A.2.7) but simplifies the algebra as the loan balance is constant:

$$B_t \equiv \mathbb{E} \int_t^{T_\mu} re^{-r(s-t)} b \mathrm{d}s = \frac{b}{1+\mu},$$

and hence we do not need to keep track of B_t as a state variable at each t.

[12] A stopping time is a random variable that is measurable with a filtration generated by the σ-algebras of events T and T_μ. For example, $\tau = T + 1$ is a stopping time, but $\tau = T - 1$ is not. In words, one cannot default a year before the disaster, because it requires beforehand knowledge of when the disaster will strike.

Lender's value functions Anticipating the borrower's default strategy $\tau = \tau^*_{\mathbf{m}}$, a lender's expected revenue from a mortgage contract $\mathbf{m}$ is:

$$R_{\bar{\lambda}}(\mathbf{m}) \equiv \mathbb{E}_{\bar{\lambda}} \left[\underbrace{\int_0^{\tau \wedge T_\mu} re^{-rt} b \mathrm{d}t}_{\text{value of repayment stream}} + \underbrace{\mathbf{1}_{\tau \leq T_\mu} re^{-r\tau} \min\{\bar{p}_\tau, B_\tau / r\}}_{\text{value of seized collateral and remaining loan balance}} \Bigg|_{\tau = \tau^*_m} \right]. \quad (3)$$

The expectation is based on the lender's belief parameter $\bar{\lambda}$, and not the borrower's belief parameter λ as in (2). A lender's expected profit from contract $\mathbf{m}$ is:

$$\Pi_{\bar{\lambda}}(\mathbf{m}) \equiv \underbrace{R_{\bar{\lambda}}(\mathbf{m})}_{\text{expected revenue}} - \underbrace{rl}_{\text{cost of loan}} - \underbrace{\kappa(\mu)}_{\text{servicing cost}} . \quad (4)$$

Here, $\kappa(\cdot) > 0$ is the operational cost of servicing the loan, where $\kappa' < 0$, i.e., it is costlier to service a loan with a longer average maturity. To guarantee a unique interior solution ($\mu^* > 0$ in equilibrium), we assume $\kappa'' > 0$ and $\kappa'(0) = -\infty$, i.e., mortgages that never mature are extremely costly to serve (relaxed in Section 4.4). Furthermore, each lender incurs a fixed cost $\kappa_0 > 0$ to enter the loan market to offer the mortgage contract $\mathbf{m}$.

Competitive search The borrower is matched with a lender (out of the pool of competitive lenders) through a competitive search and matching process.[13] With search frictions, the borrower has an endogenous probability $\alpha_{\mathbf{m}}$ of finding a lender offering a mortgage contract $\mathbf{m}$. Similarly, each lender has probability $\eta_{\mathbf{m}}$ of finding a borrower. There is an exogenous matching function η that maps $\eta_{\mathbf{m}} = \eta(\alpha_{\mathbf{m}})$, where η is strictly decreasing and convex.[14]

Taking into account the search frictions as summarized by the matching function η, and given the solution $V_\lambda(\mathbf{m})$ to optimal default problem (2), the *optimal mortgage contract* $\mathbf{m}^*$ and the associated *leverage probability* $\alpha^*_{\mathbf{m}}$ maximize the borrower's value:

$$U_\lambda \equiv \max_{\alpha_{\mathbf{m}}, \mathbf{m}} \quad \alpha_{\mathbf{m}} \cdot \underbrace{[-r(p-l) + V_\lambda(\mathbf{m})]}_{\text{PV of buying a house with leverage}} + (1 - \alpha_{\mathbf{m}}) \cdot \underbrace{(v_\lambda - rp)}_{\text{PV of buying without leverage}} , \quad (5)$$

subject to the lenders' free-entry condition:

$$\underbrace{\eta(\alpha_{\mathbf{m}}) \cdot \Pi_{\bar{\lambda}}(\mathbf{m})}_{\text{Lender's expected profit}} = \underbrace{\kappa_0}_{\text{entry cost}} , \quad (6)$$

[13] Appendix A.2.8 provides more detail. 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 also more importantly because it allows us to endogenize and characterize the probability that the home purchase is financed with a mortgage—a quantity that is key in our empirical analysis. Also, the search frictions lead to a dispersion of prices and mortgage terms like maturity, loan amount and interest rate, as we see in the data.

[14] The function η is taken as given by agents but will be endogenously determined from the matching technology. The function maps $\alpha_{\mathbf{m}}$, which is increasing in the market thickness (the ratio of lenders to borrowers), to $\eta_{\mathbf{m}}$, which is decreasing in the market tightness. Market tightness is endogenously determined by the entry of lenders. $\eta' < 0$ implies congestion and $\eta'' > 0$ implies diminishing congestion.

which states that competitive lenders enter a market until they break even. Finally, the homebuyer chooses to borrow or not by solving $\max\{U_\lambda, v_\lambda - rp\}$.

3.2 Solution

3.2.1 Optimal default

We solve the model using backward induction. The first step is to characterize the optimal default strategy. There are two relevant debt limits that determine how risky a mortgage is:

Lemma 1 (Optimal default strategy)**.** *Given a loan contract* $\mathbf{m} = (l, b, \mu)$*, the optimal default time* $\tau^*_{\mathbf{m}}$ *that solves problem (2) is:*

$$\tau^*_{\mathbf{m}} = \begin{cases} \infty \quad \textit{(no default)} & \textit{if } B \leq B^{safe} \textit{ or } T \geq T_\mu \\ T \quad \textit{(default at disaster)} & \textit{if } B \in (B^{safe}, B^{risky}] \textit{ and } T < T_\mu \\ 0 \quad \textit{(default immediately)} & \textit{otherwise} \end{cases},$$

where $B = \frac{b}{1+\mu}$ *is again the loan balance, and the debt limits are given by:*

$$B^{safe} \equiv h - d + f < B^{risky} \equiv h - \frac{\mu}{1+\mu}\frac{\lambda}{1+\lambda}d + f. \tag{7}$$

We provide all proofs in the Appendix. Intuitively, the safe-debt limit is where the borrower is indifferent between repaying and defaulting when the disaster hits at $t = T$. The risky debt limit is where the borrower is indifferent before the disaster (at any $t < T$). Any mortgage with $B \leq B^{\text{safe}}$ is safe (zero default risk) and any mortgage with $B^{\text{safe}} < B \leq B^{\text{risky}}$ is risky (the loan will be defaulted at the disaster date). Any mortgage with $B > B^{risky}$ will incur immediate default and will not be approved by lenders in equilibrium.

Given Lemma 1, the borrower's expected gain from the mortgage contract is given by

$$V_\lambda(\mathbf{m}) - v_\lambda = \begin{cases} -B & \text{if } B \leq B^{\text{safe}} \\ -\underbrace{\frac{1+\mu}{1+\mu+\lambda}B}_{\text{PV of debt repayment}} - \underbrace{\frac{\lambda}{1+\mu+\lambda}(h-d+f)}_{\text{PV of collateral loss \& cost at default}} & \text{if } B \in (B^{\text{safe}}, B^{\text{risky}}] \\ -v_\lambda - f & \text{otherwise} \end{cases}, \tag{8}$$

and similarly for the lender's expected value of the mortgage's repayment stream:

$$R_{\bar\lambda}(\mathbf{m}) = \begin{cases} B & \text{if } B \leq B^{\text{safe}} \\ \underbrace{\frac{1+\mu}{1+\mu+\bar\lambda}B}_{\text{PV of repayment stream}} + \underbrace{\frac{\bar\lambda}{1+\mu+\bar\lambda}(h-d)}_{\text{PV of collateral seized at default}} & \text{if } B \in (B^{\text{safe}}, B^{\text{risky}}] \\ r\underline{p} & \text{otherwise} \end{cases}. \tag{9}$$

3.2.2 Optimal mortgage

Given lenders' free-entry condition (6), the borrower's problem (5) can be rewritten as:

$$\max_{\alpha} \alpha \cdot \left\{ \max_{\mathbf{m}} S(\mathbf{m}) - \kappa(\mu) - \frac{\kappa_0}{\eta(\alpha)} \right\},$$

where $S(\mathbf{m})$ denotes the *joint surplus* from $\mathbf{m}$ (before the lender's service and fixed costs):

$$S(\mathbf{m}) \equiv \underbrace{V_\lambda(\mathbf{m}) - v_\lambda + rl}_{\text{borrower's expected surplus}} + \underbrace{R_{\bar{\lambda}}(\mathbf{m}) - rl}_{\text{lender's expected surplus}}.$$

With the block-recursive structure of the competitive search environment, we first solve for the optimal contract $\mathbf{m}^*$, which is simply the contract that maximizes $S(\mathbf{m}) - \kappa(\mu)$; then we solve for the leverage probability $\alpha^* \equiv \alpha_{\mathbf{m}^*}$ that arises from the competitive search.

The joint surplus $S(\mathbf{m})$ under the optimal default time τ^* features the three cases as in the above. In the first case ($B \leq B^{\text{safe}}$), the loan balance is so low that the borrower will never default. The mortgage contract essentially redistributes the cash flow l and b between the borrower and the lender, and no joint surplus is created. Contracts in this region are dominated by no borrowing at all, due to the operational and fixed costs κ and κ_0.[15]

In the third case ($B > B^{\text{risky}}$), the loan balance is so high that the borrower finds it optimal to default right after taking on the loan at $t = 0$, which is essentially to sell the house at the liquidation price $\underline{p}$. The joint surplus is negative because it involves a dead weight loss, and thus contracts in this region are also dominated by no borrowing at all.

In the remaining and most interesting case ($B^{\text{safe}} < B \leq B^{\text{risky}}$), the loan balance is sufficiently high that the borrower will optimally default (only) when the disaster hits. The joint surplus under the optimal default time $\tau^*_{\mathbf{m}} = T$ becomes:

$$S(\mathbf{m}) = \underbrace{\left(\frac{1}{1+\mu+\bar{\lambda}} - \frac{1}{1+\mu+\lambda} \right) b}_{\text{net gain from the maturity channel}} - \underbrace{\left(\frac{\lambda}{1+\mu+\lambda} - \frac{\bar{\lambda}}{1+\mu+\bar{\lambda}} \right)(h-d) - \frac{\lambda f}{1+\mu+\lambda}}_{\text{net loss from the costly default channel}}. \quad (10)$$

Equation (10) highlights two opposite channels:

Maturity channel (new) The first term of (10) captures the expected net gain from trading a defaultable loan with long maturity. Both the borrower and lender know that, given the borrower's optimal default strategy, the repayment stream of b will end at date $T \wedge T_\mu$. However, given her belief of the arrival rate of the disaster, the borrower's PV of this repayment stream is $\frac{b}{1+\mu+\lambda}$, while the lender's PV is $\frac{b}{1+\mu+\bar{\lambda}}$. The *maturity channel*—represented by the difference between the two valuations—is positive when the borrower is more *pessimistic* than the lender ($\lambda > \bar{\lambda}$). Here, the borrower believes that the default time will arrive sooner and hence the actual repayment will be shorter than what the lender believes. The maturity

[15] When we introduce another reason for trade beside belief disagreement, for example, by assuming lenders having a lower cost of funding than the borrower, then a safe mortgage with $B \leq B^{\text{safe}}$ can occur in equilibrium for a relatively *optimistic* borrower (Section 4.6).

channel is stronger at longer maturities, i.e., the net gain term decreases in μ; for example, the term converges to zero when the contract matures immediately ($\mu \to \infty$), as the long-run risk becomes irrelevant for such a short-term mortgage.

Costly default channel (conventional) The second term of (10) is standard in static models of collateralized debt with heterogeneous beliefs. It captures the expected net losses due to default due to the foreclosure cost ($-\frac{\lambda f}{1+\mu+\lambda}$) and due to the surrender of the collateral ($-\left(\frac{\lambda}{1+\mu+\lambda} - \frac{\bar{\lambda}}{1+\mu+\bar{\lambda}}\right)(h-d)$). While both the borrower and lender agree that the value of the house becomes $(h-d)/r$ once the disaster hits, they disagree on how soon it will. A relatively more pessimistic borrower ($\lambda > \bar{\lambda}$) discounts the disaster event with a higher probability than the lender does ($\frac{\lambda}{1+\mu+\lambda} > \frac{\bar{\lambda}}{1+\mu+\bar{\lambda}}$).

Leveraging the disagreement Summing up, the maturity channel and the costly default channel have opposite signs and opposite implications to the optimal maturity. Whether the maturity channel dominates depends on the strength of belief disagreement. To see this, note that whenever the borrower is more pessimistic ($\lambda > \bar{\lambda}$), the optimal mortgage contract maximizes the maturity channel in (10) by maxing out the loan balance at the risky debt limit, i.e., $B^* = B^{\text{risky}}$. In this case, the surplus $S(\mathbf{m})$ collapses to $\frac{\Delta}{1+\mu+\bar{\lambda}}$, where Δ is a *belief disagreement term* given by:

$$\Delta \equiv \frac{\lambda - \bar{\lambda}}{1+\lambda} d - \bar{\lambda} f = (1+\bar{\lambda})\left(v_{\bar{\lambda}} - v_{\lambda} - \frac{\bar{\lambda}}{1+\bar{\lambda}} f\right). \tag{11}$$

The term Δ is positive if and only if the borrower is sufficiently pessimistic: $\lambda > \lambda^*$, where

$$\lambda^* \equiv \begin{cases} \bar{\lambda}\frac{d+f}{d-\bar{\lambda}f} & \text{if } d > \bar{\lambda} f \\ \infty & \text{otherwise} \end{cases}. \tag{12}$$

Note that λ^* is increasing in the foreclosure cost. If $f = 0$, then $\lambda^* = \bar{\lambda}$, implying that there would be a positive joint surplus as long as the borrower is more pessimistic than the lenders ($\lambda > \bar{\lambda}$). Otherwise, $f > 0$ implies $\lambda^* > \bar{\lambda}$.

The following proposition characterizes the equilibrium contract, based on the house's disaster risk exposure d and buyer belief λ:

Proposition 2 (Optimal mortgage)**.**

1. *If the house is sufficiently at-risk ($d > \bar{\lambda} f$) and the homebuyer is sufficiently pessimistic ($\lambda > \lambda^*$), then the homebuyer will borrow. The optimal mortgage contract features binding risky debt limit $B^* = B^{risky}$. The optimal maturity rate μ^* solves:*

$$\max_{\mu \geq 0} \left[\frac{\Delta}{1+\mu+\bar{\lambda}} - \kappa(\mu)\right]. \tag{13}$$

and the leverage probability α^* solves:

$$M_\lambda \equiv \max_{\alpha \in [0,1]} \alpha \cdot \left[\frac{\Delta}{1 + \mu^* + \bar{\lambda}} - \kappa(\mu^*) - \frac{\kappa_0}{\eta(\alpha)} \right]. \tag{14}$$

2. *Otherwise ($d \leq \bar{\lambda} f$ or $\lambda \leq \lambda^*$), the homebuyer will not borrow.*

Figure A1 illustrates two key characteristics according to Proposition 2. Panel a and b plot the leverage probability α^* and the maturity rate μ^* as functions of the borrower's belief λ, respectively. When the borrower is sufficiently pessimistic ($\lambda > \lambda^*$), the novel maturity channel dominates the traditional costly default channel, and the optimal leverage increases in the degree of the borrower's pessimism in the following senses. At the extensive margin, the leverage probability α^* is strictly positive and strictly increasing in λ when $\lambda > \lambda^*$, and the probability is zero when $\lambda \leq \lambda^*$. At the intensive margin, the maturity rate μ^* is strictly decreasing in λ (longer maturity) when $\lambda > \lambda^*$.

Given the tractability of the model, we further have:

Corollary 3 (Comparative statics)**.** *The following table characterizes the comparative statics (partial derivatives) with respect to λ and d for the optimal maturity rate μ^*, loan approval probability α^*, loan amount l^*, and the implied loan rate $r^* \equiv R_{\bar{\lambda}}(\mathbf{m})/l^*$:*

	Belief				*Disaster exposure*			
	$\frac{\partial \mu^*}{\partial \lambda}$	$\frac{\partial \alpha^*}{\partial \lambda}$	$\frac{\partial l^*}{\partial \lambda}$	$\frac{\partial r^*}{\partial \lambda}$	$\frac{\partial \mu^*}{\partial d}$	$\frac{\partial \alpha^*}{\partial d}$	$\frac{\partial l^*}{\partial d}$	$\frac{\partial r^*}{\partial d}$
At-risk house & pessimistic buyer ($d > \bar{\lambda} f, \lambda > \lambda^*$)	$-$	$+$	?	?	$-$	$+$	?	?
Otherwise	0	0	0	0	0	0	0	0

Note: $+$ means ≥ 0, $-$ means ≤ 0, ? means ambiguous.

The comparative statics for the loan amount l^* is ambiguous 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 homebuyer to borrow. On the loan supply side, a higher λ implies a lower homebuyer's valuation of the asset v_λ, which in turn lowers their 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. Since the implied loan rate r^* is directly related to l^*, it follows that the comparative statics for r^* is ambiguous.

4 Model extensions

The following extensions show the flexibility of our model and the robustness of its results.

4.1 Disaster insurance

This extension allows for disaster insurance. The baseline results continue to hold as long as insurance coverage is incomplete or the premium is not too high—two conditions that are realistic in the relevant empirical context of flood insurance in the U.S. (Section 6.3).

Assume that at each date t before the disaster, the homebuyer has access to a disaster insurance program with an exogenous coverage c (think of the National Flood Insurance Program, or NFIP) and exogenous premium rate $r\lambda^I$. The insurance reduces the disaster damage from d to $d - c$, with c representing the pay out by the insurer when the disaster hits at T. The program charges a premium of $r\lambda^I c$ per each date $t < T$ (where λ^I can be viewed as the "effective belief" of the insurer revealed by the premium). Under this program, the homebuyer's PV of the stream of utility from an insured house is:

$$v_\lambda^I \equiv h - \frac{\lambda}{1+\lambda}(d-c) - \frac{\lambda^I}{1+\lambda}c = h^I - \frac{\lambda}{1+\lambda}d^I,$$

where $h^I \equiv h - \lambda^I c$ and $d^I \equiv d - (1+\lambda^I)c$ denote the housing utility and disaster damage with insurance.[16] To focus on the plausible case where v_λ^I is decreasing in λ (i.e., the valuation of the insured house is lower for a more pessimistic homebuyer), we assume that:

$$(1+\lambda^I)c < d. \tag{15}$$

This condition holds when insurance coverage is incomplete or the insurance premium is not too high. It is consistent with the fact that there is a maximum coverage set by the NFIP ($250,000), and that the NFIP premium rates are highly subsidized (Kousky et al., 2017).

Mandatory insurance Let us first consider a simple scenario where insurance is mandatory (think of the flood insurance requirement in the NFIP's Special Flood Hazard Areas, see Section 6.3). Then it is straightforward to show that the baseline results from Section 3.2 continue to hold, with parameters h and d replaced with h^I and d^I, respectively.[17]

Voluntary insurance Let us now consider the more complex scenario where insurance is voluntary. In the same way that the agent cannot commit to repaying their debt, we suppose that they cannot commit to buying insurance.[18] For each date t, there are two stages. In the first stage, the homeowner chooses whether or not to participate in the insurance program by paying the insurance premium $r\lambda^I c$. In the second stage, should the disaster arrives, the homebuyer will receive the insurance coverage if and only if she has paid the premium at the beginning of the period. In this extension, we assume $f = 0$ to simplify the analysis.

An interesting insight that arises from this extension is a *debt overhang effect*: leveraged households with risky debt have less incentive to invest in insurance, since the option to default acts as a form of implicit insurance. If there is no mortgage balance, then the homebuyer

[16] The expression for the post-insurance damage parameter d^I reflects the fact that when the disaster hits, the insurance program reduces the damage from d to $d - c$, and the homebuyer stops paying the stream of insurance premia, whose PV amounts to $\lambda^I c$.

[17] Similarly, if insurance is mandatory only when the home purchase is leveraged (but voluntary otherwise), then the results continue to hold, with a slight modification. There will be a belief threshold λ^* such that a pessimistic homebuyer with $\lambda > \lambda^*$ chooses a risky mortgage (and is hence required to purchase insurance). A homebuyer with $\lambda < \lambda^*$ but $\lambda \geq \lambda^I$ does not borrow and voluntarily purchases insurance. Finally, an optimistic homebuyer with $\lambda < \lambda^I$ does not borrow and buys no insurance.

[18] In practice, most flood insurance contracts are set on an annual basis, and prescribed homebuyers can always have the option to not renew in the subsequent year.

will purchase insurance if and only if the premium rate is sufficiently low such that $\lambda^I < \lambda$ (equivalently, when the homebuyer is relatively more pessimistic than the insurer). However, when the homebuyer is indebted, her demand for insurance depends on the outstanding debt, as summarized in the following lemma:

Lemma 4 (Debt overhang effect on insurance uptake). *At any $t < T \wedge T_\mu$, the borrower chooses to purchase insurance if and only if* $\lambda^I < \lambda$ and $B \leq B^{safe}_{ins} \equiv B^{safe} + \left(1 - \frac{\lambda^I}{\lambda}\right) c$.

Remark 2. Lemma 4 implies that, all else equal, home equity (price minus mortgage balance) is positively correlated with insurance uptake. This is consistent with the finding by Liao and Mulder (2021), which documents a strong positive correlation between home equity and insurance uptake using data aggregated across 271 MSAs between 2001 and 2015.

Appendix A.2.1 shows that the characterization of the equilibrium mortgage in Proposition 2 continues to hold, with risky debt limit $B^{\text{risky}}_{\text{ins}}$, and the belief threshold λ^*_{ins} and belief disagreement term Δ_{ins} slightly modified to take into account the insurance option.

4.2 Disaster assistance

This extension allows for government disaster assistance. An important source of financial assistance *specifically for mortgage borrowers* comes from disaster loan forbearance programs provided by the GSEs and federal agencies. They allow affected borrowers with federally-backed mortgages to reduce or suspend their mortgage payments for a short duration, usually up to a year, without incurring late fees (Kousky et al. 2020). In our model, a loan forbearance program can be viewed as a reduction of the loan's present value from B to $e^{-r\varepsilon}B$ at the disaster date T, where ε is the duration of forbearance (and $(1 - e^{-r\varepsilon})B$ is the fiscal cost of this program). Thus, the forbearance makes the loan balance effectively contingent on the disaster state. All agents rationally anticipate the forbearance at $t = 0$.

It turns out that the forbearance will *strengthen* our main results, as it provides another reason why a pessimist might want to leverage and to use a long-term mortgage. The borrower's expected payoff $V_\lambda(\mathbf{m})$ from a mortgage $\mathbf{m}$ now becomes:

$$V_\lambda(\mathbf{m}) = v_\lambda + \begin{cases} -B + \underbrace{\dfrac{\lambda}{1+\mu+\lambda}(1 - e^{-r\varepsilon})B}_{\text{borrower's PV of forbearance}} & \text{if } B \leq B^{\text{safe}} \\ -\frac{1+\mu}{1+\mu+\lambda}B - \underbrace{\dfrac{\lambda}{1+\mu+\lambda}e^{-r\varepsilon}(h - d + f)}_{\text{PV of postponing the default}} & \text{if } B \in (B^{\text{safe}}, B^{\text{risky}}] \\ \text{as in the third region of (8)} & \text{if } B > B^{\text{risky}} \end{cases} . \tag{16}$$

There are two changes relative to equation (8): (i) a new term in the value of a safe mortgage, representing the PV of the borrower's gain from the forbearance, and (ii) a reduced PV of the loss of default in the value of a risky mortgage, due to the borrower postponing the default to enjoy the forbearance; both of these terms are discounted at the subjective probability $\frac{\lambda}{1+\mu+\lambda}$. Intuitively, the borrower can enjoy the forbearance only if the loan has not been defaulted, and the forbearance delays the incentive to default during the disaster period. Hence, forbearance increases the borrower's payoff via two channels: postponing the repayment to a safe mortgage and postponing the default of a risky mortgage.

Using backward induction, Appendix A.2.2 characterizes the equilibrium, with the same belief threshold λ^*. Above this threshold, the borrower continues to issue a risky debt with $B = B^{\text{risky}}$ as in Proposition 2. However, below this threshold, the borrower will issue a *safe* debt with $B = B^{\text{safe}}$, whose leverage probability and average maturity increase in the borrower's pessimism λ. Intuitively, the safe debt allows the borrowers to enjoy the forbearance. The value of a safe mortgage increases in λ, as a more pessimistic borrower expects a sooner arrival of the disaster forbearance program. The value also increases in the average loan maturity (decreases in μ), as the borrower can enjoy the forbearance only if their loan has not yet matured by the time the disaster arrives.

In sum, the anticipation of a forbearance program provides another motive for leverage, further strengthening our theoretical prediction that pessimistic homebuyers are more likely to leverage and to use a long-term mortgage.

Remark 3 (Disaster aid). Another source of government assistance is disaster aid, although in practice, per-capita aid is often limited in both actual amounts[19] and amounts expected.[20] In our model, aid can be viewed as a reduction of the disaster damage from d to $d_\epsilon \equiv (1-\epsilon)d$. As long as $\epsilon < 1$, it is immediate to see that Proposition 2 continue to hold with d replaced by d_ϵ, and the effects of ϵ are summarized in the comparative statics for d in Corollary 3.

4.3 GSEs' guarantee

This extension introduces the GSEs' guarantee program and formally shows how a guarantee subsidy will encourage lenders to optimistically evaluate the risk exposure of a loan (and especially so when the loan has a long maturity). Appendix A.2.3 provides the details (Appendix A.2.9 further extends the model to explicitly incorporate the securitization process).

Suppose at $t = 0$, after entering a mortgage contract $\mathbf{m}$ with a borrower, a *GSE agent* can guarantee a fraction $1 - \theta$ of the mortgage repayment against the borrower's default risk. Here, the parameter $\theta \in [0, 1]$ represents the regulatory requirement that a lender retains some "skin in the game" in the loan origination and distribution process (Keys et al., 2010). The GSE agent charges the lender a guarantee fee (also known as "g-fee") $g \in [0, 1]$ per unit of expected deficiency amount, until either the mortgage matures or the borrower defaults. The case $g < 1$ captures an underpriced g-fee (below the actuarially fair cost); our benchmark model in Section 3 is the special cases $\theta = 1$ (no guarantee) or $g = 1$ (no subsidy).

[19]For example, FEMA provides post-disaster grants to households through the Individual and Household Program, which has a cap of just over \$30,000 per household, and the actual amount averages only a few thousand dollars (e.g., below \$9,000 for Hurricane Harvey) (Kousky et al., 2020).

[20]Homeowner expectations of post-disaster aid are modest. Based on calculations by the authors from the 2021 FEMA National Household Survey, among homeowners who identified flooding as one of the "types of disasters that would have the biggest impacts where you live," while 78.5% expected to receive aid from the federal government, only 32.9% expected to receive *financial assistance* from any external organization (including federal, state, local, and tribal governments). More common were expectations of in-kind donations of food, water, or temporary shelter. In addition, Bakkensen and Barrage (2022) find that residents expected government assistance to cover less than 17% of flood damages.

As shown in Appendix A.2.3, the characterization of the equilibrium mortgage in Proposition 2 continues to hold with a modified belief threshold $\lambda^*_{\text{GSE}} \leq \lambda^*$. As summarized in the table below, an increase in g or in θ ultimately leads to lower risky mortgage origination, lower leverage probability, and lower maturity in equilibrium, summarized in the below table. Qualitatively, the comparative statics of g and θ follow the direction of $\bar{\lambda}$, i.e., reducing the g-fee or reducing the skin in the game has a similar effect as an increase in lenders' optimism in the benchmark model.

Guarantee fee			Skin in the game			Lender's belief		
$\frac{\partial \mu^*}{\partial g}$	$\frac{\partial \alpha^*}{\partial g}$	$\frac{\partial \lambda^*_{\text{GSE}}}{\partial g}$	$\frac{\partial \mu^*}{\partial \theta}$	$\frac{\partial \alpha^*}{\partial \theta}$	$\frac{\partial \lambda^*_{\text{GSE}}}{\partial \theta}$	$\frac{\partial \mu^*}{\partial \bar{\lambda}}$	$\frac{\partial \alpha^*}{\partial \bar{\lambda}}$	$\frac{\partial \lambda^*_{\text{GSE}}}{\partial \bar{\lambda}}$
+	−	+	+	−	+	+	−	+

Note: $+$ *means* ≥ 0, $-$ *means* ≤ 0.

4.4 Rental

Our model is flexible enough to encompass the rental option. So far, we have imposed $\kappa'(0) = -\infty$ on the operational servicing cost, so that the equilibrium maturity has an interior solution ($\mu^* > 0$), and the mortgage contract has a finite maturity. We now relax this assumption and consider contracts with an infinite maturity. An infinite maturity contract can be loosely interpreted as a rental contract, where the borrower is the renter, the lender the landlord, and the payment in perpetuity b the per-period rent. When the disaster hits, instead of foreclosure, the renter now terminates the rental contract, and we interpret f as the moving cost.

Formally, consider a lease contract $\mathbf{m}^{\text{rent}} = (p - k, b, 0)$, where k is a deposit to the landlord.[21] The renter's optimization problem is a modification of the borrower's problem (5):

$$U^{\text{rent}}_{\lambda} \equiv \max_{\mathbf{m}^{\text{rent}},\alpha} \alpha \left[-rk + V_{\lambda}(\mathbf{m}^{\text{rent}})\right] + (1-\alpha)\left(-rp + v_{\lambda}\right), \tag{17}$$

where V_{λ} is the same as before. A competitive landlord's expected profit is also a modified version of the lender's free-entry condition (4):

$$\kappa_0 + rp = \eta(\alpha)\left[R_{\bar{\lambda}}\left(\mathbf{m}^{\text{rent}}\right) + rk - \kappa(\mu)\right] + \left[1 - \eta(\alpha)\right] rp,$$

where the landlord's cost of posting a lease contract is $\kappa_0 + rp$ and $R_{\bar{\lambda}}$ is the same as before. The landlord has probability $\eta(\alpha)$ of finding a renter. Otherwise, the rental property is sold at p for simplicity. The optimal lease contract solves:

$$\max_{\alpha \in [0,1]} \alpha \left\{ \max_{b,k} S\left(\mathbf{m}^{\text{rent}}\right) - \kappa(0) - \frac{\kappa_0}{\eta(\alpha)} \right\}.$$

[21] For simplicity, we assume the deposit is non-refundable. The model can be adjusted for a refundable deposit. Also, we assume competitive landlords with free entry (as was the case for competitive lenders). The model can be adjusted to have a fixed measure of landlords as in Wright et al. (2021).

The joint surplus from a given lease contract $\mathbf{m}^{\text{rent}}$ is given by:

$$S\left(\mathbf{m}^{\text{rent}}\right) = \underbrace{V_\lambda\left(\mathbf{m}^{\text{rent}}\right) - v_\lambda + r\left(p-k\right)}_{\text{renter's surplus}} + \underbrace{R_{\bar{\lambda}}\left(\mathbf{m}^{\text{rent}}\right) - r\left(p-k\right)}_{\text{landlord's surplus}}.$$

The main results continue to hold, except that there will be an additional belief cutoff threshold $\lambda^{**} \equiv \frac{(d+f)\bar{\lambda}+\kappa'(0)(\bar{\lambda}+1)^2}{d-f\bar{\lambda}-\kappa'(0)(\bar{\lambda}+1)^2} > \lambda^*$. In equilibrium, for an at-risk house ($d > \bar{\lambda}f$):

1. An optimistic homebuyer ($\lambda \leq \lambda^*$) chooses to not borrow;
2. A pessimistic homebuyer ($\lambda^* < \lambda \leq \lambda^{**}$) borrows using a risky mortgage contract (with finite maturity, where the maturity rate $\mu^* > 0$ is as specified in baseline Proposition 2);
3. A very pessimistic homebuyer ($\lambda > \lambda^{**}$) rents, using the optimal lease specified above.

4.5 Endogenous housing price

This subsection extends the baseline model to endogenize the housing price p^*. Assume that at $t = 0$, before the loan market search takes place, the homebuyer is matched with a seller, and Nash bargaining determines the equilibrium housing price:

$$p^* = \arg\max_p (U_\lambda)^\zeta (rp - v^s)^{1-\zeta}, \tag{18}$$

where p also enters the homebuyer's utility U_λ in (5), $\zeta \in (0,1)$ is their bargaining power, and v^s is the seller's (exogenous) valuation of the house. We assume $v^s < v_\lambda$, so that the seller wants to sell the house to the homebuyer. The solution to the bargaining problem is:

$$rp^* = \underbrace{(1-\zeta)v_\lambda + \zeta v^s}_{\text{standard ``hedonic'' term}} + \underbrace{(1-\zeta)M_\lambda}_{\text{mortgage term}}, \tag{19}$$

where M_λ is the expected surplus from the optimal mortgage as derived in (14).

Proposition 5 (Housing price)**.** *The housing price p^* is decreasing in the homebuyer's disaster belief λ, and decreasing in the disaster exposure d.*

Proposition 5 states that, although pessimists have a higher expected mortgage surplus M_λ, the effect of a lower subjective value v_λ still dominates for asset pricing (see proof in Appendix A.2.4). Consequently, the asset price decreases in the degree of pessimism and disaster exposure. This is a testable implication that we also evaluate in the data.

4.6 Difference in funding costs

This section introduces another reason for trade that arises from heterogeneous funding costs. It also clarifies the conceptual difference between heterogeneous beliefs and heterogeneous discount rates. Suppose that lenders have a lower discount rate $\bar{r} < r$. This assumption reflects the fact that in practice, banks have access to cheaper wholesale funding, such as the

Fed funds market or commercial papers, while homebuyers do not. Using the same backward induction logic, Appendix A.2.5 characterizes the equilibrium mortgage. There still exists a belief cutoff λ^*_ω that a relatively pessimistic homebuyer ($\lambda > \lambda^*_\omega$) will borrow with risky debt $B = B^{\text{risky}}$. The cutoff λ^* now is modified by the ratio of different discount rates, $\omega \equiv r/\bar{r} > 1$. The main difference is that even if the homebuyer is relatively optimistic ($\lambda \leq \lambda^*_\omega$) or the house is relatively unexposed ($d \leq \bar{\lambda} f$), the homebuyer will borrow using a safe mortgage contract with no default risk, $B = B^{\text{safe}}$. They do so to reap the gain from borrowing at a relatively lower funding cost. Hence, both risky and safe mortgages will be traded in equilibrium.

4.7 Comparison with the prediction in the literature

Our prediction contrasts with the standard prediction in models of heterogeneous beliefs that optimists leverage more (Fostel and Geanakoplos 2008, 2015; Geanakoplos 2010; Simsek 2013). The key mechanism is the endogenous maturity channel, which is absent in the standard framework with an exogenously fixed maturity.

To see this more clearly, consider a modified case of our extended model in Section 4.6, but assume the maturity of any mortgage contract is exogenously fixed at some T_0. The homebuyer can still choose the loan amount and repayment flow. A relatively optimistic homebuyer ($\lambda \leq \lambda^*_\omega$) will leverage with a safe loan without default, as in Fostel and Geanakoplos (2015). For a relatively pessimistic homebuyer ($\lambda > \lambda^*_\omega$), who optimally chooses a risky loan, the optimal leverage probability now solves:

$$\alpha_0 \equiv \arg\max_{\alpha \in [0,1]} \alpha \cdot \left\{ (\omega - 1)(v_\lambda + f) + \omega \Delta_\omega T_0 - \frac{\kappa_0}{\eta(\alpha)} \right\},$$

where Δ_ω denotes the belief disagreement term modified by ω. Furthermore, suppose the exogenous maturity is sufficiently short: $T_0 < \frac{1-\omega^{-1}}{1+\bar{\lambda}}$.

Then, by monotone comparative statics, the leverage probability α_0 is decreasing in λ, i.e., more pessimistic homebuyers are now *less* likely to leverage. Intuitively, when T_0 is low, the gain from maturity (captured by the term $\Delta \cdot T_0$) is relatively small, and the comparative statics is dominated by the fact that the homebuyer's PV of the flow of housing utility v_λ is decreasing in λ. In other words, the collateral channel dominates the maturity channel.

In summary, in this special case without the possibility of the borrower choosing a long-term loan contract, our model would imply that optimists would be more likely to leverage, consistent with the standard finding in the literature.

4.8 Belief convergence

Our results hold even when belief disagreement does not last forever. This extension allows beliefs to converge in a simple way by introducing an exogenous news shock about the disaster process.[22] The news shock occurs at date T_n, which arrives at a commonly known rate $r\nu$.

[22]The news shock could represent, for example, the news of an important progress in climate science, which significantly reduces the disagreement about the speed of sea level rise. One could potentially introduce belief convergence in much more sophisticated ways, such as via a communication game as in Geanakoplos and

For simplicity, we assume that upon its realization at T_n, the news shock reveals the true arrival rate of the disaster. Hence, after the news shock, agents will have common knowledge of the disaster arrival rate, and we denote this ex-post common belief by λ'. However, before the news shock, agents do not know what λ' will be, and they have different priors about the distribution of λ'. For analytical tractability, we assume that λ' can take two possible realizations: $\lambda' \in \{0, \lambda\}$. Before the news arrives, the borrower's prior places a probability weight of $\pi \in (0,1)$ on the "bad news" state $\lambda' = \lambda$, and $1-\pi$ on the "good news" state $\lambda' = 0$. Similarly, the lenders' prior places a probability weight of $\bar{\pi} \in (0,1)$ on the bad news. The borrower has a more pessimistic prior than the lenders when $\pi > \bar{\pi}$, and vice versa.

Hence, as in the baseline model, agents have heterogeneous prior beliefs at $t = 0$. However, unlike in the baseline model, *agents know that their beliefs will eventually converge at date* T_n. This leads to an interesting scenario: the realization of a *bad* news at T_n could trigger a default. In the subgame before the arrival of the news, there will be a new debt limit below which the borrower will not default immediately:

$$B^{\text{risky}}_{\text{news}} \equiv h - \frac{\mu\pi}{1+\mu+(1-\pi)(\lambda+\zeta)}\frac{\lambda}{1+\lambda}d + f > B^{\text{risky}} \equiv h - \frac{\mu}{1+\mu}\frac{\lambda}{1+\lambda}d + f.$$

The optimal default time for any given loan balance B is:

$$\tau^*_{\mathbf{m}} = \begin{cases} \infty \quad \text{(no default)} & \text{if } B \le B^{\text{safe}} \text{ or } T > T_\mu \\ T \quad \text{(default at disaster)} & \text{if } B \in (B^{\text{safe}}, B^{\text{risky}}] \text{ and } T \le T_\mu \\ T \wedge T_n \text{(default at disaster } \textit{or} \text{ at bad news)} & \text{if } B \in (B^{\text{risky}}, B^{\text{risky}}_{\text{news}}],\ T \wedge T^{\text{bad}}_n \le T_\mu \\ 0 \quad \text{(default immediately)} & \text{otherwise} \end{cases}, \tag{20}$$

where T^{bad}_n denotes the date the bad news realizes.

The third region is new: if the loan balance is sufficiently large, then it is optimal for the borrower to default upon the realization of bad news, even if the disaster has not arrived. Debt in this region is riskier with a higher debt level ($B^{\text{risky}}_{\text{news}} > B^{\text{risky}}$) and a higher probability of default (which happens when either the disaster or the bad news realizes).

Appendix A.2.6 shows that the main results continue to hold. A relatively optimistic homebuyer with prior $\pi \le \bar{\pi}$ chooses not to borrow in equilibrium. A relatively pessimistic homebuyer ($\pi > \bar{\pi}$) chooses a risky mortgage that solves a slightly more complex optimization problem (45), which reflects the fact that the optimal loan balance will be either B^{risky} or $B^{\text{risky}}_{\text{news}}$, depending on parameters. Focusing on the tractable case of $f \to 0$, we can show that the latter option dominates, and hence in equilibrium, the borrower chooses a risky mortgage with $B = B^{\text{risky}}_{\text{news}}$ and will default when either the disaster or the bad news hits.

In summary, this extension shows that our main results continue to hold, even if agents know that beliefs will eventually converge after the realization of an exogenous news shock.

Polemarchakis (1982); however, interactions between agents do not necessarily lead to common beliefs when agents have different and incomplete models of learning about uncertainty (Mailath and Samuelson 2020). Leaving this complexity aside, we model belief convergence in a simple way via an exogenous news shock, following the literature in macroeconomics (e.g., Barsky et al. 2015).

However, there is an added layer of complexity, as the realization of a bad news shock could trigger equilibrium default through a repricing shock.

4.9 Deterministic maturity

Appendix A.2.7 provides a robustness check when mortgage maturity is deterministic instead.

5 Empirical analysis

In this section, we now test the model's implications, as summarized in Table 1.

	Pessimistic homebuyer ($\lambda > \lambda^*$) & exposed house ($d > \bar{\lambda} f$)	Otherwise
Housing price	lower	higher
Leverage probability	higher	lower
Maturity	longer	shorter

Table 1: Main testable implications of the model.

5.1 Data

We develop an original large-scale dataset of coastal property sales along the U.S. East 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 leverage an extensive proprietary set of real estate transactions data from CoreLogic, a data provider 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 loan maturity and amount at origination, the lender, and other characteristics.

CoreLogic provides each property's *precise* coordinates. This allows us to compute *each* house's distance to the nearest coast (and also each house's precise SLR risk exposure, as to be described below). We restrict attention to single-family properties that lie within 1km of the coast. We 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 maps from NOAA's SLR Viewer. These high-resolution maps allow us to extract property-specific exposure to permanent coastal inundation, projected under various SLR levels. NOAA utilizes a bathtub-style model to project future inundation based on local land elevation, local and regional tidal variability, topographical 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 confounded by local economic conditions. 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 obtain each property's minimum bare-earth elevation as a control variable from First Street Foundation.

For climate beliefs, we utilize data from the 2014 Yale Climate Opinion Survey (Howe et al. 2015). This innovative dataset provides estimates of the average beliefs about climate change among the adult population in each county, based on >13,000 individual responses to their national survey across multiple waves since 2008. The Yale dataset 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. We provide a series of robustness checks with alternative belief data sources and specifications in Section 6.1. We also include a suite of county-by-year level socioeconomic and neighborhood variables as additional controls, listed in Appendix B.1.

Table A1 provides the summary statistics of selected key variables. The final sample 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 fact that buyers of coastal properties tend to be wealthier on average (Kahn and Smith 2017; Bakkensen and Ma 2020).

Remark 4 (East Coast). We focus on the East Coast for several reasons. The rate of SLR is especially high in the East Coast (e.g., twice as fast as that in the West Coast in the next three decades, Sweet et al., 2022), and the East Coast houses a significant fraction of capital stock in SLR harm's way.[23] Furthermore, while the Gulf Coast also experiences substantial SLR risk, the risk of coastal inundation there is confounded by land subsidence due to endogenous economic factors (oil and gas extraction and groundwater depletion).[24]

Remark 5 (NOAA). While the NOAA SLR data publicly provides maps of areas projected to be inundated at specific heights of SLR (e.g., 3 feet), it does *not* provide projections on the *speed* of SLR (e.g., when 3 feet of SLR is expected). In fact, there is substantial uncertainty regarding the speed of SLR.[25] Thus, our working assumption is that while NOAA's SLR maps are common knowledge, there is *significant belief heterogeneity about the speed of SLR*. This is

[23]For example, it was estimated that by 2100, under the 2014 National Climate Assessment "high scenario," more than $1.07 trillion of residential and commercial properties will be at risk of chronic flooding (Dahl et al., 2018) and more than 80% of these properties are located along the East Coast.

[24]For example, Ohenhen et al. (2024) estimate that between 23% and 35% of Gulf Coast inundation by 2050 will be due to land subsidence and not SLR; the subsidence rates are far smaller elsewhere in the U.S.

[25]For example, it is not highly controversial that a home at one foot elevation would be permanently inundated if two feet of SLR occurred. In contrast, there is significant uncertainty and disagreement surrounding the time at which seas will rise enough to inundate a house. The Intergovernmental Panel on Climate Change (IPCC) concludes that while it is "virtually certain" that mean global sea level will rise over the coming century, there is considerable uncertainty regarding the rate at which it will occur. Under the most moderate GHG emissions scenario (SSP1-2.6), the IPCC predicts an increase of 1.05-2.04 feet (0.32-0.62 meters) SLR in 2100 relative to 1995-2014. In contrast, the very high SSP5-8.5 scenario predicts 3.22-6.18 feet of SLR (0.98–1.88 meters) by 2100. In addition, the IPCC do not rule out SLR above 6.56 feet (2 meters) by 2100 given uncertainties surrounding modeling parameters like the melting of ice sheets (Masson-Delmotte et al., 2021). See `https://www.ipcc.ch/srocc/` for more detail. Note also that we do not need any particular climate belief to be correct in order for our results to hold but rather just that disagreement exists.

consistent with the setup of our model where disaster risk exposure d is common knowledge, but agents have different beliefs about how soon the disaster will arrive.

5.2 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:

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

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 SLR risk exposure. Following BGL and BGY, we define SLR_i as equal to one if property i is predicted to be underwater if the sea level rises by six feet, and zero otherwise (we will use 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).[26] 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 exploit the high-resolution spatial variation in SLR exposure by comparing 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.[27] 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 3 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 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.[28]

In line with our model (Proposition 5) and the previous literature, we hypothesize that:

[26] 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.

[27] 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.

[28] Another advantage of the high-dimension fixed effects is that they reduce the concern that other types of natural disaster risks can confound our analysis. Under the ZIP code × distance to coast × elevation fixed effects, a potentially confounding variation in another type of disaster risk would need to vary across properties at this fine of a spatial scale and be correlated with SLR risk. However, most other types of disaster risks such as earthquakes, hurricane winds, wildfires, tornadoes or extreme precipitation tend to not vary as much across localized spatial unit relating to SLR.

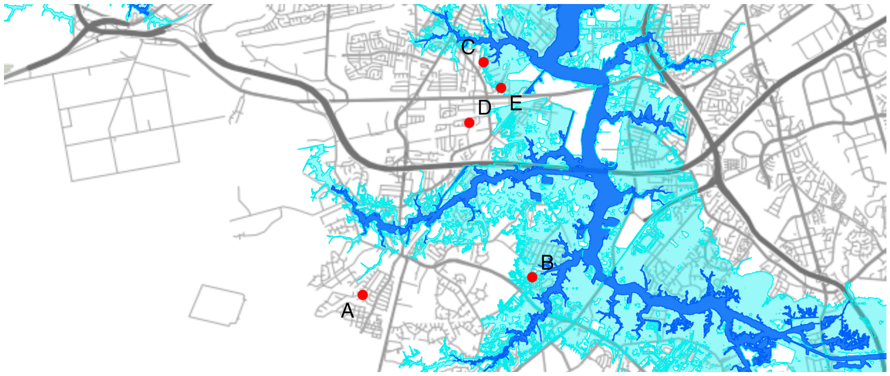

Figure 3: Illustration of our empirical identification strategy in Chesapeake, Virginia. Five properties (points A through E) that are within the same ZIP code, same distance bin to the coast, same elevation bin, having the same number of bedrooms, and having the same month and year of transaction. Properties 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 reveal locations of actual observations).

Hypothesis 1 ($\beta_P < 0$)**.** *All else equal, at-risk properties ($SLR_i = 1$) sell at a discount (relative properties with $SLR_i = 0$).*

Going deeper, we re-investigate the literature's findings on the effect of heterogeneous climate beliefs in the pricing of SLR risk via the following specification:

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

Here, $PessBuyer_c$ is an indicator variable equal to one if the average climate belief in the county $c = c(it)$ where the buyer of property i at date t comes from is above the sample median and zero otherwise.[29] We interpret $PessBuyer = 1$ as an indicator of a likely pessimistic homebuyer. Based on Proposition 5 and the previous literature, we further hypothesize:

Hypothesis 2 ($\gamma_P < 0$)**.** *The SLR discount is stronger 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

[29]We utilize a binary version of climate beliefs and SLR risk for several reasons. First, we follow Bernstein et al. (2019) in our main specification definition of SLR risk ($SLR = 1$ if inundated with 6 feet of SLR, 0 otherwise) for ease of comparison across existing literature. In addition, similar to Bakkensen and Barrage (2022), we discretize our beliefs variable for ease of interpretation and connection to our theoretical model given the discrete predictions (e.g., behavior of pessimists versus optimists). Finally, to the extent that there may be measurement error in either variable, it is more conservative to discretize the variables instead of including the fully continuous versions. Reassuringly, our results hold in our robustness exercises allowing for more continuous versions of beliefs (e.g., quartiles in Table A3, more nuanced SLR definitions in Table A9).

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 6.1.

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 climate beliefs affect the likelihood that transactions are leveraged:

$$Leveraged_{it} = \beta_L SLR_i + \delta_L PessBuyer_c + \gamma_L SLR_i \times PessBuyer_c + \rho_L \ln Price_{it} + \phi_L' X_i + \theta_L' Z_{ct} + \xi_L' SLR_i \times Z_{ct} + \Lambda_{ZDEBM}^L + \varrho_L + \epsilon_{it}^L. \quad \text{(L1)}$$

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 (this is consistent with our model, where buyers choose a debt contract given a housing price), but our results are robust to omitting it (see Section B.2.4). The dummy $PessBuyer_c$ is defined as in (P1). Based on Table 1, we hypothesize that:

Hypothesis 3 ($\gamma_L > 0$)**.** *In transactions of at-risk properties, more pessimistic buyers are more likely to leverage.*[30]

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.[31] We then run the following regression on the sub-sample of leveraged transactions:

$$LongMaturity_{it} = \beta_M SLR_i + \delta_M PessBuyer_c + \gamma_M SLR_i \times PessBuyer_c + \rho_M \ln Price_{it} + \phi_M' X_i + \theta_M' Z_{ct} + \xi_M' SLR_i \times Z_{ct} + \Lambda_{ZDEBM}^M + \Lambda_L + \varrho_M + \epsilon_{it}^M. \quad \text{(M1)}$$

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.[32] Based on Table 1, we hypothesize that:

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[30] Recall from Proposition 2 that a sufficiently pessimistic buyer ($\lambda > \lambda^*$) purchasing a sufficiently exposed property ($d > \bar{\lambda} f$) should have high leverage probability and long maturity. This motivates why we include the SLR dummy and its interaction with the pessimistic buyer dummy in the empirical specification.

[31] 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.

[32] For transactions with more than one mortgage, we use the lender from the first mortgage for the lender fixed effect. 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.

Hypothesis 4 ($\gamma_M > 0$). *In leveraged transactions of at-risk properties, more pessimistic buyers are more likely to pick a mortgage with long maturity.*

Specifications (L1) and (M1) are our main regression equations. We estimate them using the ordinary least squares (OLS) estimator.[33]

5.3 Results

5.3.1 Setting the stage: Housing price

Table 2 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 risk and price. This is not surprising: 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 2: 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: transactions of single-family homes within 1km from the East Coast between 2001 and 2016. See Section 5.1 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 literature that the coastal property market is discounting future SLR risks.

[33] 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).

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 (summarized by Hypotheses 1 and 2), we now move on to our main results on mortgage outcomes.

5.3.2 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 3: 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 2 for the definitions of the remaining variables.

Table 3 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 at-risk properties 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 at-risk properties 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 corresponds to specification (L1) that tests Hypothesis 3. It 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, at-risk properties 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.[34] 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*×*PessBuyer* remains strongly statistically significant. The magnitude of the coefficient reduces slightly to about 3.4%, but it 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.[35] Column 5 aims to address this concern. It repeats the exercises in column 4 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. (Section 6.4 provides additional robustness checks regarding the SLR risk measure.)

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* × *PessBuyer* is larger and statistically different from the estimate of 2.6% for *Moderate SLR Risk* × *PessBuyer*. Consistent with our model's comparative static

[34] Ideally, we would like to control for buyer-specific characteristics such as income, wealth, or credit score. However, as described in Section 5.1, the only individual-level information we observe is the location that a buyer comes from. Thus, we also include aggregated statistics from the buyer's origin.

[35] 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. 2013).

prediction on d in Corollary 3, the more exposed a property is, the higher the likelihood that its transaction with a pessimistic buyer is going to be leveraged.

Overall, our findings on the relationship between SLR risk and leverage are consistent with our theoretical prediction on the extensive margin of leverage (Proposition 2).

5.3.3 Intensive margin: Maturity

	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 4: Effects of exposure to SLR risk and its interaction with climate belief on *Long Maturity*, an indicator for whether the mortgage term is at least 30 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 3.

With a similar structure to Table 3, Table 4 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 has no 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, corresponding to specification (M1), shows that among leveraged transactions with likely pessimistic buyers, at-risk properties 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. 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 at-risk properties, likely pessimistic buyers are more likely to leverage (Hypothesis 3) and use debt contracts with longer maturities (Hypothesis 4).

6 Robustness and further analysis

6.1 Climate beliefs

If climate optimists are more likely to sort toward coastal properties (e.g., Bakkensen and Barrage 2022), 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, there are several reasons to believe it is not a dominant biasing force in our context.

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.[36] 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 toward 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 2 that we instead find a strong and robust negative capitalization of SLR risk into home prices.

Nonetheless, since beliefs play a central role in our analysis, this section provides a battery of robustness checks of our results to alternative definitions of the pessimistic buyer variable.

6.1.1 Inferring individual-level climate beliefs from home prices

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 at the time of sale. The underlying idea is that the housing price should reflect the homebuyer's climate belief (recall

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

the model in Section 4.5). Hence, the extent to which the housing price capitalizes the SLR risk should reveal the extent to which the homebuyer is concerned about the risk.[37]

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 5.2, suppose that housing price is given by:

$$\ln Price_{it} = \beta_P SLR_i + \gamma_P SLR_i \times \lambda_{it} + \delta_P \lambda_{it} + \text{controls}_{it} + \epsilon_{it}^{\lambda}, \tag{21}$$

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).[38]

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

$$\ln Price_{it} = \beta_P SLR_i + \text{controls}_{it} + \zeta_{it}. \tag{22}$$

We then predict the residual from equation (22) 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 (21).[39] Intuitively, if we observe a homebuyer paying a lower price for an identical property in a location exposed to SLR risk, ceteris paribus, then they must be more pessimistic. Define our imputed (cardinal) climate belief parameter as:

$$\hat{\lambda}_{it} \equiv -\hat{\zeta}_{it}. \tag{23}$$

Under the assumptions above, $\hat{\lambda}_{it}$ is positively correlated with the unobserved climate pessimism λ_{it} of the homebuyer in transaction it. Finally, we define the (ordinal) dummy $\widehat{PessBuyer}_{it}$ to be one if $\hat{\lambda}_{it}$ is above the median predicted sample value and $SLR_i = 1$, and zero otherwise.[40]

Replacing the county-level dummy $PessBuyer_c$ with the transaction-level dummy $\widehat{PessBuyer}_{it}$ for whether the buyer in the transaction is a likely pessimist, we re-estimate the main mortgage regressions (L1) and (M1). As reported in Table 5, our result for the leveraged regression continues to hold: largely consistent with our previous estimates in Table 3, 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 ($p < 0.1$).

[37] In Section 4.5, we showed that price differences between optimists and pessimists are influenced by a standard hedonic term—more negative for pessimists—and a mortgage term from the expected surplus of an optimal mortgage contract—more positive for pessimists. Following existing literature (see a review in Beltrán et al. 2018), we exclude the mortgage term for simplicity. However, as indicated by the significant price difference estimated in Table 2, the impact of the mortgage term is likely minor.

[38] In particular, $\text{controls}_{it} = \phi_P' X_i + \theta_P' Z_{ct} + \xi_P' SLR_i \times Z_{ct} + \Lambda_{ZDEBM}^P + \varrho_P$.

[39] Note that SLR_i is a binary variable and γ_P and δ_P are scalar transformations of λ_{it}. From the findings in Section 5.3.1, climate pessimists tend to pay less for an at-risk property relative to climate optimists ($\gamma_p + \delta_p < 0$). Hence, $\hat{\zeta}_{it}$ can be used to proxy individual climate beliefs.

[40] 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 $\widehat{PessBuyer}_{it} = 0$ for these transactions.

	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 × D × E × B × T fe	Y	Y
Property & buyer county controls	Y	Y
Buyer county controls × SLR	Y	Y
Lender fe		Y
N	210,764	62,926
R^2	0.440	0.442

Table 5: Robustness with alternative specifications for the belief measure using transaction-level imputed beliefs. Beliefs are imputed following the procedure in Section 6.1.1. 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 3 and 4.

Furthermore, Table A2 provides the pairwise correlation between the continuous and binary versions of our imputed $\hat{\lambda}_{it}$ beliefs data and other beliefs specifications 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 specifications.[41]

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.

6.1.2 Alternative specifications using Yale Climate Opinion data

Furthermore, Table A3 provides a series of robustness checks for benchmark regressions (L1) and (M1) with alternative specifications for the the belief variable based on the Yale Climate Opinion Survey. The set of controls and fixed effects remain as in the benchmark regressions. For brevity, we only report the estimates for the relevant coefficients of the interaction term between SLR Risk and the corresponding belief variable.

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 ten 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 *n*th quartile of belief and zero otherwise.

[41]See Section 6.1.4 for a description of our Gallup data beliefs exercise.

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 ten years.

Overall, our results consistently hold across this variety of climate beliefs specifications.

6.1.3 Omitted belief covariates

A related concern is that climate beliefs in the Yale survey could be correlated with other individual-level unobservable characteristics that could confound the analysis. To address these concerns, we include a variety of additional control variables in our main specifications. In Table A4, 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).[42] In Table A5, 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.

6.1.4 Beliefs using Gallup data

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. We utilize annual waves of Gallup survey data from 2000 to 2020, totalling 10,339 observations where climate beliefs are elicited.[43] In parallel with the Yale climate beliefs estimation methodology described in Howe et al. (2015), we model beliefs based on respondent age, race and ethnicity, education, gender, as well as state and year fixed effects. We then use the model results to predict climate beliefs at the county-by-year level, based on county-by-year level averages of these socioeconomic variables.

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 A6 displays the Gallup beliefs model replicating our leverage and maturity results, which are very similar to our main results.

[42] 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.

[43] 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 check, we also estimate beliefs based on how worried the respondent is regarding climate change.

6.1.5 Placebo test

As a final check for beliefs, we examine the role of climate beliefs for transactions with low SLR risk. Given our identification strategy, climate beliefs should not impact mortgage behaviors in these transactions. Thus, we re-estimate our main results for the subset of homes where $SLR = 0$ in Table A7. Reassuringly, we find that climate beliefs have no predictive power.

6.2 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). 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. 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' securitization rules and guarantee fees tend to only reflect current official floodplain maps and not future SLR risks.

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 should expect that our mechanisms to strengthen in the segment of conforming loans:

Hypothesis 5. *The leverage and maturity channels are stronger among the subsample of conforming loans than among nonconforming loans* ($\gamma_L^{conforming} > \gamma_L^{nonconforming}$, $\gamma_M^{conforming} > \gamma_M^{nonconforming}$).

We investigate this securitization mechanism in Table 6. 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. We then match each property with the conforming loan limit in the county and year of purchase (see Appendix B.1 for details). In column 1, we repeat the main 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 Hypothesis 5, 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 uses a long-maturity mortgage *and* the mortgage is conforming (nonconforming) in column 3 (column 4). The estimates for $SLR \times PessBuyer$ are positive and significant for the conforming long-maturity outcome (column 3), but negative and significant for the nonconforming long-maturity outcome (column 4).

Overall, the results in Table 6 confirm Hypothesis 5.[44]

	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 6: 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 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 3 and 4.

6.3 Flood insurance

A potential confounding factor is the presence of flood insurance in this setting. In the U.S., the flood insurance market is dominated (≥95% of policies) by the National Flood Insurance Program (NFIP), which is managed by the Federal Emergency Management Agency (FEMA) (Kousky et al., 2018). While we do not observe whether a property in our sample is covered by flood insurance, we can proxy for insurance by using official floodplain maps. A property inside one of FEMA's Special Flood Hazard Areas (SFHAs) is required to have flood insurance if it is purchased with a GSE-backed mortgage, and voluntary insurance uptake is low outside of such areas (Kousky and Michel-Kerjan, 2017; Kousky et al., 2017; Sastry, 2021).

We match each property with its flood risk zone using NFIP Flood Insurance Rate Maps,

[44]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. 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. 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. Table A12 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.

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 a variable *FEMA zone* that is equal to one if a property is in a high risk flood zone (A- or V-type zone in FEMA's classification of SFHAs) and zero otherwise.

In Table A8, we include this FEMA zone dummy as an additional variable in our main regressions and also interact it with our climate beliefs variable. Our main results remain robust in sign, magnitude, and significance. Furthermore, the coefficient of the FEMA zone dummy is negative and significant in the leveraged regression, which is consistent with the fact that lending regulations increase the cost of leverage in the flood zone (e.g., the requirement that the homebuyer purchases flood insurance if they want to use a federally-backed mortgage or mortgage issued by a federally-regulated lender, Blickle and Santos 2022). Interestingly, the interaction between climate beliefs and FEMA flood zone does not significantly impact the leverage decision. This further reassures us that our results are being driven by beliefs over future SLR and not by current flood risk or insurance requirement.

6.4 Additional exercises

Appendix B.2 provides five additional robustness checks (alternative SLR risk measurement, alternative fixed effects, owner occupied vs. non-owner occupied transactions, excluding bad controls, results over time) and an additional analysis of other intensive margins of leverage.

7 Potential implications to financial stability

Having provided robust evidence of the model's implications, we now discuss potential policy implications. The U.S. mortgage debt market is dominated by the prevalence of long-term fixed-rate 30-year mortgages,[45] making its financial system exposed to long-run risks. We can analytically analyze the effects of potential policy reforms on the stability of the financial system to long-run SLR and climate-related disaster risks through the lens of our model.

7.1 Aggregate measure of financial risk

To do so, we first generalize the baseline model to have multiple types of borrowers' beliefs (λ) and houses' exposure to the disaster (d). There is a unit measure of atomistic homebuyers. At $t = 0$, each homebuyer is exogenously matched with a house. Homebuyers have different beliefs about the arrival rate of the disaster. Each house's disaster exposure parameter d and the matched homebuyer's belief parameter λ are distributed according to a joint probability distribution function ϕ. As before, there are competitive lenders with a common belief parameter $\bar{\lambda}$.[46] Homebuyers search for lenders through competitive search and matching, and markets clear in equilibrium (see details in Appendix A.2.8).

[45] For example, more than 70% of GSE-backed mortgages (Section 7.5) have a maturity of at least 30 years.

[46] The assumption that lenders have the same belief is without loss of generality: if lenders were to have different beliefs in $[\bar{\lambda}, \bar{\bar{\lambda}}]$, then only the lenders with the most optimistic belief $\bar{\lambda}$ will lend in equilibrium.

The general model has a direct measure of how climate disasters can affect financial stability—the measure of risky mortgages that will be defaulted when the disaster hits:

$$\mathcal{A}_T^{\text{risky}} \equiv \int_{\underbrace{\lambda > \lambda^*, d > \bar{\lambda} f}_{\text{risky mortgage domain}}} \overbrace{\phi_T^*(\lambda, d)}^{\text{equilibrium density}}, \tag{24}$$

where the belief cutoff threshold $\lambda^* = \lambda^*(d)$ is given by (12), and the joint density of mortgages in equilibrium ϕ^* is derived from the exogenous joint density ϕ of homebuyer and house types, equilibrium leverage probability α^* and maturity rate μ^*:

$$\phi_T^*(\lambda, d) \equiv \overbrace{e^{-r\mu^*(\lambda,d)T}}^{\text{measure of outstanding mortgages at } T} \overbrace{\alpha^*(\lambda, d)}^{\text{loan approval probability}} \phi(\lambda, d). \tag{25}$$

Hence, $\mathcal{A}_T^{\text{risky}}$ is the count of all risky mortgages that are outstanding (have not matured) at the disaster date T. This number has a direct welfare meaning: the aggregate dead weight loss due to default at the disaster date is $\mathcal{A}_T^{\text{risky}} f$. Hence, through the lens of the model, we view $\mathcal{A}_T^{\text{risky}}$ as an aggregate measure of mortgages at risk in the financial market.

7.2 Phasing out GSEs' guarantee subsidy

The macrofinance literature has argued that subsidized GSEs' guarantees lead to riskier mortgage originations (and a higher incidence of default and ultimately a higher fragility of the financial system (Jeske et al. 2013; Elenev et al. 2016)). Our analysis adds a novel time dimension to this discussion: subsidized guarantee fees especially lead to riskier *long-term* mortgage origination, thus making the mortgage market more exposed to *long-run* risks.

Hence, a policy implication of our model is that *phasing out the guarantee subsidy in at-risk areas would lower the mortgage market's exposure to long-run (SLR) risks.*[47]

To see this, recall the GSE extension in Section 4.3: a smaller guarantee fee g translates to more optimism in lenders' evaluation of a risky loan, especially one with a longer maturity. Hence an increase in g, representing a phasing out of the guarantee subsidy, translates to less lender optimism—*especially* in evaluating long-term risky loans. The effect of g on $\mathcal{A}_T^{\text{risky}}$ can be decomposed in to several components:

$$\frac{\partial}{\partial g}\mathcal{A}_T^{\text{risky}} = \underbrace{-\int_{d>\bar{\lambda}f} \underbrace{\frac{\partial \lambda^*}{\partial g}}_{>0} \phi^*(\lambda^*, d)}_{\text{aggregate extensive margin, } <0} + \underbrace{\int_{\substack{\lambda>\lambda^*,\\ d>\bar{\lambda}f}} e^{-r\mu^* T} \underbrace{\frac{\partial}{\partial g}\alpha^*}_{<0}}_{\text{individual extensive margin, } <0} + \underbrace{\int_{\substack{\lambda>\lambda^*,\\ d>\bar{\lambda}f}} \phi^*(\lambda, d) \underbrace{\left(-rT\frac{\partial}{\partial g}\mu^*\right)}_{<0}}_{\text{intensive margin, } <0}. \tag{26}$$

The terms capture the fact that an increase in g reduces (i) the domain of risky borrowers by

[47] For example, Gete et al. (2024) estimate that currently the g-fees in counties with the highest hurricane risks are about 40% below the market-implied g-fees (i.e., what the fees should be if the default risk was priced by the market). GSEs' guarantee fees generally tend to be rigid and do not reflect relevant spatial variations, including predictable regional variations in default risks, leading to an implicit cross subsidization from less at-risk areas to more at-risk areas (Hurst et al. 2016; Gete et al. 2024).

raising the belief threshold λ^* for risky borrowers in equilibrium, (ii) the equilibrium probability α^* that a risky mortgage is approved, and (iii) the equilibrium mortgage maturity and hence the measure of risky mortgages that have not matured by the disaster period T. All of the components are negative, reinforcing an ultimate reduction in the volatility of the mortgage market due to the disaster shock. The effects of an increase in the skin-in-the-game parameter θ on $\mathcal{A}^{\text{risky}}$ are similar to those of an increase in g.

Remark 6 (MBS). The GSEs' guarantee plays a crucial role in pricing agency MBSs (mortgage-backed securities guaranteed by the GSEs). As witnessed in the Great Recession, the agency MBS has long been an important market for financial stability. The GSEs' guarantee effectively transforms the default risk to a prepayment risk to MBS investors (Weiner, 2016). Intuitively, when a mortgage is defaulted, the GSEs make a lump-sum guarantee payment of the unpaid balances to MBS investors, like a prepayment of the loan. Appendix A.2.9 formalizes the relationship between the GSEs' guarantee and the volatility in the MBS price, and shows that the disaster causes a drop in the MBS price. Our policy discussion above applies: a phasing out of the GSE subsidy will reduce the prepayment risk in the MBSs.

Remark 7 (News shocks). While we have focused on the ramifications of the disaster shock, the analysis in this section can also be applied to study the ramifications of a *news* shock about the disaster process.[48] Recall the extension in Section 4.8. There, a bad news shock that make agents more pessimistic can trigger equilibrium defaults. Similarly, an unanticipated news shock that increases the dispersion of beliefs, which make *some* agents more pessimistic, will also trigger equilibrium defaults by the borrowers who become more pessimistic about the value of the underlying collateral. Thus, our model can connect to a major policy concern that with the potential for sudden shifts in the perceptions of risk, slow-moving hazards like SLR can still pose risks to mortgages, MBSs, and ultimately increases the fragility of the financial system (Brunetti et al., 2021). Our policy discussion above applies: an increase in g will reduce the aggregate number of defaults due to a bad news shock.

Remark 8 (Phasing out maturity subsidies). Through the GSEs and other government agencies, the U.S. government has a long history of policies that aims to make homeownership more affordable by subsidizing long-term mortgage lending, which spreads out the cost of paying for a house over time.[49] So far we have treated g as a parameter, but we can also think of g is an increasing function of μ (a lower guarantee fee for a long-term mortgage with a lower

[48] An example is the release of more pessimistic SLR forecasts that led to increased capitalization of SLR risk in financial markets (Goldsmith-Pinkham et al., 2023) since 2013.

[49] For example, the National Housing Act of 1934 established the Federal Housing Administration (FHA), which guaranteed long-term fixed-rate mortgages with low down payment. In 1938, to further encouraging mortgage lending, the government chartered the Federal National Mortgage Association, or Fannie Mae, a GSE that purchased FHA-guaranteed loans and kept them on its own balance sheet. In 1970, to further improve the liquidity of the mortgage market, the U.S. Congress established another GSE, the Federal Home Loan Mortgage Corporation, or Freddie Mac, which bought mortgages from lenders on the secondary market, pooled them, and sold them as mortgage-backed securities (MBS) on the open market. Since then, the GSEs have been the key players in major developments of the U.S. mortgage and MBS markets, and their presence are essential for the prevalence of long-term fixed-rate mortgages. In the aftermath of the 2008 housing crisis, these GSEs have been placed under government conservatorship, whereby the federal government retains operational control and effective ownership. See, e.g., Wells (2023) for further historical context.

maturity rate μ), due to the presence of such policies. We can similarly show that a phasing out of GSEs' support for long-term mortgages (a decline in the slope of g with respect to μ) reduces the mortgage market's exposure to long-run risks.

7.3 Insurance mandate

Our model also implies that *an insurance mandate reduces the mortgage market's SLR risk exposure.* Recall the insurance extension in Section 4.1. There, without a mandate, the risky leverage option reduces the voluntary demand for insurance and hence exacerbates the underinsurance problem. With a mandate, the insurance program reduces the disaster damage, and hence reduces the measure of risky mortgages (because $\partial \mathcal{A}^{\text{risky}}/\partial d < 0$).

In practice, as noted in Section 6.3, flood insurance is mandatory for borrowers if their loans are backed by the GSEs and their properties lie in Special Flood Hazard Areas on official FEMA floodplain maps. However, official FEMA floodplain maps tend to underestimate current and future flood risks (Sastry 2021).[50] Hence, a corollary of the implication above is that an improvement of the official floodplain maps will help reduce the mortgage market's exposure to flood risks. In practice, an example of such improvement include Risk Rating 2.0, a 2021 FEMA initiative to reform the NFIP with the modernization of outdated maps with more detailed property-specific assessment of flood risks that account for climate change.[51]

Similarly, the model implies that *an increase in the insurance coverage cap* (currently set by the NFIP at \$250,000) reduces the risky mortgage measure, as $\partial \mathcal{A}^{\text{risky}}/\partial c < 0$. Conversely, the withdrawal of coverage by private insurers, as documented by Sastry et al. (2023), will exacerbate the mortgage market's risk exposure.

7.4 Disaster forbearance

Homeowners with GSE-backed mortgages are eligible for a temporary loan forbearance after a natural disaster, and recall from the positive analysis in Section 4.2 that this forbearance provides an additional motive for pessimistic homeowners to leverage. Hence, another implication is that *an expansion of the forbearance ($\uparrow \varepsilon$)* increases *the measure of risky mortgages*:

$$\frac{\partial \mathcal{A}_T^{\text{risky}}}{\partial \varepsilon} = \underbrace{\int_{\substack{\lambda>\lambda^*,\\ d>\bar{\lambda}f}} e^{-r\mu^* T} \underbrace{\frac{\partial}{\partial \varepsilon}\alpha^*}_{>0}}_{\text{extensive margin, }>0} + \underbrace{\int_{\substack{\lambda>\lambda^*,\\ d>\bar{\lambda}f}} \phi^*(\lambda, d) \underbrace{\left(-rT\frac{\partial}{\partial \varepsilon}\mu^*\right)}_{>0}}_{\text{intensive margin, }>0}.$$

The following table summarizes our discussion in from Section 7.2 to Section 7.4:

[50] For example, 20% of properties that are projected to be inundated with 6ft of SLR in our sample lies outside of official FEMA floodplains. First Street Foundation finds almost 70% more properties are at high flood risk (1 in 100 annual probability) relative to FEMA's official estimates (First Street Foundation, 2020).

[51] However, such reforms have proven to be politically difficult in practice. For example, in 2023, several states filed a lawsuit against FEMA for implementing Risk Rating 2.0 (also known as Equity in Action). Among other things, the lawsuit challenged the reform for "the inappropriate factor of future climate change, which does not relate to the risk a property actually faces today" and alleged that "FEMA acted pretextually because it imposed Equity in Action to further the Administration's climate-change agenda" (Louisiana v. Mayorkas, 2023). Hurst et al. (2016) has documented a similar political difficulty in reforming GSE pricing policies.

Phasing out GSE guarantee subsidy ($\uparrow g$ or $\uparrow \theta$)	Expanding insurance mandate or expanding coverage ($\uparrow c$)	Expanding disaster forbearance ($\uparrow \varepsilon$)
$\mathcal{A}^{\text{risky}} \downarrow$	$\mathcal{A}^{\text{risky}} \downarrow$	$\mathcal{A}^{\text{risky}} \uparrow$

Table 7: Summary of model's policy implications on financial stability.

Remark 9 (Time inconsistency problem). The fact that the measure of risky mortgages is increasing in the disaster forbearance parameter implies an interesting time-inconsistency problem in disaster forbearance policies, similar to the well-known time-inconsistency problem in bailout policies (Chari and Kehoe 2016; Keister 2016). Suppose the government cannot commit to limiting future forbearance, which is aimed at reducing the bankruptcy costs in the aftermath of the disaster. Anticipating a more generous forbearance due to the government's lack of commitment, borrowers find it optimal to increase their exposure to the disaster via (safe and risky) leverage. Hence, the lack of commitment leads to more risky debt and eventually more costly defaults in equilibrium. (Appendix A.2.10 provides a parsimonious model to illustrate this point further.)

7.5 Further empirical investigation of aggregate financial risk

To get a sense of the overall magnitude of mortgages at risk ($\mathcal{A}^{\text{risky}}$) in the U.S. economy, we examine the exposure of the portfolio of GSE-backed mortgages to future flood risks (both coastal and inland, taking into account climate change).[52] In particular, we analyze a comprehensive database of more than 100 million fully amortizing single-family fixed-rate mortgages that Fannie Mae and Freddie Mac backed (purchased or guaranteed) between 1999 and 2023 across the whole U.S. The database provides the history of each loan's performance over time, including the timing of missed payments and default. We combine this GSE balance sheet data with a comprehensive database of projected flood risks for 145 million properties across the whole U.S., provided by the First Street Foundation (FSF). The FSF data provides a risk score, the Flood Factor, that estimates each property's risk of flooding (both coastal and inland), cumulative between 2020 and 2050, assuming moderate Shared Socioeconomic Pathways 2-4.5 for climate change (see Appendix B.4 for details).

While comprehensive, a drawback of the GSE data is that, due to confidentiality, the GSEs do not provide the exact address of each mortgage, but only the 3-digit ZIP containing the underlying property. Hence, we could only assign a coarse estimate of each loan's flood risk: we match the loan to the average flood factor of properties that lie in the same ZIP.[53]

Restricting attention to mortgages that are outstanding in the latest year of available data

[52] Our estimates of the total number of at-risk mortgages should be viewed as a lower-bound for $\mathcal{A}^{\text{risky}}$, as our GSE dataset does cover non-GSE-backed mortgages. For comparison, in the third quarter of 2023, outstanding mortgage debt owed by U.S. households was \$12.9 trillion; GSE MBS accounted for 65.1% (\$9 trillion) of that outstanding debt (Urban Institute, 2023). However, to the extent that risky loans are sold to the GSEs at higher rates relative to safe loans, then our estimates of the *fraction* of mortgages that are at risk in Table 8 should be an upper bound for the overall fraction of at-risk mortgages in the U.S. economy.

[53] We acknowledge that this may lead to a biased estimate of a loan's risk. Specifically, to the extent that there is adverse selection into the GSE loan sample (i.e., all else equal, mortgages with higher flood risks are more likely to be sold to the GSEs), then our proxy is likely an underestimate of the loan's actual flood risk.

(2023), Table 8 summarizes the exposure of the GSEs to future flood risk. The table shows that according to our calculation, more than a quarter of outstanding mortgages (or more than 23 million loans, with a total outstanding balance of more than $2 trillion dollars in our sample) are *at risk* of future flooding, defined in this subsection as lying in a ZIP code with an average Flood Factor of at least 2. A smaller fraction of more than 5% are at *higher risk*, defined as lying in a ZIP code with an average Flood Factor of at least 3.[54,55]

	Total sample	% at risk	% at higher risk
Number of outstanding loans	89.58m	26% (23.34m)	5.7% (5.10m)
Total outstanding balances	$8.17tr	27% ($2.22tr)	5% ($0.41tr)

Table 8: Summary statistics of GSE exposure to future flood risk. Sample: outstanding (as of Jan 2023) single-family fixed-rate mortgages that Fannie Mae and Freddie Mac purchased or guaranteed since 1999. A loan is classified as *at risk* (*at higher risk*) if it lies in a 3-digit ZIP that has an average Flood Factor of at least 2 (at least 3).

A key mechanism in our model is the ability of borrowers to default on their mortgages following a disaster. We examine this mechanism by conducting an event study to investigate default frequencies before and after a large hurricane. We focus on the sample of more than half a million GSE loans in coastal Florida 1.5 years before and 1.5 years after Irma, a Category 4 hurricane that made landfall in the state on September 10, 2017 (see Appendix B.4 for details). Our difference-in-differences regression of the default dummy includes a stringent set of loan fixed effects and time fixed effects. The regression reveals that Hurricane Irma significantly increased the default frequency in affected ZIP codes by more than 40 basis points (bps) (standard error: 3 bps) in the subsequent six quarters. In comparison, the baseline cumulative default frequency in the preceding 6 quarters was 80 bps. Figure A3 plots the observed means and linear trends of the default frequencies among the loans in ZIP codes affected by Irma (the treatment group) and those in unaffected ZIP codes (the control group).

Our estimate of 40 bps for Hurricane Irma in Florida is comparable to an independent estimate in Du et al. (2020) of 10 bps for Hurricane Harvey in Texas and 86 bps for Hurricane Maria in Puerto Rico. Using a larger sample of disasters that caused at least a billion dollars in direct damage according to NOAA estimates, Ouazad and Kahn (2022) (Figure Ca) estimated that on average such a disaster increased the foreclosure frequency in affected ZIP codes by about 150 bps. Together, these estimates provide evidence that climate-related disasters led to a significant increase (both statistically and economically) in the default frequency of mortgages in affected areas. However, these estimates rely on relatively coarse definitions of disaster (at the ZIP code level), and may underestimate the effects of the disaster damage.[56]

[54] According to our own calculation using FSF's property-level projections, the average probability of having at least one flood in the next 30 years is more than 18% among the at-risk sample (properties with Flood Factor ≥ 2), and more than 32% among the at-higher-risk sample (properties with Flood Factor ≥ 3).

[55] Our estimates are similar to a recent report by DeltaTerra Capital that found 13.3% of 32 million GSE-backed loans analyzed were at high risk for flooding (Burt 2021).

[56] For example, Kousky et al. (2020) studied the performance of a smaller sample of loans, for which there is property-level information of flood damage from Hurricane Harvey. They found that, compared with similar properties having no damage, moderate to severe flood damage increases the frequency of mortgage default or

8 Conclusion

What makes climate-related disaster risks special? There are several outstanding characteristics: (i) they could have potentially large damages to collateralized capital, (ii) the risks are back-loaded (most damages will occur in the future, and there is limited insurance today against such long-run damages), and (iii) there is substantial belief disagreement over climate risks, especially in the U.S. Our paper theoretically and empirically examines the case of flood risks due to SLR, arguing that the combination of these features is key in understanding the effects of SLR risks on the financial market. 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.

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 (for the distribution of climate risks across the financial system and broader financial stability) due to the strategic transfers of climate risks. We have only scratched the surface of analyzing 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. Future work could explore additional 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 time-consistent 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 Acharya et al. 2023) should take the strategic transferring of climate-related risks into account.

Future work could also explore the roles of several important margins not considered in this paper. For instance, one could extend our theoretical model to allow agents to resell the house, and expand our empirical analysis to study whether climate risks and climate beliefs affect how resalable a property is. One could extend our framework to study potential interactions between mortgage choice and residential sorting (à la Bakkensen and Ma 2020; Bakkensen and Barrage 2022). Finally, one could examine the financial implications of belief disagreement about transition risks, including the disagreement over the paths of future climate policies (e.g., carbon taxes, emission regulations, climate treaties). These are some open questions that will remain pertinent for decades to come.

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severe delinquency by 2.6 times. Similarly, using high-resolution data of California wildfire perimeter, Biswas et al. (2023) estimated that the delinquency of mortgages of damaged properties increased by up to 400 bps, compared to mortgages of undamaged ones.

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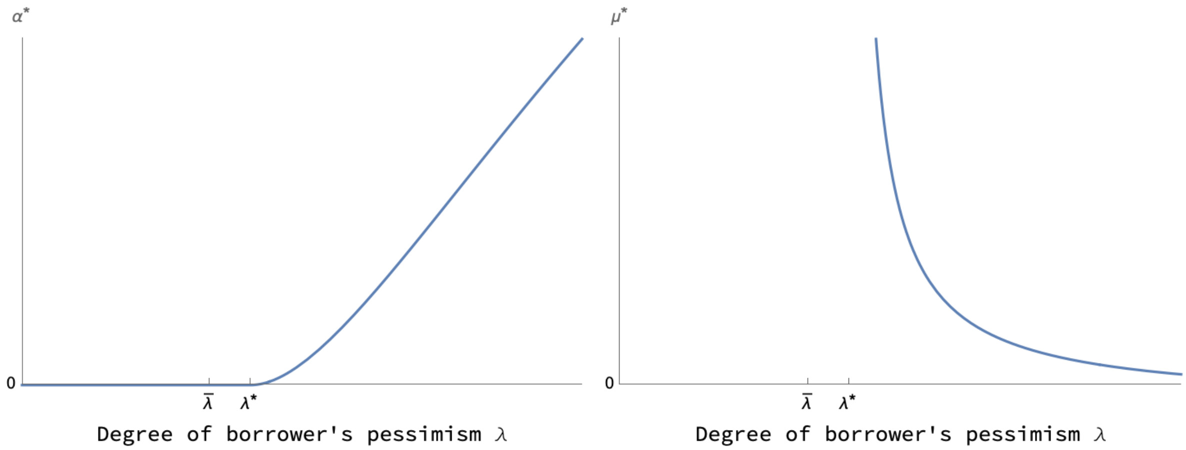
A Online Appendix: Theory



(a) Equilibrium leverage probability.

(b) Equilibrium maturity rate (note: lower maturity rate μ^* implies a mortgage with a longer maturity).

Figure A1: Equilibrium leverage probability α^* and maturity rate μ^* (assuming the house is sufficiently exposed that $d > \bar{\lambda} f$).

A.1 Omitted proofs

A.1.1 Proof of Lemma 1

Since there are only two events, namely disaster and loan maturity, the optimal default time is contingent on the timing of the disaster and loan maturity and takes the following form:

$$\tau^* = \begin{cases} \tau_0 & \text{before the disaster and loan maturity} \\ T + \tau_d & \text{after the disaster but before loan maturity} \\ \infty & \text{after loan maturity} \end{cases},$$

where τ_0 and τ_d are constants to be determined.

Solving the buyer's default decision backward, consider the subgame after the disaster has happened at $t = T$ but before the loan matures. Denote $t_\mu = T_\mu - T$ as the distance to the maturity date, where t_μ follows the exponential distribution with parameter $r\mu$. The buyer's continuation value at $t = T$ from the strategy of defaulting at $T + \tau_d$ is given by:

$$W(\tau_d) \equiv \int r\mu e^{-r\mu t_\mu} \left\{ \begin{array}{l} \int_0^{t_\mu \wedge \tau_d} re^{-rt} (h - d - b)\, dt \\ +e^{-r\tau_d} 1_{\tau_d \le t_\mu} \left[-f + \{h - d - B\}_+\right] \\ +e^{-rt_\mu} 1_{\tau_d > t_\mu} (h - d) \end{array} \right\} \mathrm{d}t_\mu,$$

where we have made use of the fact that the housing price after the disaster is given by its fundamental value $(h-d)/r$. The value function satisfies the following Hamilton–Jacobi–Bellman (HJB) equation:

$$\frac{d}{d\tau} W(\tau) = r(h - d - b) + r\mu [h - d - W(\tau)] - rW(\tau). \tag{27}$$

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, $r(h - d - b)$, 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 (27):

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

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

$$W(\tau) = \left[1 - e^{-r(1+\mu)\tau}\right](h - d - B) + e^{-r(1+\mu)\tau} \left[-f + \{h - d - B\}_+\right]. \tag{28}$$

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 (without loss of generality) a tie-breaking rule that a borrower chooses to repay when they are indifferent. The first term is a downward-sloping curve in B; the second term is a downward-sloping curve in B with the same slope for all $B < h - d$ but then flat at $-f$ for all $B \ge h - d$. 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:

$$B^{\text{safe}} = h - d + f. \tag{29}$$

The optimal stopping time of default thus follows the bang-bang rule:

$$\tau_d \equiv \arg\max_{\tau} W(\tau) = \begin{cases} \infty & \text{if } B \le B^{\text{safe}} \\ 0 & \text{if } B > B^{\text{safe}} \end{cases},$$

and the continuation value under this optimal default strategy is:

$$W^{*}(B) \equiv W(\tau_d) = \begin{cases} h-d-B & \text{if } B \leq B^{\text{safe}} \\ -f & \text{if } B > B^{\text{safe}} \end{cases}. \tag{30}$$

Now, consider the subgame at $t=0$ before the disaster and loan maturity. Recall that the maturity date arrives at rate $r\mu$ while, according to the borrower's belief, the disaster date arrives at rate $r\lambda$. At $t=0$, the buyer's continuation value of defaulting at τ_0, where $\tau_0 \leq T$, is given by:

$$V_0(\tau_0) \equiv \int r\lambda e^{-r\lambda T} \int r\mu e^{-r\mu T_\mu} \left\{ \begin{array}{l} \int_0^{\min(T_\mu,\tau_0,T)} re^{-rt}(h-b)\,dt \\ +e^{-rT} 1_{T\leq \min(T_\mu,\tau_0)} W^{*}(B_T) \\ +e^{-r\tau_0} 1_{\tau_0 \leq T_\mu, \tau_0 < T} \left[-f + \left\{r\underline{p} - B_{\tau_0}\right\}_+\right] \\ +e^{-rT} 1_{T_\mu < \tau_0, T_\mu < T} v_\lambda \end{array} \right\} dT_\mu dT \tag{31}$$

The value function satisfies the following HJB equation:

$$\frac{d}{d\tau} V_0(\tau) = r(h-b) + r\mu\left[v_\lambda - V_0(\tau)\right] - r\lambda\left[V_0(\tau) - W^{*}(B)\right] - rV_0(\tau). \tag{32}$$

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, $r(h-b)$, and the expected gain of paying off the loan, $r\mu\left[v_\lambda - V_0(\tau)\right]$, minus the expected loss from the exposure to the disaster, $r\lambda\left[V_0(\tau) - W^{*}(B)\right]$, and the cost of discounting, $rV_0(\tau)$. At $\tau = 0$, the borrower defaults immediately, which gives the boundary condition to (32):

$$V_0(0) = -f + \left\{r\underline{p} - B\right\}_+.$$

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

$$V_0(\tau) = \left[1 - e^{-r(1+\lambda+\mu)\tau}\right] \underbrace{\frac{h - (1+\mu)B + \lambda W^{*}(B) + \mu v_\lambda}{1+\lambda+\mu}}_{V_1(B)} + e^{-r(1+\lambda+\mu)\tau} \underbrace{\left[-f + \left\{r\underline{p} - B\right\}_+\right]}_{V_2(B)}. \tag{33}$$

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 (30), $V_1(B)$ is given by:

$$V_1(B) = \begin{cases} v_\lambda - B & \text{if } B \leq B^{\text{safe}} \\ \frac{h-\lambda f+\mu v_\lambda}{1+\lambda+\mu} - \frac{1+\mu}{1+\lambda+\mu} B & \text{if } B > B^{\text{safe}} \end{cases}.$$

$V_1(B)$ 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 decreasing 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 $B \leq r\underline{p}$; otherwise the slope equals 0. Also, notice that we have $V_1(0) = v_\lambda > r\underline{p} - f = V_2(0)$. 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 A2. Denote the intersection as $B = B^{\text{risky}}$, i.e., $V_1\left(B^{\text{risky}}\right) = V_2\left(B^{\text{risky}}\right) = -f$, where $V_1(b) > V_2(b)$ if $B < B^{\text{risky}}$ and vice versa. Notice that since $V_1\left(B^{\text{safe}}\right) = v_\lambda - (h - d + f) > -f = V_1\left(B^{\text{risky}}\right)$, we must have $B^{\text{risky}} > B^{\text{safe}}$. In sum, B^{risky} is given by setting the second region of $V_1\left(B^{\text{risky}}\right)$ to $-f$:

$$B^{\text{risky}} = h - \frac{\mu}{1+\mu}\frac{\lambda}{1+\lambda}d + f. \tag{34}$$

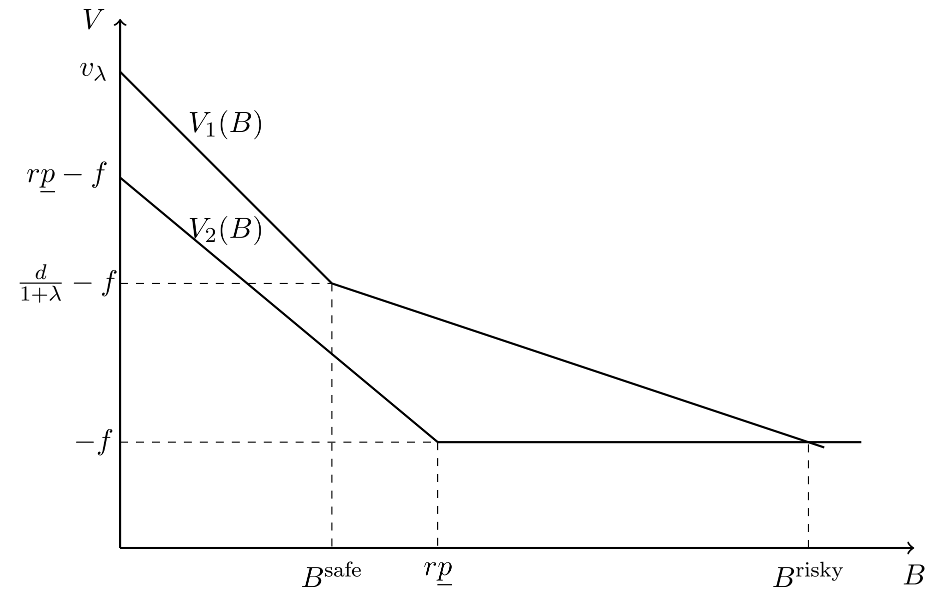


Figure A2: Illustration of value functions $V_1(B)$ and $V_2(B)$ from equation (33) and the determination of the risky debt limit B^{risky} in (34). Note that B^{safe} can be on the left-hand side or right-hand side of $r\underline{p}$ without affecting B^{risky}.

Summarizing the above cases, the optimal default time is as stated in Lemma 1. □

A.1.2 Proof of Proposition 2

Equations (8) and (9) an be rewritten as:

$$V_\lambda(\mathbf{m}) - v_\lambda = \begin{cases} -B & \text{if } B \leq B^{\text{safe}} \\ -B - \frac{\lambda}{1+\mu+\lambda}(h - d + f - B) & \text{if } B \in (B^{\text{safe}}, B^{\text{risky}}] \\ -v_\lambda - f & \text{otherwise} \end{cases}$$

$$R_{\bar{\lambda}}(\mathbf{m}) = \begin{cases} B & \text{if } B \leq B^{\text{safe}} \\ B + \frac{\bar{\lambda}}{1+\mu+\bar{\lambda}}(h - d - B) & \text{if } B \in (B^{\text{safe}}, B^{\text{risky}}] \\ r\underline{p} & \text{otherwise} \end{cases}.$$

Hence, the joint surplus $S(\mathbf{m}) = V_\lambda(\mathbf{m}) - v_\lambda + R_{\bar{\lambda}}(\mathbf{m})$ from any mortgage contract $\mathbf{m}$ can be written as:

$$S(\mathbf{m}) = \begin{cases} 0 & \text{if } B \leq B^{\text{safe}} \\ \left(\frac{1+\mu}{1+\bar{\lambda}+\mu} - \frac{1+\mu}{1+\lambda+\mu}\right)(B - B^{\text{safe}}) - \frac{\bar{\lambda}}{1+\bar{\lambda}+\mu} f & \text{if } B \in (B^{\text{safe}}, B^{\text{risky}}] \\ r\underline{p} - (v_\lambda + f) < 0 & \text{otherwise} \end{cases}.$$

It is immediate that choosing a mortgage contract with the loan balance exceeding the risky limit ($B > B^{\text{risky}}$) will never occur in equilibrium, since it will yield a negative surplus of $r\underline{p} - (v_\lambda + f) < 0$. Hence, it suffices to focus on contracts with $B \leq B^{\text{risky}}$.

For a risky mortgage ($B \in (B^{\text{safe}}, B^{\text{risky}}]$), given the linearity of the joint surplus, it is immediate that the surplus is maximized by choosing $B = B^{\text{risky}}$ if $\lambda > \bar{\lambda}$, and by choosing $B = B^{\text{safe}}$ otherwise. Furthermore, when $\lambda > \bar{\lambda}$, the surplus from choosing $B = B^{\text{risky}}$ can be simplified further as:

$$\left(\frac{1+\mu}{1+\bar{\lambda}+\mu} - \frac{1+\mu}{1+\lambda+\mu}\right)(B^{\text{risky}} - B^{\text{safe}}) - \frac{\bar{\lambda}}{1+\bar{\lambda}+\mu} f = \frac{\Delta}{1+\mu+\bar{\lambda}},$$

which is positive if and only if $\Delta > 0$, which is the case if and only if $\lambda > \lambda^*$ and $d > \bar{\lambda} f$.

Hence, if $\lambda \leq \lambda^*$ or $d \leq \bar{\lambda} f$, then it is never optimal to choose a risky mortgage contract. In this case, maximal joint surplus is achieved by choosing a safe mortgage contract. However, a safe contract only yields a joint surplus of zero. Given the presence of the maintenance cost $\kappa(\mu)$ and the fixed cost of entry κ_0, borrowing with any mortgage contract is never optimal in this case.

However, if $\lambda > \lambda^*$ and $d > \bar{\lambda} f$, then it is optimal to choose a risky mortgage with the risky debt limit binding $B = B^{\text{risky}}$. The equilibrium contract will have a per-period payment of $b^* = (1+\mu)B^{\text{risky}}$, a maturity rate μ^* that maximizes:

$$\max_{\mu \geq 0} \frac{\Delta}{1+\mu+\bar{\lambda}} - \kappa(\mu),$$

and a leverage probability α^* that maximizes:

$$\max_{\alpha\in[0,1]} \alpha \cdot \left\{ \frac{\Delta}{1+\mu^*+\bar{\lambda}} - \kappa(\mu^*) - \frac{\kappa_0}{\eta(\alpha)} \right\},$$

with a loan amount given by lenders' free-entry condition (6):

$$rl^* = \frac{1+\mu}{1+\mu+\bar{\lambda}} B^{\text{risky}} + \frac{\bar{\lambda}}{1+\mu+\bar{\lambda}}(h-d) - \frac{\kappa_0}{\eta(\alpha^*)} - \kappa(\mu^*).$$

□

A.1.3 Proof of Corollary 3

The comparative statics of μ^* and α^* are straightforward following the application of monotone comparative statics to their definition in Proposition 2.

For the comparative statics of the loan amount l^*, notice that the free-entry (6) condition implies that:

$$rl^* = \frac{1+\mu^*}{1+\mu^*+\bar{\lambda}} B + \frac{\bar{\lambda}}{1+\mu^*+\bar{\lambda}} (h-d) - \kappa(\mu^*) - \frac{\kappa_0}{\eta(\alpha^*)}. \tag{35}$$

For $\lambda > \lambda^*$, we have $\partial\mu^*/\partial\lambda < 0$. So, via μ, an increase in λ additionally increases the first two terms of (35), but decreases the third term. The overall sign of $\partial l^*/d\lambda$ becomes ambiguous for $\lambda > \lambda^*$. The same is true for $\partial l^*/\partial d$ for $\lambda > \lambda^*$.

Finally, since the loan rate r^* is defined as:

$$r^* \equiv \frac{R_{\bar{\lambda}}(\mathbf{m}^*)}{l^*} = r + \frac{\kappa(\mu^*) + \frac{\kappa_0}{\eta(\alpha^*)}}{l^*}, \tag{36}$$

which depends on l^*, so the overall signs of $\partial r^*/\partial\lambda$ and $\partial r^*/\partial d$ are ambiguous for $\lambda > \lambda^*$. □

A.2 Model extensions: Details

A.2.1 Disaster insurance

Proof of Lemma 4 We solve the equilibrium default strategy assuming that the borrower buys the insurance. Of course, if the borrower defaults, they will stop buying insurance for his asset. Consider the subgame after the disaster has happened but the debt contract has not matured yet. Let $i \in \{0,1\}$ denote the borrower's insurance uptake. Let τ denote their default period. Given insurance coverage c, the borrower's HJB equation is:

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

The optimal stopping time of default τ_i^* is given by

$$W_i^*(B) \equiv W_i(\tau_i^*) = \begin{cases} h-d+ic-B & \text{if } B \le \overbrace{B^{\text{safe}}}^{h-d} + ic \\ 0 & \text{if } B > B^{\text{safe}} + ic \end{cases}.$$

Now, consider the subgame before the disaster and before the loan matures. The HJB equation has the following solution:

$$V(\tau) = \left[1 - e^{-r(1+\lambda+\mu)\tau}\right] \underbrace{\max_{i\in\{0,1\}} \frac{h - i\lambda^I c - (1+\mu)B + \lambda W_i^*(B) + \mu v_\lambda^{\text{ins}}}{1+\lambda+\mu}}_{V_1(B)} + e^{-r(1+\lambda+\mu)\tau} \underbrace{\{r\underline{p} - B\}_+}_{V_2(B)}.$$

Thus, the borrower will buy insurance ($i = 1$) if and only if the cost is smaller than the benefit:

$$\frac{\lambda^I c}{\lambda} < W_1^*(B) - W_0^*(B) = \begin{cases} c, \text{ if } B \le B^{\text{safe}} \\ h - d + c - B, \text{ if } B \in (B^{\text{safe}}, B^{\text{safe}} + c] \\ 0, \text{ if } B > B^{\text{safe}} + c \end{cases}$$

Rearranging the above terms, we have:

$$i = 1 \Leftrightarrow \frac{\lambda^I c}{\lambda} < W_1^*(B) - W_0^*(B) \Leftrightarrow B < B_{\text{ins}}^{\text{safe}} \equiv B^{\text{safe}} + \left(1 - \frac{\lambda^I}{\lambda}\right) c.$$

Following the similar logic in the previous proof, we can summarize the borrower's value in the following regions:

$$V_\lambda(\mathbf{a}) = \begin{cases} v_\lambda^{\text{ins}} - B, \text{ if } B \le B_{\text{ins}}^{\text{safe}} \\ \frac{1+\mu}{1+\lambda+\mu}\left(B_{\text{ins}}^{\text{risky}} - B\right), \text{ if } B \in (B_{\text{ins}}^{\text{safe}}, B_{\text{ins}}^{\text{risky}}] \\ 0, \text{ if } B > B_{\text{ins}}^{\text{risky}} \end{cases}$$

where

$$B_{\text{ins}}^{\text{risky}} \equiv h - \frac{\mu}{1+\mu}\frac{\lambda}{1+\lambda}\left[d - \left(1 - \frac{\lambda^I}{\lambda}\right)c\right].$$

In the first region, the borrower buys the insurance and never defaults. In the second region, the borrower defaults when the disaster hits and buys the insurance only after the loan has matured (and not defaulted). In the last region, the borrower defaults immediately (and does not buy insurance, of course). □

Equilibrium characterization Assume $\lambda^I \le \bar{\lambda}$ and $f = 0$. Using the same steps as in Section A.1.2, we can characterize the equilibrium mortgage and insurance uptake as follows. There is a belief cutoff threshold:

$$\lambda_{\text{ins}}^* \equiv \bar{\lambda} + \frac{\bar{\lambda} - \lambda^I}{\frac{1}{1+\bar{\lambda}}\frac{d}{x} - 1} \ge \bar{\lambda} \ge \lambda^I,$$

such that:

1. A sufficiently pessimistic homebuyer with $\lambda > \lambda_{\text{ins}}^*$ at $t = 0$ chooses a risky mortgage contract with a risky loan amount $B = B_{\text{ins}}^{\text{risky}} \ge B^{\text{risky}}$. The buyer participates in the insurance program only after the mortgage contract has matured (i.e., at all $t \in [T_\mu, T)$). As before, the equilibrium leverage probability α^* increases and the loan maturity rate

μ^* solves:

$$\max_{\alpha} \alpha \cdot \left\{ \max_{\mu} \left[\frac{\Delta_{\text{ins}}}{1+\mu+\bar{\lambda}} - \kappa(\mu) \right] - \frac{\kappa_0}{\eta(\alpha)} \right\},$$

where $\Delta_{\text{ins}} = \Delta - \frac{1+\bar{\lambda}}{1+\lambda}(\lambda - \lambda^I)x \leq \Delta$. As before, α^* increases and μ^* decreases in λ.

2. A sufficiently optimistic homebuyer with $\lambda \leq \lambda^*_{\text{ins}}$ chooses not to borrow at $t = 0$. A very optimistic homebuyer with $\lambda \leq \lambda^I$ will never purchase insurance. A moderately optimistic homebuyer with $\lambda^I < \lambda \leq \lambda^*_{\text{ins}}$ purchases insurance at all $t \in [0, T)$.

In summary, our baseline results continue to hold, with the cutoff threshold λ^*, risky debt limit B^{risky}, and belief disagreement term Δ replaced by λ^*_{ins}, $B^{\text{risky}}_{\text{ins}}$, and Δ_{ins}, respectively. Moreover, since risky debt crowds out insurance uptake (Lemma 4), insurance uptake is a nonmonotone function of the homebuyer's belief. While a moderately optimistic buyer with $\lambda^I < \lambda \leq \lambda^*_{\text{ins}}$ purchases insurance at all $t \in [0, T)$, a pessimistic buyer with $\lambda > \lambda^*_{\text{ins}}$ instead chooses to leverage with a risky mortgage and purchase insurance only after the mortgage has matured, at $t \in [T_\mu, T)$.[57]

A.2.2 Disaster forbearance

Anticipating the forbearance program, the joint surplus at $t = 0$ from a mortgage $\mathbf{m}$ becomes:

$$S(\mathbf{m}) = \begin{cases} \underbrace{\frac{\lambda(1-e^{-r\varepsilon})B}{1+\mu+\lambda}}_{\text{new}} > 0 & \text{if } B \leq B^{\text{safe}} \\ \underbrace{\left(\frac{1+\mu}{1+\mu+\bar{\lambda}} - \frac{1+\mu}{1+\mu+\lambda} \right)(B-h+d-f) - \frac{\bar{\lambda}}{1+\mu+\bar{\lambda}} f}_{\text{as before}} & \\ + \underbrace{\frac{\lambda\,(1-e^{-r\varepsilon})}{1+\mu+\lambda}(h-d+f)}_{\text{new}} & \text{if } B \in (B^{\text{safe}}, B^{\text{risky}}] \\ \underbrace{r\underline{p} - (v_\lambda + f)}_{\text{as before}} & \text{if } B > B^{\text{risky}} \end{cases}.$$

Whenever the first option is optimal, it is optimal to set $B = B^{\text{safe}}$. The optimal maturity $\mu^{*\text{safe}}(\lambda)$ and leverage probability $\alpha^{*\text{safe}}(\lambda)$ solve:

$$\max_{\alpha \in [0,1]} \alpha \left\{ \max_{\mu \geq 0} \left[\frac{\delta}{1+\mu+\lambda} - \kappa(\mu) \right] - \frac{\kappa_0}{\eta(\alpha)} \right\},$$

where

$$\delta \equiv \lambda(1-e^{-r\varepsilon}) \overbrace{(h-d+f)}^{B^{\text{safe}}}.$$

[57] Recall that both T_μ and T are random variables. If the disaster realizes before the mortgage matures ($T \leq T_\mu$), then the borrower will default at T and hence will never purchase insurance.

The surplus from an optimal safe contract is given by:

$$S^{\text{safe}}(\lambda) \equiv \frac{\delta}{1+\mu^{*\text{safe}}+\lambda}.$$

Whenever the second option is optimal, it is optimal to set $B = B^{\text{risky}}$. As before, the optimal risky contract solves:

$$\max_{\alpha\in[0,1]} \alpha \left\{ \max_{\mu\geq 0} \left[\frac{\Delta}{1+\mu+\bar{\lambda}} + \frac{\delta}{1+\mu+\lambda} - \kappa(\mu) \right] - \frac{\kappa_0}{\eta(\alpha)} \right\},$$

where recall that $\Delta \equiv \frac{\lambda-\bar{\lambda}}{1+\lambda} d - \bar{\lambda} f$, and the surplus from an optimal risky contract is given by:

$$S^{\text{risky}}(\lambda) \equiv \frac{\Delta}{1+\mu^*+\bar{\lambda}} + \frac{\delta}{1+\mu^*+\lambda}.$$

Note that $S^{\text{risky}}(\lambda) > S^{\text{safe}}(\lambda)$ iff $\Delta > 0$. Thus, we have $S^{\text{risky}}(\lambda) > S^{\text{safe}}(\lambda)$ if and only if $\lambda > \lambda^*$. When $\lambda \leq \lambda^*$, the borrower prefers the optimal safe debt. When $\lambda > \lambda^*$, they prefer the optimal risky debt.

A.2.3 GSE guarantee

The lender's expected profit from obtaining GSE guaurantee for a fraction $1-\theta$ of its mortgage cash flow is now:

$$\Pi_{\bar{\lambda}}(\mathbf{m}) \equiv \theta R_{\bar{\lambda}}(\mathbf{m}) + (1-\theta)\left[B - gD_{\bar{\lambda}}(\mathbf{m})\right], \tag{37}$$

where $D_{\bar{\lambda}}(\mathbf{m})$ is the expected discounted deficiency amount, given by:

$$D_{\bar{\lambda}}(\mathbf{m}) = \begin{cases} 0 & \text{if } B \leq B^{\text{safe}} \\ \frac{\bar{\lambda}}{1+\mu+\bar{\lambda}}(B-h+d) & \text{if } B \in (B^{\text{safe}}, B^{\text{risky}}] \end{cases}, \tag{38}$$

where without loss of generality we rule out the excessively risky debt region $B > B^{\text{risky}}$ by assuming that the GSEs do not guarantee any loan in this region.

Focusing on the second region, the lender's expected present value of the cash flow is thus:

$$\theta R_{\bar{\lambda}}(\mathbf{m}) + (1-\theta)\left[B - gD_{\bar{\lambda}}(\mathbf{m})\right] = B - \frac{\bar{\lambda}\left[\theta + (1-\theta)g\right]}{1+\mu+\bar{\lambda}}(B-h+d).$$

Recall that the borrower's surplus is:

$$V_\lambda(\mathbf{m}) - v_\lambda = -B + \frac{\lambda}{1+\mu+\lambda}(B-h+d+f).$$

Thus, the joint surplus is:

$$S(B) \equiv V_\lambda(\mathbf{m}) - v_\lambda + \Pi_{\bar{\lambda}}(\mathbf{m}) = \left(\frac{\lambda}{1+\mu+\lambda} - \frac{\left[\theta+(1-\theta)g\right]\bar{\lambda}}{1+\mu+\bar{\lambda}} \right)(B-h+d+f) - \frac{\left[\theta+(1-\theta)g\right]\bar{\lambda}}{1+\mu+\bar{\lambda}} f$$

So, $B > B^{\text{safe}}$ is optimal if and only if:

$$\frac{\lambda}{1+\mu+\lambda} > \frac{[\theta + (1-\theta) g] \bar{\lambda}}{1+\mu+\bar{\lambda}}. \tag{39}$$

In this case, we have:

$$S\left(B^{\text{risky}}\right) = [\theta + (1-\theta) g] \Delta \bar{T} + \frac{(1-\theta)(1-g) \lambda d}{\left(1/\bar{T} - \bar{\lambda}\right)(1+\lambda)},$$

where recall that $\bar{T} \equiv \frac{1}{1+\mu+\bar{\lambda}}$. Note that $S\left(B^{\text{risky}}\right)$ is increasing and convex in $\bar{T}$.

Thus, $\bar{T} > 0$ only if

$$\begin{aligned} 0 \quad &< \quad \left.\frac{\partial S\left(B^{\text{risky}}\right)}{\partial \bar{T}}\right|_{\bar{T}=0} = [\theta + (1-\theta) g] \Delta + \frac{(1-\theta)(1-g) \lambda d}{1+\lambda} \\ \Leftrightarrow \quad &\lambda > \lambda^{*}_{\text{GSE}} \equiv \bar{\lambda} [\theta + (1-\theta) g] \underbrace{\frac{1+f/d}{1-\bar{\lambda}[\theta+(1-\theta)g]\frac{f}{d}}}_{>1}. \end{aligned} \tag{40}$$

Note that (40) implies (39) for any $\mu \geq 0$ under the maintained assumption $d > \bar{\lambda} f$. Hence, the homebuyer will borrow iff $\lambda > \lambda^{*}_{\text{GSE}}$, and when they do, they will use a risky mortgage with balance $B = B^{\text{risky}}$.

The definition of λ^{*}_{GSE} implies that $\lambda^{*}_{\text{GSE}} \leq \lambda^{*}$, and the inequality is strict when $(1-\theta)(1-g) > 0$. In words, the subsidized GSE guarantee leads to more risky borrowing in equilibrium.

Regarding comparative statics, from the formula of λ^{*}_{GSE} in (40), we have $\partial \lambda^{*}_{\text{GSE}} / \partial g > 0$, $\partial \lambda^{*}_{\text{GSE}} / \partial \theta > 0$, and $\partial \lambda^{*}_{\text{GSE}} / \partial \bar{\lambda} > 0$. Furthermore:

$$\begin{aligned} \frac{\partial}{\partial g} S\left(B^{\text{risky}}\right) &= (1-\theta) \bar{T} \left[\Delta - \frac{\lambda d}{\left(1-\bar{\lambda}\bar{T}\right)(1+\lambda)}\right] < 0, \\ \frac{\partial}{\partial \theta} S\left(B^{\text{risky}}\right) &= (1-g) \bar{T} \left[\Delta - \frac{\lambda d}{\left(1-\bar{\lambda}\bar{T}\right)(1+\lambda)}\right] < 0, \\ \frac{\partial^2}{\partial \bar{T} \partial g} S\left(B^{\text{risky}}\right) &= (1-\theta) \left[\Delta - \frac{\lambda d}{\left(1-\bar{\lambda}\bar{T}\right)^2 (1+\lambda)}\right] < 0, \\ \frac{\partial^2}{\partial \bar{T} \partial \theta} S\left(B^{\text{risky}}\right) &= (1-g) \left[\Delta - \frac{\lambda d}{\left(1-\bar{\lambda}\bar{T}\right)^2 (1+\lambda)}\right] < 0, \\ \frac{\partial^2}{\partial \bar{T} \partial \bar{\lambda}} S\left(B^{\text{risky}}\right) &= -[\theta + (1-\theta) g] \left(\frac{d}{1+\lambda} + f\right) - \frac{2(1-\theta)(1-g)\lambda d}{\left(1-\bar{\lambda}\bar{T}\right)^3 (1+\lambda)} \bar{T} < 0. \end{aligned}$$

Thus, we have $\partial \alpha^{*} / \partial g < 0$, $\partial \alpha^{*} / \partial \theta < 0$, $\partial \bar{T} / \partial g < 0$, $\partial \bar{T} / \partial \theta < 0$, and $\partial \bar{T} / \partial \bar{\lambda} < 0$. Finally, note that:

$$\frac{\partial}{\partial \bar{\lambda}} S\left(B^{\text{risky}}\right) = -[\theta + (1-\theta) g] \bar{T} \left(\frac{d}{1+\lambda} + f\right) + \frac{(1-\theta)(1-g) \lambda d}{\left(1/\bar{T} - \bar{\lambda}\right)^2 (1+\lambda)},$$

Since $\frac{\partial^2}{\partial \bar{T} \partial \bar{\lambda}} S\left(B^{\text{risky}}\right) < 0$, we have

$$\frac{\partial}{\partial \bar{\lambda}} S\left(B^{\text{risky}}\right) < \frac{\partial}{\partial \bar{\lambda}} S\left(B^{\text{risky}}\right)\Big|_{\bar{T}=0} = 0.$$

Hence, we have $\partial \alpha^* / \partial \bar{\lambda} < 0$.

A.2.4 Endogenous housing price

Proof of Proposition 5 Recall that M_λ denotes the borrower's expected value from the optimal mortgage:

$$M_\lambda \equiv \max_{\alpha \in [0,1]} \alpha \cdot \left\{ \frac{\Delta}{1 + \mu^* + \bar{\lambda}} - \kappa(\mu^*) - \frac{\kappa_0}{\eta(\alpha)} \right\}.$$

The envelope theorem implies that

$$\frac{\partial M_\lambda}{\partial \lambda} = -\alpha \frac{1 + \bar{\lambda}}{1 + \mu + \bar{\lambda}} \frac{\partial v_\lambda}{\partial \lambda},$$

Given the bargaining solution of the house price $rp^* = (1-\zeta)v^\lambda + \zeta v^s + (1-\zeta)M_\lambda$, we have

$$r\frac{\partial p^*}{\partial \lambda} = (1-\zeta)\left[\frac{\partial v_\lambda}{\partial \lambda} + 1_{M_\lambda \neq 0} \frac{\partial M_\lambda}{\partial \lambda}\right] = (1-\zeta) \underbrace{\left[1 - 1_{M_\lambda \neq 0} \alpha \overbrace{\frac{1 + \bar{\lambda}}{1 + \mu + \bar{\lambda}}}^{<1}\right]}_{>0} \underbrace{\frac{\partial v_\lambda}{\partial \lambda}}_{<0} < 0.$$

Similarly,

$$r\frac{\partial p^*}{\partial d} = (1-\theta) \underbrace{\left[1 - 1_{M_\lambda \neq 0} \overbrace{\frac{\alpha\left(1 - \frac{\bar{\lambda}}{\lambda}\right)}{1 + \mu + \bar{\lambda}}}^{<1}\right]}_{>0} \underbrace{\frac{\partial v_\lambda}{\partial d}}_{<0} < 0.$$

□

A.2.5 Difference in funding costs

With funding costs, the homebuyer's optimization problem in (5) becomes:

$$U_\lambda \equiv \max_{\mathbf{m}} \quad \alpha\left[-r(p-l) + V_\lambda(\mathbf{m})\right] + (1-\alpha)\left(-rp + v_\lambda\right), \tag{41}$$

where $V_\lambda(\mathbf{m})$ is the same as before. The lender's expected profit in (4) becomes:

$$\Pi_{\bar{\lambda}}(\mathbf{m}) \equiv R_{\bar{\lambda}}(\mathbf{m}) - \bar{r}l - \kappa(\mu). \tag{42}$$

where $R_{\bar{\lambda}}(\mathbf{m})$ is now given by

$$R_{\bar{\lambda}}(\mathbf{m}) = \begin{cases} B & \text{if } B \leq B^{\text{safe}} \\ \frac{b}{1+\mu+\bar{\lambda}} + \frac{\bar{\lambda}}{1+\mu+\bar{\lambda}} \frac{h-d}{\omega} & \text{if } B \in \left(B^{\text{safe}}, B^{\text{risky}}\right], \\ \bar{r}\underline{p} & \text{otherwise} \end{cases}$$

where $\omega \equiv r/\bar{r} > 1$.

The joint surplus from a given mortgage $\mathbf{m}$ is given by:

$$\begin{aligned} S(\mathbf{m}) &= V_\lambda(\mathbf{m}) - v_\lambda + \omega R_{\bar{\lambda}}(\mathbf{m}) \\ &= \begin{cases} (\omega - 1) B & \text{if } B \leq B^{\text{safe}} \\ \begin{array}{l} (1+\mu)\left(\frac{\omega}{1+\mu+\bar{\lambda}} - \frac{1}{1+\mu+\lambda}\right)\left(B - B^{\text{safe}}\right) \\ +(\omega-1) B^{\text{safe}} - \frac{\bar{\lambda}}{1+\mu+\lambda}\left[(\omega-1) B^{\text{safe}} + f\right] \end{array} & \text{if } B \in \left(B^{\text{safe}}, B^{\text{risky}}\right]. \\ r\underline{p} - v_\lambda - f & \text{otherwise} \end{cases} \end{aligned}$$

To avoid unrealistic mortgage contracts that mature immediately, we impose an upper bound on the maturity rate: $\mu \in [0, \mu^{\max}]$. We set $\mu^{\max}$ sufficiently large so that the constraint $\mu \leq \mu^{\max}$ does not bind in equilibrium for risky mortgages. However, as shown below, an optimistic borrower will use a safe mortgage contract with a short maturity where this constraint binds. Using the same steps as in Section A.1.2, we can characterize the equilibrium mortgage as follows: There is a belief cutoff threshold given by:

$$\lambda_\omega^* \equiv \begin{cases} \frac{\bar{\lambda}(d+f)+\Delta_2}{d-\bar{\lambda}f-\Delta_1} & \text{if } d > \bar{\lambda} f + \Delta_1 \\ \infty & \text{otherwise} \end{cases}, \tag{43}$$

where

$$\begin{aligned} \Delta_1 &\equiv \bar{\lambda}\left(1 - \omega^{-1}\right)(h - d), \\ \Delta_2 &\equiv \left(1 - \omega^{-1}\right)\left[\bar{\lambda} h - \left(1 + \mu^{\max} + 2\bar{\lambda}\right) d\right]. \end{aligned}$$

The equilibrium mortgage contract is now given by:

1. If the house is sufficiently exposed ($d > \bar{\lambda} f + \Delta_1$) and the homebuyer is sufficiently pessimistic with $\lambda > \lambda_\omega^*$, then:

   (a) chooses a risky mortgage contract with loan balance $B = B^{\text{risky}}$, while maturity rate μ^* and loan approval rate α^* solve:

$$\max_{\alpha \in [0,1]} \alpha \cdot \left\{ \max_{\mu \in [0, \mu^{\max}]} \left[\frac{\omega \Delta_\omega}{1 + \mu + \bar{\lambda}} - \kappa(\mu) \right] - \frac{\kappa_0}{\eta(\alpha)} + (\omega - 1)(v_\lambda + f) \right\}, \tag{44}$$

   where

$$\Delta_\omega \equiv \Delta - \bar{\lambda}\left(1 - \omega^{-1}\right)(h - d).$$

2. Otherwise, the borrower chooses a safe mortgage contract with loan balance $B = B^{\text{safe}}$, maturity rate $\mu = \mu^{\max}$ (implying short maturity), and loan approval rate α^s solve:

$$\max_{\alpha\in[0,1]} \alpha \cdot \left\{ \omega B^{\text{safe}} - \kappa(\mu^{\max}) - \frac{\kappa_0}{\eta(\alpha)} \right\}.$$

A.2.6 Belief convergence

At $t = 0$, the borrower's expected gain from the mortgage is:

$$V_\pi(\mathbf{m}) - v_\pi = \begin{cases} -B & \text{if } B \leq B^{\text{safe}} \\ \pi\left[-\frac{1+\mu}{1+\mu+\lambda}B - \frac{\lambda}{1+\mu+\lambda}(h-d+f)\right] - (1-\pi)B & \text{if } B \in (B^{\text{safe}}, B^{\text{risky}}] \\ \pi\begin{bmatrix} -\frac{1+\mu}{1+\mu+\lambda+\nu}B - \frac{\lambda}{1+\mu+\lambda+\nu}(h-d+f) \\ -\frac{\nu}{1+\mu+\lambda+\nu}(h - \frac{\lambda}{1+\lambda}d + f) \end{bmatrix} - (1-\pi)B & \text{if } B \in (B^{\text{risky}}, B^{\text{risky}}_{\text{news}}] \\ -v_\pi - f & \text{if } B > B^{\text{risky}}_{\text{news}} \end{cases}$$

where the expected (subjective) value of the house is:

$$v_\pi \equiv \pi\left(h - \frac{\lambda}{1+\lambda}d\right) + (1-\pi)h = h - \frac{\pi\lambda}{1+\lambda}d.$$

Note that the borrower is indifferent between the first and second region when $B = B^{\text{safe}}$, indifferent between the second and third region when $B = B^{\text{risky}}$, and indifferent between the third and forth region when $B = B^{\text{risky}}_{\text{news}}$, where:

$$B^{\text{risky}}_{\text{news}} \equiv h - \frac{\mu\pi}{1+\mu+(1-\pi)(\lambda+\zeta)}\frac{\lambda}{1+\lambda}d + f > B^{\text{risky}} = h - \frac{\mu}{1+\mu}\frac{\lambda}{1+\lambda}d + f.$$

Similarly, the lenders' expected value of the repayment stream is:

$$R_{\bar{\pi}}(\mathbf{m}) = \begin{cases} B & \text{if } B \leq B^{\text{safe}} \\ -\frac{\bar{\pi}\lambda}{1+\mu+\lambda}\left(B - B^{\text{safe}}\right) + B - \frac{\bar{\pi}\lambda}{1+\mu+\lambda}f & \text{if } B \in (B^{\text{safe}}, B^{\text{risky}}] \\ -\frac{\bar{\pi}(\lambda+\nu)}{1+\mu+\lambda+\nu}\left(B - B^{\text{safe}}\right) + B + \frac{\bar{\pi}\nu}{1+\mu+\lambda+\nu}\frac{d}{1+\lambda} - \frac{\bar{\pi}(\lambda+\nu)}{1+\mu+\lambda+\nu}f & \text{if } B \in (B^{\text{risky}}, B^{\text{risky}}_{\text{news}}] \\ r\underline{p} & \text{if } B > B^{\text{risky}}_{\text{news}} \end{cases}.$$

The joint surplus $S(\mathbf{m}) = V_\pi(\mathbf{m}) - v_\pi + R_{\bar{\pi}}(\mathbf{m})$ becomes:

$$S(\mathbf{m}) = \begin{cases} 0 & \text{if } B \leq B^{\text{safe}} \\ S_1(B,\mu) \equiv \frac{(\pi-\bar{\pi})\lambda}{1+\mu+\lambda}\left(B - B^{\text{safe}}\right) - \frac{\lambda\bar{\pi}}{1+\mu+\lambda}f & \text{if } B \in (B^{\text{safe}}, B^{\text{risky}}] \\ S_2(B,\mu) \equiv \frac{(\pi-\bar{\pi})(\lambda+\nu)}{1+\mu+\lambda+\nu}\left(B - B^{\text{safe}}\right) + \frac{\frac{(\pi-\bar{\pi})\nu}{1+\lambda}d - \bar{\pi}(\lambda+\nu)f}{1+\mu+\lambda+\nu} & \text{if } B \in (B^{\text{risky}}, B^{\text{risky}}_{\text{news}}] \\ r\underline{p} - f - v_\pi < 0 & \text{if } B > B^{\text{risky}}_{\text{news}} \end{cases}.$$

When $\pi \leq \bar{\pi}$ (the borrower is relatively more optimistic), both S_1 and S_2 are decreasing in B, and hence it is not optimal for the borrower to use a risky mortgage with $B > B^{\text{safe}}$. However, a safe mortgage with $B \leq B^{\text{safe}}$ yields a joint surplus of zero. Given the presence of the maintenance cost κ and the fixed cost of entry κ_0, it is thus not optimal to issue any mortgage contract in equilibrium.

When $\pi > \bar{\pi}$ (the borrower is relatively more pessimistic), both S_1 and S_2 are strictly increasing in B. Thus, the risky surpluses S_1 is maximized at $B = B^{\text{risky}}$ and S_2 is maximized at $B = B^{\text{risky}}_{\text{news}}$, which yields:

$$S^{\text{dis}}(\mu) \equiv S_1(B^{\text{risky}}, \mu) = \frac{1}{1+\mu} \frac{(\pi - \bar{\pi})\,\lambda d}{1+\lambda} - \frac{\bar{\pi}\lambda f}{1+\mu+\lambda}.$$

$$S^{\text{news}}(\mu) \equiv S_2(B^{\text{risky}}_{\text{news}}, \mu) = \frac{1 + \left[1 - \frac{\mu\pi}{1+\mu+(1-\pi)(\lambda+\nu)}\right](\lambda+\nu)}{1+\mu+\lambda+\nu} \frac{(\pi - \bar{\pi})\,\lambda d}{1+\lambda} - \frac{\bar{\pi}\,(\lambda+\nu)\,f}{1+\mu+\lambda+\nu}.$$

Putting these options together, the optimal contract (μ^*, α^*) solves:

$$\max_{\alpha \in [0,1]} \alpha \cdot \left\{ \max_{\mu \geq 0} \left[\max\left\{ S^{\text{dis}}(\mu), S^{\text{news}}(\mu) \right\} - \kappa(\mu) \right] - \frac{\kappa_0}{\eta(\alpha)} \right\}. \tag{45}$$

Whether the borrower will choose a risky mortgage contract with $B = B^{\text{risky}}$ (and gets the surplus S^{dis}) or a risky mortgage contract with $B = B^{\text{risky}}_{\text{news}}$ (and gets the surplus S^{news}) depends on parameters, in particular the foreclosure cost f. However, focusing on the simple case where the foreclosure cost vanishes ($f \to 0$), it is always the case that $S^{\text{dis}} < S^{\text{news}}$ for all μ. Hence, in equilibrium the borrower will choose a risky mortgage contract in the new risky region $(B^{\text{risky}}, B^{\text{risky}}_{\text{news}}]$. In this region, the borrower will default when the disaster hits or when the bad news hits.

A.2.7 Deterministic maturity

Suppose a mortgage is now a loan contract $\mathbf{m} = (l, b, \bar{T})$ that specifies a promised repayment flow of b per each period between $t = 0$ and a deterministic maturity period $t = \bar{T}$. At each period $0 \leq t \leq \bar{T}$, the loan balance B_t is the present value of the remaining stream of promised repayments:

$$B_t = \int_t^{\bar{T}} r e^{-r(t'-t)} b dt' = (1 - e^{-r(\bar{T}-t)})b,$$

and follows the following law of motion:

$$\frac{dB}{dt} = -r(b - B) = -re^{-r(\bar{T}-t)}b, \tag{46}$$

which shows that the loan balance decreases over time.

The borrower's continuation value V_λ given loan balance B and repayment flow b now satisfies the following HJB equation, which takes into account law of motion (46):

$$(1+\lambda)rV_\lambda(B,b) \quad = \quad r(h-b) - r(b-B)\frac{\partial V_\lambda}{\partial B} + r\lambda\left[1_{B \leq B^{\text{safe}}}(h - d - B) - 1_{B > B^{\text{safe}}} f\right],$$

where $B^{\text{safe}} \equiv h - d$, and the initial condition $V_\lambda(0, b) = v_\lambda = h - \frac{\lambda}{1+\lambda} d$. The risky debt limit $B^{\text{risky}}(b)$ is the level of loan balance such that $V_\lambda(B, b) = 0$.

Similarly, the lenders' continuation value satisfies:

$$(1 + \bar{\lambda}) r R_{\bar{\lambda}}(B, b) \quad = \quad rb - r(b - B) \frac{\partial R_{\bar{\lambda}}}{\partial B} + r\bar{\lambda} \left[1_{B \le B^{\text{safe}}} B + 1_{B > B^{\text{safe}}} (h - d) \right].$$

For tractability, for the rest of the section, we assume $f = 0$. Then, solving these equations yields:

$$B^{\text{risky}}(b) = b - (b - h)^{\frac{1}{1+\lambda}} (b - B^{\text{safe}})^{\frac{\lambda}{1+\lambda}},$$

$$V_\lambda(B, b) = \begin{cases} \frac{h-b}{1+\lambda} + \frac{b - B^{\text{safe}}}{1+\lambda} \left(\frac{b-B}{b-B^{\text{safe}}} \right)^{1+\lambda} & \text{if } B^{\text{safe}} < B \le B^{\text{risky}}(b) \\ v_\lambda - B & \text{if } B \le B^{\text{safe}} \end{cases},$$

and

$$R_{\bar{\lambda}}(B, b) = \begin{cases} \frac{b + \bar{\lambda}(h-d)}{1+\bar{\lambda}} - \frac{b - B^{\text{safe}}}{1+\bar{\lambda}} \left(\frac{b-B}{b-B^{\text{safe}}} \right)^{1+\bar{\lambda}} & \text{if } B^{\text{safe}} < B \le B^{\text{risky}}(b) \\ B & \text{if } B \le B^{\text{safe}} \end{cases}.$$

Hence, the surplus $S \equiv V_\lambda - v_\lambda + R_{\bar{\lambda}}$ is given by:

$$S(B, b) = \begin{cases} \left[\frac{\lambda - \bar{\lambda}}{(1+\lambda)(1+\bar{\lambda})} + \frac{1}{1+\lambda} \left(\frac{b-B}{b-B^{\text{safe}}} \right)^{1+\lambda} - \frac{1}{1+\bar{\lambda}} \left(\frac{b-B}{b-B^{\text{safe}}} \right)^{1+\bar{\lambda}} \right] (b - B^{\text{safe}}) & \text{if } B^{\text{safe}} < B \le B^{\text{risky}}(b) \\ 0 & \text{if } B \le B^{\text{safe}} \end{cases}.$$

Note that for a given risky mortgage, the surplus is strictly increasing (decreasing) in B when $\lambda > \bar{\lambda}$ ($\lambda < \bar{\lambda}$). Hence, pessimistic homebuyers with $\lambda > \bar{\lambda}$ will choose the maximal risky mortgage at $B = B^{\text{risky}}(b)$, but optimistic homebuyers with $\lambda > \bar{\lambda}$ will not borrow, i.e., $B = 0$. In other words, $\lambda^* = \bar{\lambda}$ when maturity is deterministic.

Finally, as in Proposition 2, at $t = 0$, a relative optimistic homebuyer ($\lambda \le \lambda^*$) will not borrow; a relatively pessimistic homebuyer ($\lambda > \lambda^*$) will borrow, and will choose a mortgage with $b^*, \bar{T}^*$ and α^* that solve:

$$\max_{\alpha \in [0,1]} \alpha \cdot \left\{ \max_{b, \bar{T}} \left[S(B^{\text{risky}}(b), b) - k(\bar{T}) \right] - \frac{\kappa_0}{\eta(\alpha)} \right\}$$

subject to $B^{\text{risky}}(b) = (1 - e^{-r\bar{T}}) b$, and the loan amount l^* is given by the lender's free-entry condition:

$$\eta(\alpha) \cdot (R_{\bar{\lambda}}(B^{\text{risky}}(b^*), b^*) - rl^* - k(\bar{T}^*)) = \kappa_0,$$

where $k(\bar{T})$ and κ_0 denote the servicing cost and entry cost, with$k'(\bar{T}) > 0$ and $k''(\bar{T}) > 0$.

A.2.8 Aggregate model with general heterogeneity

Homebuyers/borrowers search for lenders in submarkets. For each type of house d, each type of borrower λ, and for each mortgage contract $\mathbf{m}$, a *submarket* consists of an (endogenous) measure $n^b_{\mathbf{m}}$ of type-λ homebuyers of a type-d house for whom contract $\mathbf{m}$ solves their optimization problem, and an (endogenous) measure $n^l_{\mathbf{m}}$ of lenders for whom approving contract $\mathbf{m}$ to a type-λ borrower satisfies their free-entry condition. Within each submarket, given $n^b_{\mathbf{m}}$ and $n^l_{\mathbf{m}}$, the number of matches produced is given by $N(n^b_{\mathbf{m}}, n^l_{\mathbf{m}})$, where N is a constant-returns-to-scale matching technology function.

The probability a borrower in the submarket finds a match (the leverage probability) is given by:

$$\alpha_{\mathbf{m}} \equiv \frac{N(n^b_{\mathbf{m}}, n^l_{\mathbf{m}})}{n^b_{\mathbf{m}}} = \mathcal{N}\left(n_{\mathbf{m}}\right) \equiv N(1, n_{\mathbf{m}}), \tag{47}$$

where $n_{\mathbf{m}} \equiv n^l_{\mathbf{m}}/n^b_{\mathbf{m}}$ is the loan market thickness and $\mathcal{N}$ is increasing and concave. Similarly, the probability that a lender finds a match is:

$$\eta_{\mathbf{m}} \equiv \frac{N(n^b_{\mathbf{m}}, n^l_{\mathbf{m}})}{n^l_{\mathbf{m}}} = N(1/n_{\mathbf{m}}, 1). \tag{48}$$

For each submarket, the lenders' free-entry condition is:

$$\eta_{\mathbf{m}}(\mathbf{m})\Pi_{\bar{\lambda}}(\mathbf{m}) = \kappa_0. \tag{49}$$

Definition 1. A *competitive search equilibrium* consists of (i) a menu of all available loan contracts $\mathcal{M}(\lambda, d)$, (ii) measures $n^b_{\mathbf{m}}(\lambda, d)$ and $n^l_{\mathbf{m}}(\lambda, d)$ of borrowers and lenders in each submarket, and (iii) their matching probabilities $\alpha_{\mathbf{m}}(\lambda, d)$ and $\eta_{\mathbf{m}}(\lambda, d)$, for each borrower type λ, house type d, and mortgage $\mathbf{m} \in \mathcal{M}(\lambda, d)$, such that:

1. Given $\alpha_{\mathbf{m}}$ and $\mathcal{M}$, $n^b_{\mathbf{m}}$ is the measure of type-λ borrowers choosing loan contract $\mathbf{m}$ to finance the purchase of a type-d house in their optimization problem (5);

2. Given $\eta_{\mathbf{m}}$ and $\mathcal{M}$, $n^l_{\mathbf{m}}$ is the measure of lenders offering loan contract $\mathbf{m}$ to type-λ homebuyers of a type-d house, subject to (49);

3. Given $n^b_{\mathbf{m}}$ and $n^l_{\mathbf{m}}$, $\alpha_{\mathbf{m}}$ and $\eta_{\mathbf{m}}$ are given by (47) and (48);

4. $\mathcal{M}$ is the set of mortgage contracts $\mathbf{m}$ such that free-entry (49) holds with equality;

5. Each submarket clears:

$$\int_{\mathbf{m} \in \mathcal{M}(\lambda, d)} n^b_{\mathbf{m}}(\lambda, d) = \phi(\lambda, d), \quad \forall \lambda, d,$$

   where ϕ is the density function of the joint distribution of belief and exposure types.

It is straightforward to show that Proposition 2 continues to hold in this environment, except that now the probability that a lender is matched with a borrower $\eta_{\mathbf{m}}$ can be derived endogenously from (47) and (48) as a function of $\alpha_{\mathbf{m}}$:

$$\eta_{\mathbf{m}} = \eta(\alpha_{\mathbf{m}}) \equiv \frac{\alpha_{\mathbf{m}}}{\mathcal{N}^{-1}\left(\alpha_{\mathbf{m}}\right)}, \tag{50}$$

where

$$\eta'(\alpha_{\mathbf{m}}) = -\frac{1}{n_{\mathbf{m}}^2} < 0,$$
$$\eta''(\alpha_{\mathbf{m}}) = \frac{1}{n_{\mathbf{m}}^3}\frac{1}{\mathcal{N}'(n_{\mathbf{m}})} > 0,$$

as stated in the baseline model.

A.2.9 MBS pool

We further extend the model to incorporate the securitization process more explicitly. Consider the generalized model with multiple types of homebuyers and houses in Section 7.1. We introduce the GSE agent as in 4.3, who guarantees and purchases the mortgages issued by the lenders to the borrowers. Following (Dubey and Geanakoplos, 2002; Dubey et al., 2005), we assume that mortgages are pooled together and shares of the pool are sold to a set of investors (think of investors in the MBS market).

Given the guarantee payment, the MBS price at the disaster date $t = T$ is simply:

$$\mathcal{P}_T = \int_{\lambda>\lambda^*, d>\bar{\lambda}f} \frac{B^{\text{risky}}(\lambda, d)}{r}\phi_T^*(\lambda, d), \tag{51}$$

where ϕ_T^* is the measure of defaulting loans defined in (25). At the disaster date T, all the risky debts at-risk are defaulted. For each defaulting loan, the GSE repays the MBS investors the remaining loan balance $B^{\text{risky}}(\lambda, d)/r$.

Let λ^i and r^i denote the belief parameter and the discount rate of MBS investors. We focus on the relevant case of patient investors: $r^i < r$.[58] The MBS price in any pre-disaster period $t < T$ is given by the investors' present value of the pool of mortgage repayment streams (which are guaranteed by the GSEs):

$$r^i\mathcal{P}_t = \int_{\lambda>\lambda^*, d>\bar{\lambda}f} \left(\frac{1+\mu^*}{1+\mu^*+\lambda^i} + \frac{r^i}{r}\frac{\lambda^i}{1+\mu^*+\lambda^i}\right) B^{\text{risky}}(\lambda, d)\phi_t^*(\lambda, d), \tag{52}$$

where the term in the brackets takes into account the investors' belief and discount rate.

For MBS investors, the mortgage default risk is effectively transformed to a prepayment risk, due to the guaranteed provided by the GSEs (Weiner, 2016). In equilibrium, when the disaster arrives, risky mortgages are defaulted, and the GSE agent makes a lump-sum payment of the unpaid balances to the MBS investors. Hence, investors receive a one-time guarantee payment, instead of the regular repayment *flows*. This prepayment of the balances is undesirable for patient MBS investors, reflected by the fact that the "prepayment penalty" term $\frac{1+\mu^*}{1+\mu^*+\lambda^i} + \frac{r^i}{r}\frac{\lambda^i}{1+\mu^*+\lambda^i}$ in equation (52) is less than one.

[58] This is a reasonable assumption, as the biggest investors in agency MBSs are depository institutions and the Federal Reserve (Fuster et al., 2022).

Hence, even with the GSE guarantee, the disaster causes a drop in the MBS price:

$$\mathcal{P}_T < \lim_{t \to T-} \mathcal{P}_t.$$

Since a subsidized g-fee encourages risky mortgage origination, leading to a pool of mortgages with a higher default risk in equilibrium, it follows that a subsidized g-fee also has an unintended consequence of increasing the sensitivity of the MBS price to the disaster shock.

A.2.10 Time-inconsistency problem in disaster forbearance policies

First, consider a committed planner who at the beginning of $t = 0$ (before mortgage decisions are made) chooses and commits ex-ante to a disaster forbearance policy, represented by the choice of parameter ε in Section 7.4. The optimal forbearance under commitment solves a cost minimization problem:

$$\varepsilon_0^* \equiv \arg\min_{\varepsilon \in [0,\bar{\varepsilon}]} \mathbb{E}\left\{ e^{-rT} \underbrace{\mathcal{A}_T^{\text{risky}}(\varepsilon)}_{\text{number of defaulting loans}} \left[\underbrace{e^{-r\varepsilon} f}_{\text{benefit of postponing default loss}} + \underbrace{\Psi(\varepsilon)}_{\text{fiscal cost}} \right] \right\},$$

where Ψ is a convex function ($\Psi > 0$, $\partial\Psi/\partial\varepsilon > 0, \partial^2\Psi/\partial\varepsilon^2 > 0$), capturing the fiscal cost of forbearing each defaulted loan, and the expectation is with respect to T according to the planner's belief. Assuming an interior solution, the first-order condition for ε_0^* is:

$$\Psi'\left(\varepsilon_0^*\right) = re^{-r\varepsilon_0^*} f - \frac{\mathbb{E}\left\{ e^{-rT} \frac{\partial \mathcal{A}_T^{\text{risky}}(\varepsilon_0^*)}{\partial \varepsilon} \right\}}{\mathbb{E}\left\{ e^{-rT} \mathcal{A}_T^{\text{risky}}(\varepsilon_0^*) \right\}} \left[e^{-r\varepsilon_0^*} f + \Psi(\varepsilon_0^*) \right]. \tag{53}$$

The key thing to notice that *the committed planner internalizes how their policy choice of ε affects the measure of risky debt in the market $\mathcal{A}_T^{risky}$*.

Second, consider a planner with limited commitment who, at date $t = T$ (after the disaster realizes), can deviate from the ex-ante policy ε_0^* and select the disaster forbearance parameter ε ex-post.[59] We will show that this planner will deviate and choose a more generous forbearance $\varepsilon_T^* > \varepsilon_0^*$. The key factor here is that at $t = T$, the mortgage choices have already been made at $t = 0$. Hence, *the limited commitment planner takes $\mathcal{A}_T^{risky}$ as given* when choosing its policy:[60]

$$\varepsilon_T^* \equiv \arg\min_{\varepsilon \in [0,\bar{\varepsilon}]} \mathcal{A}_T^{\text{risky}} \left[e^{-r\varepsilon} f + \Psi(\varepsilon) \right].$$

Again assuming interior solutions, the equilibrium ε_T^* solves the following first-order condition:

$$\Psi'(\varepsilon_T^*) = re^{-r\varepsilon_T^*} f. \tag{54}$$

[59]For simplicity, we assume that the limited commitment planner only has one window of opportunity to change the policy at $t = T$. One can also consider a more complex model where the limited commitment planner can instead choose at all $t \geq T$ whether to continue the forbearance.

[60]There is no expectation operator because all uncertainty will have resolved by $t = T$.

The main difference between the committed and uncommitted first-order conditions is the absence of the second term of (53) in (54). This absence reflects the fact that the limited commitment planner at $t = T$ takes the mortgage choices made at $t = 0$ as given, and hence does not internalize how their policy affects the measure of risky mortgages $\mathcal{A}^{\text{risky}}$.

In a rational expectation equilibrium, private agents at $t = 0$ correctly expect the planner's choice at $t = T$, so $\mathcal{A}_T^{\text{risky}}$ in (54) is given by $\mathcal{A}_T^{\text{risky}} = \mathcal{A}_T^{\text{risky}}(\varepsilon_T^*)$. The resulting planner's choice of ε_T^* is thus time-consistent.

Since $\partial \mathcal{A}_T^{\text{risky}} / \partial \varepsilon > 0$, it follows from (53) and (54) that $\Psi'(\epsilon_T^*) > \Psi'(\epsilon_0^*)$. Furthermore, since $\partial^2 \Psi / \partial \epsilon^2 > 0$, it follows that the disaster forbearance with limited commitment is more generous:

$$\varepsilon_T^* > \varepsilon_0^*,$$

and as private agents rationally anticipate more forbearance, there will be more risky mortgages under limited commitment:

$$\mathcal{A}_T^{\text{risky}}(\varepsilon_T^*) > \mathcal{A}_T^{\text{risky}}(\varepsilon_0^*).$$

This result is very similar to how the rational expectation of more bailout from a limited commitment planner (or more inflation from a limited commitment central bank) will lead to higher equilibrium bankruptcies (or higher equilibrium inflation), as in Chari and Kehoe (2016) (or Barro and Gordon 1983).

B Online Appendix: Empirics

B.1 Data: Details

NOAA SLR Viewer maps are publicly available at `https://coast.noaa.gov/digitalcoast/tools/slr.html`. The Yale Climate Opinion Survey data is publicly available at `https://climatecommunication.yale.edu/visualizations-data/ycom/`.

As mentioned in Section 5.1, 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 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.

For the exercise using Gallup data (Section 6.1.4), we use 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-five-year average estimates for educational attainment from the U.S. Census' American Community Survey.

For the securitization exercise in Section 6.2, we collect Fannie Mae and Freddie Mac's conforming loan limits for single-unit single family homes between 2001 and 2016. 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).[61] We then match each property with the conforming loan limit in the county and year of purchase.

B.2 Additional exercises

B.2.1 SLR measures

We further examine the sensitivity of our results to alternative specifications 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 A9 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.

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

B.2.2 Fixed effect specifications

Recall that our main results include ZIP code × distance to coast bin × elevation bin × number of bedrooms × time (transaction month-year) fixed effects (Z×D×E×B×M), in addition to lender fixed effects in our long maturity results. Table A10 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 × distance to coast bin × elevation bin × number of bedrooms (Z×D×E×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×D×E×B×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.

B.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 A10 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×D×E×B×Q×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.

B.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.[62]

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 A11 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.

B.2.5 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 A13 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.

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

B.2.6 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.[63] Thus, we re-estimate our main regression specifications using the loan amount and interest rates as outcome variables. Table A14 reports these results. Consistent Corollary 3, 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.[64]

B.3 Omitted tables

	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 A1: Summary statistics of key variables. Leveraged is a binary variable equal to one when a transaction is associated with a mortgage and zero otherwise. Long Maturity is a binary variable equal to one when the mortgage term is at least 30 years and zero otherwise. Mortgage amount and term statistics are reported conditional on having a mortgage. Inundated at 6ft of SLR is a binary variable equal to one if the property is predicted to be inundated at 6ft of SLR according to NOAA and zero otherwise. Moderate SLR Risk (High SLR Risk) is equal to one if a property will be inundated with $>$3 but $\leq$6 feet of SLR ($\leq$3 feet of SLR) and zero otherwise. Main data sources: CoreLogic, NOAA SLR Viewer, and Yale Climate Opinion Survey.

[63] Recall from Section B.2.4 that we do not include these in endogenous mortgage characteristics in our main regression models as they are bad controls.

[64] 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.

Continuous	Yale happening	Yale worried	Yale timing	Gallup when	Gallup worry	Individual $\widehat{\lambda}$	County mean $\widehat{\lambda}$
	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)

(a) Continuous belief variables.

Above median	Yale happening	Yale worried	Yale timing	Gallup when	Gallup worry	Individual $\widehat{\lambda}$	County mean $\widehat{\lambda}$
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 mean $\hat{\lambda}$	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)

(b) Binary belief variables (one if corresponding variable is above sample median, zero otherwise).

Table A2: Pairwise correlation of belief variables. Panel (a) displays pairwise correlations between continuous versions of belief variable specifications. Panel (b) displays pairwise correlations between binary belief variables defined as equal to 1 if the county is above the variable sample median and zero otherwise. Yale beliefs variables from the Yale Climate Opinions Survey are defined as the average county-level climate beliefs as described in Section 6.1.2. Beliefs from the Gallup data are imputed at the county-by-year level by the authors as described in Section 6.1.4. Individual $\widehat{\lambda}$ is the transaction-level beliefs at the time of property sale imputed by the authors as described in Section 6.1.1. County mean $\widehat{\lambda}$ represents a county-level mean value of the continuous $\widehat{\lambda}$ variable averaged across buyers from that county. $\widehat{PessBuyer}$ is the binary belief variable at the county level equal to one if the county belief is above the sample median and zero otherwise, as described in Section 6.1.1. County mean $\widehat{\lambda}$ is similar to $\widehat{PessBuyer}$ but equal to one if the county's average of $\widehat{PessBuyer}$ is above the sample mean and zero otherwise. Pairwise correlation p-values are shown in parentheses. * ($p < 0.1$), ** ($p < 0.05$), *** ($p < 0.01$).

	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 A3: 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 ten 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 ten 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 3 and 4.

	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 A4: Robustness to the inclusion of a variety of additional county-by-year 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 3 and 4.

	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 A5: Robustness to the inclusion of political affiliation data (percent of Republican or Democratic vote shares in the previous presidential election at the county level). The rest is the same as in Tables 3 and 4.

	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 A6: Robustness with *PessBuyer* derived from county-by-year climate beliefs interpolated from Gallup survey data according to 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 is the same as in Tables 3 and 4.

	Leveraged	Long maturity
PessBuyer	0.006	0.000
	(0.010)	(0.004)
Z × D × E × B × T fe	Y	Y
Property & buyer county controls	Y	Y
Lender fe		Y
N	310,217	119,508
R^2	0.464	0.445

Table A7: Placebo test on beliefs using only properties in our original sample not at risk for SLR. The rest of the table is the same as in Tables 3 and 4.

	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 A8: Robustness with the inclusion of current National Flood Insurance Program flood zone information. FEMA Zone is a binary variable equal to one if the property lies in a Special Flood Hazard Area as classified by FEMA and zero otherwise. The rest is the same as in Tables 3 and 4.

	Leveraged	Long Maturity
1.SLR (6ft)	0.0180	0.0169
	(0.014)	(0.017)
2.SLR (5ft)	0.0140	-0.0042
	(0.020)	(0.026)
3.SLR (4ft)	-0.0343	-0.0038
	(0.027)	(0.020)
4.SLR (≤3ft)	-0.0362	-0.0305
	(0.031)	(0.024)
1.SLR × PessBuyer	0.0154	0.0140
	(0.012)	(0.009)
2.SLR × PessBuyer	0.0246*	0.0321**
	(0.015)	(0.014)
3.SLR × PessBuyer	0.0455**	0.0323**
	(0.018)	(0.014)
4.SLR × PessBuyer	0.0856***	0.0322*
	(0.023)	(0.018)
Property & buyer county controls	Y	Y
Buyer county controls x SLR	Y	Y
Z × D × E × B × M fe	Y	Y
Lender fe		Y
N	405,893	150,746
R^2	0.473	0.441

Table A9: Robustness with more refined measure of SLR risk. $i.SLR\ Risk$ where $i \in \{1, \dots, 4\}$ 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 3 and 4.

	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	0.123	0.365	0.400	0.466

Table A10: Robustness with alternative fixed effects. Top table: dependent variable is *Leveraged* (equal to one if the transaction is associated with a mortgage and zero otherwise). Bottom table: dependent variable is *Long Maturity* (equal to one if the mortgage term is 30 years and zero if 15 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 3 and 4.

	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 A11: Robustness where housing price is *not* included as a control variable. The rest is the same as in Tables 3 and 4.

	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 A12: 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. Columns 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 3 and 4.

	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 A13: 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 2, 3, and 4.

	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 A14: 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 3 and 4.

B.4 GSE loan analysis

We access the GSE database (containing Freddie Mac Single Family Loan-Level Data and Fannie Mae Single-Family Loan Performance Data) and the First Street Foundation (FSF) data via the Federal Reserve data warehouse.

The FSF is a major provider of high-resolution climate risk projections for U.S. real estate, and its risk scores are being used by researchers, government agencies, and major real estate listing agencies (https://firststreet.org/risk-factor/flood-factor/). The Flood Factor (FF) assigns each property a flood risk score between 1 (safe/minimal risk) to 10 (extreme risk). In FSF data, about 80 percent of properties are safe ($FF = 1$), and 20 percent are at risk ($FF \geq 2$).

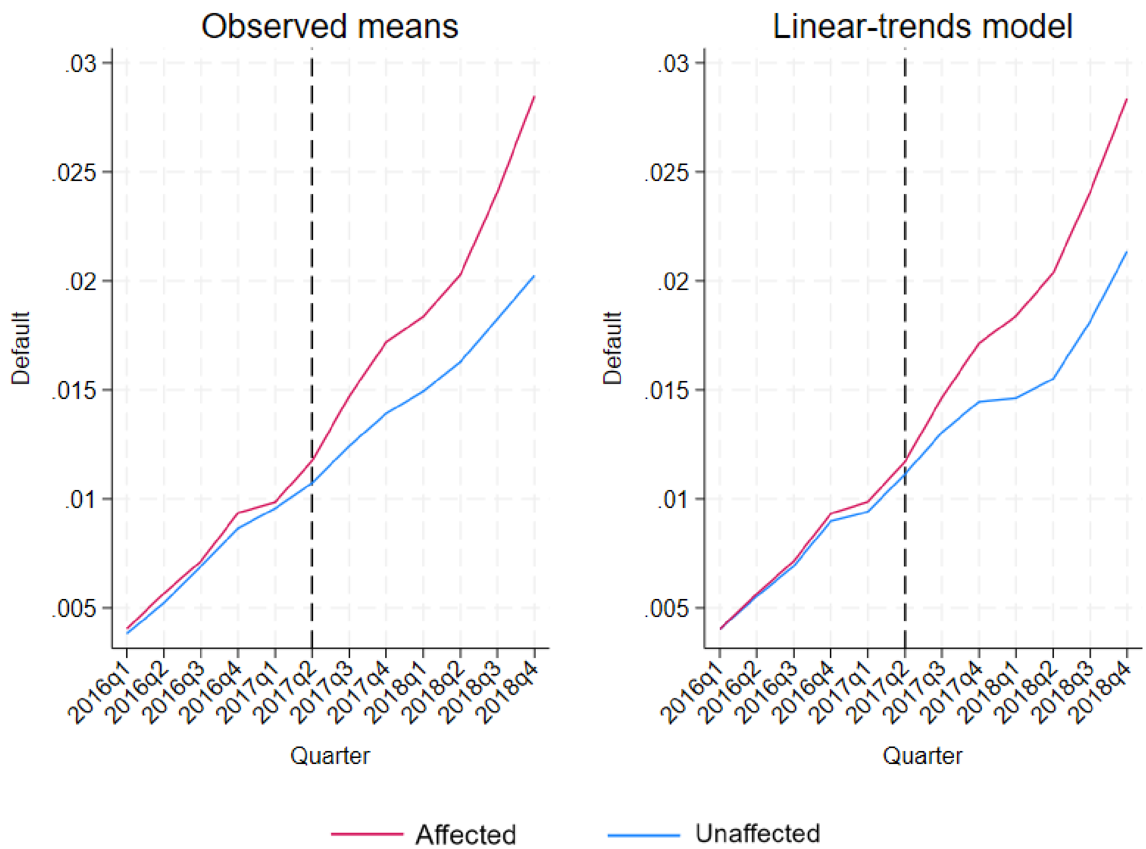


Figure A3: Event study of the effect of Hurricane Irma on mortgage default. The figure plots the default frequency of GSE-backed mortgages before and after Hurricane Irma (2017q3) in affected (red) and unaffected (blue) three-digit ZIP codes in Florida. The figure on the left plots the observed means. The figure on the right normalizes using a linear-trends model where both the treatment and control group are normalized to the same point at the beginning of our data period. The difference-in-differences regression includes loan fixed effects and quarter fixed effects. The hurricane led to a 40 basis point increase (standard error: 3 basis points) in the default frequency of loans in the treated sample, relative to that in the control sample. We find the parallel trends assumption holds as we fail to reject the null hypothesis of parallel (pretreatment) trends (Prob>F=0.169). See data descriptions in Appendix Section B.4.

To conduct an event study of how Hurricane Irma affects the default frequency of mortgage loans, we use a sample of 550,953 GSE loans in 3-digit ZIP codes within coastal counties in Florida. The analysis compares the incidence of default 1.5 years before and 1.5 years after the hurricane (the sample consists of 6,611,436 loan-quarter observations from 2016Q1 to 2018Q4) of loans in 3-digit ZIP codes that are affected (the treatment group) against loans in ZIP codes that are not affected (the control group). The dependent variable is the default dummy def_{it}, which is one if loan i has reached zero balance due to default[65] before quarter t, and zero otherwise. The key independent variable is the interaction between a treatment dummy for whether the loan i is in an affected area and a post dummy for whether the quarter t is on or after 2017q3. We use FEMA Disaster Declarations Summary v2's dataset to identify the areas affected by Hurricane Irma. The dataset contains information on which disaster recovery programs were declared for each hurricane. We consider a 3-digit ZIP code as affected when more than 80% of the housing units in the area were eligible for an individual disaster assistance. The linear probability model includes loan and time fixed effects. The standard errors are clustered at the loan level. The results are shown in Appendix Figure A3.

[65]That is, the loan has reached zero balance according to the GSE data, but not because of (pre)payment or third party sale.