Going Underwater? Flood Risk Belief Heterogeneity and Coastal Home Price Dynamics

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Abstract

How do climate risk beliefs affect coastal housing markets? This paper provides theoretical and empirical evidence. First, we build a dynamic housing market model and show that belief heterogeneity can reconcile prior mixed evidence on flood risk capitalization. Second, we implement a door-to-door survey in Rhode Island, finding significant flood risk underestimation and sorting based on risk perceptions and amenity values. Third, we estimate that coastal prices exceed fundamentals by 6%-13% in our benchmark area, with potentially higher overvaluation in other locations. Finally, we quantify both allocative inefficiency and distributional consequences arising from flood risk misperceptions and insurance policy reform.

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How do climate risks affect coastal housing markets? In a world with homogeneous rational expectations, prices of vulnerable housing should already incorporate the present value of future increases in flood risk due to sea level rise (SLR). Hedonic analyses, however, have repeatedly found that flood and climate risks are not (yet) fully reflected in housing markets.[1] This paper presents novel evidence regarding the role of belief heterogeneity and the implications of flood risk misperceptions in coastal U.S. housing markets. From an asset pricing perspective, heterogeneity in beliefs about the future value of fundamentals can lead to inflated prices and a host of associated risks including bubbles, excess volatility, and overinvestment (e.g., Harrison and Kreps 1978; Abreu and Brunnermeier 2003; Scheinkman and Xiong 2003; Geanakoplos 2010; Simsek 2013; Xiong 2013). In the present study, we investigate whether flood risk misperceptions pose similar risks to coastal housing markets.

First, we develop a dynamic housing market model and use it to review prior empirical evidence. The model builds on recent advancements in the study of heterogeneous beliefs and housing prices (e.g., Piazzesi and Schneider 2009; Favara and Song 2014; Burnside, Eichenbaum, and Rebelo 2016). Our theoretical innovation is the introduction of three novel dimensions of heterogeneity, specifically (i) in the housing stock, differentiating coastal from noncoastal homes; (ii) in households' amenity valuations of waterfront living; and (iii) in households' current and future flood risk perceptions. A rich empirical literature (described below) has generally reported mixed results on the capitalization of climatic risks while acknowledging that flood events typically result in sharp declines in the prices of vulnerable homes. We show that these findings can be predicted by a model where some agents underestimate flood and climate risks but update their beliefs based on flood realizations. This market state results in sorting and different equilibria depending on the distribution of beliefs and other housing market characteristics. At the same time, the model also demonstrates some limitations of using reduced-form hedonic approaches for isolating

[1] Examples span both new studies focusing on future SLR capitalization (e.g., Bernstein, Gustafson, and Lewis 2019; Murfin and Spiegel 2020; Baldauf, Garlappi, and Yannelis 2020) and a larger literature on present-day flood zone status (see, e.g., reviews by Daniel, Florax, and Rietveld [2009]; Beltrán, Maddison, and Elliott [2018]).

flood risk beliefs due to confounders such as sorting dynamics and the role of higher-order beliefs.

Second, this paper provides novel direct evidence regarding the role of flood risk beliefs in coastal housing markets by reporting the results of a door-to-door survey campaign we conduct in Rhode Island. We elicit the joint distribution of current and future flood risk perceptions, coastal amenity values, and potential confounders, such as flood damage expectations, at the household level. Importantly, we elicit risk perceptions and valuations among both households that did and those that did not purchase properties on the coast in a given community, thus directly informing the relevant counterfactuals. These critical elements are not available in other belief survey products such as that from the Yale Program on Climate Change Communication (Howe et al. 2015).[2] We find evidence of significant flood risk underestimation and that selection into at-risk homes is driven by lower risk perceptions and higher waterfront amenity values. Around 40% of residents of high-risk flood zones say they are "not at all" worried about flooding over the next 10 years. In contrast, a plurality of inland respondents in the same communities indicate they would be "very worried" about flooding if they lived on the coast. In addition, the majority of coastal residents in our survey underestimate their homes' flood risks relative to inundation models. Importantly, we confirm that these differences in coastal versus noncoastal flood risk perceptions are not driven by confounders such as differential expectations of damages, government assistance, or insurance reimbursements in case of flood. Those who experienced a flood in the past are more concerned about future flooding than those who did not, and coastal residents who are very worried about flooding are significantly more likely to plan on selling their homes in the next 5 years than coastal residents who are less worried.

Third, we quantify the model and simulate future coastal housing market outcomes under different belief, flood risk, and policy scenarios. Our quantification utilizes probabilistic

[2] The Yale data provide estimates of the fraction of the population in a county or city adopting a general climate change belief (e.g., "global warming is happening"). Internet Appendix 3.3 explains why the Yale data or other survey products could not be used as a substitute for our survey.

projections of location-specific flood risk increases due to SLR based on Buchanan, Oppenheimer, and Kopp (2017) and Kopp et al. (2014). The results imply that coastal housing prices in our benchmark setting in Rhode Island currently exceed fundamentals by around 6%-13% depending on expectations of global climate policy.[3] This overvaluation is economically highly significant as it corresponds to around 40% of our benchmark households' average annual income. If SLR turns out to be worse (better) than expected, this overvaluation may become significantly larger (smaller) in the absence of policy intervention. These estimates are robust to a range of sensitivity checks and extensions, such as alternative belief updating rules. The simulations do, however, reveal that households' beliefs about long-run flood insurance policy can significantly affect coastal housing prices in the present.

In order to gauge the broader relevance of these effects, we extend our analysis to several cities across the United States. We extrapolate from our survey results to other cities by mapping our flood risk belief measures onto county-level general climate change belief estimates from the Yale Program on Climate Change Communication (Howe et al. 2015). The results reveal the potential for significantly higher overvaluation in other locations. Indeed, Rhode Island faces lower expected flood risk increases than the median across tidal gauges in the continental United States (Buchanan, Oppenheimer, and Kopp 2017) and may thus ultimately be a conservative benchmark.

These findings have important policy and welfare implications. We quantify the allocative inefficiency of agents with high amenity values for waterfront living being priced out of coastal areas by agents with lower amenity values but optimistic flood risk beliefs. We also consider distributional consequences of flood insurance policy reform.[4] The dominant insurer for flooding in the United States is the National Flood Insurance Program (NFIP).

[3] No future climate policy scenario can fully rationalize current flood risk beliefs as agents already underestimate present-day flood risk in the absence of SLR.

[4] While we do not model mortgages and the use of coastal properties as collateral, significant additional welfare costs may arise through this channel. For example, the devaluation of coastal properties could lead to defaults and adverse credit market impacts (see, e.g., Geanakoplos 2010), exacerbating market incompleteness. New research indicates that lenders are not (yet) adjusting mortgages appropriately to increasing climatic risks (Ouazad and Kahn 2019; Garbarino and Guin 2020).

The need for NFIP reform is well established. For example, the program has been fiscally insolvent, owing \$30.4 billion to the U.S. Treasury in 2017 (GAO 2018). Despite insurance subsidies for many policies and an insurance requirement for homes with federally insured or regulated mortgages in high-risk areas, NFIP take-up is low. Only an estimated 30%-50% of structures in high flood risk areas are insured (Harrison, Smersh, and Schwartz 2001; Kousky et al. 2018). We model an enforced insurance mandate at actuarially fair rates, which would realign coastal housing prices with fundamentals. While it is efficient, this policy has significant distributional effects. Within our framework, the main winners from immediate reform would be excessively optimistic agents who currently live inland but would have purchased an overvalued coastal home in the future in the absence of policy reform. The main losers would be coastal agents who are concerned about flooding and would have sold their homes to optimists at higher prices absent policy reform. Our analysis thus adds to a growing literature studying the impacts of flood insurance reform across different types of households (e.g., Bakkensen and Ma 2020; Wagner 2019). Most fundamentally, our results highlight the value of better flood risk information. While the Federal Emergency Management Agency (FEMA) publishes official flood maps, these are backwards-looking and often out of date, with one in six maps being more than 20 years old.[5] Our analysis demonstrates how poor flood risk information can threaten the efficiency of coastal housing markets.

The contributions of this work to the broader literature are as follows. First, our paper builds on the literature on housing price dynamics (see, e.g., recent reviews by Davis and Van Nieuwerburgh 2015, and Glaeser and Nathanson 2014) and residential sorting (e.g,. Kuminoff, Smith, and Timmins 2013; Bayer et al. 2016). Most closely related are recent papers that consider heterogeneous beliefs. Both Piazzesi and Schneider (2009) and Burnside, Eichenbaum, and Rebelo (2016; BER) present (quasi)linear utility search models of housing

[5] Authors' calculations based on FEMA National Flood Insurance Program Community Status Book, accessed February 1, 2017: https://www.fema.gov/national-flood-insurance-program-community-status-book

markets coupled with Michigan Consumer and American Housing Survey data on households' expectations. Piazzesi and Schneider consider a one-time unanticipated shock that makes all renters optimistic about future prices to study the effects of momentum traders. BER study social dynamics. With a known probability, the fundamental value of homes may change permanently each period. "Optimists" expect this new value to be higher than do "skeptical" or "vulnerable" agents. Agents can "infect" each other with their opinions, generating housing booms and busts. Our approach both builds on and differentiates itself from BER's. On the one hand, our approach extends BER's model by adding several dimensions of heterogeneity relevant for flood risks and allowing beliefs to evolve in response to external shocks (flood events) in a flexible Bayesian learning framework. On the other hand, ours does not employ a search model and does not focus on infectious social dynamics.

Second, we build on a rich empirical literature on environmental risk capitalization into housing prices. A first-generation strand investigates the effects of current flood risk. Empirical studies generally find weak capitalization of flood zone status into coastal housing prices (see, e.g., meta-analyses by Daniel, Florax, and Rietveld [2009] and Beltrán, Maddison, and Elliott [2018]), though estimates range from large, negative capitalization to positive (e.g., Bin and Kruse 2006; Bin et al. 2008; Atreya and Czajkowski 2016). A new nationwide analysis by Hino and Burke (2020) examining the impact of flood zone changes on housing prices also finds very modest overall effects. The present work contributes to this literature in two ways. First, our model can potentially account for the range of results on capitalization as flood risk penalties are predicted to depend on market-specific variables, such as the distribution of risk beliefs and amenity valuations relative to the size of the coastal housing segment. Second, our survey provides direct evidence that present-day flood risk misperceptions is a potential driver of incomplete capitalization.

Another strand analyzes the impacts of flood events. These studies find that prices of properties that are at high risk of (but are not damaged by) a flood drop 5%-20% in the aftermath of an event (e.g., Hallstrom and Smith 2005; Kousky 2010; Bin and Landry 2013;

Ortega and Taspinar 2018). It is difficult to rationalize that these price fluctuations are based on changes in fundamentals, but they are consistent with flood risk learning. Gibson and Mullins (2020) similarly find that FEMA flood map updates—another flood risk signal— are associated with decreases of 18% in the prices of nonflooded homes in New York City after Hurricane Sandy. Studies that track longer-run effects typically find that prices return to baseline within 4-10 years (e.g., Bin and Landry 2013; Atreya, Ferreira, and Kriesel 2013). Gallagher (2014) documents an analogous pattern in national flood insurance markets, where take-up rises sharply after floods but decreases back to baseline within a decade, and argues that the pattern is most consistent with a modified Bayesian updating model. We incorporate these findings into our model by allowing for Bayesian learning about flood risks. Though a future flood event is not a targeted moment in our calibration, our model quantitatively predicts coastal home price declines of around 10% in the aftermath of such an event, in line with empirical studies.

A newer strand studies the capitalization of future SLR risks. While their methods and results vary, these studies indicate that SLR risks are not fully reflected in home prices. Bernstein, Gustafson, and Lewis (2019; BGL) present evidence from coastal housing markets across the United States. For regular owner-occupied homes, BGL fail to detect a significant SLR vulnerability discount, even when controlling for waterfront amenity values in detailed distance bins. In the non-owner-occupied segment, however, they find a significant and large (7%) discount associated with SLR exposure. Murfin and Spiegel (2020) similarly combine detailed national housing market data with SLR forecasts. Using land rebound and subsidence to tease apart SLR and elevation, they fail to detect a significant effect of SLR on property prices. Giglio et al. (2018) combine housing transactions with information from home listings to create a "climate attention index" based on the frequency with which terms such as *hurricanes* or *flood zones* are mentioned in listings. Their results indicate that this climate attention index predicts flood risk capitalization.

Closest to our work, Baldauf, Garlappi, and Yannelis (2020) investigate the role of general climate change beliefs in SLR risk capitalization. Building on BER, they present a model with heterogeneity in SLR expectations. In their framework, homophily—that is, agents with similar beliefs deriving utility from being near each other—generates stationary sorting of belief types into different areas. The authors show that this sorting should attenuate SLR capitalization in areas with more skeptics. Combining housing transactions data with SLR forecasts and county-level estimates of climate beliefs from the Yale data (Howe et al., 2015), they show this prediction to be empirically true. On the one hand, these empirical results support our model and main mechanism. On the other hand, we note important differences between our model and that of Baldauf, Garlappi, and Yannelis (2020). The latter's model focuses on cross-sectional properties of housing prices in stationary equilibrium with sorting based on fixed beliefs and across homogeneous homes. In contrast, our analysis distinguishes coastal from noncoastal homes; models flood events, flood risk changes, and learning dynamics; and features heterogeneity in coastal amenity values as well as higher-order beliefs. Importantly, while Baldauf et al. focus on theoretical insights from their model, we develop a quantitative framework to project future price dynamics, welfare, and policy counterfactuals. Lastly, while Baldauf et al. rely on county-level estimates of general climate change beliefs, our original survey can more precisely inform questions about flood risk beliefs, potential confounders, and their roles in driving sorting behavior.

Our study also adds to nascent work on the effects of climate skepticism on asset markets (Severen, Costello, and Deschenes 2018; Kahn and Zhao 2018; Barrage and Furst 2019). We relate to a broader finance literature that has documented significant effects of personal experiences. For example, Malmendier and Nagel (2011) show that agents who experienced the Great Depression are more pessimistic about and less likely to participate in the stock market. Kuchler and Zafar (2019) show that individuals' experiences of local home price movements inform their beliefs about aggregate prices. Our survey results similarly show that agents who have experienced floods are more concerned about flooding than those who have not, and our model highlights the potential effects of such belief changes on coastal home price dynamics.

1 Model Intuition

This section presents a simplified version of our model and illustrates how empirically observed flood risk premiums would be expected to differ under alternative belief distributions. As the purpose of this section is to provide basic intuition, several model elements are left implicit until Section 3, which presents a full specification with proper formality.

Our setup follows Burnside, Eichenbaum, and Rebelo (2016; BER) in studying an economy populated by a continuum of agents with linear utility and utility discount rate β. As in BER, agents can own one home or rent, houses cannot be sold short, and there is a fixed stock of houses available for sale $k < 1$.[6] We first introduce heterogeneity in the housing stock: fraction $k_1 < k$ of homes are "coastal" properties (empirically later defined as within 400 feet of the waterfront). Coastal properties differ from inland homes in two dimensions. One, they provide an additional flow utility value of ξ^i, which is indexed by i to indicate that it may vary across households. Two, each period, coastal homes incur net flood damages δ with probability π_t^*. In principle, one could model households as expecting gross damages $\widetilde{\delta}^i$ net of government transfers G^i in case of a flood and allow these expectations to vary across households. However, we focus on net damages δ as FEMA disaster aid is, in reality, very small (typically a few thousand dollars; Kousky [2013]), and our survey results suggest that heterogeneity in flood risk concern is not driven by optimism about public assistance. By the same token, we also leave insurance premiums and payouts implicit in the model but note that they would be straightforward to add. Importantly, however, we allow households to disagree with scientifically forecast flood risks, which we informally denote $E_t^*\{\pi_s^*\}_{s=t}^{\infty}$, and

[6] We thus abstract from housing construction. Empirical estimates find supply in coastal areas to be highly inelastic, driven by topographic constraints (Glaeser, Gyourko, and Saks 2005; Green, Malpezzi, and Mayo 2005). Saiz (2010) estimates metropolitan-statistical-area-level elasticities in the United States, finding Miami, Los Angeles, Fort Lauderdale, and San Francisco to have the lowest supply elasticities. For a theoretical analysis of how developers may respond to climate risks, see Bunten and Kahn (2017).

to hold their own first-order beliefs denoted $E_t^i\{\pi_s^i\}_{s=t}^{\infty}$. Both the full information dynamics of future flood risk changes and higher-order beliefs are left implicit in the expectations operator here but made explicit in Section 3.

The rental market, also as in BER, consists of $1-k$ homes that are produced by competitive firms charging a rental rate of w per period. The flow utilities of owning versus renting a home are given by ε^h and ε^r, respectively. Each period, households thus face the decision of whether to (i) buy a noncoastal home at price P_t^{NC}, (ii) buy a coastal home at price P_t, or (iii) rent (inland). We focus on a frictionless housing market where prices are determined by the valuation of the marginal buyer.[7] Letting m_t index the marginal buyer's identity at time t, in equilibrium the buyer must be just indifferent between the available options:

$$-P_t + \beta(\varepsilon^h + \xi^{m_t} - \pi_t^{m_t}\delta + E_t^{m_t}[P_{t+1}]) = \beta(\varepsilon^r - w) = -P_t^{NC} + \beta(\varepsilon^h + E_t[P_{t+1}^{NC}]), \qquad (1)$$

where $E_t^{m_t}[P_{t+1}]$ is m_t's expectation of the resale value of a coastal home in period $t+1$. Further defining $e^h \equiv \varepsilon^h - (\varepsilon^r - w)$ as the net flow utility of being a homeowner rather than a renter in Equation (1) thus yields the following pricing condition for coastal homes:

$$P_t = \beta(e^h + \xi^{m_t} - \pi_t^{m_t}\delta + E_t^{m_t}[P_{t+1}]). \qquad (2)$$

Intuitively, Equation (2) indicates that coastal home prices depend on the marginal buyer's amenity values, current flood risk beliefs, and resale value expectations, which, in turn, depend on the marginal buyer's (first- and higher-order) beliefs about future flood risks.

For the remainder of this illustration, we will assume that scientists can predict SLR perfectly. The full model in Section 3 accounts for uncertainty over SLR. We also assume in this illustration that coastal amenity values are independently and uniformly distributed with $f_\xi(\xi^i) \sim U[0, \Xi]$. The parameter Ξ thus denotes the maximum per-period willingness

[7] The Internet Appendix considers transaction costs in a stylized version of the model. We show that the level of overvaluation due to flood risk misperceptions is unaffected by transaction costs.

to pay for waterfront living among the population.

1.1 Homogeneous rational beliefs

We first consider the implications of the benchmark assumption of homogeneous rational flood risk beliefs, implying that $E_t^i\{\pi_s^i\}_{s=t}^{\infty} = E_t^*\{\pi_s^*\}_{s=t}^{\infty}$ $\forall i$ and thus that $E_t^i[P_{t+1}] = E_t[P_{t+1}]$ $\forall i, t$. For completeness, consider a housing market that starts in a "pre-climate-change predictions" equilibrium where SLR and its implications for flood risks are not yet a part of official or widely disseminated scientific predictions. If everyone believes that flood risks will remain constant at a low level $\pi_t^* = \pi^L$ $\forall t$, the initial ($t = -1$) equilibrium coastal home price will be given by the stationary solution to (2)

$$P_{-1} = \frac{\beta(e^h + \Xi(1-k_1) - \pi^L\delta)}{(1-\beta)}. \tag{3}$$

The term $\Xi(1-k_1)$ captures the k_1^{st}, and thus market-clearing, amenity value. Through the lens of the model, the empirically estimated hedonic coastal housing premium $PREM_t^{\text{Coast}}$ $\equiv (P_t - P_t^{NC})$ and the flood risk premium $PREM_t^{Flood} \equiv \frac{\partial P_t}{\partial \pi_t^*}$ should thus correspond to

$$\begin{aligned} PREM_{-1}^{\text{Coast}} &= \left[\Xi(1-k_1) - \pi^L\delta\right]\left(\frac{\beta}{1-\beta}\right) \lesseqqgtr 0 \text{ and} & (4) \\ PREM_{-1}^{Flood} &= -\delta\left(\frac{\beta}{1-\beta}\right) < 0. & (5) \end{aligned}$$

The overall coastal premium represented by Equation (4) thus depends on both the amenity value Ξ and expected damages $\pi^L\delta$ and could be positive or negative. The ceteris paribus effect of flood risk represented by Equation (5), however, should be unambiguously negative in the homogeneous rational beliefs model.

Next, consider a stylized representation of climate change expectations where, at $t = 0$, it is announced that flood risk will permanently increase to $\pi^H > \pi^L$ at some future time T_1. That is, $\pi_t^* = \pi^L$ for $t < T_1$ and $\pi_t^* = \pi^H$ for $t \geq T_1$. In order to derive predictions for the resulting flood risk premium, the correlation between current and future flood risks must be specified. Since waterfront flood risk is mainly a function of elevation, we first consider a simple relationship with proportional flood risk increase γ^{SLR} :

$$\pi^H = \gamma^{SLR} \cdot \pi^L. \tag{6}$$

It is easy to show (through backwards iteration) that the flood risk premium should immediately fall to reflect the new forecast and should continue to grow more negative until it reaches its new long-term value. That is, the flood risk premium should immediately incorporate the present value of future flood risk increases:

$$\begin{aligned} PREM_t^{Flood} &= \underbrace{-\delta\left(\frac{\beta}{1-\beta}\right)}_{\text{Current Risk Effect}} - \underbrace{\{\gamma^{SLR}-1\}\frac{\beta^{T_1+1-t}}{(1-\beta)}\delta}_{\text{Present Value of Future Risk Effect}} \quad \text{for } t \in \{0, 1, ...T_1\} \text{ and} & (7) \\ &= -\{\gamma^{SLR}\}\delta\left(\frac{\beta}{1-\beta}\right) \quad \text{for } t > T_1. & (8) \end{aligned}$$

With homogeneous rational beliefs, observed flood risk penalties should thus be unambiguously negative and growing in full anticipation of future risk increases induced by climate change. This prediction is clearly counterfactual for many segments of the U.S. housing market, as described in the previous section. The Internet Appendix further presents hedonic estimates of the flood risk premium based on housing market transactions data over a longer time horizon (1970–2017) in our empirical setting. These estimates also fail to match this predicted pattern. The next subsection consequently proposes a generalization of the standard model to accommodate disagreement with official forecasts as potential explanation for these empirically observed risk capitalization patterns.

1.2 Skepticism

We now consider the possibility that at least some agents' beliefs diverge from the scientific forecast. Specifically, we generalize the homogeneous rational beliefs model to allow for a second belief type.[8] Fraction $(1-\theta^o)$ of the population remain "realists" who believe in the scientific forecast ($\{\pi^r_s\}_{s=t}^{\infty} = \{\pi^*_s\}_{s=t}^{\infty}$), whereas fraction θ^o hold more optimistic beliefs with $\pi^o_t \leq \pi^*_t \; \forall t$. In Section 3, optimists' beliefs are microfounded via skepticism of the scientific forecast, which they believe to be true only with some prior probability. Here, for ease of illustration, we present a simpler specification where optimists' flood risk perceptions lie a fraction $\lambda_t^{Opt} \in [0,1]$ below official estimates π^*_t:

$$\pi^o_t = (1-\lambda_t^{Opt}) \cdot \pi^*_t. \tag{9}$$

As before, the market-clearing marginal buyer will be the agent with the k_1^{st} valuation for coastal properties. There are now three general cases to consider.

1.2.1 Case 1.

If there are more optimists than coastal homes ($\theta^o > k_1$), it is possible that only optimists will live on the coast if even the realist with the highest amenity value ($\xi^r = \Xi$) assigns a lower value to buying a coastal home than the (then marginal) optimist:

$$\underbrace{\beta(e^h + \Xi - \pi^r_t\delta + E^r_t[P_{t+1}])}_{\text{Maximum willingness to pay (WTP) for coastal home among realists}} < \underbrace{\beta(e^h + \widehat{\overline{\xi^o}} - \pi^o_t\delta + E^o_t[P_{t+1}])}_{\text{WTP for coastal home of (marginal) optimist}}. \tag{10}$$

In this case, the marginal optimist's amenity value $\widehat{\overline{\xi^o}}$ must clear the market:

$$\frac{\theta^o}{\Xi}(\Xi - \widehat{\overline{\xi^o}}) = k_1. \tag{11}$$

Rearranging Equation (11) reveals that Equation (10) will hold if risk perceptions are sufficiently different:

$$\Xi\frac{k_1}{\theta^o} + \{E^r_t[P_{t+1}] - E^o_t[P_{t+1}]\} < \delta(\pi^r_t - \pi^o_t). \tag{12}$$

[8] Our model also allows for the possibility of homogeneously misinformed agents if $\theta^o = 1$. Figure A6 in the Internet Appendix also presents quantitative results for this case.

The equilibrium coastal home price in this setting is then defined by

$$P_t = \beta(e^h + \Xi\left(1 - \frac{k_1}{\theta^o}\right) - \pi_t^o\delta + E_t^o[P_{t+1}]).$$

The cross-sectional flood risk premium—estimated as home price change with respect to official risk π_t^*—now differs from the homogeneous model's prediction (7):

$$PREM_t^{Flood} = \underbrace{-(1-\lambda_t^{Opt})\delta}_{\text{Current Risk Effect}}\beta + \underbrace{\Delta E_t^o[P_{t+1}]\beta}_{\text{Future Risk Effect}} \text{ for } t \geq 0. \tag{13}$$

Here, $\Delta E_t^o[P_{t+1}]$ denotes the change in optimists' expectations of the resale value of coastal homes across areas with higher official flood risk. The capitalization of current risk is now attenuated by optimists' discounting of flood risk $(1-\lambda_t^{Opt})$. Our survey results suggest that 50% of coastal homeowners in our sample underestimate their homes' flood risk by 50% or more, implying a potentially substantive value for λ_t^{Opt}. In addition, the internalization of future flood risk is generally also attenuated compared to the rational beliefs case. We formalize this statement in Section 3. The central point here, however, is that a model with belief heterogeneity can account for the empirically observed undercapitalization of current and future flood risks in markets with a sufficient density of excessively optimistic (or climate skeptical) households.[9]

1.2.2 Case 2.

Case 2 occurs when both optimists and realists buy coastal homes. The marginal buyers' valuations are then equated:

$$\beta(e^h + \overline{\xi_t^r} - \pi_t^r\delta + E_t^r[P_{t+1}]) = \beta(e^h + \overline{\xi_t^o} - \pi_t^o\delta + E_t^o[P_{t+1}]) = P_t. \tag{14}$$

We recognize intuitively that the marginal realist in this case has a sufficiently high

[9] Case 1 also covers the setting with homogeneous misperception ($\theta^o = 1$) as optimists would be trivially pricing coastal homes, thus leading to an attenuation of the flood risk premium as in Equation (13).

amenity value $\overline{\xi^r_t}$ so as to equate their coastal home valuation to that of the marginal optimist. The marginal amenity values and equilibrium prices are then pinned down jointly by Equation (14) and market clearing:

$$\frac{\theta^o}{\Xi}(\Xi - \overline{\xi^o}_t) + \frac{(1-\theta^o)}{\Xi}(\Xi - \overline{\xi^r}_t) = k_1. \tag{15}$$

A ceteris paribus increase in official flood risk π^*_t now has the interesting effect that it will alter the identities and thus amenity values of the marginal buyers in addition to changing the valuation of flood risks. That is, the cross-sectional flood risk premium (across two otherwise identical housing markets in equilibrium Case 2) will contain effects of both sorting and potentially underestimated current and future risks:

$$PREM^{Flood}_t = (\Delta\overline{\xi^r_t} - \delta + \Delta E^r_t[P_{t+1}])\beta = (\Delta\overline{\xi^o_t} - (1-\lambda^{Opt}_t)\delta + \Delta E^o_t[P_{t+1}])\beta. \tag{16}$$

Since the direct effect of higher flood risk on optimists' valuations is weakly less negative than its effect on the realists' ($-(1-\lambda^{Opt}_t)\delta \geq -\delta$), and assuming that the same will be true of the effect on future price expectations ($\Delta E^o_t[P_{t+1}] \geq \Delta E^r_t[P_{t+1}]$), the marginal realist in the higher-risk setting must have higher amenity values for waterfront living ($\Delta\overline{\xi^r_t} > 0$), whereas the marginal optimists moving to the coast after the change in risk must have lower amenity values ($\Delta\overline{\xi^o_t} < 0$). This comparative static also illustrates the allocative inefficiency resulting from flood risk misperceptions. Importantly for our purposes, however, Equation (16) highlights why the presence of some market participants with realistic flood risk beliefs is not necessarily sufficient to ensure that those risks are fully capitalized into coastal housing prices, in line with the empirical evidence.

1.2.3 Case 3.

Finally, if there are fewer optimists than coastal homes ($\theta^o < k_1$), the marginal buyer is trivially a realist. In this case, the marginal realist's amenity value $\widehat{\xi^r}$ must clear the market for coastal homes net of the space already occupied by the optimists:

$$\frac{(1-\theta^o)}{\Xi}(\Xi - \widehat{\xi^r}) = k_1 - \theta^o.$$

The equilibrium price in this setting will then satisfy

$$P_t = \beta(e^h + \Xi\left(1 - \frac{(k_1 - \theta^o)}{(1-\theta^o)}\right) - \pi_t^r \delta + E_t^r[P_{t+1}]). \tag{17}$$

The flood risk premium in this type of market would then be

$$PREM_t^{Flood} = \underbrace{-\delta\beta}_{\text{Current Risk Effect}} + \underbrace{\Delta E_t^r[P_{t+1}]\beta}_{\text{Future Risk Effect}} \text{ for } t \geq 0. \tag{18}$$

The current flood risk capitalization in this market thus matches that of the homogeneous rational expectations setting. Since realists will remain marginal buyers, their future risk internalization should, moreover, capture the full climate change forecast. It should be noted that coastal home price levels, as represented in Equation (17), are still distorted in this setting as some optimists with lower amenity values take up coastal real estate that should, from an efficiency perspective, go to realists with higher amenity values. If realists expect that these optimists will one day change their beliefs to match the official forecast, thus exiting the coastal property market, they will anticipate an additional future devaluation due to this correction to optimists' beliefs. Overall, however, the heterogeneous beliefs model can also accommodate the finding that markets dominated by agents with realistic flood risk beliefs are likely to internalize these and future climate risks, again in line with the empirical evidence.[10]

[10] Adding pessimists (i.e., agents who overestimate flood risk) is unlikely to change the results as pessimists should be less likely to buy, and thus price, coastal homes. In Case 1, only optimists buy coastal homes. A modified version of Case 2 could exist where pessimists, realists, and optimists all live on the coast; however, the presence of pessimists would not eliminate the mispricing induced by optimists for the same reasons outlined in Case 2 with regard to realists. There could theoretically be a Case 4 where pessimists are the sole marginal buyers of coastal homes, but this would only be the case if there were more coastal homes than realists and optimists. Our survey results and extension to other cities suggest that the share of optimists is generally larger than the share of coastal homes.

2 Direct Evidence: Field Survey

The analysis thus far indicates that a housing market model with flood risk misperceptions fits the empirical findings better than a benchmark homogeneous rational beliefs model. At the same time, the model also illustrates the structural challenges inherent in seeking to isolate risk beliefs from hedonically estimated flood risk premiums. We therefore turn to surveys as a methodology that can elicit flood risk perceptions and confounding beliefs and provide direct evidence on heterogeneity and sorting. In light of well-known potential concerns about stated preference elicitation, we complement the survey with a hedonic analysis of housing prices, and use its results to inform the robustness analysis in the Internet Appendix.

2.1 Design

We conduct in-person surveys through a door-to-door campaign in Rhode Island, targeting communities with both coastal (defined as within 400 feet of the waterfront) and noncoastal homes.[11] The surveys are conducted in two waves across February and July 2017. The survey instruments are provided in the Internet Appendix. The key components of the survey are as follows. First, we elicit households' ceteris paribus willingness to pay (WTP) for living within 400 feet of the water using a double-bounded dichotomous choice (DBDC) contingent valuation mechanism (Hanemann, Loomis, and Kanninen 1991).[12] We use contingent valuation (CV) instead of the often-utilized hedonic model for several reasons. For one, estimating the coastal amenity value is difficult with the hedonic model given the strong correlation between coastal amenities and flood risk that can potentially bias results in a

[11] Two key model features motivate the need for an original door-to-door survey campaign rather than the leveraging of existing survey products. First, while prominent publicly available surveys exist that assess flood risk perception across the United States (e.g., FEMA 2013), our model requires the joint distribution of both waterfront living valuation and flood risk perception at the household level. Second, to assess the existence and frequency of optimists in the market, we need to compare homeowner flood risk perception with hydrological flood risk at the property level, the latter of which is often not collected or is collected at a coarser level (see review by Kellens, Terpstra, and De Maeyer 2013). Also, see the Internet Appendix for a copy of our survey instrument for coastal and noncoastal residents.

[12] DBDC has been shown to be a more efficient WTP estimate than a single-bounded approach (Hanemann, Loomis, and Kanninen 1991). For sensitivity, we also estimate WTP using a single-bounded dichotomous choice with the first bid and find the mean WTP to be similar (11% lower).

revealed-preference setting (Bin et al. 2008). In addition, as our model indicates, hedonic estimates confound amenity values with sorting and future price expectations. Also, our model needs information on amenity values for both residents who choose to live on the coast and those who do not, whereas the hedonic model only estimates a value for the marginal buyer. Lastly, while the CV technique has been subject to criticism, including for its elicitation of nonuse values (Diamond and Hausman 1994), researchers who follow best practices have used the technique for decades to accurately estimate environmental values (Kling, Phaneuf, and Zhao 2012). Kenneth Arrow, Robert Solow, and others who participated in the National Oceanic and Atmospheric Administration's Blue Ribbon Panel on the CV method have laid out best practices (Arrow et al. 1993). Both our use of face-to-face interviews and the DBDC mechanism are motivated by best-practice recommendations in CV survey design (Arrow et al., 1993; Mitchell and Carson, 2013).

Guided by the literature on efficient starting-bid design (Kanninen 1993; Alberini 1995), the three starting bids of $150, $250, and $350 are chosen based on our hedonic estimation of the annualized waterfront living premium using U.S. Census American Housing Survey data for 2013. The DBDC question is asked early in the survey to avoid bias due to priming with flood risk information (Cameron and James 1987; Arrow et al. 1993; Hanemann 1994; Carson and Mitchell 1995).

Second, we elicit coastal flood risk perceptions. In line with best practices in the risk elicitation literature (Manski 2004), we consider both qualitative and quantitative subjective risk measures. As a qualitative measure, we ask subjects to indicate on a 10-point scale how worried they are about the risk of a flood affecting their or a coastal home over the next 10 years. The design of this question is motivated by the findings of Schade, Kunreuther, and Koellinger (2012) that such a worry scale performs significantly better as a predictor of demand for insurance against low-probability disasters than quantitative subjective probability measures. The quantitative elicitation asks subjects about their perception of the probability of experiencing at least one flood over the course of the next 10 years.[13] Coastal residents are asked about their homes specifically, whereas noncoastal residents are asked to consider a home like theirs located within 400 feet of the waterfront in their community. As a visual aid, subjects are shown a table of both natural frequencies and probabilities.

Third, the survey asks subjects about potential confounders that could affect concern about flooding, including expectations over flood damages, insurance reimbursements, and government assistance, as well as flood risk mitigation. We also ask about flood experiences and intentions to sell or buy a home in the next 5 years. Finally, the survey asks subjects to describe their beliefs about changes in future flood risk and the climate. We supplement demographic information elicited in the survey with publicly available information on home characteristics from tax assessor records.

This section reports results from 187 interviews (52% coastal) conducted in several Rhode Island communities.[14] This sample size is in line with prior survey studies of flood risk perceptions, particularly those using face-to-face interviewing techniques.[15] Close to 40% of people who answer their doors agree to take the survey. The overall estimated response rate (including unanswered doors) of approximately 12.5% is similar to DellaVigna, List, and Malmendier's (2012) response rates of 10%–15% in their unannounced door-to-door survey treatment groups. Though not designed to be statistically representative, our sample of sur-

[13] We deliberately do not attempt to financially incentivize subjects' subjective flood risk responses because any scoring rule would have to pit subjects' answers against official flood risk projections based on inundation models as the true benchmark. It is, of course, precisely the deviations between subjects' subjective beliefs and the official FEMA announcements of flood risk that we are seeking to understand. In contrast to economic experiments that can benchmark subjective probabilities against events occurring in the laboratory in real time, we also cannot wait for flood risk realizations over the next year(s) to financially impact respondents. Indeed, for these and similar reasons, field surveys eliciting expectations commonly do not incentivize these responses (Manski 2004). See the Internet Appendix for a copy of the visual probablity aid.

[14] The study design and implementation was approved by the Institutional Review Boards of Brown University and the University of Arizona, and all surveyors completed training through the Collaborative Institutional Training Initiative. Spoken informed consent was obtained from all respondents. Respondents were also compensated $5 for agreeing to take the survey, though some respondents declined compensation.

[15] For example, Pagneux, Gísladóttir, and Jónsdóttir (2011) present face-to-face interviews on flood risk perceptions with 112 subjects in Iceland. Lindell and Hwang (2008) present a mail survey with 321 responses. Kellens, Zaalberg, and De Maeyer (2012) utilize 266 complete online surveys (based on 313 responses). See also the meta-analysis by Kellens, Terpstra, and De Maeyer (2013).

vey respondents also appears to be demographically comparable to county-level populations, although our sample skews slightly older and more educated (see Internet Appendix).

Before proceeding, we highlight several survey quality checks, which are described in further detail in the Internet Appendix. In order to test whether survey respondents are providing sensible responses or simply randomizing, we compare their answers to available external benchmarks. First, we compare homeowners' stated guesses of their homes' current market values against Zillow Zestimates.[16] We find a correlation of 0.89, indicating a high level of agreement. This result is all the more reassuring as the question on home market values is at the end of the survey, making it relatively more vulnerable to the effects of survey fatigue. Second, we compare homeowners' stated purchase years with tax assessor data. In the cases where we can establish the purchase date of a home with reasonable confidence (e.g., where the most recent deed on record is a sale to new owners at a positive price), there is a very high level of agreement between the survey and the deed records. With the exception of one outlier, the correlation is 0.996.[17] Third, respondents' stated expectations of key outcomes such as damages in case of a flood event compare favorably with data-based estimates. In particular, our survey-based median gross damage estimate of 20% of property values is comparable to Kousky and Michel-Kerjan's (2017) estimate of average flood losses of 24.8% of home values based on microdata from NFIP flood damage claims. Finally, predictions based on our survey results of the percentage of residents who are flood risk optimists in each of the three counties we visit correlate strongly (up to 0.99) with county-level estimates of general climate change concern from the Yale Program on Climate Change Communication, as described in Section 5.

[16] We thank an anonymous referee for suggesting this comparison.

[17] As discussed in the Internet Appendix, the outlier household is a flood zone resident who express high levels of worry, so excluding them from our sample would only strengthen our main results.

2.2 Main survey results

First, we find strong evidence of heterogeneity in flood risk perceptions. In line with the sorting mechanism implied by the model, we find that coastal residents living in official FEMA high-risk flood zones are significantly less worried about flooding than those whose homes are outside the flood zone, as shown in Figure 1.

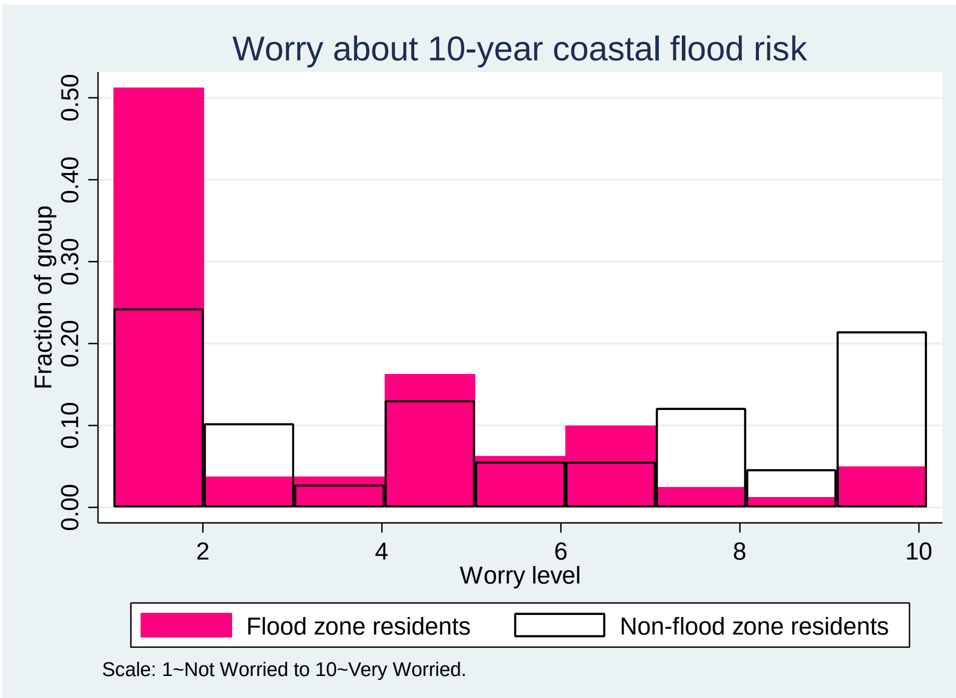

Figure 1: **Flood worry distribution** Figure plots the distribution of level of worry about the risk of a coastal flood in the next 10 years for flood zone residents and non-flood zone residents. Level of worry was elicited on a 10-point scale with 10 being most worried. Mean worry of flood zone residents was significantly less than that of non-flood zone residents.

Of course, a low degree of worry could indicate expectations of a low risk of losses from a flood rather than concern about flood risk itself. Figure 2 showcases the distribution of expected flood damages (as a percentage of home value) net of expected insurance reimbursements and government assistance.[18] While flood zone residents generally expect slightly

[18] Households whose (net) estimates imply flood damages in excess of 100% (below 0%) of home values are recoded as 100% damage (0%) estimates.

lower damages than non-flood zone residents, they also expect less insurance and government assistance (see Table 1). The net damage expectations are thus very similar across the two groups, and the means are statistically indistinguishable, suggesting that differences in flood worries are not driven by differential expectations of damages or ex post flood assistance.

Other potential confounders include the following. First, flood zone residents could be secondary homeowners who are disproportionately less concerned about flooding. To address this possibility, we use property tax records to construct a measure of secondary homeownership and verify that the results are virtually unchanged if secondary homeowners are excluded (see Internet Appendix). Second, another potential explanation for low worry among some coastal residents is that they may have taken flood risk mitigation measures, such as installing a water pump. We ask about such mitigation measures in the second wave of the survey. While the sample size is smaller, being from the second wave only, the results indicate that flood zone residents who report low worry also report fewer mitigation measures than flood zone residents who report high worry, though not significantly so (see Internet Appendix). Focusing on the most effective mitigation measures—sea walls and home elevation[19]—we further find that respondents listing these protection efforts appear, if anything, more worried about flooding on average than those who do not list them, though again not significantly so.[20] Our results are thus consistent with the notion that worry drives risk-reducing behaviors, including residential location choice.

Table 1 presents survey results for flood zone and non-flood zone residents. Both demographic and home characteristics appear similar across the two groups. Beyond exhibiting

[19] Homes that have been elevated sufficiently to reduce their annual flood risk below 1% can be removed from FEMA's high-risk flood zone through a Letter of Map Revision. Our analysis would then not count those homes as being in the high-risk flood zone.

[20] One may also be concerned about households' beliefs about future public protective infrastructure projects. Our survey asks respondents who express a belief in future flood risk increases or decreases for the reasons for their belief. Excluding the four respondents who mention sea walls or construction does not change the result of significantly lower flood risk worry among flood zone residents. Further excluding those expressing a belief that future flood risk will remain unchanged—who were not asked about reasons for their beliefs—also leaves our main result intact. See the Internet Appendix for details.

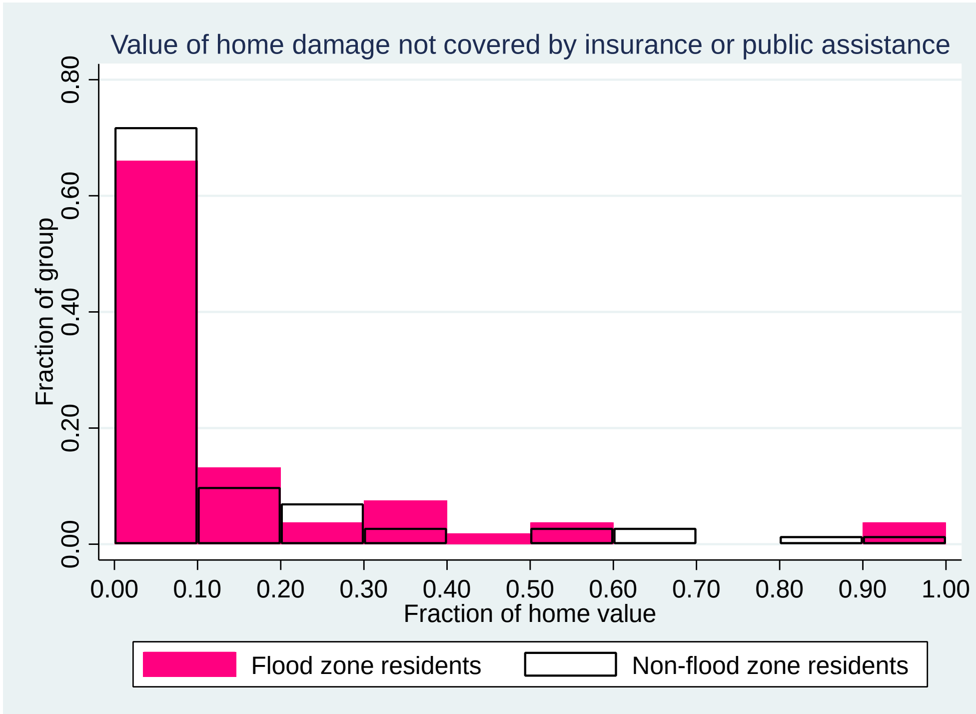

Figure 2: **Expectations of net damages** Figure displays the distribution of expected damages from a flood event (as a percentage of home value) net of expected insurance reimbursements and government assistance. The distribution for flood zone residents is shown in pink and non-flood zone residents in white. Mean expectations of net damages do not significantly differ between the two groups.

significantly lower flood risk concerns, flood zone residents differ from non-flood zone residents mainly in having smaller households and homes.[21] The central take-home point is that there is significant heterogeneity in concerns about flooding that does not appear to be driven by differences in confounders such as expectations of government or insurance assistance.

The results presented thus far focus on flood risk perceptions measured by a worry index. However, we also elicit quantitative flood risk beliefs. Figure 3 compares these quantitative beliefs with the actual 10-year flood risk for respondents' homes. We define this risk as the probability of floodwater levels reaching the home in the next 10 years. We estimate this risk using property-specific elevation data from a LiDAR-based 1-meter-resolution digital

[21] For the living-area variable, we use finished area for Barrington, Bristol, and Warren and effective area for Portsmouth and Warwick. We set the living area for one home with a recorded finished area of 0 to missing.

elevation model from the University of Rhode Island Environmental Data Center in combination with STORMTOOLS, a set of inundation maps and flood return rates for Rhode Island developed by partners including the University of Rhode Island and NOAA (Rhode Island Coastal Resources Management Council, n.d.).[22] The sample for this survey question is restricted to those with coastal homes, so responses reflect individuals' flood inundation estimates specific to their own homes. On the one hand, we find that the actual probability of flooding is a highly significant predictor of perceived flood inundation probabilities (see Internet Appendix for regression results). On the other hand, coastal residents appear to systematically underestimate their flood risk relative to inundation models. Assessments that agree with the storm surge model are near the 45° line in Figure 3. Yet 60%–70% of estimates are located under that line, indicating that these coastal residents underestimate their homes' flood risk relative to the inundation model. Further, the average perceived flood risk is significantly lower than model-based estimates.[23]

With regards to flood risk perceptions, the survey provides evidence on two additional elements of the model. First, households that have experienced a naturally caused flood at their homes are significantly more likely to be concerned about flooding than those who have not (see Internet Appendix Figure A5). Second, coastal residents who are very worried about flooding are significantly more likely to plan on selling their homes within the next 5 years than those who are not very worried, as shown in Figure 4.[24] Both results are in line with our model's central mechanisms that households learn about flooding from past events

22 We utilize STORMTOOLS estimates of the annual inundation footprints for once-in-1-, 3-, 5-, 10-, 25-, 50-, and 100-year-return-period events generated based on current sea levels and tides. Inundation footprints in STORMTOOLS are modeled in the U.S. Army Corps of Engineers' North Atlantic Coast Comprehensive Study using NOAA's SLOSH model and ADCIRC/WAM/STWAVE hydrodynamic/wave model to estimate inundation extents from 100 historical extratropical storms and 1050 synthetic tropical cyclones (Spaulding et al. 2017). We assign flood probabilities to properties based on the shortest return period in which the property will be inundated. We rescale annual inundation probabilities to 10-year probabilities assuming no increase in flood risk over that period, a conservative assumption.

23 A two-sided t-test for the mean perceived risk (0.21) and mean actual estimated risk (0.37) rejects the null of equal means with a p-value < 0.0001. See the Internet Appendix for details.

24 Defining "very worried" as flood worry levels of 9 or 10 out of 10, the difference is significant with a p-value of 0.0375 for one-sided and 0.075 for two-sided t-test.

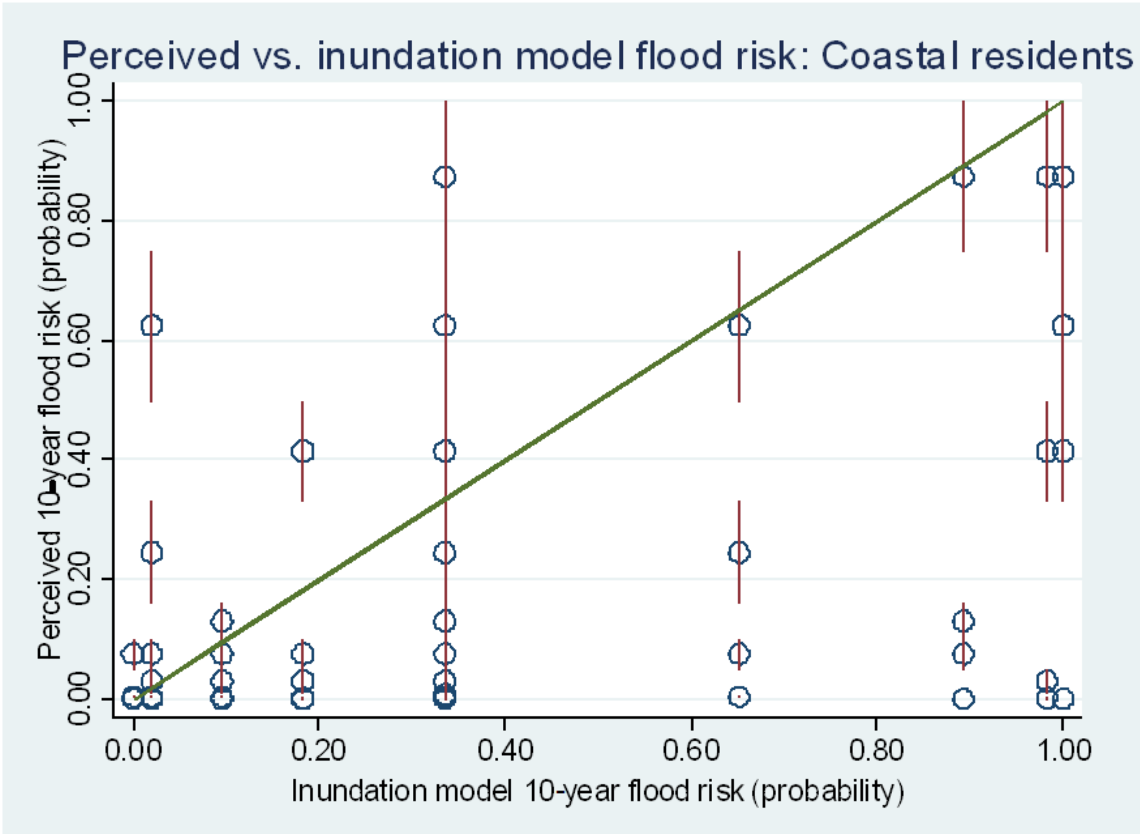

Figure 3: **Perceived vs inundation model flood risk** Figure displays coastal residents' perceived flood inundation probabilities for their own properties versus actual inundation model-based estimates of the probability. Red lines indicate range of perceived 10-year flood risk probability (e.g., 5%–10%) and blue circles mark the midpoints. Observations falling below the green 45° line (> 60% of respondents) underestimate their 10-year risk of flooding relative to data-based estimates from the STORMTOOLS inundation model.

and are more likely to select out of coastal property markets as their perceived flood risk increases.

The second main finding of the survey is the assessment household-specific willingness to pay (WTP) for living within 400 feet of the waterfront. The survey question asks respondents about their WTP assuming that all other home attributes—including environmental risks—remain unchanged compared to their current homes. If respondents ask for clarification, surveyors explain that this includes flood risks and that the question asks strictly about the amenity value of living by the water without changes in flood risks or insurance requirements. Additional details of the estimation of WTP are presented in the Internet Appendix.

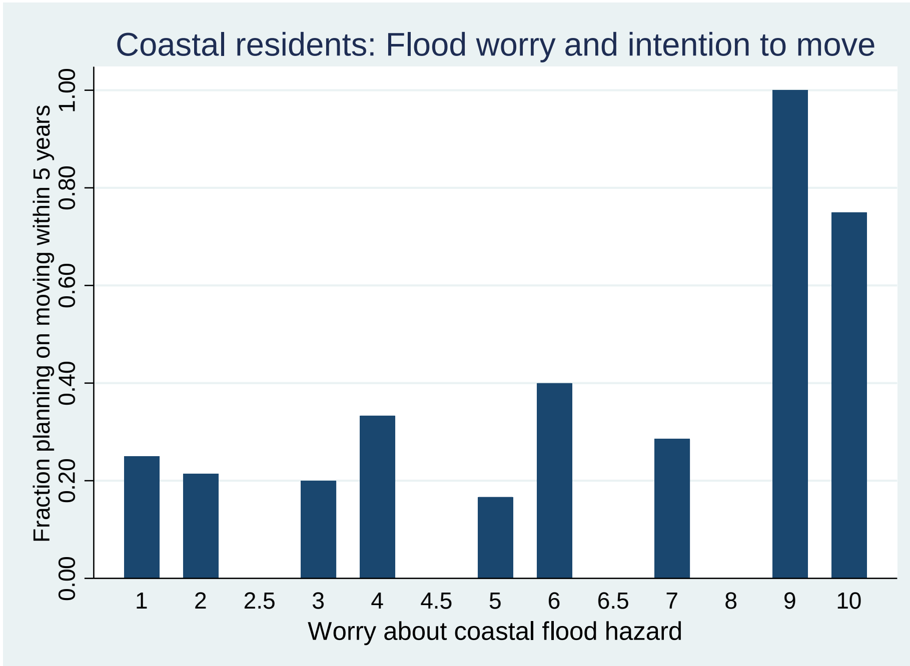

Figure 4: **Flood worry and intentions to move** Figure displays the distribution of worry about the risk of a coastal flood among coastal residents and the fraction of respondents planning to move in the next 5 years. Coastal residents who are more worried about flood risk are significantly more likely to plan to move in the next 5 years relative to those who are less worried. Worry levels of 2.5 and 4.5 are included as we observe respondents who state these levels of worry; none, however, are planning to move. Worry is measured on a scale of 1 to 10 where “1” means “not worried at all” and “10” means “very worried.”

Figure 5 plots the joint distribution of coastal amenity values and flood risk perceptions among coastal (circles) and noncoastal (x’s) residents. The results indicate that selection into coastal homes is driven by a combination of higher amenity values and lower flood risk concerns, in line with the core mechanisms of the model. Figure 5 also provides a visual gauge on allocative inefficiency, which appears modest at present.

With regard to risk belief types, we classify respondents as optimists if they underestimate coastal 10-year flood risk by at least ∼50%. In our sample, respondents are "optimists" if their subjective coastal 10-year flood risk assessment is between 0% and 5%. In fact, in FEMA high-risk flood zones, the annual probability of flooding is at least 1%, implying a 10-year probability of at least one flood of 9.6%.[25] We define "realists" as respondents

[25] While not all coastal homes in our sample are in a FEMA flood zone due to their elevation, risks exceed 1% per year for some homes in the sample. As we estimate the average annual flood risk for coastal

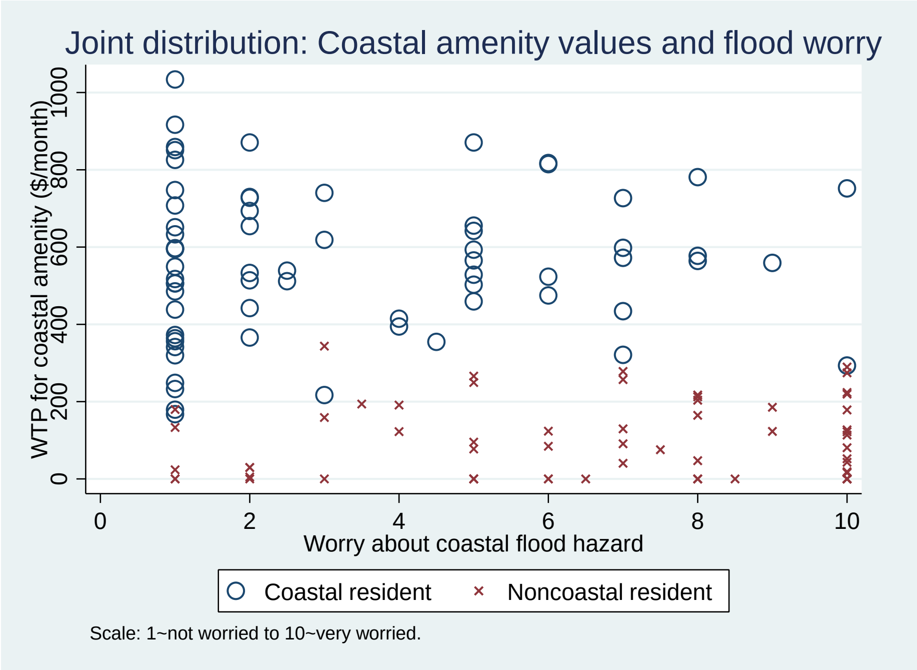

Figure 5: **Joint amenity value and flood worry distribution** Figure plots the level of worry about coastal flood risk (on a 10-point scale) and estimated WTP for the coastal amenity (in \$/month) of coastal and noncoastal residents. The data indicate that selection into coastal living is driven by both higher coastal amenity value and lower flood risk concerns.

whose subjective subjective coastal 10-year flood risk assessment is greater than 5%.While the mean amenity value is slightly higher for optimists than for realists, the distributions appear sufficiently similar in the two populations that we maintain the assumption of equal ξ distributions as a benchmark in the calibration below. The Internet Appendix presents a further comparison of demographic and other variables between optimists and realists. The two groups appear statistically indistinguishable on most dimensions. Prior literature has likewise found that demographics have little explanatory power over general housing market optimism (Piazzesi and Schneider 2009). We return to this issue in the discussion of welfare effects in Section 4.2.

The final survey result is that the majority of respondents expect future flood risks to be at least "somewhat greater" than current risks. Figure 6 plots the distribution of these beliefs across types. As expected, realists are more likely to assume greater future flood risk

homes in our sample to exceed 1% per year, using a 1% figure is thus conservative.

increases than optimists.[26] However, even the majority of optimists anticipate some increase in flood risks. Informed by these results, our model assumes that optimistic agents anticipate the possibility of a future flood risk increase and that they become Bayesian learners with some positive prior on the probability that SLR has occurred.

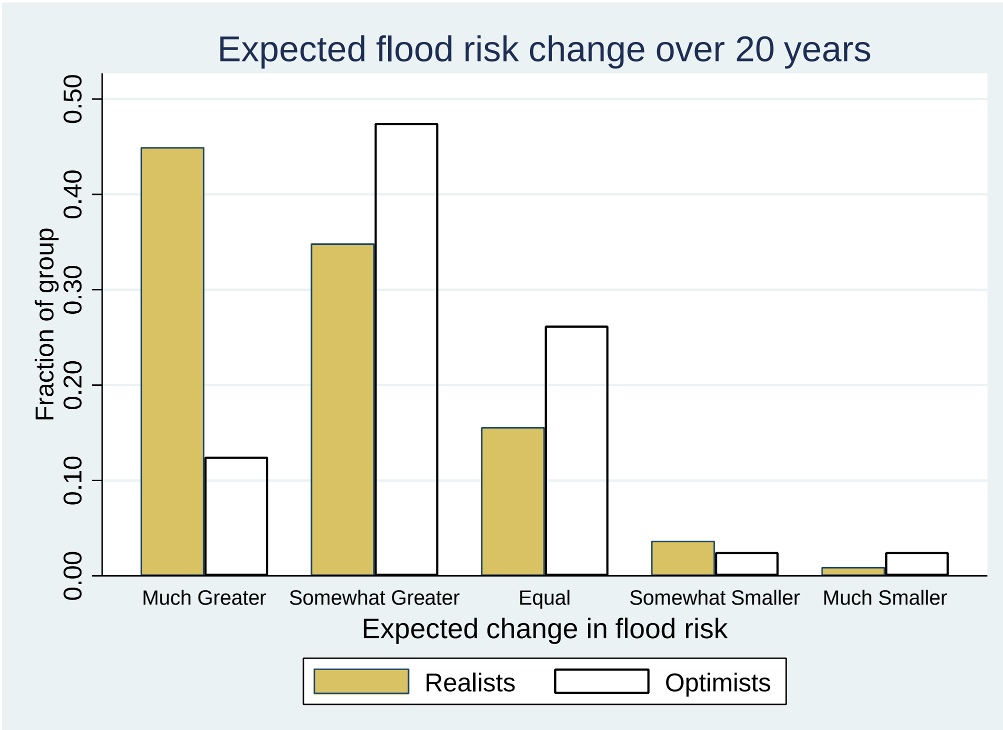

Figure 6: **Expectations of future flood risk** Figure displays the distribution of expectations of changes in flood risk over the next 20 years for realists and optimists. While a majority of respondents expect flood risk to increase in the future, realists are more likely to assume greater future flood risk increases than optimists.

3 Full Structural Model

This section presents the remaining assumptions and the solution method employed to simulate future coastal home price trajectories across different scenarios.

[26] One may be concerned about expectations of future public flood risk mitigation measures, such as sea walls. Our survey asks subjects expecting a change in future risk, "Why do you think flood risk will change this way?" Only four respondents mention sea walls or construction as a reason why they expect flood risk to decrease in the future. Indeed, Rhode Island has statewide regulations that prohibit or highly restrict the construction of new structural shoreline protection measures across many of the state's coastal areas (Rhode Island Coastal Resources Management Council 2013, 2020).

3.1 Flood risk and beliefs

First, we assume that current flood risk is known to scientists. Realists adopt this official estimate as their belief. Optimists, in line with the survey, underestimate current flood risk. In the future, flood risk will change due to SRL, but the magnitude of future SLR is uncertain. The official scientific estimate is thus a probability distribution over future flood risk levels. This specification abstracts from deep uncertainty, which is discussed in the Internet Appendix. Realists form their expectations based on this official forecast. Optimists are aware, but skeptical, of the forecast. They hold a prior belief about the probability that flood risk will change or has truly changed to the official distribution (level) and update their beliefs in the future as they observe whether or not flood events occur.

More formally, we assume that flood risk is initially at a low level $\pi_0^* = \pi^L$. We generally use an asterisk to denote the official or scientific value. We discretize SLR as flood risk changing to random variable Π_1 at time $t = T_1$ and again to Π_2 at time $t = T_2 > T_1$. The scientific forecast takes the form of a probability distribution $f(\boldsymbol{\pi})$ with $\boldsymbol{\pi} = \{\pi_1, \pi_2\}$. Due to the limited availability of estimates of conditional future flood risk increase distributions, we assume that, at time T_1, scientists learn both π_1 and π_2.[27] Realists immediately update their beliefs in line with the scientific announcement.[28] Optimists assign a prior probability $0 < q_{T_1}^o < 1$ to the possibility that SLR is real and will begin happening at time T_1 but maintain that flood risk will remain at the optimists' initial belief level $\pi_0^o < \pi^L$ with positive probability $(1 - q_{T_1}^o)$. Before SLR is realized, that is, at times $0 \leq t < T_1$, optimists expect that their future flood risk beliefs will update to $(q_{T_1}^o)E_t^*[\Pi_1] + (1 - q_{T_1}^o)(\pi_0^o)$ at time T_1 and to $q_{T_2}^o(E_t^*[\Pi_2]) + (1 - q_{T_2}^o)(\pi_0^o)$ at time T_2 (where they further initially expect that $q_{T_1}^o = q_{T_2}^o$, as discussed below). Our framework for belief updating is adapted from Dieckmann (2011) for the present setting. As of time $T_1 \leq t < T_2$, optimists' contemporaneous flood risk beliefs

27 We were unable to find projections of the probability distribution of, for example, year 2050 flood risk increases conditional on year 2030 realizations. We thus assume that the percentile of the realization in 2030 equals the percentile of the 2050 realization.

28 Realists' beliefs are thus $E_t^r[\{\pi_s\}_{s=0}^{\infty}] \sim \{\pi^L$ for $t < T_1$, $E_0^*[\Pi_1]$ for $T_1 \leq t < T_2$, $E_0^*[\Pi_2]$ for $t \geq T_2\}$ for $0 \leq t < T_1$, and update for $t \geq T_1$ to $E_t^r[\{\pi_s\}_{s=T_1}^{\infty}] \sim \{\pi_1$ for $T_1 \leq t < T_2$, π_2 for $t \geq T_2\}$.

are given by $\pi_t^o = q_t^o(\pi_1) + (1 - q_t^o)(\pi_0^o)$, and their expectations of future flood risk after time T_2 are given by $E_t^o[\pi_{T_2}] = q_t^o(\pi_2) + (1 - q_t^o)(\pi_0^o)$. Note that we use lower-case letters for flood risks after SLR has been observed (after T_1) but that flood risk beliefs remain uncertain. In line with the empirical literature, the optimists' beliefs are updated each period based on whether or not flood events occur:

$$
\begin{aligned}
q_{t+1}^o|_{\text{Flood}=1} &= \Pr(\pi_1|_{\text{Flood}=1}) = \frac{\pi_1 \cdot q_t^o}{\pi_1 q_t^o + (1 - q_t^o)\pi_0^o}, \text{ and} \\
q_{t+1}^o|_{\text{Flood}=0} &= \Pr(\pi_1|_{\text{Flood}=0}) = \frac{(1 - \pi_1) \cdot q_t^o}{(1 - \pi_1)q_t^o + (1 - q_t^o)(1 - \pi_0^o)}.
\end{aligned} \tag{19}
$$

While the benchmark specification assumes rational Bayesian updating, the results are robust to a behavioral extension introducing an overreaction parameter to better match the empirical literature's evidence on the speed at which, for example, insurance demand responds to flood events (Gallagher, 2014; see the Internet Appendix).

With regard to higher-order beliefs, our benchmark assumption is that realists have rational higher-order expectations of optimists' belief changes, meaning they take into account that, in each future period $t+j$, a flood will occur with probability $E_t^r[\Pi_{t+j}]$ and change optimists' beliefs according to Equation (19). We stress two aspects of this assumption. First, it is conservative in that more rationality should generally lead us to predict less mispricing of coastal homes. Second, this assumption does not imply that realists know optimists' future beliefs; it only implies that they understand optimists' updating rules. In contrast, optimists expect that they will update their beliefs at time T_1 but do not anticipate subsequent belief changes correctly, including with regard to their expectations of realists' future beliefs about their (optimists') flood risk perceptions. Together, the benchmark case thus implies that, for example, at $T_1 \leq t < T_2$ (after new sea levels are observed)

$$\begin{aligned} E_t^o[\pi_{t+1}^o] &= \pi_t^o \text{ and} \qquad (20) \\ E_t^r[\pi_{t+1}^o] &= \pi_t^r \left[(q_{t+1}^o|_{\text{Flood}=1})(\pi_1) + (1 - q_{t+1}^o|_{\text{Flood}=1})(\pi_0^o)\right] \\ &\quad +(1-\pi_t^r)\left[(q_{t+1}^o|_{\text{Flood}=0})(\pi_1) + (1 - q_{t+1}^o|_{\text{Flood}=0})(\pi_0^o)\right]. \end{aligned}$$

While contemporaneous flood risk beliefs are common knowledge, agents may thus have different expectations of how optimists' beliefs will evolve in the future. We again stress that these are likely conservative assumptions. If, instead, we assume that realists fail to anticipate optimists' potential future learning about higher flood risks, it follows that realists may overestimate optimists' future WTP for vulnerable properties and thus the resale price of coastal homes, further contributing to contemporaneous overvaluations.

3.2 Solving the model

We solve for pricing dynamics through backwards iteration. We assume that effective flood risk beliefs will not diverge indefinitely. Over our model horizon of interest, arguably the most likely and interesting scenario forcing effective belief convergence is reform of the NFIP. Congress enacted the NFIP in 1968 in response to rising damages from flooding and limited private-market insurance take-up. To this day, NFIP remains the dominant insurer for flooding in the United States, with more than 5 million policies in force as of January 2017 covering more than $1.2 trillion of property and contents (FEMA 2017; Moore Resources Insurance 2017). NFIP is, however, considered fiscally unsustainable and has been labeled as a "high risk" program due its failure to charge actuarially fair rates for many policies (GAO 2017). The program has traditionally subsidized one in five policies, charging less than half of full risk levels on average (Beider 2014). The extent to which even full risk rates are actuarially fair is, moreover, an open question (Beider 2014). The Biggert-Waters Flood Insurance Reform Act of 2012 sought to bring the program closer into fiscal balance through subsidy phaseouts and immediate price increases (FEMA 2013). However, due to concerns over effects on homeowners, the Homeowner Flood Insurance Affordability Act of 2014 partially repealed and modified Biggert-Waters. A future move towards real risk rates and more strictly enforced insurance mandates is highly likely.

In theory, a fully enforced flood insurance requirement would force all agents—regardless of their actual beliefs—to internalize flood risks at the probability implied by the insurance rate. In the context of our linear utility model, policy reform mandating actuarially fair insurance is thus equivalent to a convergence of effective flood risk beliefs towards their true values.[29] We formally assume that, at some future time T, effective flood risk beliefs will converge to true risk values.[30] We stress again that we do not assume that actual beliefs converge, only that flood insurance mandates will be enforced. It is also not necessary for the validity of our approach to assume that insurance rates will be actuarially fair or reflect true probabilities. Even if continued climate change after the policy reform period were to remain uncertain, our approach would be valid as long as agents' expectations of insurance rates align after the policy reform. Indeed, we set up the model to permit continued SLR after insurance reform. That is, we assume $T_1 < T < T_2$, meaning that some SLR occurs before and some after insurance reform. At time $T-1$ the realists and optimists each hold expectations regarding the announced schedule of current and future flood risks or insurance rates, $E^r_{T-1}[\boldsymbol{\pi}^*]$ and $E^o_{T-1}[\boldsymbol{\pi}^*]$, respectively, where $\boldsymbol{\pi}^* = \{\pi^*_T, \pi^*_{T_2}\}$. Note that this formulation assumes that period $T-1$ is after period T_1, when SLR is first observed.

Given our model's assumptions about beliefs, it is straightforward to solve for prices at time $T-1$. Once $\boldsymbol{\pi}^*$ becomes common knowledge, both optimists and realists will be in the market for coastal property and the marginal buyer will consequently be the one with the k_1^{st}

[29] One might also argue that, in the very long run, flood risk beliefs must converge as sea levels continue to rise to the point of making annual flood risks undeniable (approaching unity as sea levels rise to reach current coastal properties).

[30] Implicit in this setup is the assumption that the timing of policy reform is known, which is obviously an abstraction. Robustness analysis in the Internet Appendix shows that the main quantitative results are not sensitive to changing the assumed date T. Eliciting beliefs and extending the model to formally consider uncertainty and disagreement about policy reform would be an interesting area for future work.

amenity value $\overline{\xi} = \Xi(1-k_1)$. Consequently, at time $T-1$, realists expect the price of coastal homes at time T and thereafter to be given by the stationary solution to (2) adjusted for changes in flood risk between times T and T_2. If there are $n = T - T_2$ periods after insurance reform and before continued SLR, this expectation will be

$$E^r_{T-1}[P_T] = \sum_{j=0}^{n-1} \beta^{j+1} \left[e^h + \Xi(1-k_1) - E^r_{T-1}[\pi^*_T]\delta\right] + \frac{\beta^{n+1}\left[e^h + \Xi(1-k_1) - E^r_{T-1}[\pi^*_{T_2}]\delta\right]}{(1-\beta)}. \tag{21}$$

Optimists reason analogously, but with a potentially different expectation regarding the flood risk announcement $E^o_{T-1}[\boldsymbol{\pi}^*]$ defining $E^o_{T-1}[P_T]$. Given both groups' price expectations, Condition (12) determines the identity of the marginal buyer at $T-1$. In particular, if

$$\Xi\frac{k_1}{\theta^o} + \left\{E^r_{T-1}[P_T] - E^o_{T-1}[P_T]\right\} < \delta(\pi^r_{T-1} - \pi^o_{T-1}), \tag{22}$$

only optimists are in coastal real estate (Case 1) at $T-1$ and the market-clearing price is

$$P_{T-1} = \beta(e^h + \Xi\left(1 - \frac{k_1}{\theta^o}\right) - \pi^o_{T-1}\delta + E^o_{T-1}[P_T]), \tag{23}$$

If Condition (22) does not hold, both types are in the market (Case 2) and the $T-1$ price solves

$$\begin{aligned} P_{T-1} &= \beta(e^h + \overline{\xi^o}_{T-1} - \pi^o_{T-1}\delta + E^o_{T-1}[P_T]) \text{ and} \qquad (24) \\ \overline{\xi^o}_{T-1} &= \Xi(1-k_1) - \delta(1-\theta^o)(\pi^r_{T-1} - \pi^o_{T-1}) + (1-\theta^o)\{E^r_{T-1}[P_T] - E^o_{T-1}[P_T]\}. \end{aligned}$$

Next, consider P_{T-2} to illustrate the process of finding prices further back in time. For illustration assume that $T-2 \geq T_1$, so that the true extent of SLR is known at time $T-2$. The identity of the marginal buyer then again depends on whether

$$\Xi\frac{k_1}{\theta^o} + \left\{E^r_{T-2}[P_{T-1}] - E^o_{T-2}[P_{T-1}]\right\} < \delta(\pi^r_{T-2} - \pi^o_{T-2}). \tag{25}$$

Importantly, however, each type's expectation of prices in the next period now depends on agents' expectations of their own and others' expectations about flood risk beliefs in subsequent periods. For example, the realists' prediction at time $T-2$ of the coastal price at time $T-1$ depends on their expectation regarding who the marginal buyer will be at $T-1$, which, in turn, depends on their time $T-2$ expectation of the marginal-buyer condition (22). That is, if

$$[\Xi\frac{k_1}{\theta^o} + \left\{E^r_{T-2}[E^r_{T-1}[P_T]] - E^r_{T-2}[E^o_{T-1}[P_T]\right\} < \delta(E^r_{T-2}[\pi^r_{T-1}] - E^r_{T-2}[\pi^o_{T-1}])], \tag{26}$$

then the realists at time $T-2$ expect that optimists will dominate the coastal housing market at time $T-1$ and will expect prices to be determined by their $T-2$ expectation of (23):

$$E^r_{T-2}[P_{T-1}] = \beta(e^h + \Xi\left(1 - \frac{k_1}{\theta^o}\right) - E^r_{T-2}[\pi^o_T]\delta + E^r_{T-2}[E^o_{T-1}[P_T]]).$$

If Inequality (26) does not hold, realists expect that both types will be in the coastal housing market in the next period, and $E^r_{T-2}[P_{T-1}]$ is given by the realists' expectations at time $T-2$ of (24) and (21). Analogous calculations for optimists yield their expectations at time $T-2$ of resale prices at time $T-1$, $E^o_{T-2}[P_{T-1}]$. Given each type's respective price expectations, we can then use Inequality (25) to identify the marginal buyer at time $T-2$, and solve for the market-clearing P_{T-2} accordingly. We solve for prices at earlier times $T-n$ analogously through backwards iteration through the relevant expectation matrices. On the one hand, accounting for dynamic belief heterogeneity in a nonstationary setting thus clearly introduces a curse of dimensionality that limits our ability to consider a richer set of belief types.[31] On the other hand, however, our setup enables us to compute equilibrium price dynamics while flexibly accounting for different belief and policy reform structures in a setting that strictly generalizes the benchmark homogeneous-beliefs framework.

[31] Calculating the P_{T-n} price requires iteratively imputing $2 \times (\sum_{k=0}^{n-1} 2(2^k)) - 2$ expectations.

3.2.1 Policy reform beliefs

The last element of the model is to specify agents' beliefs about enforced policy rates after time T. Realists are assumed to adopt the scientifically forecast probability distribution of SLR and then update their beliefs to the relevant flood risk realizations:

$$E_t^r[\pi_T^*] = \begin{cases} E_t^*[\Pi_1] & \text{if } t < T_1 \\ \pi_1 & \text{if } t \geq T_1 \end{cases}, \quad E_t^r[\pi_{T_2}^*] = \begin{cases} E_t^*[\Pi_2] & \text{if } t < T_1 \\ \pi_2 & \text{if } t \geq T_1. \end{cases}$$

For optimists, our benchmark assumption is that they believe that enforced rates after time T will correspond to a weighted average of beliefs at the time:

$$\begin{aligned} E_t^o[\pi_T^*] &= (\omega^o)E_t^o[\pi_T^o] + (1-\omega^o)E_t^r[\pi_T^r] \\ &= \begin{cases} (\omega^o)[q_{T_1}^o(E_t^*[\Pi_1]) + (1-q_{T_1}^o)(\pi_0^o)] + (1-\omega^o)E_t^*[\Pi_1] & \text{if } t < T_1 \\ (\omega^o)[q_t^o(\pi_1) + (1-q_t^o)(\pi_0^o)] + (1-\omega^o)\pi_1 & \text{if } t \geq T_1. \end{cases} \end{aligned} \tag{27}$$

The optimists' expectation of $E_t^o[\pi_{T_2}^*]$ is analogous to Equation (27). Our benchmark assumption is that optimists consider the population-weighted average ($\omega^o = \theta^o$), but our quantitative analysis considers two polar alternatives as well ($\omega^o = 0$, $\omega^o = 1$).

3.3 Model calibration

3.3.1 Flood risk changes

We quantify future flood risk changes based on probabilistic SLR projections by Kopp et al. (2014, 2017) and on corresponding flood frequency amplification factors (AFs) estimated by Buchanan, Oppenheimer, and Kopp (2017). These studies are widely used in both policy and academic analyses.[32] In addition to this section, see the Internet Appendix for greater detail on flood frequency AFs and our procedure for estimating future flood risk. For New-

[32] For example, the estimates of Kopp et al. (2014) are routinely used in government analyses of SLR (e.g., NOAA 2017; EPA 2017) and in economic studies (e.g., Desmet et al. 2021).

port, RI, Kopp et al. (2014) project median SLR of 20 cm by 2030 and 38 cm by 2050 in a business-as-usual, or high-greenhouse-gas-emissions, scenario (Representative Concentration Pathway [RCP] 8.5, Van Vuuren et al. 2011), with a 5%–95% range of 19–56 cm (values relative to the year 2000). Buchanan, Oppenheimer, and Kopp (2017) estimate joint probability distributions over SLR and flood frequencies to generate probabilistic estimates of the corresponding 100-year flood frequency AFs. Importantly, in contrast with scenario-based approaches focusing on median outcomes, their estimates of expected values for each location account for positive skew in the underlying distributions, such as in SLR distributions arising due to uncertainty over the contributions of the Antarctic ice sheet (Buchanan, Oppenheimer, and Kopp 2017). By 2050 in Newport, RI, the frequency of events currently expected to be 100-year floods is projected to increase 11.5-fold (with a 5%–95% range of 1.5–22.2 fold) in RCP 8.5. Consideration of other locations reveals that this increase is comparatively modest: Buchanan, Oppenheimer, and Kopp (2017) estimate a median AF for 100-year flood risk of around 40 across tidal gauge locations in the contiguous United States by 2050. We extend our model to other locations in Section 5. We also showcase results under a global climate policy scenario with moderate emissions (RCP 4.5). In Newport, RI, the AF for expected flood risk by 2050 falls to 7.4 in this scenario (5%–95% range 1.3-15.0 fold).[33]

In our model, we discretize SLR as increasing flood risk in 2030 and 2050. We interpolate flood risk amplification by 2030 exponentially based on the decadal SLR projections from Kopp et al. (2017) and Buchanan, Oppenheimer, and Kopp's (2017) 2050 and subsequent flood risk AF projections (see Internet Appendix for details). For Newport, RI, this yields a 2030 mean AF of 4.79 (RCP 8.5). Given that the SLR projections are relative to the year 2000, we use the same procedure to correct for flood risk increases that have already occurred

[33] While Buchanan et al. (2017) do not report AF estimates for other climate scenarios (RCP 2.6 and 6.0), over our model time horizon the SLR projections for these scenarios are almost identical to our projections for scenario 4.5. Kopp et al. (2017) estimate median 2030 SLR of 17 cm for RCP scenarios 2.6, 4.5, and 6.0 and project 2050 SLR of 32 cm in both RCPs 2.6 and 6.0 compared to 34 cm in RCP 4.5.

by our model base year of 2017.[34] Finally, while we treat the probability distribution of SLR outcomes as known, we discuss concerns over deep uncertainty in the Internet Appendix.

3.3.2 Calibration summary

This section presents our calibration. Table 2 summarizes the benchmark parameters.

Some points should be noted. First, we select the net value of living in an owner-occupied home e^h to match the initial median coastal home price ($410k) at our benchmark parameters. Second, we set the utility discount rate to 4% per year, matching recent literature (e.g., Favilukis and Van Nieuwerburgh 2018; Glaeser and Nathanson 2017; Head, Lloyd-Ellis, and Sun 2014; Glaeser et al. 2014). Third, while the calibration makes arbitrary assumptions about the number and timing of future flood events, these do not affect the main results as current prices and fundamental values depend only on expectations of storm events (see Internet Appendix Table A9). For computational reasons, we run the model with one period corresponding to two calendar years, and adjust the relevant calibration parameters accordingly. Finally, the benchmark share of optimists represents a reweighted average of the survey population to correct for oversampling of coastal homes.

4 Quantitative Results

4.1 Main results

Figure 7 presents the main results for the benchmark calibration with SLR realizations matching their expected values in a business-as-usual, or high-emissions, climate scenario (RCP 8.5). We run the model varying the percentage of optimists from 0 to 45%, including our benchmark estimate of $\theta^o = 35\%$. The first central finding is that flood risk underestima-

[34] This adjustment is for 10 cm SLR as per NOAA data for Newport, RI (2017 mean), yielding a flood AF of 1.21. We apply this factor to our base 100-year flood risk level of 1% as per standard FEMA designation to compute the initial flood risk. Importantly, however, we maintain 1% as a reference number when computing the share of optimists in the population.

tion leads to a significant overvaluation of coastal homes compared to their fundamental value (black line with stars) implied by the homogeneous rational beliefs model. Our benchmark estimates imply that current prices exceed fundamentals for RCP 8.5 by 13%. Economically, an overvaluation of this magnitude would be highly significant.

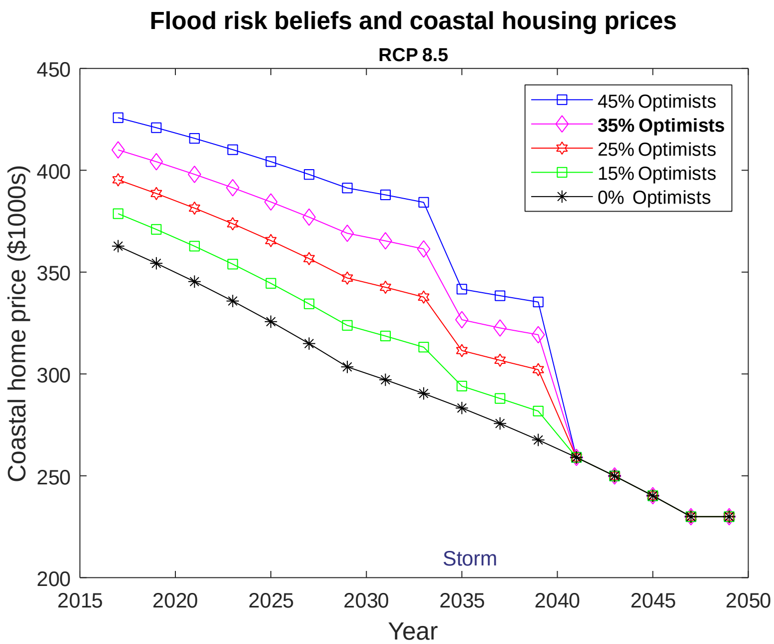

Figure 7: **Flood risk beliefs and coastal housing prices** Figure displays the future coastal home price trajectories (in $1000s) from 2017 to 2050, assuming an RCP 8.5 climate scenario, for coastal populations whose share of optimists range from 0 to 45%.

Before proceeding, we note two "tests" of the model. First, the model's projected initial noncoastal housing price of $319K is close to our sample average of $324K, despite being a nontargeted moment. Second, the model's predicted relative change of -9.6% in coastal versus inland housing prices after a future storm event aligns well with the empirical literature's difference-in-differences estimates of storm impacts on relative prices, which range from -5% to -20% (e.g., Hallstrom and Smith 2005; Kousky 2010; Bin and Landry 2013; Ortega and Taspinar 2018).[35]

[35] Conceptually, the model only pins down the difference between coastal and noncoastal housing prices. This is because the price of houses—which are in fixed supply—is determined by their differential value

The scenarios featured in Figure 7 assume that SLR matches its expected values. We next consider alternate realizations. Figure 8 showcases projected coastal housing prices and fundamental values in our benchmark setting ($\theta^o = 35\%$) for SLR realizations ranging from the 5th to 95th percentile.[36] The range of projected medium-run outcomes is wide, from coastal homes becoming worthless to these homes gaining substantially in value if SLR turns out to be less severe than anticipated. We note two important points. One, the initial overvaluation results are unchanged as they depend only on expectations of future SLR (note that we consider uncertainty over SLR distributions in the Internet Appendix). Two, overvaluation persists across different future SLR realizations. By 2033, for example, while the 5th percentile SLR outcome yields an overvaluation of only about 1%, with the 95th percentile, the overvaluation reaches over 1,000% as the fundamental value collapses but prices remain high for a number more years.

In sum, the results indicate that benchmark flood risk misperceptions may be contributing to an economically significant overvaluation of coastal homes relative to their fundamental value, preventing housing assets from fully reflecting climatic risks.

4.1.1 Robustness.

The Internet Appendix presents a robustness analysis that includes varying optimist shares, coastal amenity values, expected SLR, and nine additional calibration parameters. We also showcase results under a global climate policy scenario (RCP 4.5) that reduces our benchmark overvaluation estimate to 6.3%. In addition, we consider the effects of alternative flood insurance reform scenarios, transaction costs, overreactions to flood events, and ex

above and beyond the outside option of renting. For noncoastal homes, this value does not change. For coastal homes, it does change due to changes in flood risk and marginal-buyer amenity values.

[36] We take the flood risk AFs for 2050 as the 5th and 95th percentiles estimated by Buchanan, Oppenheimer, and Kopp (2017). For 2030, the 5th percentile SLR estimate in the underyling Kopp et al. (2014) framework was 8 cm above 2000 levels, which had already been reached by 2017. We consequently assume zero additional flood risk increase by 2030 above 2017 levels for the 5th percentile. For the 95th percentile, Kopp et al. (2014) project 33 cm of SLR by 2030 under RCP 8.5. Buchanan, Oppenheimer, and Kopp (2017) estimate a flood risk AF of 15 associated with 34 cm of SLR in another scenario. We thus adopt 15 as the relevant 2030 flood risk AF for the 95th percentile.

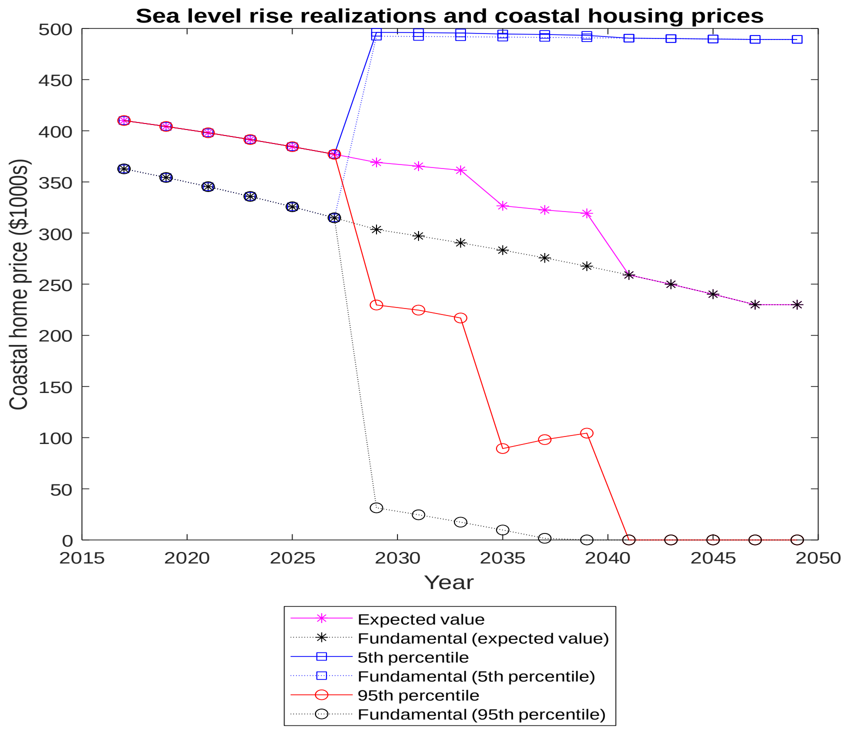

Figure 8: **Sea level rise realizations and coastal housing prices** Figure displays the future coastal home price trajectories and fundamental values (in \$1000s) from 2017 to 2050 assuming an RCP 8.5 climate scenario and 35% share of optimists in the market. We vary the SLR realizations from the 5th to the 95th percentile.

post rationalization of beliefs. The results indicate that coastal home prices appear especially sensitive to beliefs about long-run flood insurance rates. Finally, we discuss deep uncertainty and model misspecification.

4.2 Welfare

This section describes both the efficiency costs and some distributional consequences of flood risk misperceptions and insurance reform. Within the context of our framework, the only efficiency cost associated with mispricing is the allocative inefficiency of realists with high amenity values being priced out of coastal markets. That is, a utilitarian social planner would allocate coastal homes to the optimists and realists with the k_1 highest valuations, equating the marginal buyers' valuations at the optimum ($\overline{\xi}^{o,*} = \overline{\xi}^{r,*} = \Xi(1-k_1)$). In contrast, allocative inefficiency from belief heterogeneity occurs whenever the marginal realist's valuation exceeds that of the marginal optimist (i.e., $\overline{\xi}_t^r > \overline{\xi}^{r,*}$ and $\overline{\xi}_t^o < \overline{\xi}^{o,*}$). Let q_t^i denote the quantity of coastal housing consumed by group i in period t, which equals $q_t^o = \frac{\theta^o}{\Xi}(\Xi - \overline{\xi}_t^o)$ for optimists and $q_t^r = \frac{(1-\theta^o)}{\Xi}(\Xi - \overline{\xi}_t^r)$ for realists. The net loss in consumer surplus CS_t from coastal housing in period t due to belief heterogeneity is then given by:

$$\Delta W_t \equiv CS_t^* - CS_t = \int_{q^{*,o}}^{q_t^o} \left[\Xi - \frac{\Xi}{\theta^o} q\right] dq - \int_{q_t^r}^{q^{*,r}} \left[\Xi - \frac{\Xi}{(1-\theta^o)} q\right] dq. \qquad (28)$$

Brunnermeier, Simsek, and Xiong (2014) develop a belief-neutral efficiency welfare criterion for settings where beliefs are distorted and heterogeneous, but the social planner does not know the objective belief. The criterion asks the planner to consider all convex combinations of reasonable beliefs. Our setting differs from theirs in that we generally assume that flood risk is scientifically estimable rather than unknown, or that excessively low flood risk beliefs are not in the set of reasonable beliefs. Importantly, however, our welfare cost calculation Equation (28) does not actually depend on whether the social planner adopts the realists' or the optimists' beliefs. That is, even if a utilitarian social planner agreed with the optimists, the planner would perceive an allocative inefficiency cost from excessively pessimistic beliefs keeping some realists with high coastal amenity valuations away from the water. The equilibrium allocation with heterogeneous beliefs is thus inefficient even in the belief-neutral welfare criterion sense of Brunnermeier, Simsek, and Xiong (2014).

Table 3 summarizes the allocative inefficiency costs on a per-household basis, computed specifically as the present value of the flow costs (28) until policy reform.[37] The benchmark costs are estimated at \$555 per household (\$2017)—a modest amount, though it should be noted that this is the average net cost across all households, not just those relocated due to flood risk optimism. For the whole of Bristol and Newport counties, the projected welfare costs thus amount to over \$70 million. Alternative assumptions for the maximum

[37] The Internet Appendix presents a visualization of the allocative inefficiency over time.

coastal amenity value (Ξ)—set at either our hedonic regression estimate ($3.9k/year, see the Internet Appendix) or at the 75th percentile of amenity value for coastal residents in our survey ($8.5k/year)—only modestly affect this estimate as higher losses for realists are partly offset by higher gains for optimists. In contrast, enacting flood insurance reform sooner than in the benchmark reduces the efficiency cost by more than half. Finally, Table 3 also shows that global climate policy can cut the allocative inefficiency by almost 80%.

Table 3

Allocative inefficiency costs

Scenario	Net costs per household
Benchmark ($\Xi = \$7.7\mathrm{K}$)	$555
Lower amenity value $\Xi = \$3.9\mathrm{K}$	$373
Higher amenity value $\Xi = \$8.5\mathrm{K}$	$597
Early insurance reform $T = 2035$	$223
Global climate policy RCP 4.5	$118

Underlying these aggregate effects are large distributional consequences. Table 4 illustrates the effects of immediate insurance reform for three key types of agents. First, ″realists in waiting″ are realists who currently live away from the coast but who would be living by the waterfront with efficient risk pricing. Second, "hot-potato sellers" are realists who currently live in coastal homes but will, with continued mispricing, sell their homes to an optimist before prices adjust (in line with our survey results). Third, "hot-potato buyers" are optimists who currently live away from the coast but who would buy a coastal home in the future in the absence of insurance reform. We compare welfare for each agent in a variant of our benchmark scenario to one with immediate (year 2020) surprise insurance reform.[38] The results show that the biggest winners are the hot-potato buyers, who would go on to buy coastal property at inflated prices in the absence of policy reform. For example, a

[38] We specifically consider the present discounted value of realized (ex post) utility in a scenario assuming zero flood events over the model time horizon (to ensure a clean comparison of the welfare effects of price and location adjustments alone) and that SLR takes its expected value.

currently noncoastal optimist with a coastal amenity value of $376 per month would gain over $47k in present value from avoided losses (net of coastal amenity benefits) as a result of the reform. Conversely, some of the biggest losers are the hot-potato sellers, who would no longer be able to sell their homes at above-fundamental value after the reform. For example, a currently coastal realist with a coastal amenity value of $563 is projected to lose over $24k from immediate reform.[39] Currently inland realists, in contrast, who are priced out of the market by coastal optimists, would gain substantially from insurance reform.

Table 4

Distributional effects of insurance reform

Type	Location			Coastal amenity ($/month)	Insurance reform Δ welfare
	Initial	Interim	Post reform		
Realist in waiting	Noncoastal	Noncoastal	Coastal	$549	+$34.2k
Hot-potato seller	Coastal	Noncoastal	Coastal	$563	-$24.2k
Hot-potato buyer	Noncoastal	Coastal	Noncoastal	$376	+47.1k

Table displays change in present value of utility, comparing a scenario with immediate (2020) insurance reform to one with delayed (2041) reform. Calculations consider realized utility assuming no storm events and SLR at expected values for each scenario.

Before proceeding, we address some caveats to our welfare calculations. First, our analysis assumes that inaccurate flood risk beliefs represent an informational distortion. Under certain behavioral models, however, agents might optimally choose to hold inaccurate beliefs. For example, Brunnermeier and Parker (2005) find that, if agents maximize the expected time average of their felicity, they may optimally choose to hold excessively optimistic beliefs. The intuition of their model is that agents balance anticipatory utility gained from thinking positively about the future against the cost of the erroneous decisions that result from holding inaccurate beliefs.[40] To the extent that inaccurate beliefs represent an optimal

[39] We note that current coastal home owners who are projected to stay in their homes regardless of the policy scenario are not counted as suffering the "loss" of a price correction due to insurance reform since this reflects a reduction in fundamental value due to SLR. That is, in the long run, prices are assumed to reflect fundamental values in both scenarios.

[40] Rational expectations will still be optimal beliefs in this setting if preferences are the canonical time-separable specification without memory or anticipatory utility.

choice, we may be overestimating welfare costs. While preferences may certainly play a role in driving sorting into high-risk locations, we note several reasons why this is unlikely to be the only factor in our setting. First and foremost, the evidence on how agents respond to flood risk information signals is at odds with the notion that their decisions are optimized while fully accounting for true risk. After flood events, housing prices in at-risk areas tend to fall by 5%–20%, even in areas that are not damaged but received salience signals such as near-miss hurricanes (see, e.g., Hallstrom and Smith 2005). Demand for flood insurance similarly spikes upwards after flood events, including in locations that do not experience the event but are in the same media market (Gallagher 2014). A model of flood risk learning arguably fits these empirical facts better than a model where sorting into high-risk areas is driven solely by perfectly informed preferences.[41]

A second caveat is that we assume linear utility throughout. In reality, risk aversion likely increases the welfare gains associated with adoption of increased flood insurance (see Wagner 2019). More broadly, risk aversion should also lead to a higher sensitivity of coastal home valuations to perceived flood risks. Our estimates of coastal home overvaluations resulting from flood risk optimism may thus be a lower bound on their true value.

A final caveat is that coastal mispricing is likely to create welfare costs through channels that are not represented in our model. One example is overinvestment in at-risk properties (Barrage and Furst 2019). Another is that, if optimists obtain loans using coastal properties as collateral, the devaluation of those properties due to flood events or policy changes could lead to defaults, further losses in asset value, and adverse effects on credit markets (see, e.g., Geanakoplos 2010), thereby exacerbating market incompleteness. When coastal properties constitute an important source of local tax revenues, both fluctuations and permanent reductions in their value could create additional efficiency costs depending on the fiscal policy response. As our model does not incorporate these effects, the efficiency cost estimates thus likely represent a lower bound.

[41] The Internet Appendix compares demographics across optimists and realists as a further test for learning- versus preference-based flood risk beliefs.

5 Extended Calibration

This section expands our analysis by applying our framework to coastal cities beyond Rhode Island. We first demonstrate that the results of our survey—which is designed to measure the precise role that flood risk optimism plays in sorting into high-risk housing at the household level—can be mapped into county-level estimates of general climate change worry calculated by the Yale Program on Climate Change Communication (Howe et al. 2015). As explained in the Internet Appendix, while the Yale data cannot be used as a substitute to confirm the results of this study, we do use them as a complement to extend the analysis. Our survey covers three counties in Rhode Island (Bristol, Kent, and Newport). Instead of pooling the results, we now generate county-level estimates of the percentage of respondents who are flood risk optimists using the same definition as before, namely, the fraction that underestimate coastal flood risk by at least 50%.[42] We then compare our county-level optimist shares against three potentially relevant measures from the Yale survey:[43] the estimated percentages who "think global warming will harm people in the US not at all/only a little" (Figure 9, panel A), "think global warming will harm them personally not at all/only a little" (Figure 9, panel B), and "are not very/not at all worried about global warming" (Figure 9, panel C). Though our number of observations is limited, we find a strong association between our survey-based optimist measures and these general belief measures. As explained in the Internet Appendix, we leverage this association to predict the share of flood optimists in other cities.

Table 5 presents the key model inputs and main results for an illustrative set of locations across the United States.[44] We discuss in the Internet Appendix our method for calibrating these results for each county using location-specific data on the share of coastal homes,

[42] We correct for our survey's oversampling of coastal homes using county-specific weights for the share of homes that are coastal, specifically, 20.94% in Newport, 13.4% in Bristol, and 9.16% in Kent.

[43] We collect Yale survey estimates for the year 2018 from https://climatecommunication.yale.edu/visualizations-data/ycom-us-2018 (accessed June 2020).

[44] We select locations that (i) have all calibration inputs available, including detailed future flood risk AF predictions in Buchanan et al. (2017) (ruling out, e.g., Miami, FL), (ii) have a strong correlation between coastal and flood zone status (ruling out, e.g., Malibu, CA), (iii) do not have large-scale flood-protective infrastructure (ruling out, e.g., New Orleans, LA), and (iv) represent a range of climate belief and flood risk amplification scenarios.

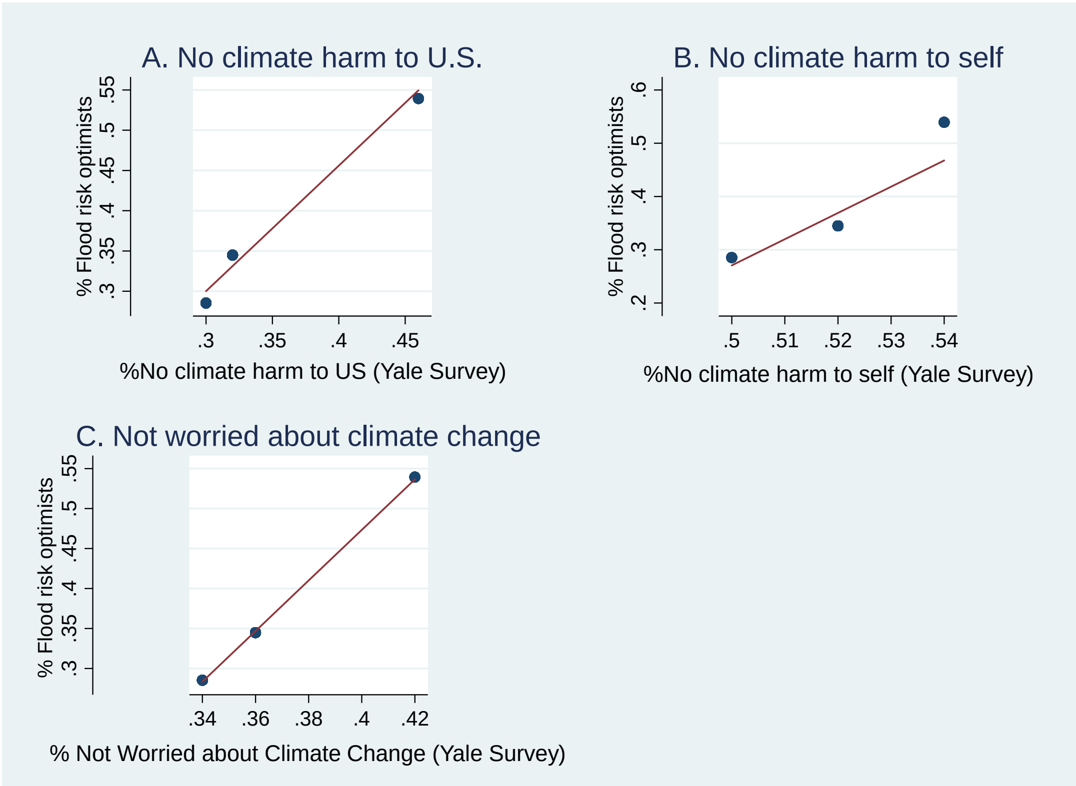

Figure 9: **Correspondence between Yale climate survey data and present survey data on flood risk beliefs** Figure displays the correlation between county-level Yale survey data on climate beliefs (x-axes) and our survey-based estimates of flood risk optimism (y-axes). Specific Yale survey instruments include those measuring the percentage of people who think global warming will harm people in the United States not at all or only a little (panel A), think global warming will not harm them personally at all or only a little (panel B), and are not very or not at all worried about climate change (panel C).

flood risk AFs, coastal amenity values, and flood damages. Compared to our benchmark, the results imply significantly larger overvaluation potential in other locations. Table 5 presents results under an unmitigated-warming scenario, RCP 8.5, whereas results for a global climate policy scenario are presented in the Internet Appendix. First, consider Boston, Massachusetts. While there are projected to be fewer flood risk optimists (16%) than in our Rhode Island area (35%), the share of coastal housing (2.3%) is also smaller compared to our benchmark (14.5%), allowing optimists to be relatively more dominant in the coastal market. Importantly, Boston also faces significantly higher expected flood risk AFs (over 50 in 2050) compared to our benchmark (11.5). Consequently, the projected initial overvaluation of 80%

is considerably higher than the initial overvaluation for our benchmark. For Wilmington, North Carolina, the model projects an even larger overvaluation. This outcome is due to the combination of a high share of flood risk optimists (48%) and very high climate vulnerability. In contrast, for Tampa, Florida, the model projects a modest overvaluation (4%), driven mainly by the modest projected flood risk increases, especially in the medium run. Two other example cities—Charleston, South Carolina, and Corpus Christi, Texas—both show considerably higher projected overvaluation than our benchmark.

In sum, these extended results suggest that (i) Rhode Island may be a conservative benchmark given the relatively modest projections for increased flood risk[45] and (ii) flood risk optimism may thus play an even more important role and contribute to larger overvaluations in other coastal housing markets across the country.

[45] Indeed, Buchanan et al. (2017) estimate a median expected 100-year flood risk AF of around 40 (by 2050) for tidal gauge locations across the contiguous United States.

Table 5

Extended calibration: Results

Area	Coastal homes k_1 (%)	Optimists θ^o (%)	Max. amenity Ξ ($K/yr)	E[Flood Risk AF] 2030	E[Flood Risk AF] 2050	e^h	Dam. δ ($K)	P_0^{NC} ($K)	P_0 ($K)	Over-valuation$_0$
	Inputs									Results
Benchmark, RI	0.145	0.35	7.7	4.79	11.5	20.1	82	316	410	13%
Boston, MA	0.023	0.16	13.2	4.01	50.7	57.8	133	540	664	81%
Wilmington, NC[1]	0.066	0.48	5.1	3.67	96.9	33.4	51	208	256	420%
Corpus Christi, TX[2]	0.046	0.38	3.7	2.34	58.6	29.0	37	152	187	93%
Tampa, FL[3]	0.109	0.44	4.6	1.07	4.4	32.0	47	190	234	4%
Charleston, SC	0.035	0.48	8.7	2.02	40.3	39.8	79	291	358	58%

Table displays model inputs and results for different cities in an unmitigated-warming (RCP 8.5) scenario. [1]Optimist share based on New Hanover County Yale survey results and our survey correspondence. Flood risk and SLR based on tidal gauges in [2]Rockport, TX, and [3]St. Petersburg, FL. Dam. = Damages. AF = amplificationf actor. P_0^{NC} = Noncoastal price. P_0 = Coastal price.

6 Conclusion

To what extent do asset prices reflect climatic risks? This issue is of growing interest, not only because of its policy importance (Anderson et al. 2019), but also because it speaks to the fundamental question of the empirical determinants of asset prices. Flooding has long been one of the costliest natural disasters in the United States (NOAA NCEI 2017), and risks will increase as sea levels rise over the coming decades. At the same time, however, a rich empirical literature has documented that capitalization of these risks into housing prices is often weak and variable across housing markets and segments (e.g., Daniel, Florax, and Rietveld 2009; Bernstein, Gustafson, and Lewis 2019; Murfin and Spiegel 2020; Baldauf Garlappi, and Yannelis 2020).

This paper has explored the role of flood risk belief heterogeneity and, specifically, of flood risk misperceptions in accounting for these present and potential future pricing dynamics in coastal U.S. housing markets. We provide both a theoretical explanation and novel evidence by presenting a dynamic housing market model that allows for heterogeneity in home types, consumer preferences, and flood risk beliefs in combination with a field survey providing direct evidence of belief distributions among coastal and inland residents, as well as information on potential confounders.

The main results are threefold. First, we find that, by allowing for flood risk optimism, our model can reconcile the mixed evidence on flood risk penalties as being driven by sorting and different equilibria across markets that may vary in the distribution of beliefs and housing market characteristics. Second, the survey results provide direct evidence that coastal flood zone residents have both significantly lower flood risk perceptions and significantly higher coastal amenity valuations than their inland counterparts. Close to 40% of flood zone residents indicate that they are "not at all" worried about flooding over the next decade. This lower degree of flood worry does not appear to be driven by different beliefs about flood damages, insurance payouts, or postdisaster public aid.

Third, calibrating the model to these survey results and probabilistic flood risk projections under SLR, we estimate that coastal housing prices exceed fundamentals by 6%–13% in our benchmark setting in Rhode Island. Extending our results to other cities reveals the potential for significantly larger overvaluations, especially in locations that face higher SLR vulnerability and more climate change skepticism. The overvaluation results are robust to a range of checks but sensitive to households' long-run flood policy beliefs, highlighting the potential power of policy expectations to mitigate—or exacerbate—current inefficiencies. Future work could potentially elicit policy beliefs and explicitly model uncertainty about policy reform. The results also indicate the potential of flood insurance reform to have large distributional effects across agents with different beliefs: Optimists who currently live inland but, in the absence of reform, would soon purchase an overvalued coastal home may gain substantially from immediate policy reform, whereas current coastal residents who, in the absence of reform, would have been able to sell to said optimists stand to lose from a price correction. While our model can only capture aggregate welfare effects in the form of allocative inefficiency, devaluations in at-risk markets may also be a significant policy concern due to their potential effects on mortgage and credit markets. A formalization of these impact mechanisms would be another highly interesting topic for future work.

While our analysis focuses on a select set of locations, coastal housing markets and flood risks are of national importance. By some estimates, the current asset value of U.S. real estate within one-eighth of a mile of the coastline exceeds \$1.4 trillion (McNeill, Nelson, and Wilson 2014). Many areas face significant risks from climate change. Neumann et al. (2000) estimate that 3 feet of SLR—a plausible scenario by the end of the century (Melillo, Richmond, and Yohe 2014)—would result in substantial inundations plus a 7,000-square-mile (38%) increase in U.S. flood zones. At the same time, many households remain skeptical, with 60% of respondents in a recent national survey indicating that they do not believe rising sea levels to be a "very likely" consequence of climate change (Pew Research Center 2016). The results reported in this paper highlight the potential of these beliefs to inhibit the efficient pricing of climate risks into housing assets, and the importance of accurate flood risk information and policy in ensuring the efficiency and stability of coastal housing markets moving forward.

References

Abreu, D., and M. K. Brunnermeier. 2003. Bubbles and crashes. *Econometrica* 71:173–204.

Alberini, A. 1995. Optimal designs for discrete choice contingent valuation surveys: Single-bound, double-bound, and bivariate models. *Journal of Environmental Economics and Management* 28:287–306.

Anderson, S. E., T. L. Anderson, A. C. Hill, M. E. Kahn, H. Kunreuther, G. D. Libecap, H. Mantripragada, P. Mérel, A. J. Plantinga, and V. K. Smith. 2019. The critical role of markets in climate change adaptation. *Climate Change Economics* 10:1950003.

Arrow, K., R. Solow, P. R. Portney, E. E. Leamer, Roy Radner, and Howard Schuman. 1993. Report of the NOAA panel on contingent valuation. *Federal Register* 58:4601–14.

Atreya, A., and J. Czajkowski. 2019. Graduated flood risks and property prices in Galveston County. *Real Estate Economics* 47:807–44.

Atreya, A., S. Ferreira, and W. Kriesel. 2013. Forgetting the flood? An analysis of the flood risk discount over time. *Land Economics* 89:577–96.

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

Baldauf, M., L. Garlappi, and C. Yannelis. 2020. Does climate change affect real estate prices? Only if you believe in it. *Review of Financial Studies* 33:1256–95.

Barrage, L., and J. Furst. 2019. Housing investment, sea level rise, and climate change beliefs. *Economics Letters* 177:105–8.

Bayer, P., R. McMillan, A. Murphy, and C. Timmins. 2016. A dynamic model of demand for houses and neighborhoods. *Econometrica* 84:893–942.

Beltrán, A., D. Maddison, and R. Elliott. 2018. Is flood risk capitalised into property values? *Ecological Economics* 146:668–85.

Beider, P. 2014. Understanding FEMA's rate-setting methods for the National Flood Insurance Program. Presentation, Congressional Budget Office, Washington, DC. https://www.cbo.gov/sites/
femaratemethodsnfip.pdf.

Bernstein, A., M. T. Gustafson, and R. Lewis. 2019. Disaster on the horizon: The price effect of sea level rise. *Journal of Financial Economics* 134:253–72.

Bin, O., T. W. Crawford, J. B. Kruse, and C. E. Landry. 2008. Viewscapes and flood hazard: Coastal housing market response to amenities and risk. *Land Economics* 84:434–48.

Bin, O., and J. B. Kruse. 2006. Real estate market response to coastal flood hazards. *Natural Hazards Review* 7:137–44.

Bin, O., and C. E. Landry. 2013. Changes in implicit flood risk premiums: Empirical evidence from the housing market. *Journal of Environmental Economics and Management* 65:361–76.

Brunnermeier, M. K., and J. A. Parker. 2005. Optimal expectations. *American Economic Review* 95:1092–118.

Brunnermeier, M. K., A. Simsek, and W. Xiong. 2014. A welfare criterion for models with distorted beliefs. *Quarterly Journal of Economics* 129:1753–97.

Buchanan, M. K., M. Oppenheimer, and R. E. Kopp. 2017. Amplification of flood frequencies with local sea level rise and emerging flood regimes. *Environmental Research Letters* 12:064009.

Bunten, D., and M. E. Kahn. 2017. Optimal real estate capital durability and localized climate change disaster risk. *Journal of Housing Economics* 36:1–7.

Burnside, C., M. Eichenbaum, and S. Rebelo. 2016. Understanding booms and busts in housing markets. *Journal of Political Economy* 124:1088–147.

Cameron, T. A., and M. D. James. 1987. Efficient estimation methods for "closed-ended" contingent valuation surveys. *Review of Economics and Statistics* 69:269–76.

Carson, R. T., and R. C. Mitchell. 1995. Sequencing and nesting in contingent valuation surveys. *Journal of Environmental Economics and Management* 28:155–73.

Daniel, V. E., R. Florax, and P. Rietveld. 2009. Flooding risk and housing values: An economic assessment of environmental hazard. *Ecological Economics* 69:355–65.

Davis, M. A., and S. Van Nieuwerburgh. 2015. Housing, finance, and the macroeconomy. In *Handbook of regional and urban economics*, vol. 5, ed. G. Duranton, J. V. Henderson, and W. C. Strange, 753–811. Amsterdam: Elsevier.

DellaVigna, S., J. A. List, and U. Malmendier. 2012. Testing for altruism and social pressure in charitable giving. *Quarterly Journal of Economics* 127:1–56.

Desmet, K., R. E. Kopp, S. A. Kulp, D. K. Nagy, M. Oppenheimer, E. Rossi-Hansberg, and B. H. Strauss. 2021. Evaluating the economic cost of coastal flooding. *American Economic Journal: Macroeconomics* 13:444–86.

Diamond, P. A., and J. A. Hausman. 1994. Contingent valuation: Is some number better than no number?. *Journal of Economic Perspectives* 8:45–64.

Dieckmann, S. 2011. Rare event risk and heterogeneous beliefs: The case of incomplete markets. *Journal of Financial and Quantitative Analysis* 46:459–88.

EPA (Environmental Protection Agency). 2017. Multi-model framework for quantitative sectoral impacts analysis: A technical report for the Fourth National Climate Assessment. Report no. 430-R-17-001, U.S. Environmental Protection Agency, Washington, D.C.

Favara, G., and Z. Song. 2014. House price dynamics with dispersed information. *Journal of Economic Theory* 149:350–82.

Favilukis, J., and S. Van Nieuwerburgh. 2021. Out-of-town home buyers and city welfare. *Journal of Finance*. Advance Access published May 22, 2021, 10.1111/jofi.13057.

FEMA (Federal Emergency Management Agency). 2013. Public survey findings on flood risk. https://www.fema.gov/public-survey-findings-flood-risk.

———. 2017. Policy & claim statistics for flood insurance. https://www.fema.gov/press-release/20210318/fema-publishes-nfip-claims-and-policy-data.

Gallagher, J. 2014. Learning about an infrequent event: Evidence from flood insurance take-up in the United States. *American Economic Journal: Applied Economics*: 206–33.

Garbarino, N., and B. Guin. 2020. High water, no marks? Biased lending after extreme weather. Bank of England Staff Working Paper, no. 856.

GAO (Government Accountability Office). 2017. Progress on many high-risk areas, while substantial efforts needed on others. Report, GAO-17-317. https://www.gao.gov/products/GAO-17-317.

———. 2018. The nation's fiscal health: Actions is needed to address the federal government's fiscal future. Report, GAO-18-299SP. https://www.gao.gov/assets/700/693001.pdf.

Geanakoplos, J. 2010. The leverage cycle. *NBER Macroeconomics Annual* 24:1–66.

Gibson, M., and J. T. Mullins. 2020. Climate risk and beliefs in New York floodplains. *Journal of the Association of Environmental and Resource Economists* 7:1069–111.

Giglio, S., M. Maggiori, J. Stroebel, and A. Weber. 2018. Climate change and long-run discount rates: Evidence from real estate. National Bureau of Economic Research Working Paper, no. 21767. 10.3386/w21767

Glaeser, E. L., J. Gyourko, E. Morales, and C. G. Nathanson. 2014. Housing dynamics: An urban approach. *Journal of Urban Economics* 81:45–56.

Glaeser, E. L., J. Gyourko, and R. E. Saks. 2005. Urban growth and housing supply. *Journal of Economic Geography* 6:71–89.

Glaeser, E. L., and C. G. Nathanson. 2014. Housing bubbles. National Bureau of Economic Research Working Paper, no. w20426.

———. 2017. An extrapolative model of house price dynamics. *Journal of Financial Economics* 126:147–70.

Green, R. K., S. Malpezzi, and S. K. Mayo. 2005. Metropolitan-specific estimates of the price elasticity of supply of housing, and their sources. *American Economic Review* 95:334–9.

Hallstrom, D. G., and V. K. Smith. 2005. Market responses to hurricanes. *Journal of Environmental Economics and Management* 50:541–61.

Hanemann, M., J. Loomis, and B. Kanninen. 1991. Statistical efficiency of double-bounded dichotomous choice contingent valuation. *American Journal of Agricultural Economics* 73:1255–63.

Hanemann, W. M. 1994. Valuing the environment through contingent valuation. *Journal of Economic Perspectives* 8:19–43.

Harrison, D., G. T. Smersh, and A. Schwartz. 2001. Environmental determinants of housing prices: The impact of flood zone status. *Journal of Real Estate Research* 21:3–20.

Harrison, J. M., and D. M. Kreps. 1978. Speculative investor behavior in a stock market with heterogeneous expectations. *Quarterly Journal of Economics* 92:323–36.

Head, A., H. Lloyd-Ellis, and H. Sun. 2014. Search, liquidity, and the dynamics of house prices and construction. *American Economic Review* 104:1172–210.

Hino, M., and M. Burke. 2020. Does information about climate risk affect property values? National Bureau of Economic Research Working Paper, no. w26807.

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

Kahn, M. E., and D. Zhao. 2018. The impact of climate change skepticism on adaptation in a market economy. *Research in Economics* 72:251–62.

Kanninen, B. J. 1993. Optimal experimental design for double-bounded dichotomous choice contingent valuation. *Land Economics* 69:138–46.

Kellens, W., T. Terpstra, and P. De Maeyer. 2013. Perception and communication of flood risks: A systematic review of empirical research. *Risk Analysis: An International Journal* 33:24–49.

Kellens, W., R. Zaalberg, and P. De Maeyer. 2012. The informed society: An analysis of the public's information-seeking behavior regarding coastal flood risks. *Risk Analysis: An International Journal* 32:1369–81.

Kling, C. L., D. J. Phaneuf, and J. Zhao. 2012. From Exxon to BP: Has some number become better than no number?. *Journal of Economic Perspectives* 26:3–26.

Kopp, R. E., R. M. DeConto, D. A. Bader, C. C. Hay, R. M. Horton, S. Kulp, M. Oppenheimer, D. Pollard, and B. H. Strauss. 2017. Evolving understanding of Antarctic ice-sheet physics and ambiguity in probabilistic sea-level projections. *Earth's Future* 5:1217–33.

Kopp, R. E., R. M. Horton, C. M. Little, J. X. Mitrovica, M. Oppenheimer, D. J. Rasmussen, B. H. Strauss, and C. Tebaldi. 2014. Probabilistic 21st and 22nd century sea-level projections at a global network of tide-gauge sites. *Earth's Future* 2:383–406.

Kousky, C. 2010. Learning from extreme events: Risk perceptions after the flood. *Land Economics* 86:395–422.

———. 2013. Facts about FEMA household disaster aid: Examining the 2008 floods and tornadoes in Missouri. *Weather, Climate, and Society* 5:332–44.

Kousky, C., H. Kunreuther, B. Lingle, and L. Shabman. 2018. The emerging private residential flood insurance market in the United States. Wharton Risk Management and Decision Processes Center Working Paper.

Kousky, C., and E. Michel-Kerjan. 2017. Examining flood insurance claims in the United States: Six key findings. *Journal of Risk and Insurance* 84:819–50.

Kuchler, T., and B. Zafar. 2019. Personal experiences and expectations about aggregate outcomes. *Journal of Finance* 74:2491–542.

Kuminoff, N. V., V. K. Smith, and C. Timmins. 2013. The new economics of equilibrium sorting and policy evaluation using housing markets. *Journal of Economic Literature* 51:1007–62.

Lindell, M. K., and S. N. Hwang. 2008. Households' perceived personal risk and responses in a multihazard environment *Risk Analysis: An International Journal* 28:539–56.

Malmendier, U., and S. Nagel. 2011. Depression babies: Do macroeconomic experiences affect risk taking? *Quarterly Journal of Economics* 126:373–416.

Manski, C. F. 2004. Measuring expectations. *Econometrica* 72:1329–76.

McNeill, R., D. J. Nelson, and D. Wilson. 2014. Water's edge: The crisis of rising sea levels. Report, Reuters. https://www.reuters.com/investigates/special-report/waters-edge-the-crisis-of-rising-sea-levels/

Melillo, J. M., T. Richmond, and G. W. Yohe, eds. 2014. Climate change impacts in the United States: The Third National Climate Assessment. U.S. Global Change Research Program, Washington, D.C. https://www.globalchange.gov/browse/reports/climate-change-impacts-united-states-third-national-climate-assessment-0

Mitchell, R. C., and R. T. Carson. 2013. *Using surveys to value public goods: The contingent valuation method*. Washington, DC: Resources for the Future.

Moore Resources Insurance. 2017. NFIP vs. private flood insurance. http://www.davemooreinsurance.c
and-resources/nfip-vs-private-flood-insurance/.

Murfin, J., and M. Spiegel. 2020. Is the risk of sea level rise capitalized in residential real estate? *Review of Financial Studies* 33:1217–55.

Neumann, J. E., G. Yohe, R. Nicholls, M. Manion. 2000. Sea-level rise & global climate change: A review of impacts to US coasts. Pew Center on Global Climate Change.

NOAA (National Oceanic and Atmospheric Administration). 2017. Global and regional sea level rise scenarios for the United States. NOAA Technical Report NOS CO-OPS 083, Silver Spring, MD.

NOAA NCEI (National Centers for Environmental Information). 2017. U.S. billion-dollar weather and climate disasters. 10.25921/stkw-7w73.

Ortega, F., and S. Ta■pınar. 2018. Rising sea levels and sinking property values: Hurricane Sandy and New York's housing market. *Journal of Urban Economics* 106:81–100.

Ouazad, A., and M. E. Kahn. 2019. Mortgage finance in the face of rising climate risk. National Bureau of Economic Research Working Paper, no. w26322.

Pagneux, E., G. Gísladóttir, and S. Jónsdóttir. 2011. Public perception of flood hazard and flood risk in Iceland: A case study in a watershed prone to ice-jam floods. *Natural Hazards* 58:269–87.

Pew Research Center. 2016. The politics of climate. Report, Pew Research Center, Washington, DC. http://www.pewinternet.org/2016/10/04/public-views-on-climate-change-and-climate-scientists/.

Piazzesi, M., and M. Schneider. 2009. Momentum traders in the housing market: Survey evidence and a search model. *American Economic Review* 99:406–11.

Rhode Island Coastal Resources Management Council. 2013. Protecting Rhode Island's shorelines from flooding and erosion. http://www.beachsamp.org/wp-content/uploads/2013/04/sea-wall-fact-sheet-sept-27.pdf.

———. 2020. Coastal Management Program. http://www.crmc.ri.gov/regulations.html.

———. n.d. Derived inundation surfaces - Scaled SLR. http://www.beachsamp.org/stormtools/.

Saiz, A. 2010. The geographic determinants of housing supply. *Quarterly Journal of Economics* 125:1253–96.

Schade, C., H. Kunreuther, and P. Koellinger. 2012. Protecting against low-probability disasters: The role of worry. *Journal of Behavioral Decision Making* 25:534–43.

Scheinkman, J. A., and W. Xiong. 2003. Overconfidence and speculative bubbles. *Journal of Political Economy* 111:1183–220.

Severen, C., C. Costello, and O. Deschenes. 2018. A forward-looking Ricardian approach: Do land markets capitalize climate change forecasts? *Journal of Environmental Economics and Management* 89:235–54.

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

Spaulding, M. L., T. Isaji, C. Damon, and G. Fugate. 2017. Application of STORMTOOLS' simplified flood inundation model with and without sea level rise to RI coastal waters. In *Coastal structures and solutions to coastal disasters 2015: Resilient coastal communities*, ed. L. Wallendorf and D. T. Cox, 126–134. Reston, VA: American Society of Civil Engineers.

Van Vuuren, D. P., J. Edmonds, M. Kainuma, K. Riahi, A. Thomson, K. Hibbard, G. C. Hurtt, T. Kram, V. Krey, J. F. Lamarque, and T. Masui. 2011. The representative concentration pathways: An overview. *Climatic Change* 109:5–31.

Wagner, K. 2019. Adaptation and adverse selection in markets for natural disaster insurance. Working Paper, Yale University. 10.2139/ssrn.3467329.

Xiong, W. 2013. Bubbles, crises, and heterogeneous beliefs. In *Handbook on systemic risk*, ed. J.-P. Fouque and J. A. Langsam, 663–713. New York: Cambridge University Press.

Table 1

Demographic characteristics and survey responses for coastal residents of flood and non-flood zones (n = 187)

Variable	Non-flood zone (n = 90)	Flood zone (n = 97)	Difference (Standard Error)
Flood worry index (1–10)	5.62	3.65	1.97*** (0.46)
Flood probability (midpoint)	0.27	0.24	0.02 (0.05)
Age (years)	53.09	52.74	0.34 (2.25)
Household annual income ($1000s)	118.72	130.39	-11.67 (9.37)
Education index (1–9)	6.92	7.00	-0.08 (0.31)
Household size	3.10	2.55	0.55*** (0.20)
Parcel area (square feet)	10,884	8,049	2,835*** (932)
Living area (square feet)	1,758	1,597	161* (93.0)
Expected value of gross flood damage (% of perceived home value)	41.7	33.5	8.2 (6.3)
Expected value of gross flood damage ($1,000s)	194.1	117.9	76.2 (51.0)
Expected government assistance (% of expected flood damage)	15.1	10.6	4.5 (3.5)
Expected insurance reimbursement (% of expected flood damage)	63.1	50.3	12.9** (5.1)

Values provided are means unless otherwise indicated. Flood worry index ranges from 1 "Not at all worried" to 10 "Very worried." Education index represents highest level of schooling completed from 1 "8th grade or less," 2 "Some high school," 3 "High school graduate or equivalent," 4 "Some college," 5 "Trade/technical/ vocational training," 6 "Associate degree," 7 "Bachelor's degree," 8 "Some graduate school," to 9 "Graduate degree." Two-sided t-test *$p < .1$; **$p < .05$; ***$p < .01$

Table 2

Benchmark model calibration

Parameter	Definition	Value	Source
k_1	Share of coastal homes	0.145	Authors' calculation from RIGIS properties and coastline (Bristol, Kent, Newport counties)
θ^o	Share of optimists	0.35	Survey: Share estimating $\pi_{10yr}^{Flood} < 5\%$
Ξ	Max. coastal amenity ξ (\$/yr)	\$7.7K	Survey: Max. WTP within 10% of median coastal home price
δ	Flood damages (\$)	\$82K	Survey: Median damage/price $\times$ Median price
e^h	Net value of living in own home	Variable	Match initial median coastal home price \$410k
β	Annual discount factor	0.96	
π_L	Initial annual flood risk	1.21%	FEMA benchmark adjusted to 2017 SLR
$E_0^*[\Pi_1]$	Expected annual flood risk as of 2030 in RCP 8.5	4.79%	Interpolated from Buchanan et al. (2017), Kopp et al. (2014)
$E_0^*[\Pi_2]$	Expected annual flood risk as of 2050 in RCP 8.5	11.5%	Buchanan et al. (2017)
T	Policy reform period	2041	
$q_{T_1}^o$	Optimists' prior belief on SLR	0.1	
π_0^o	Optimists' initial flood risk belief	$0.5 \cdot \pi^L$	50% below official value in line with the *optimist* definition from survey
Flood event occurs in the year 2035. RIGIS = Rhode Island Geographic Information System.			