

Flood Risk Belief Heterogeneity and Coastal Home Price Dynamics: Going Under Water?

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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 the mixed empirical evidence on flood risk capitalization. Second, we implement a door-to-door survey in Rhode Island. We find significant flood risk underestimation and sorting based on flood risk beliefs and amenity values. Third, we quantify the model and estimate that coastal prices currently exceed fundamentals by around 13% in our benchmark setting, with the potential for significantly higher overvaluation in other areas. Finally, we quantify both allocative inefficiency and distributional consequences arising from flood risk misperceptions and flood insurance policy reform.

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1 Introduction

How do climate risks affect coastal housing markets? In a world with homogeneous rational expectations, vulnerable housing prices should have already adjusted to incorporate the present value of future flood risk increases due to sea level rise. Empirically, however, hedonic analyses have repeatedly found that flood and climate risks are not (yet) fully reflected in housing markets.¹ This paper presents novel evidence for the role of belief heterogeneity and the implications of flood risk misperceptions in coastal U.S. housing markets. From an asset pricing perspective, it is well known that heterogeneity in beliefs about the future value of fundamentals can lead to inflated prices and a host of associated risks including bubbles, excess volatility, overinvestment, and credit crises (e.g., Harrison and Kreps, 1978; Abreu and Brunnermeier, 2003; Scheinkman and Xiong, 2003; Geanakoplos, 2010; Simsek, 2013; Xiong, 2013). This paper investigates whether flood risk misperceptions pose similar risks to coastal housing markets. While skepticism of climatic risks appears intuitively relevant in the United States, standard approaches to modeling the economic impacts of sea level rise have assumed homogeneous rational beliefs, thus potentially underestimating its broader economic ramifications.

First, we develop a dynamic housing market model and use it to review prior empirical evidence. The model builds on recent literature advancements on 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 non-coastal 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 found mixed results on the capitalization of climatic *risks*,

¹ Examples span both new studies focusing on future sea level rise 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).

but that flood *events* typically result in sharp declines in the prices of vulnerable homes. We show that these findings can be matched by a model where some agents underestimate flood and climate risks but update their beliefs based on flood realizations, resulting 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 reduced-form hedonic approaches in isolating flood risk beliefs due to confounders such as sorting dynamics and the role of higher order beliefs.

Second, this paper provides novel *direct evidence* on the role of flood risk beliefs in coastal housing markets by implementing a door-to-door survey campaign 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 coastal risk perceptions and valuations both among households that did and 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 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 both lower risk perceptions and higher amenity values for waterfront living. Among residents of official high risk flood zones, a full 40% say they are "not at all" worried about flooding over the next ten years. In contrast, a plurality of respondents living inland in the same communities indicate that they would be "very worried" about flooding if they lived on the coast. We also find that the majority of coastal residents underestimate their homes'

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"). While these estimates have been used to derive important insights on climate beliefs and risk capitalization (e.g., Bernstein et al., 2019; Baldauf et al., 2020), they could not be used as a substitute for our survey. First, they only measure climate beliefs, whereas our analysis requires a joint assessment of households' amenity valuations, risk beliefs, and confounders such as flood damage and government assistance expectations. Second, the smallest geographic unit in the Yale data is the county or city. Consequently, one cannot compare risk perceptions inside and outside high risk flood zones, or among coastal vs. non-coastal households. Third, the Yale survey does not elicit flood risk beliefs, but rather general climate change concern or beliefs. Lastly, we require information on counterfactual beliefs of households about homes they did *not* purchase. No such data is available in the Yale study or other surveys products we are aware of.

flood risks relative to inundation models. Importantly, we confirm that these differences are not driven by confounders such as differential expectations of damages, government assistance, or insurance reimbursements in case of flood event.³ Those who have experienced a flood in the past are significantly more concerned about flooding going forward, and coastal residents who are very worried about flooding are significantly more likely to plan on selling their homes in the next five years.

Third, we present a quantitative version of the model in order to simulate future coastal housing market outcomes under different belief, flood risk, and policy scenarios. Our quantification utilizes probabilistic projections of location-specific future flood risk increases due to sea level rise based on Buchanan et al. (2017) and from Kopp et al. (2014). The results imply that coastal housing prices currently exceed fundamentals by 13% in our benchmark setting in Rhode Island under a business-as-usual climate change scenario. This overvaluation is economically highly significant as it corresponds to around 40% of our benchmark households' average annual income.⁴ If future sea level rise 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 results do, however, vary under alternate future sea level rise scenarios. For example, global climate policy reduces overvaluations to 6%. The simulations also reveal that households' beliefs about long-run flood insurance policy can significantly affect coastal housing prices in the present, highlighting the potential power of policy expectations to mitigate - or exacerbate - current mispricing.

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 in Rhode Island to other cities by creating a mapping between our flood risk belief measures and 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

³ They also do not appear to be due to differential expectations of future coastal protection measures.

⁴ Housing wealth also plays a prominent role in households' retirement savings (Campbell, 2006).

overvaluation in other locations. For example, in Charleston, South Carolina, we estimate an initial overvaluation of over 50% due to both higher projected flood risk optimism and higher expected future flood risk increases due to sea level rise. Indeed, our benchmark Rhode Island location faces lower expected flood risk increases than the median across tidal gauges in the continental United States (Buchanan et al., 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, and consider distributional consequences of flood insurance policy reform.⁵ The dominant insurer for flooding in the United States is the National Flood Insurance Program (NFIP). 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 as of the end of the 2017 fiscal year (GAO, 2018a). Despite offering many policies at subsidized rates and despite flood insurance being technically required for homes with federally insured or regulated mortgages in high risk areas, NFIP take-up is low. By some estimates, *only 30 to 50 percent* of structures in high flood risk areas are insured (Harrison, Smersh, Schwartz, 2001; Kousky et al., 2018). We model an enforced insurance mandate at actuarially fair rates which would force the internalization of real risk rates and re-align coastal housing prices with fundamentals. Though efficient, this policy has significant distributional impacts. Within our framework, the main winners from immediate reform include 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 losers include 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

⁵ While we do not model the mortgage origination process and the use of coastal properties as collateral, we note the potential for significant additional welfare costs through this channel. For example, the devaluation of coastal properties could lead to defaults and adverse credit market impacts (see, e.g., Geanakoplos, 2010), thereby exacerbating market incompleteness. Indeed, new research indicates that lenders are not (yet) adjusting mortgages appropriately to increasing climatic risks (Ouazad and Kahn, 2020; Garbarino and Guin, 2020).

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 1 in 6 maps being over 20 years old.⁶ Our framework demonstrates how poor flood risk information can threaten the efficiency of coastal housing markets.

The broader literature context and our contributions thereto are as follows. First, our paper builds on the general literature on housing price dynamics (see, e.g., recent reviews by Davis and Van Nieuwerburgh, 2015, and Glaeser and Nathanson, 2014). Most closely related are recent papers that incorporate heterogeneous beliefs into housing market models. Both Piazzesi and Schneider (2009) and Burnside, Eichenbaum, and Rebelo (2016, "BER") present (quasi)-linear utility search models of housing 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 in housing markets. With a known probability, each period the fundamental value of homes may change permanently to a new level. 'Optimists' expect this new value to be higher than 'skeptical' or 'vulnerable' agents. However, agents can 'infect' each other with their opinions, generating housing booms and busts. Our approach builds on, but differentiates itself from, BER in several ways. On the one hand, we do not employ a search model and do not focus on infectious social dynamics. On the other hand, we extend BER's model by adding several dimensions of heterogeneity relevant for flood risks and by allowing beliefs to evolve in response to external shocks (flood events) in a flexible Bayesian learning framework.⁷

⁶ Authors' calculations based on FEMA National Flood Insurance Program Community Status Book, accessed 02/2017: <https://www.fema.gov/national-flood-insurance-program-community-status-book>

⁷ Another related branch of the housing literature studies residential sorting and its implications for hedonic valuations of amenity values (e.g., Kuminoff, Smith, and Timmins, 2013; Bayer, McMillan, Murphy, and Timmins, 2016). While our framework takes a different approach, some results relate closely. For example, our finding of the importance of future expectations as a driver of current sorting and thus home prices echoes Bayer et al.'s (2016) finding that static estimates of amenity values may over- or under-estimate true values if those amenities are expected to change in the future.

Second, we relate to a rich and growing empirical literature on environmental risk capitalization into housing prices. A first generation strand in this literature investigates the effects of *current flood risk* and official flood zone status. That is, FEMA produces flood risk maps for most coastal communities across the United States, and designates places with an annual inundation risk exceeding 1 in 100 as "Special Flood Hazard Areas." Empirical studies generally find weak capitalization of this flood zone status into coastal housing prices (see, e.g., meta analyses by Daniel, Florax, and Rietveld, 2009; Beltrán, Maddison, and Elliott, 2018). Studies often fail to detect significant negative effects, or may even find positive premiums (e.g., Bin and Kruse, 2006; Atreya and Czajkowski, 2016). Others find flood risk discounts that are significant but less than the present value of insurance premiums, suggesting only partial capitalization (Harrison, Smersh, Schwartz, 2001). Some studies also find significant flood risk penalties (e.g., Bin, Crawford, Kruse, and Landry, 2008), particularly for inland flood zones. A new nation-wide analysis by Hino and Burke (2020) identified off of flood zone changes also finds very modest overall effects. We contribute to this literature in two ways. One, our model can potentially account for this range of results 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. In addition, our survey provides *direct* evidence for present-day flood risk misperceptions as a potential driver of incomplete capitalization.

Another strand analyzes the impacts of flood *events*. These studies have repeatedly found that prices of properties that are at high risk of, but were not damaged by, a flood typically drop sharply in the aftermath of an event, with estimates ranging from around 5-20 percent (e.g., Hallstrom and Smith, 2005; Kousky, 2010; Bin and Landry, 2013; Gibson and Mullins, 2017; Ortega and Taspinar, 2018). These price fluctuations are difficult to rationalize as based on changes in fundamentals, but are consistent with flood risk learning. Gibson and Mullins (2017) similarly find that FEMA flood map updates - another flood risk signal - decreased the prices of non-flooded homes in New York City after Hurricane Sandy

by 18%. Interestingly, studies that track longer run impacts typically find that prices return to baseline within 4-10 years (e.g., Bin and Landry, 2013; Atreya, Ferreira, Kiresel, 2013). Gallagher (2014) documents an analogous pattern in national flood insurance markets, where take-up rises sharply after floods but declines back to baseline within a decade. Gallagher (2014) demonstrates that this pattern is most consistent with a modified Bayesian updating model. We incorporate these findings by allowing for Bayesian learning about flood risks. Though not a targeted moment in our calibration, our model quantitatively predicts coastal home price declines of around -10% in the aftermath of a future flood event, in line with empirical studies.

A newer strand studies the capitalization of *future sea level rise risks*. While their methods and results vary, these studies all indicate that sea level rise (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. They combine national Zillow ZTRAX data on housing prices and characteristics with National Oceanic and Atmospheric Administration (NOAA) elevation and SLR exposure measures, such as whether a home will be inundated at a certain SLR level. For regular owner-occupied homes, BGL fail to detect a significant SLR vulnerability discount, even when controlling for waterfront proximity 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 from CoreLogic with NOAA forecasts. In order to isolate the effects of sea level rise from those of elevation, they further use differential regional patterns of land rebound and subsidence to generate identifying variation. They fail to detect a significant effect of SLR on property prices. Next, Giglio et al. (2018) combine housing transactions with home listings information across four coastal states. They use the latter 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 flood risk capitalization depends on this climate attention index.

Most closely related to our work, Baldauf, Garlappi, and Yannelis (2020) investigate the role of general climate change beliefs in SLR risk capitalization. They present a housing price model with heterogeneity in SLR expectations also building on BER. 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. Baldauf et al. (2020) show that this sorting should generate attenuated SLR capitalization in areas with more skeptics, and show this to be empirically the case. They combine housing transactions data with sea level rise forecasts and county-level estimates of the population share believing that "global warming is happening" from the Yale data (Howe et al., 2015). They identify a significant negative SLR effect but only in areas with sufficiently high climate change belief, echoing similar results in BGL. On the one hand, these empirical results are in support of our model and main mechanism. On the other hand, we note important differences between our models. Baldauf et al. (2020) focus 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 non-coastal 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. (2020) 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. (2020) rely on county-level estimates of general climate change beliefs, our original survey can more precisely inform questions about flood risk beliefs versus house-specific flood risk, potential confounders, and their roles in driving sorting behavior.

Our study also adds to new work on the asset market impacts of climate skepticism. In an empirical analysis of agricultural land markets, Severen, Costello, and Deschenes (2018) find that counties with more climate skepticism incorporate future expectations to a lesser degree. Kahn and Zhao (2018) theoretically analyze the impacts of skeptics in a spatial equilibrium between two cities, finding that skeptics lower the price of land in the cooler

city less impacted by climate change. Barrage and Furst (2019) empirically show that new housing investment is negatively associated with sea level rise exposure but only in areas with sufficiently high levels of climate change belief.

Finally, we also relate to a broader finance literature that has documented significant effects of personal experiences on beliefs and investment behavior. 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 that have experienced floods are more concerned about flooding, in line with prior empirical studies, and our model highlights the potential effects of such belief changes on coastal home price dynamics.

The remainder of this paper proceeds as follows. Section 2 presents a simplified version of our model for intuition. Section 3 describes our field survey and results. Section 4 contains the full structural model and calibration details. The main quantitative results and robustness checks are described in Section 5. We present an extension to other cities in Section 6. Section 7 concludes.

2 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 4, 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 $k < 1$.⁸ We first introduce heterogeneity in the housing

⁸ We thus abstract from housing construction. Empirical estimates find supply in coastal areas to be

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 $\tilde{\delta}^i$ 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 as 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, especially given the linear utility framework. Importantly, however, we allow households to disagree with scientifically forecast flood risks, which we informally denote $E_t^*\{\pi_s^*\}_{s=t}^\infty$, and 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 4.

The rental market, also as in BER, consists of $1 - k$ homes which 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 non-coastal 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*.⁹ Letting m_t index his identity at time t , in equilibrium, the marginal buyer must be just indifferent between his options:

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

highly inelastic, driven by topographic constraints (Glaeser, Gyourko, and Saks, 2005; Green, Malpezzi, and Mayo, 2005). Saiz (2010) estimates MSA-level elasticities, 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).

⁹ The Online 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.

where $E_t^{m_t}[P_{t+1}]$ is m_t 's expectation of the re-sale 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, (1) thus yields the following pricing condition for coastal homes:

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

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

For the remainder of this illustration, we will assume that scientists can predict sea level rise perfectly. The full model in Section 4 accounts for uncertainty over sea level rise. We also assume - broadly in line with the survey results - 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 to pay for waterfront living among the population.

2.1 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 which starts in a 'pre-climate change predictions' equilibrium where sea-level rise and its implications for flood risks were 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 would be given by the stationary solution to (2):

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

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:

$$PREM_{-1}^{Coast} = [\Xi(1 - k_1) - \pi^L \delta] \left(\frac{\beta}{1 - \beta} \right) \begin{matrix} \leq \\ \geq \end{matrix} 0 \quad (4)$$

$$PREM_{-1}^{Flood} = -\delta \left(\frac{\beta}{1 - \beta} \right) < 0 \quad (5)$$

The overall coastal premium (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 (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} :

$$\pi^H = \gamma^{SLR} \cdot \pi^L \quad (6)$$

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

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

$$= -\{\gamma^{SLR}\} \delta \left(\frac{\beta}{1 - \beta} \right) \quad \text{for } t > T_1 \quad (8)$$

With homogeneous rational beliefs, observed flood risk penalties should thus be unambiguously negative and growing in full anticipation of climate change-induced future risk in-

creases. This prediction is clearly counterfactual for many segments of the U.S. housing market, as described in Section 1. The Online Appendix further presents hedonic estimates of the flood risk premium over a longer time horizon (1970-2017) in our empirical setting, which also fails to match this predicted pattern. The next sub-section consequently proposes a generalization of the standard model to accommodate disagreement with official forecasts as potential explanation of these empirically observed risk capitalization patterns.

2.2 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.¹⁰ Fraction $(1 - \theta^o)$ of the population remain "realists" who believe in the scientific forecast ($\{\pi_s^r\}_{s=t}^\infty = \{\pi_s^*\}_{s=t}^\infty$), whereas fraction θ^o holds more optimistic beliefs with $\pi_t^o \leq \pi_t^* \forall t$. In Section 4, optimists' beliefs are micro-founded 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 fraction $\lambda_t^{Opt} \in [0, 1]$ below official estimates π_t^* :

$$\pi_t^o = (1 - \lambda_t^{Opt}) \cdot \pi_t^* \tag{9}$$

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.

2.2.1 Case 1

First, 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 ($\xi^r = \Xi$)

¹⁰ Our model also allows for the possibility of homogeneously misinformed agents if $\theta^o = 1$.

assigns a lower value to buying a coastal home than the (then marginal) optimist:

$$\underbrace{\beta(e^h + \Xi - \pi_t^r \delta + E_t^r[P_{t+1}])}_{\text{Maximum WTP for coastal home among realists}} < \underbrace{\beta(e^h + \widehat{\xi}^o - \pi_t^o \delta + E_t^o[P_{t+1}])}_{\text{WTP for coastal home of (marginal) optimist}} \quad (10)$$

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

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

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

$$\Xi \frac{k_1}{\theta^o} + \{E_t^r[P_{t+1}] - E_t^o[P_{t+1}]\} < \delta(\pi_t^r - \pi_t^o) \quad (12)$$

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):

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

Here, $\Delta E_t^o[P_{t+1}]$ denotes the change in optimists' expectations of the re-sale value of coastal homes across areas with higher official flood risk.

On the one hand, the current risk capitalization is now attenuated by optimists' discounting of flood risk $(1 - \lambda_t^{Opt})$. The 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 future risk internalization is generally also at-

tenuated compared to the rational beliefs case.¹¹ We formalize this statement in Section 4. The central point here, however, that a model with belief heterogeneity can account for the empirically observed under-capitalization of current and future flood risks in markets with a sufficient density of excessively optimistic (or climate skeptical) households.¹²

2.2.2 Case 2

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

$$\beta(e^h + \bar{\xi}_t^r - \pi_t^r \delta + E_t^r[P_{t+1}]) = \beta(e^h + \bar{\xi}_t^o - \pi_t^o \delta + E_t^o[P_{t+1}]) = P_t \quad (14)$$

Intuitively, the marginal realist has a sufficiently high amenity value $\bar{\xi}_t^r$ 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 (14) and market clearing:

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

A *ceteris paribus* increase in official flood risk π_t^* now has the interesting effect that it will alter the *identity* 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) would contain impacts of both sorting and potentially underestimated current and future risks:

$$PREM_t^{Flood} = (\Delta \bar{\xi}_t^r - \delta + \Delta E_t^r[P_{t+1}])\beta = (\Delta \bar{\xi}_t^o - (1 - \lambda_t^{Opt})\delta + \Delta E_t^o[P_{t+1}])\beta \quad (16)$$

¹¹ Optimists may underestimate future flood risk levels π^H in (6) either by directly discounting the sea-level rise projection (γ^{SLR}), or indirectly even if they believe that sea-level rise will increase flood risks by factor γ^{SLR} if they apply this factor to an under-estimated baseline flood risk level as in (9).

¹² Case 1 also covers the setting with *homogeneous misperception* ($\theta^o = 1$) as optimists would trivially be pricing coastal homes, thus leading to an attenuation of the flood risk premium as in (13).

Since the direct effect of higher flood risk on optimists' valuations is weakly less negative than the realists' ($-(1 - \lambda_t^{Opt})\delta \geq -\delta\beta$), and assuming that the same will be true of the impact on future price expectations ($\Delta E_t^o[P_{t+1}] \geq \Delta E_t^r[P_{t+1}]$), the marginal realist in the higher risk setting must have higher amenity values for waterfront living ($\Delta \bar{\xi}_t^r > 0$), whereas the marginal optimists moving must have lower amenity values ($\Delta \bar{\xi}_t^o < 0$). This comparative static also illustrates the *allocative inefficiency* resulting from flood risk misperceptions. Importantly for our purposes, however, (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.

2.2.3 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:

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

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

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

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* (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, realists would anticipate an additional future devaluation due to this correction to optimists' beliefs. Overall, however, the heterogeneous beliefs model can thus 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.

3 Direct Evidence: Field Survey

The analysis thus far indicates that a housing market model with flood risk misperceptions fits the empirical evidence 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 and confounding beliefs directly 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 Section 5.3.

3.1 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 non-coastal homes.¹³ The surveys were conducted in two waves across February and July 2017. The

¹³ Two key model features motivate the need for an original door-to-door survey campaign rather than leveraging existing survey products. First, while prominent publicly-available surveys exist assessing 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

survey instruments are provided in the 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) choice contingent valuation mechanism (Hanemann, Loomis, and Kanninen, 1991).¹⁴ We use contingent valuation (CV) instead of the often utilized hedonic model for several reasons. First, the hedonic model has difficulty in estimating the coastal amenity value given the strong correlation between coastal amenities and flood risk that can potentially bias results in a revealed preference setting (Bin et al., 2008). Second, as our model indicates, hedonic estimates confound amenity values with sorting and future price expectations. Third, our model needs information on amenity values for both residents who chose to live on the coast and those who did not, whereas the hedonic model only estimates a value for the marginal buyer. Lastly, the CV technique, while not without criticism including for its elicitation of non-use values (Diamond and Hausman, 1994), has been shown for decades to be a useful and accurate estimate of environmental values when following best practices (Kling et al., 2012), including those laid out by, e.g., Kenneth Arrow, Robert Solow, and others who participated in National Oceanic and Atmospheric Administration's Blue Ribbon Panel on the contingent valuation method (Arrow et al., 1993).

Both our use of face-to-face interviews and the DBDC mechanism are motivated by best practices recommendations in CV survey design and implementation (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 were chosen based on a hedonic estimation of the annualized waterfront living premium using U.S. Census American Housing Survey data for 2013 performed by the authors. The DBDC question was 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).

or collected at a coarser level (see review by Kellens et al., 2013).

¹⁴ DBDC has been shown to be a more efficient WTP estimate relative to a single-bounded approach (Hanemann et al., 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).

Second, we elicit coastal flood risk perceptions. In line with best practices in the risk elicitation literature (Manski, 2004), we consider both quantitative and qualitative subjective risk 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.¹⁵ Coastal residents are asked about their homes specifically, whereas non-coastal 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. Next, as a qualitative measure we ask subjects to indicate how worried they are on a 10-point scale about the risk of a flood affecting their or a coastal home over the next 10 years. This question format 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.

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 five years. Finally, the survey asks subjects about 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 $n = 187$ interviews (52% coastal,) conducted in several Rhode Island communities.¹⁶ This sample size is in line with prior survey studies of flood

¹⁵ We deliberately do not attempt to financially incentivize subjects' subjective flood risk responses. This is because any scoring rule would have to pit subjects' answers against official inundation-model based flood risk projections as the true benchmark. However, it is precisely subjects' deviations in their subjective beliefs from official FEMA announcements of flood risk that we are seeking to understand. In contrast to economic experiments which can often benchmark subjective probabilities against events occurring in the laboratory in real time, we also could not wait for flood risk realizations over the next year(s) to financially reward respondents' answers. Indeed, for these and similar reasons, field surveys eliciting expectations commonly do not incentivize these responses (Manski, 2004).

¹⁶ The study design and implementation was approved by Brown University and the University of Arizona's Institutional Review Boards and all surveyors completed the Collaborative Institutional Training Initiative training. Informed consent was obtained from all respondents. Respondents were also compensated \$5 for agreeing to take the survey although some respondents declined compensation.

risk perceptions, particularly ones using face-to-face interviewing techniques.¹⁷ Close to 40% of people who answered their doors agreed 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 survey respondents also appear demographically comparable to county-level populations, although they skew slightly older and more educated (see Online Appendix).

Before proceeding, we highlight several reassuring survey quality checks, which are described in further detail in the Online Appendix. First, we compare homeowners’ stated guesses of their homes’ current market values against Zillow Zestimates.¹⁸ We find a correlation of 0.89, indicating a high level of agreement. This result is the more reassuring as the home market values question was placed at the end of the survey, making it relatively more vulnerable to survey fatigue. Second, we compare homeowners’ stated purchase year 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 0.996.¹⁹ 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 compares well with Kousky and Michel-Kerjan’s (2016) estimate of 24.8% average flood losses as a fraction of home values based on micro-data on NFIP flood damage claims. Finally, our survey’s predicted values of the percentage of flood risk optimists in each of the three counties we visit correlates very highly (up to 0.99) with

¹⁷ For example, Pagneux et al. (2011) present face-to-face interviews on flood risk perceptions with $n = 112$ subjects in Iceland. Lindell and Hwang (2008) present a mail survey with $n = 321$ responses. Kellens, Zaalberg, and De Maeyr (2012) utilize $n = 266$ complete online surveys (based on 313 responses). See also meta analysis by Kellens, Terpstra, and De Maeyer (2013).

¹⁸ We thank an anonymous referee for suggesting this comparison.

¹⁹ As discussed in the Online Appendix, the outlier household is a flood zone resident stating *high* levels of worry, so excluding them from our sample would only strengthen our main results.

county-level estimates of general climate change concern from the Yale Program on Climate Change communication, as described in Section 6.

3.2 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.

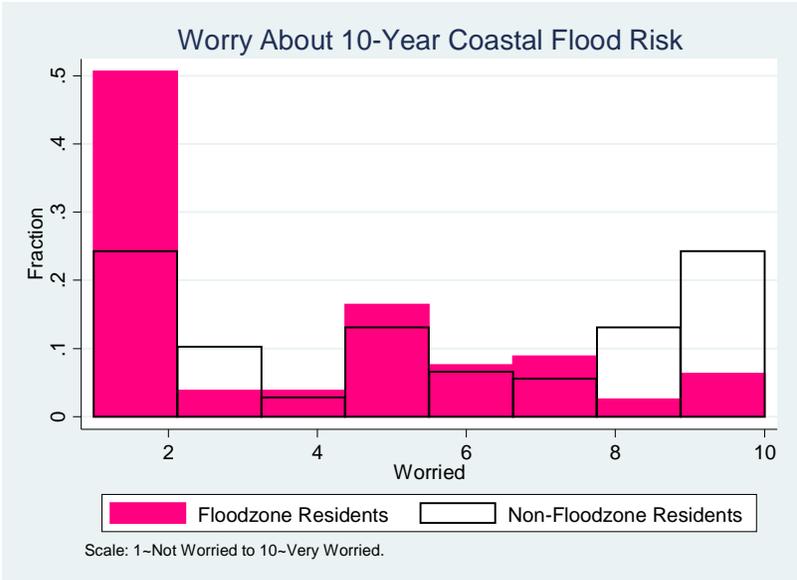


Figure 1: Flood Worry Distribution

Of course one may be concerned that a low degree of worry could be driven by differences in expectations over losses conditional on a flood, rather than flood risk itself. Figure 2 showcases the distribution of expected flood damages (as percentage of home value) net of expected insurance reimbursements and government assistance.²⁰ While flood zone residents generally expect slightly lower damages, they also expect less insurance and government assistance (see Table 1). The net damage expectations are thus very similar across the two

²⁰ Households whose (net) estimates imply flood damages in excess of 100% (below 0%) of home values are re-coded as 100% damage (0%) estimates.

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. However, using property tax records, we construct a measure of secondary homeownership and verify that the results are virtually unchanged if secondary homeowners are excluded (see Online Appendix for details). 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 correspondingly limited, the results indicate that flood zone residents who report low worry actually also report *fewer* mitigation measures, although not significantly so (see Online Appendix). Focusing on the most important mitigation measures - sea walls or home elevation²¹ - we further find that respondents listing these protection efforts appear, if anything, *more* worried about flooding on average, although again not significantly so.²² Our results are thus consistent with the notion that worry drives risk reducing behaviors, including residential location choice.

Table 1 presents differences in means and t-tests for their significance across the two groups. Both demographics and home characteristics appear similar across flood zone and non-flood zone residents. Beyond exhibiting highly significantly *lower* flood risk concerns, flood zone residents differ from non-flood zone residents mainly in having smaller households and homes.²³ The central take-home point is thus that we find evidence of significant het-

²¹ 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 so-called "Letter of Map Revision." Our analysis would then not count those homes as being in the high risk flood zone.

²² 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. Only *four* mention sea walls or construction. Excluding them 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 Online Appendix for details.

²³ For the living area variable, we use finished area information from Barrington, Bristol, and Warren, and effective area for Portsmouth and Warwick. We set one home with a recorded finished area of zero to missing. Treating the zero as data instead would render the difference in sizes in Table 1 slightly

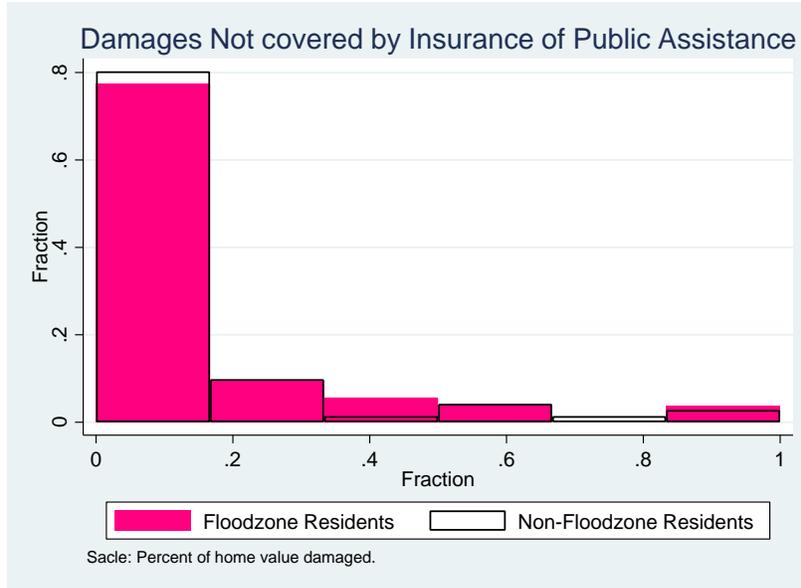


Figure 2: Net Damage Expectations

erogeneity in concerns about flooding that does not appear to be driven by differences in confounders such as government or insurance assistance expectations.

The results presented thus far focus on flood risk perceptions measured by a worry index. However, we also elicit numerical flood risk beliefs. Figure 3 compares these perceptions with respondents' homes' 10-year flood risk, which we estimate based on property-specific elevation data from 1-meter resolution digital elevation model LiDAR data from the University of Rhode Island Environmental Data Center, and STORMTOOLS, a set of Rhode Island inundation maps and flood return rates developed by partners including the University of Rhode Island and NOAA (SAMP, 2017). The sample is restricted to coastal homes so that responses reflect flood risk estimates specific to respondents' homes. On the one hand, we find that actual flood risk is a highly significant predictor of perceived flood risk (see Online Appendix for regression results). On the other hand, however, coastal residents appear to systematically under-estimate their flood risk relative to inundation models. Assessments that agree with the storm surge model should be near the 45° line. However, around 60-70% of coastal residents under-estimate their homes' flood risk relative to the inundation model,

smaller and no longer marginally significant.

Table 1: Differences in Sample Means: Flood Zone Residents

Variable	Non-Flood Zone	Flood Zone	Difference (SE)
Flood Worry Index (1-10)	5.62	3.65	1.97*** (0.46)
Flood Probability (midpoints)	0.27	0.24	0.02 (0.05)
Age	53.09	52.74	0.34 (2.25)
Household Income	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	161.1* (93.0)
Flood Damages % of Perceived Home Value	41.7%	33.5%	8.2% (6.3%)
Flood Damages: \$ '000's	194.1	117.9	76.2 (51.0)
Expectation of Gov't Assistance: % of Flood Damages	15.1%	10.6%	4.5% (3.5%)
Expectation of Insurance: % of Flood Damages	63.1%	50.3%	12.9%** (5.1%)

** (***) ~ significant difference for two-sided t-test at 5% (1%) level.

and the average perceived flood risk is significantly lower than model-based estimates.²⁴

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 (see Online 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 five years, as shown in Figure 4.²⁵

²⁴ 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 Online Appendix for details.

²⁵ 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, respectively.

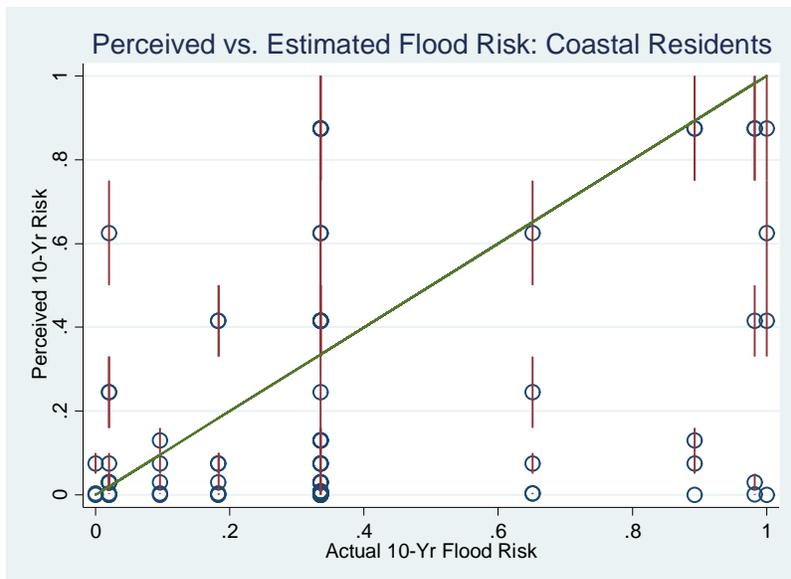


Figure 3: Perceived vs. Estimated Flood Risk. Note: Red lines span range of perceived 10-year flood risk probability (e.g., 5-10%) on the y-axis, with blue circles marking the mid-points.

Both results are in line with the model’s central mechanisms that households learn about flooding from past events, and are more likely to select out of coastal property markets as their flood risk perceptions increase.

The second main goal of the survey is to assess household-specific willingness-to-pay (WTP) for living within 400 feet of the waterfront. The survey question asks households about their WTP assuming that all other home attributes - including environmental risks - remain unchanged compared to their current homes. If households ask for clarification, surveyors were instructed to 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. Estimation details are presented in the Online Appendix.

Figure 5 plots the joint distribution of coastal amenity values and flood risk perceptions among coastal (circles) and non-coastal (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.

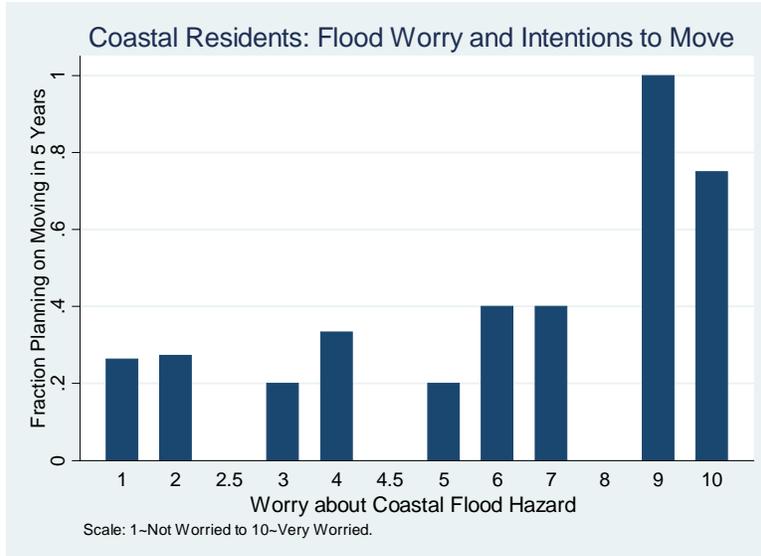


Figure 4: Flood Worry and Intentions to Move

With regards to risk belief types, we classify respondents as ‘optimists’ if they underestimate coastal 10-year flood risk by at least $\sim 50\%$. Specifically, respondents are ‘optimists’ if their subjective coastal 10-year flood risk assessment is between $0 - 5\%$. In fact, FEMA high flood risk zone residents’ annual flooding probability is at least 1% , implying a 10-year probability of at least one flood around 9.6% .²⁶ While the mean of amenity values 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 Online Appendix presents a further comparison of demographic and other variables between optimists and realists. They appear statistically indistinguishable on most dimensions. Prior literature has likewise found that demographics have little explanatory power over general housing market optimism (Pizzesi and Schneider, 2009). We return to this issue in the discussion of welfare effects in Section 5.2.

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

²⁶ While not all coastal homes in our sample are in a FEMA flood zone due to their elevation, other homes’ risks exceed 1% per year. As we estimate the average annual flood risk for coastal homes in our sample to exceed 1% per year, using a 1% figure is thus conservative.

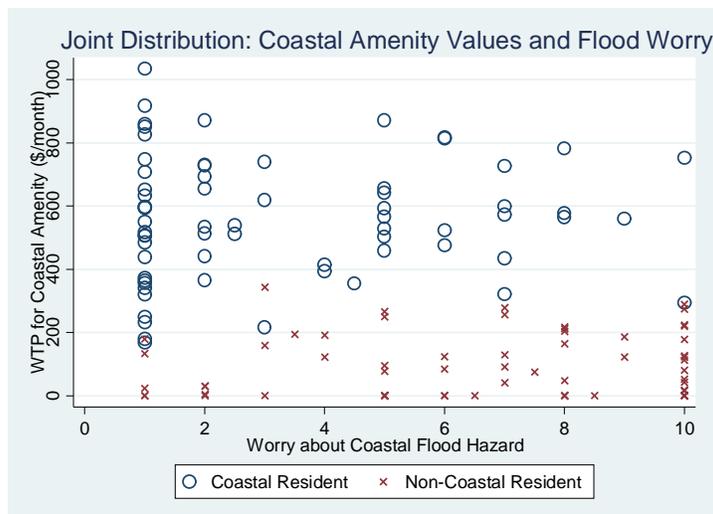


Figure 5: Joint Amenity Value and Flood Worry Distribution

beliefs across types. As expected, realists are more likely to assume higher future flood risk increases than optimists.²⁷ However, even the majority of optimists anticipates some increase in flood risks. Informed by these results, our model assumes that optimistic agents anticipate the possibility of a future flood risk increases and that they become Bayesian learners with some positive prior on the probability that sea level rise has occurred.

4 Full Structural Model

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

Flood Risk and Beliefs

First, we assume that *current* flood risk is known to scientists. Realists adopt this official announcement as their belief. Optimists, in line with the survey, under-estimate current flood

²⁷ One may be concerned about expectations of future public flood risk mitigation measures, such as sea walls. Our survey asked 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 state-wide 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).

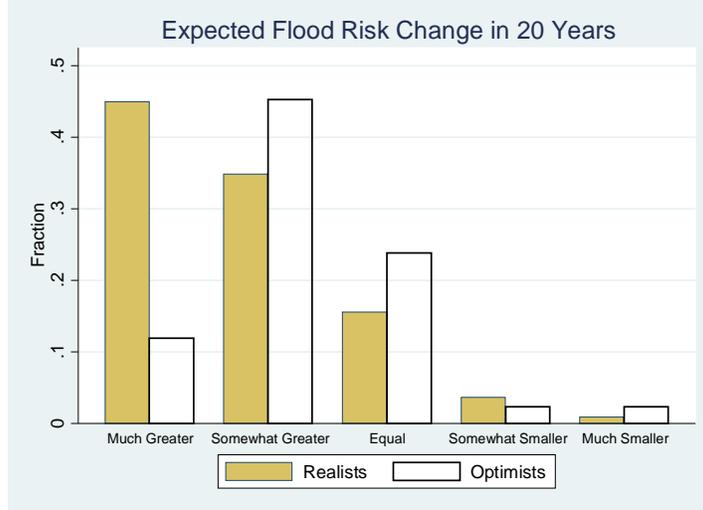


Figure 6: Future Flood Risk Expectations

risk. In the future, flood risk will change due to sea level rise. The level of future sea level rise is uncertain. The official scientific announcement is thus a *probability distribution* over future flood risk levels. This specification abstracts from deep uncertainty, which is discussed in Section 5.3. 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 or has truly change(d) to the official distribution (level), and update their beliefs in the future as they observe whether 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 scientifically announced value. We discretize sea level rise 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 , both π_1 and π_2 are learned.²⁸ Realists immediately update their beliefs in line with the scientific announcement.²⁹ Opti-

²⁸ We were unable to find projections of the probability distribution of, e.g., year 2050 flood risk increases *conditional* on year 2030 realizations. We thus assume that the percentile of the realization in 2030 also reveals the percentile of the 2050 realization.

²⁹ Realists' beliefs are thus $E_t^r[\{\pi_s\}_{s=0}^\infty] \sim \{\pi^L \text{ for } t < T_1, E_0^*[\Pi_1] \text{ for } T_1 \leq t < T_2, E_0^*[\Pi_2] \text{ for } t \geq T_2\}$ for $0 \leq t < T_1$, and update for $t \geq T_1$ to $E_t^r[\{\pi_s\}_{s=T_1}^\infty] \sim \{\pi_1 \text{ for } T_1 \leq t < T_2, \pi_2 \text{ for } t \geq T_2\}$.

mists assign a prior probability $0 < q_{T_1}^o < 1$ to the possibility that sea level rise is real and will begin happening at time T_1 , but maintain that flood risk will remain at their initial belief level $\pi_0^o < \pi^L$ with positive probability $(1 - q_{T_1}^o)$. Before sea level rise 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 belief updating framework is an adaptation from Dieckmann (2011) for the present setting. As of time $T_1 \leq t < T_2$, optimists' contemporaneous flood risk beliefs 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 is given by $E_t^o[\pi_{T_2}] = q_t^o(\pi_2) + (1 - q_t^o)(\pi_0^o)$, again reflecting the notion that q_t^o captures their belief that sea level rise is real and that flood risk is changing as per the scientific announcement. Note that we use lower case letters for flood risks after sea level rise 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:

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

While the benchmark specification assumes rational Bayesian updating, the Online Appendix shows that 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, e.g., insurance demand responds to flood events (Gallagher, 2014).

With regards 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 (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* - only 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 regards 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):

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

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 assumed that realists failed to anticipate optimists' potential future learning about higher flood risks, they may overestimate optimists' future willingness-to-pay for vulnerable properties, and thus the re-sale price of coastal homes, further contributing to contemporaneous overvaluations.

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 National Flood Insurance Program (NFIP). Congress enacted NFIP in 1968 due to rising damages from flooding and limited private market insurance penetration. To this day, NFIP remains the dominant insurer for flooding in the United States, with more than five million policies in force as of January 2017 covering more than \$1.2 trillion of property and contents (FEMA, 2017; Moore, 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). One in five policies has traditionally been subsidized, charging less than half of full risk levels on average (CBO, 2014). The extent to which even full risk rates are actuarially fair is moreover an open question (CBO, 2014). The Biggert-Waters Flood Insurance Reform Act of 2012 sought to bring the program closer into fiscal balance through insurance subsidy phase-outs and immediate price increases (FEMA, 2013). However, due to concerns over homeowner impacts, the Homeowner Flood Insurance Affordability Act of 2014 partially repealed and modified Biggert-Waters. Looking toward the future, however, a 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.³⁰ We formally assume that, at some future time T , effective flood risk beliefs will converge to true risk values.³¹ We stress again that we do *not* assume that actual beliefs converge, but only that flood insurance mandates will be enforced. Our approach also does not need 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 sea level rise after insurance reform, so that we assume $T_1 < T < T_2$, meaning that some sea level rise occurs before and some after insurance reform. At time $T - 1$ the realists and optimists each hold expectations over the announced schedule of current and future flood risks or insurance rates, $E_{T-1}^r[\pi^*]$

³⁰ Alternatively, 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).

³¹ Implicit in this setup is the assumption that the timing of policy reform is known, which is obviously an abstraction. Section 5.3 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.

and $E_{T-1}^o[\boldsymbol{\pi}^*]$, respectively, where $\boldsymbol{\pi}^* = \{\pi_{T_1}^*, \pi_{T_2}^*\}$. Note that this formulation assumes that period $T - 1$ is after period T_1 when sea level rise is first observed.

Given assumptions about beliefs, it is straightforward to solve for time $T - 1$ prices. 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} amenity value $\bar{\xi} = \Xi(1 - k_1)$. 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 sea level rise, this expectation will be:

$$E_{T-1}^r[P_T] = \sum_{j=0}^{n-1} \beta^{j+1} [e^h + \Xi(1 - k_1) - E_{T-1}^r[\pi_{T_2}^*]\delta] + \frac{\beta^{n+1} [e^h + \Xi(1 - k_1) - E_{T-1}^r[\pi_{T_2}^*]\delta]}{(1 - \beta)} \quad (21)$$

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

$$\Xi \frac{k_1}{\theta^o} + \{E_{T-1}^r[P_T] - E_{T-1}^o[P_T]\} < \delta(\pi_{T-1}^r - \pi_{T-1}^o) \quad (22)$$

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

$$P_{T-1} = \beta(e^h + \Xi \left(1 - \frac{k_1}{\theta^o}\right) - \pi_{T-1}^o\delta + E_{T-1}^o[P_T]) \quad (23)$$

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

$$\begin{aligned} P_{T-1} &= \beta(e^h + \bar{\xi}_{T-1}^o - \pi_{T-1}^o\delta + E_{T-1}^o[P_T]) \\ \bar{\xi}_{T-1}^o &= \Xi(1 - k_1) - \delta(1 - \theta^o)(\pi_{T-1}^r - \pi_{T-1}^o) + (1 - \theta^o)\{E_{T-1}^r[P_T] - E_{T-1}^o[P_T]\} \end{aligned} \quad (24)$$

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 sea level rise is known at time $T - 2$. The identity of the marginal buyer then again depends on whether:

$$\Xi \frac{k_1}{\theta^o} + \{E_{T-2}^r[P_{T-1}] - E_{T-2}^o[P_{T-1}]\} < \delta(\pi_{T-2}^r - \pi_{T-2}^o) \quad (25)$$

Importantly, however, each type's expectation of next period prices now depends on his expectation of his 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 over 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:

$$[\Xi \frac{k_1}{\theta^o} + \{E_{T-2}^r[E_{T-1}^r[P_T]] - E_{T-2}^r[E_{T-1}^o[P_T]]\} < \delta(E_{T-2}^r[\pi_{T-1}^r] - E_{T-2}^r[\pi_{T-1}^o])] \quad (26)$$

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):

$$E_{T-2}^r[P_{T-1}] = \beta(e^h + \Xi \left(1 - \frac{k_1}{\theta^o}\right) - E_{T-2}^r[\pi_T^o])\delta + E_{T-2}^r[E_{T-1}^o[P_T]]$$

If inequality (26) does not hold, realists expect that both types will be in the coastal housing market in the next period, and $E_{T-2}^r[P_{T-1}]$ is given by the realists' time $T - 2$ expectations of (24) and (21). Analogous calculations for optimists yield their time $T - 2$ expectations of re-sale prices at time $T - 1$, $E_{T-2}^o[P_{T-1}]$. Given each type's respective price expectations, we can then use (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 non-stationary setting thus clearly introduces a curse of dimensionality which limits our ability to consider a richer set of belief types.³² On the

³² Calculating the P_{T-n} price requires iteratively imputating $2 \times (\sum_{k=0}^{n-1} 2(2^k)) - 2$ expectations.

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.

Policy Reform Beliefs

The last element is to specify agents' beliefs about enforced policy rates after time T . Realists are assumed to adopt the scientifically forecast probability distribution of sea level rise and then update 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:

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

The optimists' expectation of $E_t^o[\pi_{T_2}^*]$ is analogous to (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 ($\omega^o = 0, \omega^o = 1$).

4.1 Model Calibration

Flood Risk Changes

We quantify future flood risk changes based on probabilistic sea level rise projections by Kopp et al. (2014, 2017) and of corresponding flood risk amplification factors (AF) estimated by Buchanan et al. (2017). These studies are widely used in both policy and academic analy-

ses.³³ For Newport, RI, Kopp et al. (2014) project median sea level rise of 20 cm by 2030 and 38 cm by 2050 (with a 5-95% range of 19-56 cm, values relative to 2000). Buchanan et al. (2017) estimate joint probability distributions over sea level rise and flood frequencies to generate probabilistic estimates of the corresponding 100-year flood risk amplification factors. 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 sea level rise distributions arising due to uncertainty over Antarctic ice sheet contributions (Buchanan et al., 2017). By 2050, in a business-as-usual or high greenhouse gas emissions scenario (the Representative Concentration Pathway (RCP) 8.5, Van Vuuren et al., 2011), the expected frequency increase of what used to be 100-year floods is projected to increase *11.5-fold* (with a 5-95% range of 1.5-22.2). Consideration of other locations reveals that this increase is comparatively modest: Buchanan et al. (2017) estimate a median 2050 expected 100-year flood risk amplification factor of around 40 across tidal gauge locations in the contiguous United States. We extend our model to other locations in Section 6. Our sensitivity analysis also showcases results under a global climate policy scenario with moderate emissions (RCP 4.5). In Newport, RI, the expected flood risk amplification factor by 2050 in this scenario falls to 7.4 (5-95% range 1.3-15.0).

In our model, we discretize sea level rise as increasing flood risk in 2030 and 2050. We interpolate flood risk amplification by 2030 exponentially based on the decadal sea level rise projections from Kopp et al. (2017) and both 2050 and subsequent flood risk AF projections of Buchanan et al. (2017).³⁴ For Newport, RI, this yields a 2030 mean amplification factor of 4.79 (RCP 8.5). Given that the sea level rise projections are relative to the year 2000, we use the same procedure to correct for flood risk increases that have already occurred by

³³ For example, the estimates of Kopp et al. (2014) are routinely used in government analyses of sea level rise (e.g., NOAA, 2017a; EPA, 2017) and also in economic studies (e.g., Desmet et al., 2020).

³⁴ Separately for each city, we first use SLR and mean flood risk AF projections for times 2050 and 2100 for scenarios RCP 8.5 and 4.5, respectively, from Buchanan et al. (2017) as "data" to estimate $\ln(AF_t - 1) = \beta_0 + \beta_1 \ln SLR_t$. We then use 2030 sea level rise projections for each location and scenario (from Kopp et al., 2017) to infer $\widehat{AF}_{2030} = e^{\widehat{\beta}_0} \widehat{SLR}^{\widehat{\beta}_1} + 1$.

Table 2: Benchmark Model Calibration

Parameter		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: Med. damage/price \times Med. price
e^h	Net value of own home living	Variable	Match initial med. 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	4.79%	Interpolated from Buchanan et al. (2017), Kopp et al. (2014)
$E_0^*[\Pi_2]$	Expected annual flood risk as of 2050	11.5%	Buchanan et al. (2017)
T	Policy reform period	2041	
$q_{T_1}^o$	Optimists' prior on sea level rise	0.1	
π_0^o	Optimists' initial flood risk belief	$0.5 \cdot \pi^L$	50% below official value in line with with optimist definition from survey
Flood event: 2035.			

our model base year.³⁵ Finally, while we treat the probability distribution of sea level rise outcomes as known, we discuss concerns over deep uncertainty in Section 5.3.

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 et al., 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

³⁵ This adjustment is for 10 cm SLR as per NOAA data for Newport, RI (2017 mean), yielding a flood amplification factor 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 reference number when computing the share of optimists in the population.

and fundamental values depend only on *expectations* of storm events (see Table 5). 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 re-weighted average of the survey population to correct for over-sampling of coastal homes.

5 Quantitative Results

5.1 Main Results

Figure 7 presents the main results for the benchmark calibration with sea level rise 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 underestimation 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 by 13%. Economically, an overvaluation of this magnitude would be highly significant.

Before proceeding, we note two ‘tests’ of the model. First, the model’s projected initial non-coastal housing price of \$319k matches our sample average of \$324k very closely, despite being a non-targeted moment. Second, the model’s predicted relative change in coastal versus inland housing prices after the future storm event of -9.6 percent aligns very well with the empirical literature’s difference-in-differences estimates of storm impacts on relative prices ranging from -5 to -20 percent (e.g., Hallstrom and Smith, 2005; Kousky, 2010; Bin and Landry, 2013; Ortega and Taspinar, 2018).³⁶

³⁶ Conceptually, the model only pins down the difference between coastal and non-coastal housing prices. This is because the price of houses - which are in fixed supply - is determined by their differential value

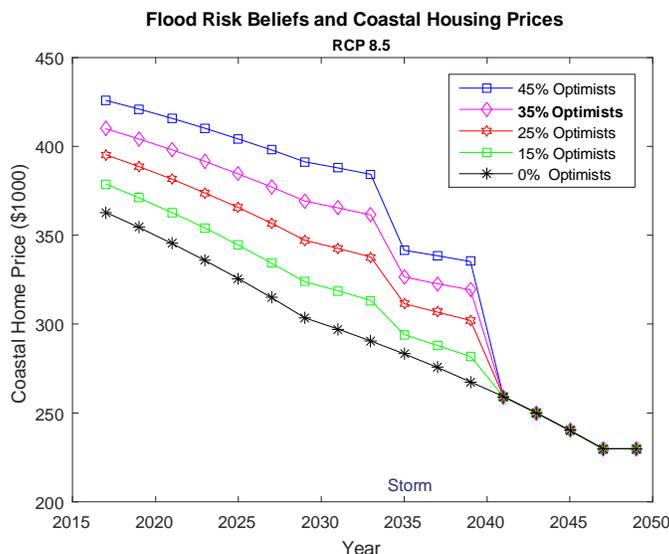


Figure 7: Flood Risk Beliefs and Housing Prices

The scenarios featured in Figure 7 assume that sea level rise 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 their 5th to 95th percentile.³⁷ The range of projected medium-run outcomes is wide, ranging from coastal homes becoming worthless to gaining substantially in value if SLR turns out to be less severe than anticipated. Importantly for our purposes, however, we note two points. One, the initial overvaluation results are unchanged as depend only on expectations of future SLR (note that we consider uncertainty over SLR distributions in Section 5.3). Two, overvaluation persists across different future SLR realizations. By 2033, for example, while the 5th percentile outcome yields an overvaluation of only about 1%, in the 95th percentile of flood risk increases, the overvaluation reaches over 1,000% as the fundamental

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

³⁷ We take the flood risk amplification factors for 2050 as the 5th and 95th percentiles estimated by Buchanan et al. (2017). For 2030, the 5th percentile SLR estimate in the underlying Kopp et al. (2014) framework was 8 cm above 2000 levels, which has 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 33cm of SLR by 2030 under RCP 8.5. Buchanan et al. (2017) estimate a flood risk amplification factor of 15 associated with 34cm of SLR in another scenario. We thus adopt 15 as the relevant 2030 flood risk amplification factor for the 95th percentile.

value collapses but prices are projected to remain high for a number more years.

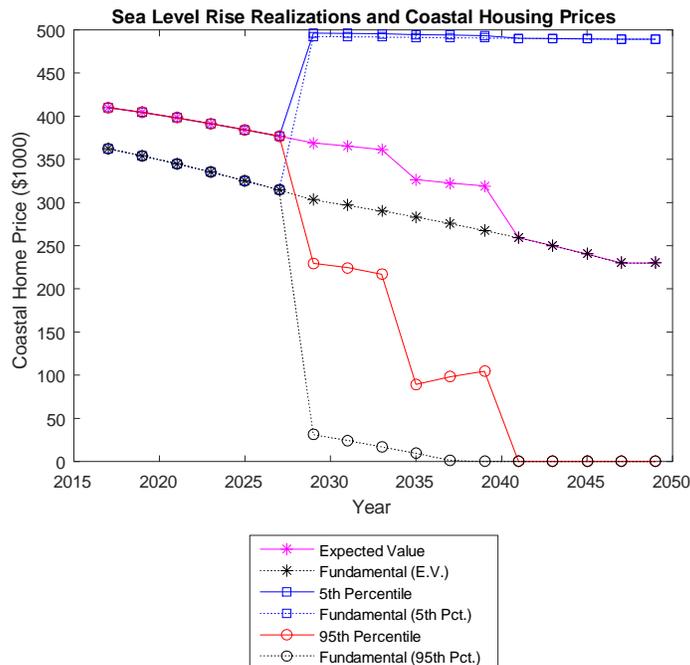


Figure 8: Sea Level Rise Realizations and Coastal Housing Prices

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.

5.2 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 ($\bar{\xi}^{o,*} = \bar{\xi}^{r,*} = \Xi(1 - k_1)$). In contrast, allocative inefficiency from belief heterogeneity occurs whenever the marginal realist's

valuation exceeds that of the marginal optimist (i.e., $\bar{\xi}_t^r > \bar{\xi}^{r,*}$ and $\bar{\xi}_t^o < \bar{\xi}^{o,*}$). Let q_t^i denote the quantity of coastal housing consumed by group i in period t , which equals $q_t^o = \frac{\theta^o}{\Xi}(\Xi - \bar{\xi}_t^o)$ for optimists and $q_t^r = \frac{(1-\theta^o)}{\Xi}(\Xi - \bar{\xi}_t^r)$ for realists. The net loss in consumer surplus CS_t from coastal housing in period t due to belief heterogeneity is then given by:

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

Brunnermeier, Simsek, and Xiong (2014) develop a belief-neutral efficiency welfare criterion for settings where beliefs are distorted and heterogeneous, but where the social planner does not know the objective belief. Intuitively, the criterion asks the planner to consider all convex combinations of *reasonable* beliefs. On the one hand, 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 (28) does not actually depend on whether the social planner adopts the realists' or optimists' beliefs. That is, even if a utilitarian social planner agreed with the optimists, he would perceive an allocative inefficiency cost from realists' excessively pessimistic beliefs keeping some 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.³⁸ The benchmark costs are estimated at \$555 per household (\$2017) - a modest amount, although 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 coastal amenity value (Ξ) - set at either our hedonic regression estimate (\$3.9k/yr, see Section 5.3), or at the 75th percentile of coastal residents in our survey (\$8.5k/yr) - only modestly affect

³⁸ The Online Appendix presents a visualization of the allocative inefficiency over time.

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 efficiency by almost 80%.

Table 3: Allocative Inefficiency Costs	
Scenario	Per Household Net Costs
Benchmark ($\Xi = \$7.7k$)	\$555
Lower Amenity Value $\Xi = \$3.9k$	\$373
Higher Amenity Value $\Xi = \$8.5k$	\$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.³⁹ 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 currently non-coastal 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

³⁹ 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 sea level rise takes its expected value.

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.⁴⁰ 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	Initial	Location		Coastal	Insurance
		Interim	Post-Reform	Amenity (\$/month)	Reform ΔW
Realist in Waiting	Non-Coastal	Non-Coastal	Coastal	\$549	+\$34.2k
Hot Potato Seller	Coastal	Non-Coastal	Coastal	\$563	-\$24.2k
Hot Potato Buyer	Non-Coastal	Coastal	Non-Coastal	\$376	+47.1k

Displays change in present value of utility comparing a scenario with immediate (2020) insurance reform with delayed (2041) reform. Considers realized utility assuming no storm events and sea level rise at expected values for each scenario.

Before proceeding, we address some potential 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. Intuitively, agents trade off anticipatory utility from thinking positively about the future against the cost of the decision errors that result from holding inaccurate beliefs.⁴¹ To the extent that inaccurate beliefs represent an optimal choice, our welfare cost estimates may be an overestimate. 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 empirical evidence on how agents respond to

⁴⁰ 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 sea level rise. That is, in the long run, price are assumed to reflect fundamental values in both scenarios.

⁴¹ Rational expectations would still be optimal beliefs in this setting if preferences are the canonical time-separable specification without memory or anticipatory utility.

flood risk information signals is at odds with the notion that their decisions were optimized whilst fully accounting for true risk. After flood events, housing prices in at-risk areas tend to fall by 5-20%, even in areas that were not damaged but only received salience signals such as near-miss hurricanes (see, e.g., Hallstrom and Smith, 2005). Demand for flood insurance has similarly been found to spike upwards after flood events, including if those occur only elsewhere but 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. As a further indicator for learning versus preference-based flood risk beliefs, we compare other beliefs and demographics across optimists and realists (see Online Appendix). Flood risk optimists do not appear to be optimistic about flood damages, and are actually significantly more pessimistic about government assistance in case of a flood event. We also compare demographics between optimists and realists as old agents and those without children and a bequest motive may face lower costs from adopting an excessively optimistic view of flood risks. Optimists are slightly older on average, but this difference is not driven by a disproportionate share of senior citizens, but rather by relatively more agents in their 50s versus 40s in the two groups. In addition, we find that household size is not significantly different across the two groups, and, by the point estimate, is slightly larger among optimists.

A second caveat to our welfare analysis is that coastal mispricing is likely to create welfare costs through channels which are not represented in our model. Examples include overinvestment in at-risk properties (Barrage and Furst, 2019), or, 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 asset value losses, 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.

5.3 Robustness

This section assesses the sensitivity of our main results in the benchmark setting. Results for other locations are discussed in Section 6. We first present quantitative robustness results, and then describe some qualitative model extensions below. Unless otherwise stated, we change one parameter at a time without adjusting other model elements.

Optimist Share: We begin with the estimated share of flood risk optimists. Uncertainty over this parameter arises both because of potential measurement error in our survey and the possibility of alternate definitions of optimists. Figure 9 displays the estimated initial coastal home price overvaluation as a function of the optimist share. While the overvaluation increases in the optimist share, the sensitivity is quantitatively modest once the share of optimists exceeds the share of coastal homes (14.51%). For example, the benchmark analysis defines "optimists" as those under-estimating coastal flood risk by at least 50% (relative to FEMA flood maps), yielding an estimated population share of 35% and an overvaluation of 13%. Defining optimists more strictly as those under-estimating flood risk by at least 70% would imply a population share of 20%, yielding an overvaluation estimate of 12%. Defining optimists more loosely to imply a 70% population share yields an only modestly higher overvaluation of 16%.

Coastal Amenity Values: Next, our benchmark analysis uses stated preference methods to quantify coastal amenity values. Uncertainty over these values arises both due to measurement error and alternate methodologies to elicit these values. In particular, hedonic regression can provide revealed preference estimates, but typically cannot cleanly disentangle the different components entering the observed coastal home price premium, as shown in Section 2. For comparison, we nonetheless collect housing price and requisite covariate data to generate a hedonic coastal amenity premium estimate, which is around +23% implying an average marginal amenity value of \$3.9k per year (see Online Appendix for details). Figure

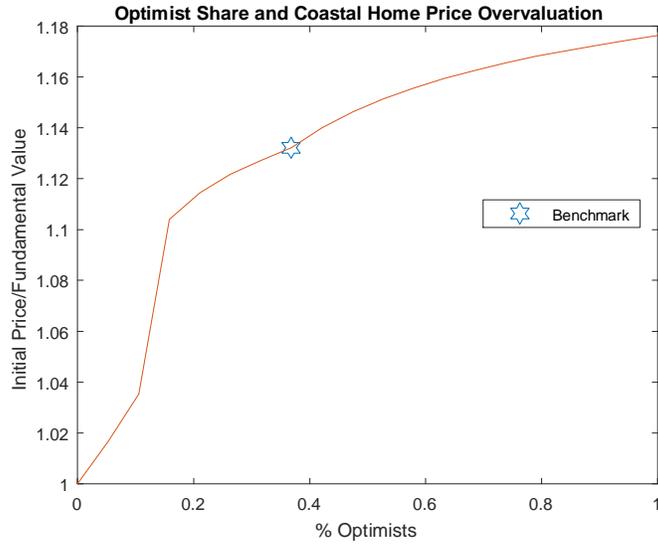


Figure 9: Optimist Share and Overvaluation

10 showcases results for a range of coastal amenity values including the hedonic estimate, although we again caution that this average marginal hedonic value is not directly comparable to the maximum coastal amenity we measure from the survey. In any event, however, the projected overvaluation does not appear very sensitive to this model input.

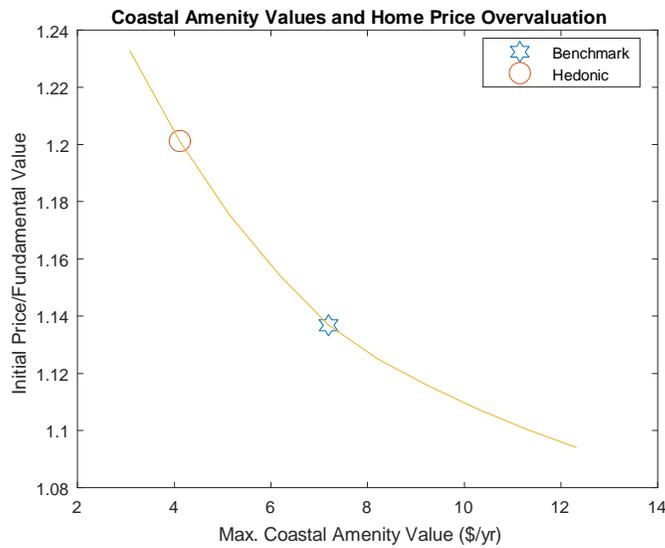


Figure 10: Max. Amenity Value and Overvaluation

Sea Level Rise Uncertainty: The next source of uncertainty we confront is over sea level rise. While our analysis already accounts for uncertainty over SLR realizations, it assumes that the relevant distribution is known. One potential concern is that long-run SLR is subject to deep uncertainty particularly over contributions from polar ice sheets, and may thus not be well captured by a single probability distribution (Jevrejeva et al., 2019; Kopp et al., 2017). Importantly, however, for our near- to medium-run focus, the representation of uncertainty through a probability distribution is arguably reasonable. For example, in exploring deep uncertainty over polar ice sheets, Kopp et al. (2017) find that introducing relevant representations of ice sheet dynamics has only limited effects on SLR projection ranges through mid-century. Consequently, in a recent review of uncertainty over sea level rise, Jevrejeva et al. (2019) explicitly note that practitioners such as coastal adaptation planners may want to be "employing probability distributions for the time period of good agreement (through about 2050)" but account for ambiguity over such distributions for longer-run considerations. In addition, even studies that do formally account for deep uncertainty find its effects to be quantitatively limited over our time horizon of interest. For example, Barnett, Brock, and Hansen (2020) consider deep uncertainty in a general climate-economic model, and find that the ambiguity-adjusted probability densities used by the planner do not start to diverge notably from the baseline density until 50 or more years into the future, for both uncertainty over the climate sensitivity (i.e., the equilibrium amount of warming due to doubling of carbon dioxide concentrations) and a climate damage parameter in the benchmark model. Similarly, Lemoine and Traeger (2016) find altogether small effects of ambiguity over climate tipping points. While these considerations motivate our benchmark approach, here we nonetheless consider sensitivity to alternative SLR forecasts. Figure 11 displays the projected initial overvaluation for a range of expected flood risk amplification values based on the 5-95% interval identified by Buchanan et al. (2017). The results suggest that initial overvaluation is convex and increasing in expected flood risk amplification. One notable implication of this finding is that our approach of running the model at the expected

flood risk amplification factor may thus underestimate the expected overvaluation.

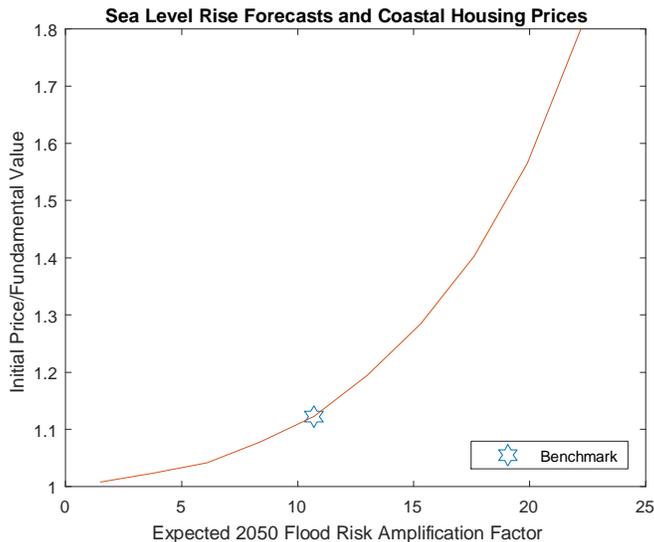


Figure 11: Sea Level Rise Forecast and Overvaluation

Flood Damages: Our final continuous sensitivity check varies the assumed level of flood damages in case of a flood event, as shown in Figure 12. Not surprisingly, mispricing is increasing in flood damages. The shape of the relationship again appears convex. The estimate also remains economically significant even for lower damage amounts.

Further Robustness: We next consider a number of discrete model changes. Results are presented in Table 5. The first is a behavioral modification that allows optimists to overreact to flood events or the lack thereof. This extension is motivated by empirical studies that have found home prices and flood insurance demand to revert to baseline within only 5-10 years after flood events (Bin and Landry, 2013; Gallagher, 2014), a pace not matched by a rational Bayesian framework. We thus introduce an overreaction parameter that increases (decreases) the agents' posterior in (19) by 15% in case of a (no) flood event to better match empirical studies (see Online Appendix). While this overreaction increases the volatility of future coastal housing prices compared to rational Bayesian updating, it does not affect the

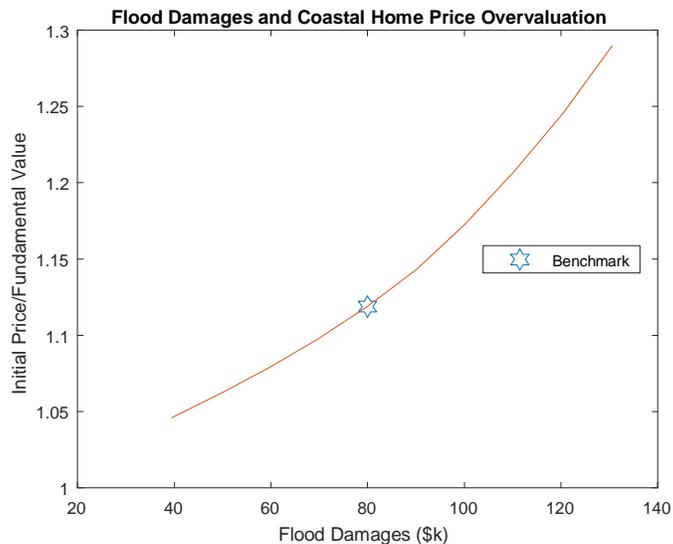


Figure 12: Flood Damages and Overvaluation

estimated overvaluation or overall price decline *levels*, as shown in Table 5. Next we consider alternative assumptions about optimists' expectations of long-run flood policy (insurance rates). In the benchmark, optimists assume flood policy will reflect the population-weighted average of beliefs ($\omega^o = \theta^o$ in (27)). Table 5 shows results for two polar alternative cases, namely that long run rates will reflect only optimists' ($\omega^o = 1$) or only realists' ($\omega^o = 0$) views. The results indicate long-run flood insurance policy changes can significantly affect coastal housing prices in the present. Expectations of long-run availability of cheap insurance leads to an estimated overvaluation of 33%. In contrast, if optimists expect to be forced to pay official risk rates eventually, overvaluation is significantly mitigated (2.5%). The latter assumption is arguably not in line with empirical evidence on limited flood risk capitalization and the responses of housing prices to flood events and flood insurance requirements (e.g., Gibson and Mullins, 2017), however.

Next we consider a global climate policy scenario consistent with the RCP 4.5 warming scenario (van Vuuren et al., 2011). This emissions scenario is projected to reduce the 2050 flood risk amplification factor in our benchmark area from 11.5 to 7.4 (Buchanan et al., 2017). Our interpolation moreover suggests that flood risk increases by 2030 would be reduced from

Table 5: Further Sensitivity Analysis

Scenario	Overvaluation	Var($\% \Delta P$)
Benchmark	13%	22
Bayesian updating overreaction (15%)	13%	29
Long-run policy optimism $\omega^o = 1$	33%	103
Long-run policy realism $\omega^o = 0$	2.5%	0.4
Global climate policy RCP 4.5 [†]	6.3%	8.4
Earlier policy reform $T = 2035$	13%	26
Flood events: none	13%	38
Flood events: double (2033 and 2037)	13%	12
Optimists' prior $q_{T_1}^o = 0.2$	12%	16
Optimists' prior $q_{T_1}^o = 0.3$	10%	12

[†]Re-scales own-home utility value e^h to hold initial coastal home price constant at \$410k.
Var($\% \Delta P$) refers to variance of year-to-year growth rates in coastal housing prices 2017-2050.

a factor of 4.79 to a factor of 1.44. As shown in Table 5, with this level of climate mitigation, the projected overvaluation falls to 6.3%. Another alternate policy scenario we consider is one with earlier flood insurance reform, which yields similar results on overvaluation, but significantly lower welfare costs (see Table 4), albeit at a cost of higher price volatility. The next two rows consider alternative flood realization scenarios. These do not affect the coastal home price overvaluation, as both the initial price and fundamental value depend only on *expectations* over flood events. The volatility of prices does, however, depend on storm realizations, as they determine accumulated learning by the time policy reform is enacted. The last two rows of Table 5 consider different values for the prior optimists are assumed to place on the probability that sea level rise forecasts are correct. Doubling or even tripling our benchmark value of 10% yields only slightly smaller estimated values for the initial overvaluation of coastal homes.

Ex-Post Rationalization: In the Online Appendix we consider an illustrative extension of the model to account for the possibility that coastal residents change their flood risk beliefs *differentially* after moving to the coast in order to rationalize their sorting choice *ex-post*. We

argue that ex-post rationalization should not fundamentally alter the main results as long as there are optimistic agents among the potential marginal buyers of coastal homes, as is consistent with the survey results. That is, while ex-post rationalization may create a class of ‘entrenched’ coastal residents (who are less likely to become marginal *sellers*), mispricing of coastal homes that are being sold (e.g., by informed agents) will continue as long as there are optimists among the marginal buyers. The survey results suggest this to be the case: 30% of (currently) non-coastal residents in our sample are optimistic about coastal flood risks, and recent *movers* (who relocated from another town to their survey area within the past 3 years) show a similar spread in the flood belief distribution to the full sample.

Transaction Costs: The Online Appendix also presents a version of the model with transaction costs in home buying. We show that, while transaction costs may affect price levels and transition dynamics in intuitive ways, importantly for our purposes, they do not affect the overvaluation arising from flood risk misperceptions.

Model Misspecification: Finally, we note that the robustness analysis presented here is all generated from within our model. In reality, our analysis is of course further subject to potential model misspecification. Important advancements in the literature have recently developed frameworks that can account for this concern in basic climate-economic models (Rudik, 2020), including alongside ambiguity and general uncertainty (e.g., Barnett, Brock, and Hansen, 2020; see also Brock and Hansen, 2018, and further references cited therein). Importantly for our purposes, however, several studies have found that deep uncertainty and model misspecification have limited quantitative effects especially over our time horizon of interest. For example, Rudik (2020) finds that insurance against model misspecification increases the optimal carbon price by only 1-2%. Given these results and the high level of complexity that the integration of a robust control approach into our heterogeneous beliefs housing market model would require,⁴² we leave this source of uncertainty for future study.

⁴² To our knowledge, robust control models with heterogeneous belief agents also remain rare especially of the form relevant in our setting. Frick (2019) considers a robust monetary policy authority which faces uncertainty over the economy’s share of rational versus non-rational agents. However, this framework features only first-order belief heterogeneity as even rational agents do not account for non-rational

6 Extended Calibration

This section expands the scope of our analysis by applying our framework to coastal cities beyond Rhode Island. We first demonstrate that our survey results - which were designed to measure precisely the 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 by the Yale Program on Climate Change Communications (YPCCC, Howe et al., 2015). Based on the estimated correspondence in Rhode Island, we then leverage the Yale estimates to extend the scope of our analysis. That is, while the Yale data cannot be used as a *substitute* to demonstrate the results of this study,⁴³ we use them as a *complement* to extend the analysis. Our survey covered three counties in Rhode Island (Bristol, Kent, and Newport). Instead of pooling the results, we now generate county-level estimates of the percentage of flood risk optimists using the same definition as before, namely the fraction that underestimates coastal flood risk by at least 50%.⁴⁴ We then compare our county-level optimist shares against three potentially relevant measures from the Yale survey:⁴⁵ the estimated percentages who "think global warming will harm people in the US not at all/only a little" (Figure 13), "are not very/not at all worried about global warming" (Figure 14),

households' belief process. Anderson et al. (2009) investigate the effects of uncertainty on excess asset returns in a model where agents solve a robust control problem. While professional forecasters' heterogeneous beliefs are used to measure uncertainty, the agents solving the problem are not themselves heterogeneous. Another example, Hansen and Sargent (2012) show that a Ramsey planner may have (endogenously) disparate beliefs from agents under different types of ambiguity.

⁴³ First, the smallest geographic unit in the Yale data is the county or city. Consequently, one cannot compare risk perceptions inside and outside high risk flood zones, or among coastal vs. non-coastal households. Second, the Yale study does not elicit flood risk beliefs, but rather general levels of climate change concern or belief. Third, we require information on counterfactual beliefs of households about flood risk at homes they did *not* purchase, no such data is available in the Yale study or any other surveys products we are aware of. Finally, our analysis requires a joint assessment of households' amenity valuations of coastal living and their risk beliefs, as well as information on potentially confounding beliefs such as about flood damages and government assistance in case of a flood. Again, no such information is available in the Yale survey or comparable surveys we are aware of.

⁴⁴ We correct for our survey's oversampling of coastal homes using county-specific weights for the shares of coastal homes, namely 20.94% in Newport, 13.4% in Bristol, and 9.16% in Kent county.

⁴⁵ We collect Yale survey estimates for the year 2018 from the URL (accessed June 2020): <https://climatecommunication.yale.edu/visualizations-data/ycom-us-2018>

and "think global warming will harm them personally not at all/only a little" (Figure 15), respectively. Though our number of observations is limited, we find a very strong association between our survey-based optimist measures and these general belief measures.

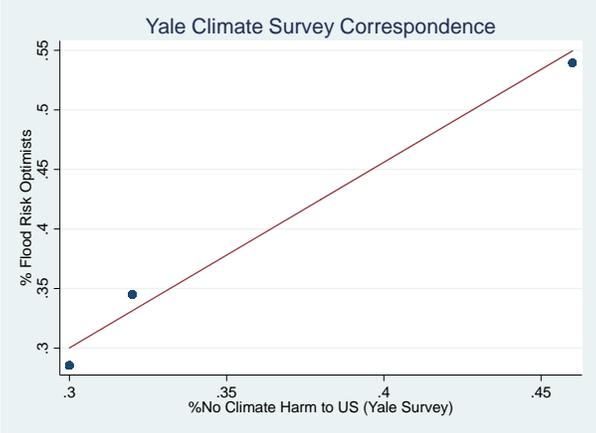


Figure 13: Yale Survey Correspondents: No U.S. Harm

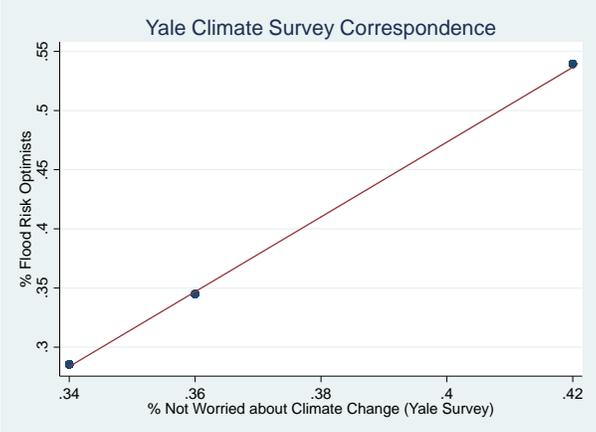


Figure 14: Yale Survey Correspondence: Not Worried

Next, we regress our county-level flood risk optimist shares on the Yale estimates of percent not worried about global warming. The results (see Online Appendix Table A2 for details) imply a predicted flood risk optimist share $\hat{\theta}^o = -.8 + 3.2(\% \text{ not worried about global warming})$. We use this result along with YPCCC estimates for other counties to calibrate the share of flood risk optimists in areas beyond our survey area.

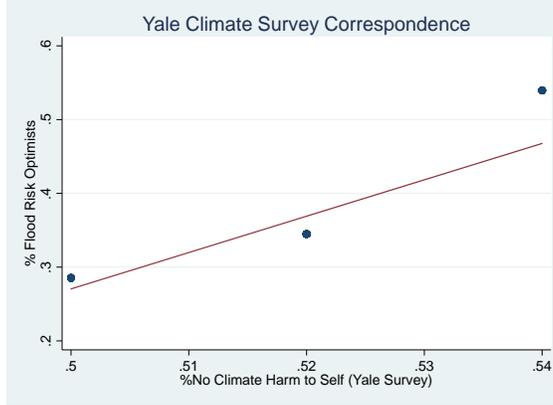


Figure 15: Yale Survey Correspondence: No Harm to Self

The remainder of the calibration proceeds as follows. We calculate the share of coastal homes k_1 using the same criterion (within 400 feet of the waterfront) and NOAA Continually Updated Shoreline Product coastline data. Flood risk amplification under sea level rise for each location is quantified based Buchanan et al. (2017) and Kopp et al. (2017) as described in Section 4.1.⁴⁶ In order to quantify the coastal amenity value distribution, we first infer the approximate marginal coastal amenity value by applying our empirical hedonic estimate (23%) to each location’s median home price, obtained from Zillow.⁴⁷ We then assume the maximum of the distribution Ξ based on the maximum-marginal ratio as in our benchmark calibration (2.6). Finally, to quantify expected flood damages δ , we adopt the benchmark value for damages relative to home price (20%) and compute values based on local median coastal home prices. All other parameters remain at benchmark values.

Table 6 presents the key model inputs and main results for an illustrative set of locations from across the United States.⁴⁸ Compared to our benchmark, the results imply significantly larger overvaluation potential in other locations. First, consider Boston, Massachusetts. While there are projected to be fewer flood risk optimists (16%) than in our Rhode Island

⁴⁶ Initial flood risk is set to the FEMA benchmark level of 1% per year in each location.

⁴⁷ We obtain the median single family home sales price for each city and compute the 2017 average.

⁴⁸ We select locations based on the criteria that they (i) have all calibration inputs available, including detailed future flood risk amplification 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.

area (35%), the share of coastal housing (2.3%) is also smaller compared to our benchmark (14.5%), allowing optimists to potentially be relatively mode dominant in the coastal market. Importantly, Boston also faces significantly higher expected flood risk amplification factors (over 50 in 2050) compared to our benchmark (11.5). Consequently, the projected initial overvaluation is considerably higher at over 80%. Next, in Wilmington, North Carolina, the model projects an even larger overvaluation of over four-fold. This is due to the combination of a high share of flood risk optimists (48%) and extremely high climate vulnerability. In contrast, in Tampa, Florida, the model projects a very modest overvaluation (4%), driven mainly by the very 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 thus suggest that (i) Rhode Island may be a conservative benchmark given the relatively modest flood risk increase projections,⁴⁹ and that (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.

⁴⁹ Indeed, Buchanan et al. (2017) estimate a median expected 100-year flood risk amplification factor of around 40 (by 2050) across tidal gauge locations across the contiguous United States.

Table 6: Extended Calibration: Results

Area	Inputs									Results
	Coastal homes k_1 (%)	Optimists θ^o (%)	Max. Amenity Ξ (\$k/yr)	E[Flood Risk AF] 2030 2050		e^h	Dam. δ (\$k)	P_0^{NC} (\$k)	P_0	Overvaluation ₀
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 [†]	0.066	0.48	5.1	3.67	96.9	33.4	51	208	256	420%
Corpus Christi, TX ^{††}	0.046	0.38	3.7	2.34	58.6	29.0	37	152	187	93%
Tampa, FL ^b	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 a business as usual warming (RCP 8.5) scenario.										
[†] Optimist share based on New Hanover county Yale survey results and our survey correspondence. Flood risk and sea level rise based on tidal gauges in ^{††} Rockport, TX and ^b St. Petersburg, FL.										

7 Conclusion

To what extent do asset prices reflect climatic risks? This issue is of growing interest due not only to its policy importance (Anderson et al., 2019), but also as 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, 2017b), and risks are set to 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 et al., 2009; Bernstein et al., 2019; Murfin and Spiegel, 2019; Baldauf et al., 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 theoretical and novel empirical evidence

through the combination of a dynamic housing market model allowing for heterogeneity in home types, consumer preferences, and flood risk beliefs, and a field survey providing direct evidence of belief distributions among waterfront and inland residents, as well as information on critical potential confounders.

The main results are threefold. First, we find that allowing for flood risk optimism enables our model to reconcile the mixed empirical evidence on flood risk penalties as 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 higher waterfront 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 post disaster public aid.

Third, calibrating the model to these survey results and probabilistic flood risk projections under sea level rise, we estimate that coastal housing prices exceed fundamentals by 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 sea level rise vulnerability and more climate change skepticism. The overvaluation results are robust to a range of robustness 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 thus 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 would soon purchase an overvalued coastal home may gain substantially from immediate policy reform, whereas current coastal residents who 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, de-

valuations in at-risk markets may also be a significant policy concern due to their potential effects on mortgage and credit markets. A formalizations and quantification of these impact mechanism 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 $1/8^{th}$ of a mile of the coastline exceeds \$1.4 trillion (McNeill et al., 2014). Many areas face significant risks from climate change. Neumann et al. (2000) estimate that three feet of sea level rise - a plausible scenario by the end of the century (Melillo et al., 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, 2016). The results of 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.

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