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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 into housing prices. Second, we implement a field survey in Rhode Island. We find significant heterogeneity and sorting based on flood risk perceptions and amenity values. Third, we calibrate the model and estimate that coastal prices currently exceed fundamentals by 10%. Ignoring heterogeneity leads to a four-fold underestimate of future coastal home price declines due to sea level rise.

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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. If, however, agents have *heterogeneous beliefs* about climate risks, the housing market implications may be starkly different. 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). While heterogeneity appears intuitively relevant for flood and climate risk perceptions in the United States, standard approaches to modeling the economic impacts of sea level rise have assumed homogeneous beliefs, thus potentially underestimating its broader economic ramifications.

This paper studies the implications of heterogeneity in flood risk beliefs for coastal U.S. housing markets. We provide both theoretical and empirical evidence. First, we develop a dynamic housing market model building 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. We first present a simplified version of the model and compare its predictions for how flood risks should factor into housing prices with the empirical evidence. A rich literature has generally found mixed results on the capitalization of climatic risks. For example, in a comprehensive national study, Bernstein, Gustafson, and Lewis (2018) find that while sea level rise vulnerability induces a significant discount in the sophisticated (non-owner occupied) housing market segment, it fails to do so in the general owner-occupied segment. Other studies have found results ranging from zero or positive flood zone premiums to significant negative effects.[1] We demonstrate that a heterogeneous beliefs model can *reconcile these results* through *sorting* resulting in different equilibria depending on the distribution of beliefs and other housing market characteristics. We therefore argue that a heterogeneous agent model matches the empirical evidence strictly better than the benchmark homogeneous rational beliefs model.

Second, in order to provide direct evidence and inform a plausible calibration of beliefs, we implement a door-to-door survey campaign in Rhode Island. Importantly, this methodology enables us to elicit flood risk perceptions and amenity values among both households that did and did *not* purchase properties on the coast.[2] The results confirm significant heterogeneity, and that selection into coastal homes appears to be driven by both lower risk perceptions and higher amenity values for waterfront living. For example, we find that the majority of coastal residents underestimate their homes' flood risks relative to inundation models, and that 40% of *flood zone* respondents say they are "not at all" worried about flooding over the next ten years. In contrast, a plurality of respondents living further inland indicate that they would be "very worried" about flooding if they lived on the coast. We also confirm that these differences are not driven by differential expectations of damages, government assistance, or insurance reimbursements in case of a flood.

Third, we present a fully specified and calibrated version of the model in order to quantify the potential implications of these beliefs for coastal housing markets under sea level rise. As the simulations require a specification of both first- and higher-order belief dynamics, here we further introduce a flexible Bayesian learning framework that allows agents to update their flood risk beliefs each period, in line with empirical evidence on response patterns after flood events (Gallagher, 2014).[3] We also couple sea level rise estimates from the National Oceanic and Atmospheric Administration (NOAA) and the U.S. Army Corps of Engineers

[1] See, e.g., Kousky (2010), Bin and Landry, (2013), Atreya and Czajkowski (2016), and Section 2.

[2] Sections 3 and 4 further motivate the use of stated preference methods by highlighting the limitations of hedonic approaches in estimating the desired parameters of interest from housing sales data.

[3] We consider both rational Bayesian learning and an 'overreactive' updating rule in order to better match the empirical literature's findings on the responses of housing prices (e.g., Hallstrom and Smith, 2005; Atreya and Ferreira, 2015) and insurance demand (Gallagher, 2014) to flood events.

with flood risk probabilities from a state-of-the-art geospatial flood model (STORMTOOLS) to estimate current and future property-specific inundation return rates.

The benchmark results imply that coastal housing prices currently exceed fundamentals by 10%, and that ignoring belief heterogeneity may lead modelers to underestimate the outstanding coastal home price declines due to sea level rise over the next 25 years by a factor of four. The estimated overvaluation is economically significant and robust to a range of robustness checks and extensions, such as alternative belief updating rules. We also conduct a hedonic analysis of housing prices in our empirical setting to ensure that the results are robust to, and in line with, revealed preference indicators of coastal amenity valuations and flood zone penalties. The main sensitivity of the results is with regards to higher future flood risk increases or higher population prevalences of flood risk optimism (and/or climate change skepticism), which are projected to increase contemporary coastal home price overvaluations up to 20%. In contrast, for markets dominated by agents with 'realistic' flood risk beliefs (i.e., in line with the scientific forecast), mispricing is predicted to be negligible (0-2%), in line with the empirical literature's findings of significant climate risk penalties in sophisticated markets (Bernstein, Gustafson, and Lewis, 2018). The simulations also reveal that households' beliefs about long-run flood insurance policy changes can significantly affect coastal housing prices in the present, highlighting the potential power of policy expectations to mitigate - or exacerbate - current inefficiencies.

These findings have important policy and welfare implications. First, they highlight the value of better flood risk information and communication. 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.[4] Our framework demonstrates how the absence of accurate flood risk information can threaten the efficiency of coastal housing markets. Second, coastal mispricing creates welfare costs. We quantify the allocative inefficiency of agents with high amenity values for waterfront living being priced out of coastal

[4] 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

areas by agents with lower amenity values but optimistic flood risk beliefs. 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.[5] Finally, our results highlight the potential impacts of flood insurance policy reform. The need for changes to the National Flood Insurance Program is well established as the program remains fiscally insolvent. As of the end of the 2017 fiscal year, FEMA owed $30.4 billion to the U.S. Treasury (GAO, 2018a).[6] We model an 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 raises fundamental distributional concerns. Our simulations moreover highlight a trade-off in the timing of reform: completing policy changes in 15 rather than 25 years can cut allocative inefficiency in half, but triples price volatility in the interim.

2 Literature

This paper builds on extremely rich literatures, including prior studies on housing prices and dynamics, residential sorting, and new work analyzing the impact of climate skepticism on asset markets. We first review and highlight our contributions to these broader literatures, and then describe the empirical evidence specific to flood risks, flood events, and housing markets in the subsection below.

First, the literature on housing price dynamics spans contributions from macroeconomics, finance, and urban economics (see, e.g., recent reviews by Davis and Van Nieuwerburgh, 2014, and Glaeser and Nathanson, 2014). Most closely related to our work are several recent papers that incorporate heterogeneous beliefs into housing market models. Both Piazzesi and Schneider (2009) and Burnside, Eichenbaum, and Rebelo (2016, "BER") present (quasi)-

[5] 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.

[6] In October 2017, Congress forgave $16 billion of this debt. In February 2018, FEMA's debt totalled $20.5 billion (GAO, 2018b) but the fiscal effects of Hurricane Florence are still being determined.

linear utility models of housing markets with search-and-matching frictions, and combine their models 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 present a detailed analysis of "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 social dynamics in beliefs and thus housing booms and busts. Our approach builds on, but differentiates itself from, BER in several ways. On the one hand, we currently abstract from search-and-matching frictions, a major simplification, 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, by allowing beliefs to evolve in response to external shocks (flood events) in a flexible Bayesian learning framework. More broadly, our paper also presents the first (to the best of our knowledge) application of these heterogeneous beliefs frameworks to formalize the effects of climatic risk belief heterogeneity on coastal housing prices, and we produce both novel survey evidence and a quantification to apply the model to this new area of critical policy importance and academic interest.

Second, another vast literature has studied residential sorting and its implications for hedonic valuations of amenity values, including environmental attributes such as air quality (Kuminoff, Smith, and Timmins, 2013). While most of this literature has focused on static settings, recent advances include dynamic structural estimation models of neighborhood choice (Bayer, McMillan, Murphy, and Timmins, 2016, "BMMT"). While our framework takes a fundamentally different approach from these studies, some of our results relate closely. For example, Section 3 demonstrates the importance of future price and flood risk expectations as a driver of current sorting and thus equilibrium home prices. Ignoring these dynamic considerations can lead to a biased assessment of risk capitalization. These results thus echo

BMMT's finding that static estimates of amenity values may over- or under-estimate true values if those amenities are expected to change in the future.

Finally, our study also contributes to new work on the asset pricing impacts of climate skepticism. In an empirical analysis of land markets, Severen, Costello, and Deschenes (2018) find that climate change predictions are incorporated in contemporary prices, but only partly so. They note that counties with greater acceptance of climate change - measured through national survey data from the Yale Project on Climate Change Communication - incorporate future expectations to a greater degree than counties with lower beliefs. As described below, these results echo the finding of Bernstein, Gustafson, and Lewis (2018) that sea level rise vulnerability is capitalized into owner-occupied housing prices only in areas with sufficiently strong climate change beliefs as measured by the Yale survey. In addition, Kahn and Zhao (2018) present a theoretical framework to analyze the potential impacts of climate change skeptics in a spatial equilibrium between two cities, finding that skeptics would be expected to lower the price of land in the cooler city less impacted by climate change. As accurate pricing of climate risks is essential for markets to incentivize efficient adaptation (Anderson et al., 2018), understanding potential impediments to efficient climate asset pricing is thus important not only for public policy, but also for this emerging literature.

2.1 Empirical Flood Risk Literature

One of our core contributions is to present a model of coastal home price dynamics that can match and reconcile the rich yet mixed empirical evidence on flood risk capitalization in housing prices. In this section, we highlight key findings in this literature and connect them with a preview of our model highlights, formally elaborated in Section 3.

One prominent approach in this literature is to study the effects of flood or sea level rise *risk* on housing prices. Of particular relevance, Bernstein, Gustafson, and Lewis (2018, "BGL") present highly detailed and comprehensive empirical evidence on sea level rise (SLR) risk impacts on coastal housing markets across the United States. They combine national

Zillow ZTRAX data on housing prices and characteristics from 2007 to 2016 with National Oceanic and Atmospheric Administration (NOAA) elevation and SLR exposure measures, such as whether a home would be inundated at a certain SLR level. Their central finding is that climate risk capitalization is heterogeneous across market segments. In the sophisticated (non-owner occupied) segment, they find a significant and large (7%) discount associated with SLR exposure. However, for regular owner-occupied homes, BGL fail to detect a significant SLR vulnerability discount (even when controlling for the amenity value of waterfront proximity in detailed distance bins).

Our model and survey evidence can potentially explain BGL's results as due to *sorting* into vulnerable properties by households with comparatively low concerns over flood and climate risks that deviate from scientific forecasts. In further support of this mechanism, BGL find that, at a national level, sea level rise exposure is significantly and *negatively* correlated with county-level measures of general worry about global warming from the Yale Climate Survey. Only in markets with sufficiently high general reported levels of worry do properties incur significant SLR exposure discounts in the owner-occupied market segment, consistent with our model's predictions. Intuitively, the more agents with realistic beliefs there are in a housing market, the more likely it is that they will be the marginal buyer pricing the asset.

Finally, our model can also account for BGL's results on the dynamics of climate risk discounts over time and in response to news about sea level rise. Among sophisticated buyers, BGL find that coastal homes' sea level rise discount jumps in response to news of worsening sea level rise predictions, and increases over time. This is what our model predicts should occur in markets dominated by agents with realistic beliefs. In contrast, BGL find no response to sea level rise news nor a trend over time in the SLR discount among owner-occupied homes. Again, our model and survey results showcase that this lack of response should occur in markets dominated by agents whose beliefs diverge from the scientific forecast, and who are more likely to sort into vulnerable properties as a result. In discussing the implications of their findings, BGL hypothesize that the lack of internalization of climate risks could expose owner-occupied homes to future value shocks, which are of particular concern given the prominence of housing wealth in households' retirement savings (Campbell, 2006). This paper develops an empirically calibrated structural model of coastal housing prices which can formalize this idea and quantify the potential magnitude of these shocks under different climate, policy, and belief scenarios.

The broader literature has commonly focused on the capitalization of current day flood risk and official flood zone status in specific geographic areas. The relevant policy background is as follows. 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." In principle, this designation activates a flood insurance requirement for homes with federally insured or regulated mortgages. Through the National Flood Insurance Program - the dominant insurer for flooding in the United States - policies may even be available at subsidized rates (see discussion in Section 5). In reality, however, flood insurance take-up is surprisingly limited. By some estimates, *only 30 to 50 percent* of structures in high risk areas are covered by insurance (Harrison, Smersh, Schwartz, 2001; Kousky et al., 2018). This finding is consistent with both limited enforcement of insurance requirements and low flood risk perceptions among flood zone home buyers.[7]

Consistent with this idea, empirical studies generally find weak capitalization of flood risk and flood zone status into coastal housing prices (see meta analyses by, e.g., Daniel, Florax, and Rietveld, 2009; Beltrán, Maddison, and Elliott, 2018). Studies often fail to detect a significant negative effects, or may even find positive premiums for coastal flood zones (e.g., Atreya and Czajkowski, 2016; Bin and Kruse, 2006). Others find flood risk discounts that are significant but less than the present value of insurance premiums, suggesting only partial

[7] Of course expectations of damages and public assistance in case of flood events could also explain low insurance take-up; we therefore elicit beliefs of both in our survey. In reality, post-disaster payouts are small, typically in the thousands of dollars, and are not meant to cover total property damage (Kousky, 2013). Indeed, FEMA assistance is capped at $33k even for eligible individuals whose homes are destroyed by a flood.

capitalization (Harrison, Smersh, Schwartz, 2001). In some cases, studies also find significant flood risk penalties (e.g., Bin, Crawford, Kruse, and Landry, 2008), particularly for inland flood zones, that suggest appropriate internalization of flood risks. Overall, the results of the broader literature thus echo those of BGL that flood risk capitalization is often limited but heterogeneous across markets. Importantly, our model can account for this stylized fact 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 contrast, a homogeneous rational beliefs framework would imply full capitalization across all markets and time, counterfactual to the empirical evidence.

A second strand of the literature analyzes the impacts of flood *events* on housing markets. 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 impact estimates ranging from around 5-20 percent (e.g., Hallstrom and Smith, 2005; Kousky, 2010; Bin and Landry, 2013; Ortega and Taspinar, 2018). These price fluctuations are difficult to rationalize as based on changes in fundamentals, but are consistent with market participants increasing their implied flood risk beliefs in response to an event. However, 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). Importantly, Gallagher (2014) documents an analogous impact pattern in national flood insurance markets, where take-up rises sharply after flood events, but gradually declines back to baseline within a decade. Given these results, Gallagher (2014) demonstrates that flood risk learning is most consistent with a modified Bayesian updating model. We incorporate these findings from the empirical literature directly into our model and calibration, specifically by allowing for Bayesian learning about flood risks (with and without relevant behavioral adjustments) in the full model specification.

A final new empirical study of note, Gibson, Mullins, and Hill (2017) analyze the impacts of three flood risk signals on property prices in New York City: (i) the Biggert-Waters Flood

Insurance Reform Act (described in Section 5), (ii) Hurricane Sandy, and (iii) updates to FEMA flood zone maps. The results indicate significant price declines due to both flooding (5-13%) and FEMA map updates (18%), consistent with a significant increase in marginal buyers' flood risk beliefs in response to the event. These empirical findings are yet again difficult to reconcile with a model of rational flood and climate risk beliefs, but can be matched by our framework, where news about flood risks (such as FEMA map updates) can be internalized to varying degrees and at differing rates depending on the distribution of beliefs and housing stock vulnerability, as described in the next section.

3 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 5, 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 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

[8] We thus abstract from (endogenous) housing supply. Empirical estimates find supply in coastal areas to be highly inelastic, driven by topographic constraints (Glaeser, Gyourko, and Saks, 2005; Green, Malpezzi, and Mayo, 2005). Saiz (2010) estimates MSA-level elasticities, finding Miami, Los Angeles, Fort Lauderdale, and San Francisco to have the lowest supply elasticities. In contrast, for a detailed theoretical analysis of how developers of open coastal real estate may respond to climate risks of land and investment destruction, see Bunten and Kahn (2017).

damages $\widetilde{\delta}^i$ net of government transfers G^i in case of a flood, and allow these expectations to vary across households. However, we focus on net damages δ as FEMA disaster aid is, in reality, very small (typically a few thousand dollars, Kousky, 2013), and as our survey results suggest that heterogeneity in flood risk concern is not driven by differences in beliefs 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 the official or scientifically forecast flood risk trajectory $\{\pi^*_s\}_{s=t}^{\infty}$ and hold their own first-order beliefs $\{\pi^i_s\}_{s=t}^{\infty}$. Higher-order beliefs are left implicit in the expectations operator here, but made explicit in Section 5.

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*. Letting m_t index his identity at time t, in equilibrium, the marginal buyer must be just indifferent between his options:

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

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 section, we 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.

3.1 Homogeneous Rational Beliefs

We first consider the implications of the benchmark assumption of homogeneous rational flood risk beliefs, implying that $\{\pi_s^i\}_{s=t}^{\infty} = \{\pi_s^*\}_{s=t}^{\infty}$ $\forall i$ 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.[9] 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):

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

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

$$PREM_{-1}^{\text{Coast}} = \left[\Xi(1-k_1) - \pi^L \delta\right] \left(\frac{\beta}{1-\beta}\right) \lesseqgtr 0 \tag{4}$$

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

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),

[9] For example, the Intergovernmental Panel on Climate Change (IPCC) did not release its first Assessment Report until 1990.

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, the new scientific forecast is that $\pi_t^* = \pi^L$ for $t < T_1$ and $\pi_t^* = \pi^H$ for $t \geq T_1$. In order to derive predictions for the resulting evolution of flood risk premia from $t = 0$ onwards, the correlation between current and future flood risks must be specified. Since waterfront flood risk is mainly a function of elevation, we first consider a simple relationship with proportional flood risk increase γ^{SLR} :

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

It is easy to show (through backwards iteration from the new long-run coastal home price after T_1) that the homogeneous rational beliefs model implies that the flood risk premium should immediately fall to reflect the new scientific 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 discounted cost of future flood risk increases:

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

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

With homogeneous rational beliefs, observed flood risk penalties should thus be unambiguously negative and growing in full anticipation of climate change-induced future risk increases.[10] This prediction is clearly counterfactual for many segments of the U.S. housing market, as described in Section 2. Our robustness analysis in Section 6.3 similarly presents hedonic estimates of the flood risk premium over a longer time horizon (1970-2017) in our

[10] Equations (7)-(8) implicitly assume that damages conditional on a flood event (δ) are not expected to change along with flood risks.

empirical setting, which also fails to match this predicted pattern. The next sub-section consequently proposes a generalization of the standard model to accommodate belief heterogeneity as potential explanation of these empirically observed risk capitalization patterns.

3.2 Heterogeneous Beliefs

With heterogeneity, the marginal buyer's flood risk beliefs pricing coastal homes (2) may well diverge from the scientific forecast. In order to illustrate specific examples of equilibria with heterogeneous beliefs, we now generalize the homogeneous beliefs model to allow for two belief types. Fraction $(1-\theta^o)$ of the population are "realists" who believe in the scientific forecast ($\{\pi^r_s\}^{\infty}_{s=t} = \{\pi^*_s\}^{\infty}_{s=t}$), whereas fraction θ^o holds more optimistic beliefs with $\pi^o_t \leq \pi^*_t$ $\forall t$. In Section 5, 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 'reduced-form' specification where optimists' flood risk perceptions lie fraction $\lambda^{Opt}_t \in [0,1]$ below official estimates π^*_t:

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

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, which we argue can broadly span the different results observed in the empirical literature.

3.2.1 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. This case occurs if even the realist with the highest possible amenity value ($\xi^r = \Xi$) assigns a lower value to buying a coastal home than the (then marginal) optimist:

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

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

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

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

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

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 ceteris paribus home price change with respect to *official* risk π_t^* - now differs from the homogeneous model's prediction (7) in two dimensions:

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

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 attenuated compared to the homogeneous beliefs case.[11] We formalize this statement in Section 5. The central point here, however, that a heterogeneous beliefs model 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.

3.2.2 Case 2

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

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

Intuitively, the marginal realist in this setting has a sufficiently high amenity value $\overline{\xi_t^r}$ so as to equate their coastal home valuation to that of the marginal optimist. The marginal amenity values and thus equilibrium prices are then pinned down jointly by (14) and the market clearing condition:

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

A ceteris paribus increase in official flood risk π_t^* now has the interesting effect that it will alter the *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:

$$PREM_t^{Flood} = (\Delta\overline{\xi_t^r} - \delta + \Delta E_t^r[P_{t+1}])\beta = (\Delta\overline{\xi_t^o} - (1-\lambda_t^{Opt})\delta + \Delta E_t^o[P_{t+1}])\beta \tag{16}$$

[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).

Since the direct effect of higher flood risk on optimists' coastal home price 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 corresponding impact on future home 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 ($\Delta\overline{\xi_t^r} > 0$), whereas the marginal optimists moving must have lower amenity values ($\Delta\overline{\xi_t^o} < 0$). This comparative static also illustrates the *allocative inefficiency* resulting from heterogeneous flood risk beliefs. 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.

3.2.3 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 $\widehat{\overline{\xi^r}}$ must clear the market for coastal homes net of the space already occupied by the optimists:

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

The equilibrium price in this setting will then satisfy:

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

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

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

The current flood risk capitalization in this market thus matches that of the homogeneous rational expectations setting. Since realists will remain marginal buyers, their future risk internalization should moreover capture the full climate change forecast. It should be noted that coastal home price *levels* (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 (Bernstein, Gustafson, and Lewis, 2018).

4 Direct Evidence: Field Survey

The analysis thus far indicates that a housing market model with heterogeneity in flood risk beliefs fits the empirical evidence better than a benchmark homogeneous rational beliefs model. At the same time, however, the model illustrates the structural challenges inherent in seeking to isolate risk beliefs from hedonically estimated flood risk premiums. Through the lens of the model, these premiums depend not only on beliefs about the current risk of flooding, but also on expectations about future housing prices $\Delta E_t^{m_t}[P_{t+1}]$ (and thus implicitly future flood risks) and net flood damages δ, which, in turn, may further depend on households' beliefs about factors such as government assistance in case of a flood. We therefore turn to surveys as a methodology that can elicit these beliefs individually, and provide more direct evidence on heterogeneity and sorting. For example, we elicit coastal flood risk perceptions among both residents that did and did *not* purchase coastal homes, the latter of which cannot be inferred through market transactions, but is critical to the question of sorting. Of course, the results are subject to the well-known limitations of stated preference elicitation. We therefore complement the survey with a hedonic analysis of housing prices in our setting, and use its results to inform the robustness analysis in Section 6.3.

4.1 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 coast) and non-coastal homes.[12] The surveys were conducted in two waves across February and July 2017. The 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).[13] Both our use of face-to-face interviews and the DBDC mechanism are motivated by best practices recommendations in Contingent Valuation 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).

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. Coastal

[12] 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 or collected at a courser level (see review by Kellens et al., 2013).

[13] 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).

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 several potential confounders that could affect concern about flooding even in the absence of heterogeneity in flood probability beliefs per se, including expectations over flood damages, insurance reimbursements, and government assistance. 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, 48% non-coastal) conducted with households in several Rhode Island communities.[14] Though not designed to be statistically representative, it should be noted that this sample size does compare reasonably with prior survey studies of household flood risk perceptions, particularly ones using face-to-face interviewing techniques.[15]

[14] 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. Close to 40% of people who answered their doors agreed to take the survey. The overall response rate (including unanswered doors) of approximately 12.5% was fully in line with DellaVigna, List, and Malmendier's (2012) response rates of 10-15% in their unannounced door-to-door survey treatment groups.

[15] 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).

4.2 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 appear significantly *less* concerned than inland residents when asked about their coastal flood risk perceptions, as shown in Figure 1. Perhaps more strikingly, we also find that those living in official FEMA high-risk flood zones appear significantly *less* worried about flood risks than those whose homes are outside the flood zone, as shown in Figure 2.

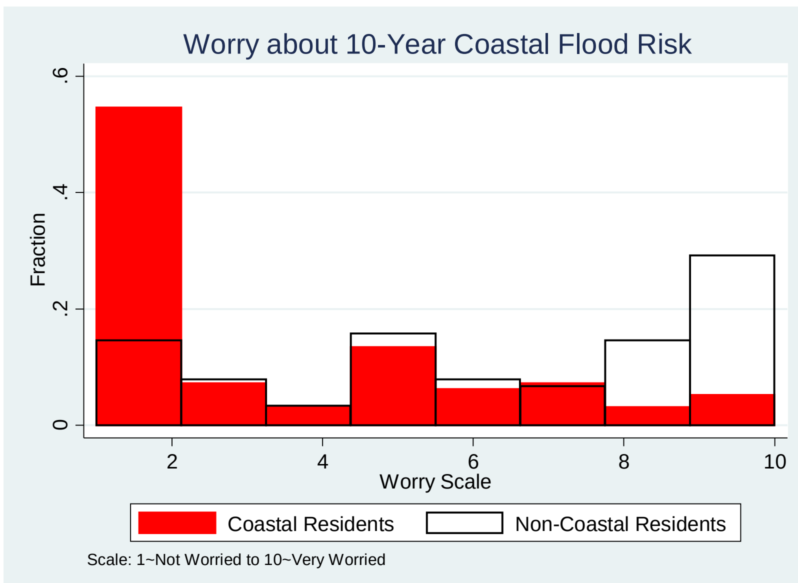

Figure 1

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 3 showcases the distribution of expected flood damages (as percentage of home value) net of expected insurance reimbursements and government assistance.[16] 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

[16] Households whose estimates imply flood damages in excess of 100% of home values are re-coded as 100% damage 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.

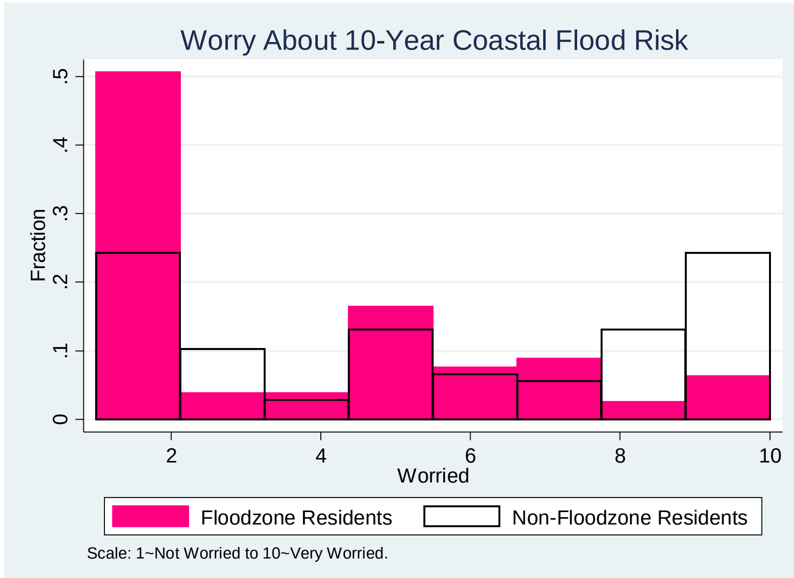

Figure 2

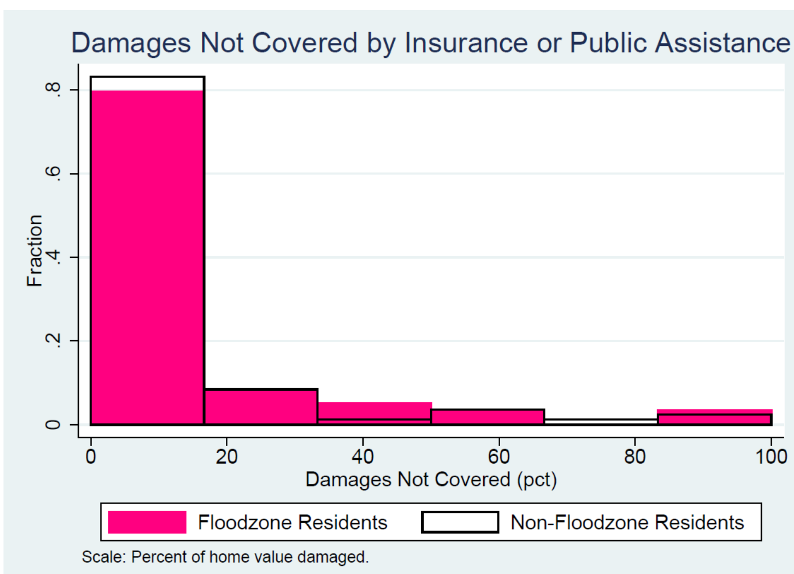

Figure 3

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

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)
Property Area (square feet)	10,884	8,049	2,835*** (932)
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%)

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

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. The central take-home point is thus that we find evidence of significant heterogeneity 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 4 compares these perceptions with respondents' homes' 10-year flood risk estimates derived from storm surge elevation risk models (described in Section 5.1.1). Importantly, this estimation takes into account each property's elevation. The sample is restricted to coastal homes so that responses reflect flood risk estimates specific to respondents' homes. Assessments that agree with the storm surge model should be near the 45° line. However, 70% of answers lie beneath the 45° line, again suggesting that many coastal residents underestimate the flood risks they face.

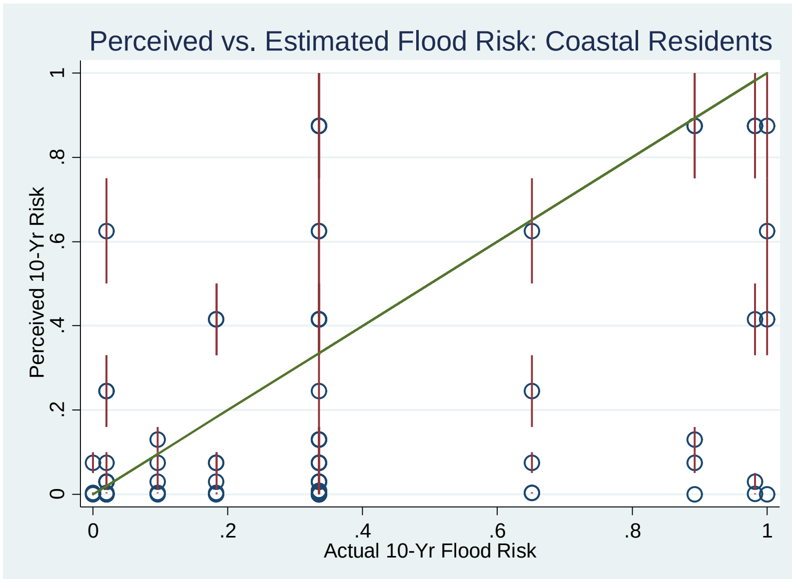

Figure 4. Note: Red lines span range of 10-year flood risk probability in respondent's answer (e.g., 5-10%) on the y-axis, with blue circles marking the mid-points of each range.

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 Appendix Figure A1). 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 5:[17]

[17] Defining "very worried" households as those rating their flood worry at a 9 or 10 out of 10, the difference in intent to move is significant with a p-value of 0.0375 for one-sided and 0.075 for two-sided t-test, respectively.

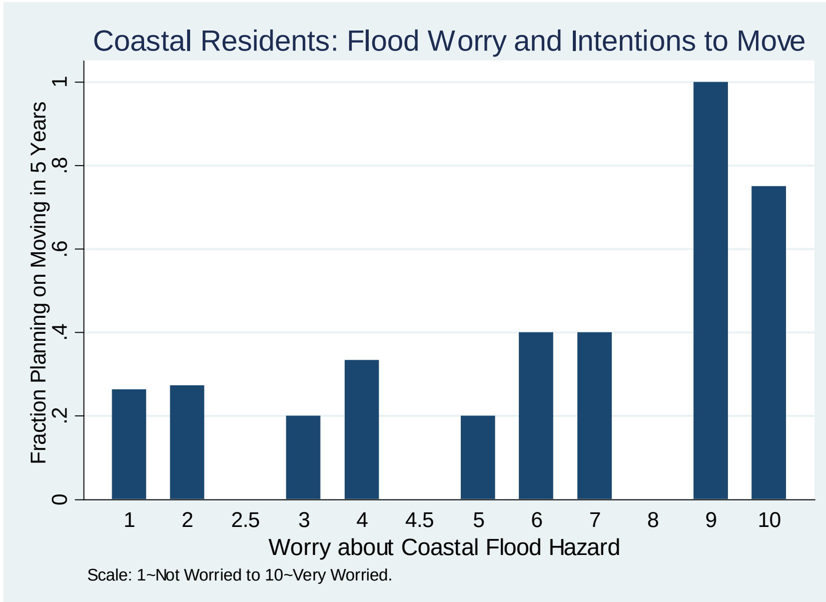

Figure 5

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. While we also present hedonic housing price estimates for comparison (see Appendix), these confound amenity values, sorting, and future coastal home price expectations, and provide information only on the marginal buyers. We therefore use the survey both in an effort to elicit ceteris paribus valuations, and to gauge the distribution of amenity values across agents who did not purchase coastal homes. The survey question thus 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 Appendix.

Figure 6 plots the joint sample 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 6 also provides a visual gauge on allocative inefficiency, which appears to be mild in our sample: few non-coastal households hold waterfront amenity values above those of coastal residents.

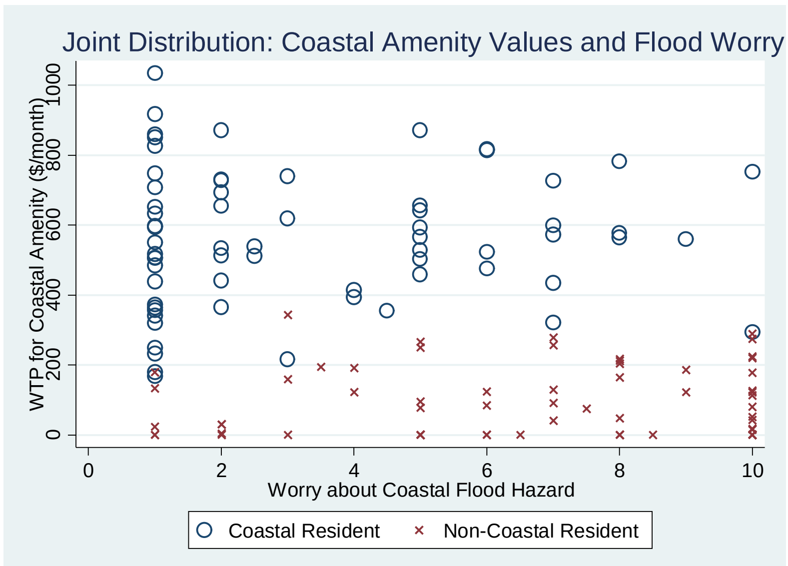

Figure 6

With regards to risk belief types, we classify respondents as 'optimists' if they underestimate coastal 10-year flood risk by at least ∼50%. Specifically, respondents are 'optimists' if their subjective coastal 10-year flood risk assessment in our study area 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%.[18] 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

[18] 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 (see Section 5.1.1), using a 1% figure is thus conservative.

as a benchmark in the calibration below. Finally, the results indicate that the majority of respondents expect future flood risks to be at least "somewhat greater" than current risks. Figure 7 plots the distribution of these beliefs across types. As expected, realists are more likely to assume higher future flood risk increases than optimists. However, even the majority of optimists anticipates some increase in flood risks. Informed by these results, the full model assumes that optimistic agents anticipate the possibility of a future flood risk increase at time T_1, and become Bayesian learners at this time with some positive prior on the probability that flood risks have indeed risen.

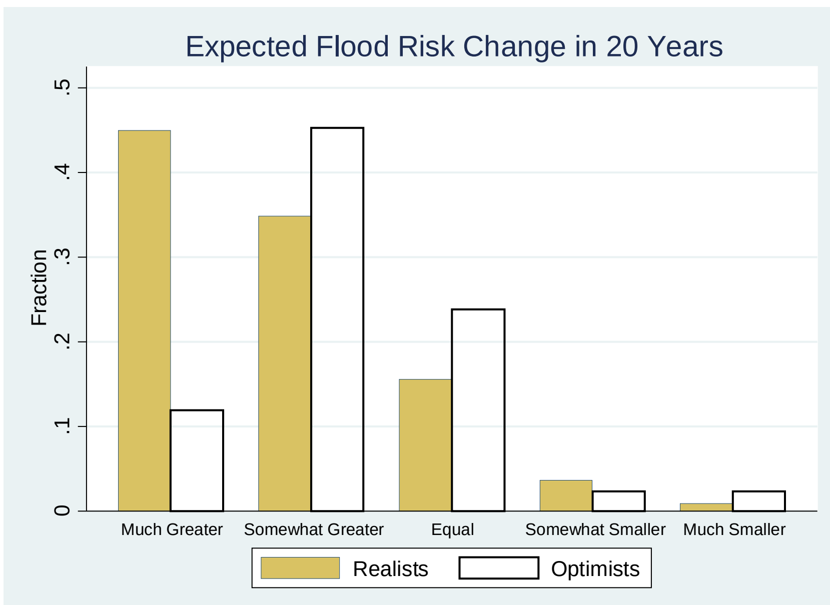

Figure 7

5 Full Structural Model

This section presents the remaining structural assumptions and the solution method employed to simulate future coastal home price trajectories under competing belief, flood risk, and policy scenarios.

5.0.1 Flood Risk Beliefs

First, based on the survey results, we assume that both realists and optimists anticipate that a flood risk change may happen in the future. However, only realists immediately adopt the official forecast $\{\pi_s^*\}_{s=t}^{\infty}$ as their belief. We stress that this assumption is *conservative* in that more rationality will generally lead us to predict less mispricing of coastal homes. That is, relaxing assumptions of rationality and introducing some degree of optimism among realists would only strengthen the magnitude of our predicted mispricing of coastal homes. We therefore adopt fully informed realists as conservative benchmark assumption.

Optimists are modeled as aware but skeptical of the scientific forecast. Their prior beliefs are such that they initially assign a probability $0 < q_{T_1}^o < 1$ to the possibility that flood risk will truly rise to higher level π^H at time T_1, and believe that official estimates are wrong and flood risk remains at the low level π^L at and after T_1 with positive probability $(1 - q_{T_1}^o)$. Formally, our updating framework is an adaptation from Dieckmann (2011) for the present setting. Optimists' contemporaneous flood risk beliefs at time $t \geq T_1$ are given by:

$$\pi_t^o = q_t^o(\pi^H) + (1 - q_t^o)(\pi^L)$$

Beliefs are then updated each period based on whether or not flood events occur:

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

While the benchmark specification assumes rational Bayesian updating, we also consider 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). The results are fully robust to these alternative specifications. Figure

8 presents an example sequence of optimists' and realists' flood risk beliefs that change in response to underlying risk changes as well as flood events:

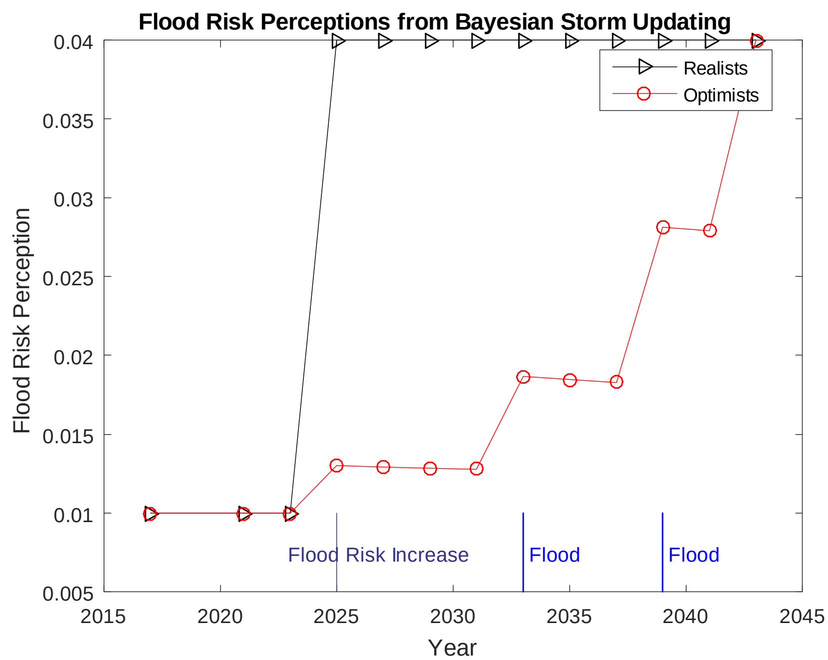

Figure 8

Next, 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 π^r_{t+j} and change optimists' beliefs according to (19). We stress two aspects of this assumption. First, it is again conservative in that more rationality will 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 do not anticipate the possibility of future changes in their own beliefs beyond T_1, 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 $t > T_1$:

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

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

5.0.2 Solving the Model

We solve for pricing dynamics through backwards iteration. At the core of our approach is the notion that flood risk valuation disagreements will not persist indefinitely. Arguably the most likely scenario forcing effective belief convergence will be continued reform efforts 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 to be fiscally unsustainable and has been labeled as a "high risk" program due its failure to charge actuarially fair rates for many of its policies (GAO, 2017). One in five policies has traditionally been officially 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 for lapsed or new policies, including those for newly sold properties which would be charged official full risk rates (FEMA, 2013). However, due to concerns over homeowner impacts, the Homeowner Flood Insurance Affordability Act of 2014 partially repealed and modified Biggert-Waters.[19] 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 at actuarially fair rates would force all agents - regardless of personal beliefs - to internalize the true flood risk. In the context of our model with linear utility, policy reform mandating real risk-rate flood insurance is thus equivalent to a convergence of (effective) flood risk beliefs towards their true value π^*.[20] We thus formally assume that, at some future time T, effective flood risk beliefs will become homogeneous at the true risk value π^*_T. At time $T-1$, the realists and optimists each hold expectations over the announced value of π^*_T, $E^r_{T-1}[\pi^*_T]$ and $E^o_{T-1}[\pi^*_T]$, respectively. Note, again, that $E^o_{T-1}[\pi^*_T]$ need not equal the optimists' actual flood risk beliefs and can reflect their beliefs about the mandated flood insurance risk rates.

Given assumptions about beliefs, it is then straightforward to solve for time $T-1$ prices. Once π^*_T 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):

$$E^r_{T-1}[P_T] = \frac{\beta(e^h + \Xi(1-k_1) - E^r_{T-1}[\pi^*_T]\delta)}{(1-\beta)} \tag{21}$$

[19] Specifically, the HFIAA impacts policyholders heterogeneously, by lowering the rate of future premium increases for some, eliminating rate increases for others, and providing premium refunds to a subset who paid the full risk rate on new insurance purchases (FEMA, 2014).

[20] 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' elevation). While we focus our analysis on medium-run flood risk increases, we note that, in the very long run, beliefs will almost surely converge even in the absence of policy reform.

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

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

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

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

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

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

Next, consider P_{T-2} to illustrate the process of finding prices further back in time. At time $T-2$, the identity of the marginal buyer once again depends on whether:

$$\Xi\frac{k_1}{\theta^o} + \left\{E^r_{T-2}[P_{T-1}] - E^o_{T-2}[P_{T-1}]\right\} < \delta(\pi^r_{T-2} - \pi^o_{T-2}) \tag{23}$$

Importantly, however, each type's expectation of next period prices now depends on his expectation of his own as well as others' expectations about the marginal buyer and flood risk beliefs in the subsequent periods. For example, the realists' prediction at time $T-2$ of the coastal home price at time $T-1$ depends on his expectation over who the marginal buyer will be at $T-1$, informally $\sim E^r_{T-2}(m_{T-1})$. The realist understands that the marginal buyer at time $T-1$ will be determined by condition (22). Consequently, his time $T-2$ expectation of prevailing beliefs at time $T-1$ ($E^r_{T-2}[\pi^r_{T-1}]$ and $E^r_{T-2}[\pi^o_{T-1}]$) determines his forecast for the future marginal buyer, which, in turn, determines his price expectations:

$$
\begin{aligned}
E^r_{T-2}[P_{T-1}] \quad &: \quad \text{If } [\Xi\frac{k_1}{\theta^o} + \left\{E^r_{T-2}[E^r_{T-1}[P_T]] - E^r_{T-2}[E^o_{T-1}[P_T]\right\} < \delta(E^r_{T-2}[\pi^r_{T-1}] - E^r_{T-2}[\pi^o_{T-1}])] \\
&\rightarrow \quad E^r_{T-2}(m_{T-1}) \sim \text{optimists (Case 1)} \\
&\Rightarrow \quad E^r_{T-2}[P_{T-1}] = \beta(e^h + \Xi\left(1 - \frac{k_1}{\theta^o}\right) - E^r_{T-2}[\pi^o_T]\delta + E^r_{T-2}[E^o_{T-1}[P_T]]) \qquad (24) \\
\text{Otherwise} \quad &: \quad E^r_{T-2}(m_{T-1}) \sim \text{optimists and realists (Case 2)} \\
&\Rightarrow \quad E^r_{T-2}[P_{T-1}] = \beta(e^h + E^r_{T-2}[\overline{\xi^o}_{T-1}] - \pi^o_{T-1}\delta + E^r_{T-2}[E^o_{T-1}[P_T]]) \qquad (25) \\
\text{where} \quad &: \quad E^r_{T-2}[\overline{\xi^o}_{T-1}] = \Xi(1-k_1) - \delta(1-\theta^o)(E^r_{T-2}[\pi^r_{T-1}] - E^r_{T-2}[\pi^o_{T-1}]) \\
&\quad +(1-\theta^o)\{E^r_{T-2}[E^r_{T-1}[P_T]] - E^r_{T-2}[E^o_{T-1}[P_T]]\}
\end{aligned}
$$

Here, the expectations of the price at time T are again given by (21) and the analogous expression for optimists, but based on time $T-2$ expectations, i.e.:

$$E^j_{T-2}[E^i_{T-1}[P_T]] = \frac{\beta(e^h + \Xi(1-k_1) - E^j_{T-2}[E^i_{T-1}[\pi^*_T]]\delta)}{(1-\beta)} \text{ for } i,j \in \{o,r\}$$

Analogous calculations for optimists yield their time $T-2$ expectations of re-sale prices at time $T-1$, $E^o_{T-2}[P_{T-1}]$. Given each type's respective price expectations, we can then use (23) to identify the marginal buyer at time $T-2$, and solve for the market-clearing P_{T-2} accordingly. Defining the notation $\mathbf{E}^{i,j,..i}_{s:t} \equiv E^i_s[E^j_{s+1}[....E^i_t[.]]]$, the algorithm to solve for a general P_t follows the same procedure and can be illustrated as follows:

$$
\underbrace{\begin{pmatrix} \mathbf{E}^{r,r,\ldots r}_{t:T-1}[\pi^*_T] & \mathbf{E}^{r,r,\ldots,o}_{t:T-1}[\pi^*_T] & \ldots \\ \mathbf{E}^{r,o,..r}_{t:T-1}[\pi^*_T] & \mathbf{E}^{r,o,\ldots,o}_{t:T-1}[\pi^*_T] & \ldots \\ \mathbf{E}^{o,r,\ldots r}_{t:T-1}[\pi^*_T] & \mathbf{E}^{o,r,\ldots,o}_{t:T-1}[\pi^*_T] & \ldots \\ \ldots & \ldots & \ldots \end{pmatrix}}_{2^{(T-t)} \text{ elements}} \rightarrow \underbrace{\begin{pmatrix} \mathbf{E}^{r,r,\ldots r}_{t:T-1}[P_T] & \mathbf{E}^{r,r,\ldots o}_{t:T-1}[P_T] & \ldots \\ \mathbf{E}^{r,o,\ldots,r}_{t:T-1}[P_T] & \mathbf{E}^{r,o,\ldots,o}_{t:T-1}[P_T] & \ldots \\ \mathbf{E}^{o,r,\ldots,r}_{t:T-1}[P_T] & \mathbf{E}^{o,r,\ldots,o}_{t:T-1}[P_T] & \ldots \\ \ldots & \ldots & \ldots \end{pmatrix}}_{2^{(T-t)} \text{ elements}} \tag{26}
$$

$$
\& \underbrace{\begin{pmatrix} \mathbf{E}^{r,r,\ldots}_{t:T-2}[\pi^r_{T-1}] & \mathbf{E}^{r,r,\ldots}_{t:T-2}[\pi^o_{T-1}] & \ldots \\ \mathbf{E}^{r,o,\ldots}_{t:T-2}[\pi^r_{T-1}] & \mathbf{E}^{r,o,\ldots}_{t:T-2}[\pi^o_{T-1}] & \ldots \\ \mathbf{E}^{o,r,\ldots}_{t:T-2}[\pi^r_{T-1}] & \mathbf{E}^{o,r,\ldots}_{t:T-2}[\pi^o_{T-1}] & \ldots \\ \ldots & \ldots & \ldots \end{pmatrix}}_{2^{(T-t)-1} \text{ elements}} \rightarrow \underbrace{\begin{pmatrix} \mathbf{E}^{r,r,\ldots r}_{t:T-2}[P_{T-1}] & \mathbf{E}^{r,r,\ldots o}_{t:T-2}[P_{T-1}] & \ldots \\ \mathbf{E}^{r,o,\ldots,r}_{t:T-2}[P_{T-1}] & \mathbf{E}^{r,o,\ldots,o}_{t:T-2}[P_{T-1}] & \ldots \\ \mathbf{E}^{o,r,\ldots,r}_{t:T-2}[P_{T-1}] & \mathbf{E}^{o,r,\ldots,o}_{t:T-2}[P_{T-1}] & \ldots \\ \ldots & \ldots & \ldots \end{pmatrix}}_{2^{(T-t)-1} \text{ elements}}
$$

$$
\& \ldots \rightarrow
$$

$$
\& \ldots \rightarrow \begin{pmatrix} E^r_t[E^r_{t+1}[P_{t+2}]] & E^r_t[E^o_{t+1}[P_{t+2}]] \\ E^o_t[E^r_{t+1}[P_{t+2}]] & E^o_t[E^o_{t+1}[P_{t+2}]] \end{pmatrix}
$$

$$
\& \begin{pmatrix} E^r_t[\pi^r_{t+1}] & E^r_t[\pi^o_{t+1}] \\ E^o_t[\pi^r_{t+1}] & E^o_t[\pi^o_{t+1}] \end{pmatrix} \rightarrow \begin{pmatrix} E^r_t[P_{t+1}] \\ E^o_t[P_{t+1}] \end{pmatrix} \& \begin{pmatrix} \pi^r_t \\ \pi^o_t \end{pmatrix} \Rightarrow P_t
$$

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.[21] On the other hand, however, (26) enables us to compute proper equilibrium price dynamics while flexibly accounting for different belief and policy reform structures, in a setting that strictly generalizes the benchmark homogeneous beliefs framework.

5.0.3 Policy Reform Beliefs

The last structural element is to specify agents' beliefs about enforced policy rates (or commonly held long-run beliefs) after time T, π^*_T. As a conservative benchmark, we again assume

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

that realists correctly anticipate long-run rates/beliefs:

$$E_t^r[\pi_T^*] = E_t^r[\pi_T^r] = \pi_T^*$$

For optimists, we consider beliefs in the range of their own and realists' flood risk beliefs:

$$E_t^o[\pi_T^*] \in [E_t^o[\pi_T^o], E_t^o[\pi_T^r]] \tag{27}$$

with a benchmark assumption that optimists believe that enforced rates after time T will correspond to the population-weighted average of beliefs at the time:

$$E_t^o[\pi_T^*] = (\theta^o)E_t^o[\pi_T^o] + (1-\theta^o)E_t^o[\pi_T^r] \tag{28}$$

Intuitively, the two extremes nested by (27) can be thought of as follows. On the one hand, if $E_t^o[\pi_T^*] = E_t^o[\pi_T^o]$, this means that optimists believe that everyone will eventually agree with them, or, equivalently, that the government will offer and require cheap flood insurance at a risk rate corresponding to optimists' beliefs. Naturally, these beliefs boost optimists' valuation of coastal properties. In contrast, if $E_t^o[\pi_T^*] = E_t^o[\pi_T^r]$ this means that optimists anticipate that they will eventually be forced to purchase flood insurance at risk rates corresponding to realists' beliefs. However, the implications of this assumption are arguably at odds with the empirical evidence on the impacts of changes in flood insurance requirements (e.g., Gibson, Mullins, Hill, 2017). Consequently, our benchmark scenario assumes (28), though we assess robustness to the range of (27) in Section (6.3).

5.1 Model Calibration

5.1.1 Flood Risks

Coastal flood risk is broadly determined by two main channels: (1) by the sea level, which is projected to increase in the coming decades, thereby increasing flood risk through high tide impacts (Rahmstorf, 2007), and (2) by extreme event surges such as tropical cyclones and other storms (Emanuel, Sundararajan, and Williams, 2008; Knutson et al, 2010). We utilize future sea level rise projections for Newport, RI, from the U.S. Army Corps of Engineers (USACE, 2017) and NOAA (Blank, Lubchenco, and Dietrick, 2012). In order to translate sea level rise to coastal inundation probabilities, we further utilize STORMTOOLS, a set of Rhode Island inundation maps and flood return rates under various projections of sea level rise developed by partners including the University of Rhode Island and NOAA (SAMP, 2017).[22] We use these estimates to project both current and future annual flood risks for each of the coastal homes in our sample. Figure 9 below presents the resulting distribution, which shifts right as sea levels rise, reflecting the increased probability of inundation. The average property in our sample faces a baseline annual flood risk of over 7%, increasing to 15% with 1 foot of sea level rise. However, flood events here are defined as the water level reaching the ground height of the property structure or higher if surge occurred at high tide, so that not all 'flood events' would cause serious damage. Consequently, we use more conservative flood risk probabilities in the calibration below.

[22] A full explanation of the methodology can be found at http://www.beachsamp.org/stormtools/.

While the STORMTOOLS approach is arguably the most comprehensive publicly available sea level rise inundation layer for Rhode Island, the approach assumes additive inundation increases from sea level rise and does not account for local flood mitigation strategies that may change over time.

Table 2: Benchmark Model Calibration

Parameter		Value	Source
k_1	Share of coastal homes	0.134	Authors' calculation from RIGIS properties and coastline
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 med. home price
δ	Flood damages (\$)	\$65.65k	Survey: Med. damage/price $\times$ Med. price
e^h	Net value of own home living	2.98 | Variable	Match initial med. coastal home price \$410k
β	Annual discount factor	0.98	
π_L	Initial annual flood risk	1%	FEMA
π^H	New higher flood risk	4%	STORMTOOLS; elevation mapping
T_1	Flood risk increase	2023	
T	Policy reform period	2043	
$q_{T_1}^o$	Optimists' prior $\Pr(\pi = \pi^H)$	0.1	
Flood events: 2031, 2037			

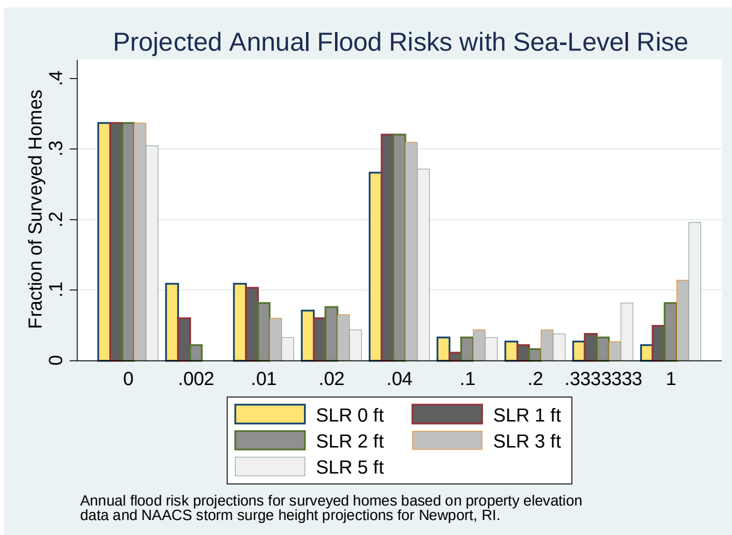

Figure 9

5.1.2 Calibration Summary

Based on the survey and flood risk assessment, this section presents our calibration. Table 2 summarizes key parameters for the benchmark scenario.

Several points should be noted. First, we select the net value of living in an owner-occupied home e^h to match the 2017 median coastal home price in our setting of \$410k. That is, we begin the model simulations in today's housing market rather than a past 'pre-climate change awareness' equilibrium as considered in the theoretical discussions of Section 3. Intuitively, this is because there is no unique empirical counterpart to the theoretical device of an initial climate change announcement. We do, however, discuss price dynamics in the context of their full trajectory from initial to long-run fundamental values.

Second, there are at least two approaches to varying belief distributions across model runs. Our preferred approach calibrates e^h to match observed 2017 coastal home prices conditional on the estimated benchmark share of optimists ($\theta^o = 35\%$), and conducts counterfactual simulations that change the optimist share while holding e^h fixed. Intuitively, this approach simulates where coastal housing prices should or would be in 2017 under alternative belief structures, holding constant their fundamental value. An alternative approach ("Alt.") is to hold the model's predictions for the 2017 housing price fixed at \$410k by re-calibrating e^h across belief scenarios. Intuitively, this approach illustrates the potential pitfalls of interpreting today's housing prices through the lens of a homogeneous rational beliefs model, and thus over-estimating their fundamental value e^h. Results for both are presented below.

Next, while the calibration makes arbitrary assumptions about the number and timing of future flood events, we show later on that these do not affect the main results (see Table 5), as current prices and fundamental values depend only on *expectations* of storm events, not on their realizations. Other calibration notes include the following. For computational reasons, we run the model with one period corresponding to two calendar years, and adjust the relevant calibration parameters accordingly.[23] For reasons described above, we adopt the FEMA lower bound on flood event risk of 1% as a conservative measure of baseline risk. As for future risk, we focus on a 1 foot of sea level rise scenario based on USACE projections over

[23] The bi-annual calibration features $\beta' = 0.9702$, $\pi'_L = 1.99\%$, $\pi'_H = 7.84\%$, and flow values doubled.

the time horizon of our simulation. Again, however, we select a more conservative annual probability of 4% in order to represent the probability of a serious event. The sensitivity analysis below also consider 2% and 6%. Finally, the benchmark share of optimists represents a re-weighted average of the survey population to correct for over-sampling of coastal homes.

6 Quantitative Results

6.1 Main Results

Figure 10 presents the main results for the benchmark calibration. We run the model varying the percentage of optimists from 0% to our sample population estimate of $\widehat{\theta^o} = 35\%$. Table 3 summarizes the results numerically. The first central finding is that flood risk belief heterogeneity 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 coastal housing prices exceed fundamentals by 10%. Economically, an overvaluation of this magnitude would be highly significant. For comparison, during the Great Recession, the median U.S. home sale price decline from peak (Q1 2007) to trough (Q1 2009) was about 19%.[24]

[24] While prices fell over a shorter time horizon during the Great Recession, it should be noted that the speed of the corrections in Figure 12 is a function of the assumed storm event and policy reform schedule. Faster policy reform (or belief changes) would imply a faster price decline to fundamentals.

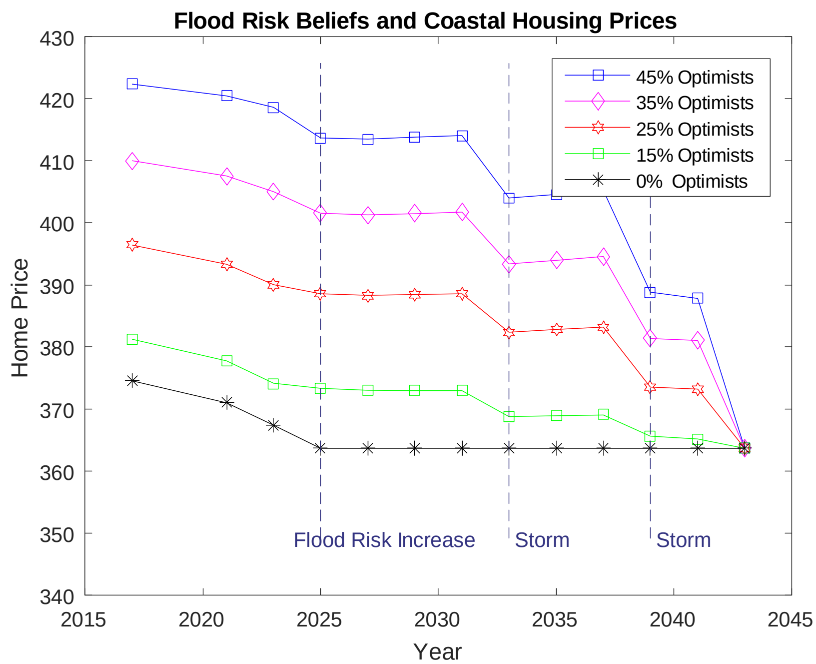

Figure 10

Figure 11 presents the main results under the alternative approach which effectively views current prices through the lenses of models with different belief assumptions. Under homogeneous rational beliefs (0% optimists), the present value of climate change impacts should have already capitalized into home prices, leaving only a modest *additional* decline (-3%) over the next 25 years. In contrast, if 35% of the population are excessively optimistic, the remaining coastal home price decline more than quadruples to -13%. While the total fundamental value loss induced by sea level rise is, of course, the same across belief scenarios, Figure 11 highlights that we may empirically underestimate this amount if we view home price data through the implicit lens of a rational homogeneous beliefs framework.

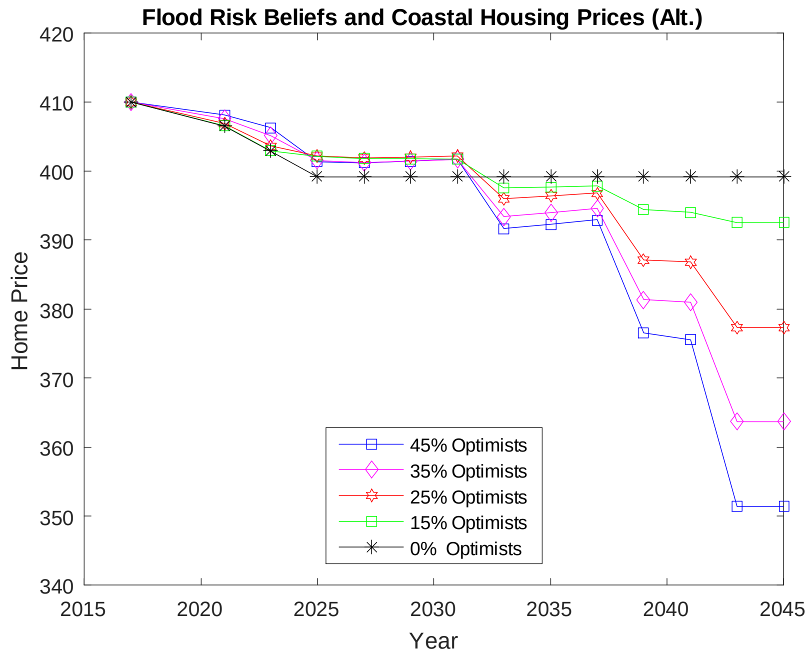

Figure 11

Table 3: Benchmark Simulation Results

Scenario	Overvaluation $\frac{P_{2017}}{P_{2017}^{\text{Fundamental}}}-1$	Future Price Change $1-\frac{P_{2017}}{P_{2043}}$
0% Opt.	-	-3%
15% Opt.	2%	-4%
25% Opt.	6%	-9.0%
35% Opt.	10%	-13%
45% Opt.	13%	-17%

In sum, the results indicate that benchmark belief heterogeneity may be contributing to an economically significant overvaluation of coastal homes relative to their fundamental value, preventing housing assets from fully reflecting climatic risks. Giving credibility to these projections, our central quantitative estimate of 10% overvaluation aligns well with the empirical finding of Bernstein, Gustafson, and Lewis (2018) that the general owner-occupied segment of the housing market *lacks* the significant 7% sea level rise vulnerability discount found in the sophisticated (non-owner occupied) segment. In addition to formalizing and substantiating a mechanism accounting for this differential discount, our structural model further enables us to gauge the welfare costs of the allocative inefficiency induced by belief heterogeneity, and to simulate future coastal housing market scenarios under alternative belief and policy scenarios. Indeed, below we present extensive sensitivity checks for the main results, finding them to be broadly robust, including to consideration of evidence from a hedonic analyses specific to our empirical setting.

6.2 Allocative Inefficiency Costs

Within the context of our framework, the only efficiency cost associated with coastal home mispricings is the allocative inefficiency of realists with high amenity values being priced out of coastal markets. In reality, coastal mispricing is likely to create welfare costs through important additional channels. For example, if we modeled the mortgage process whereby optimists obtain loans using coastal properties as collateral, then 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 represent a strictly lower bound.[25]

A social planner would allocate coastal homes to the optimists and realists with the k_1 highest valuations, equating the marginal buyers' valuations at the optimum ($\overline{\xi}^{o,*} = \overline{\xi}^{r,*} = \Xi(1-k_1)$). In contrast, allocative inefficiency from belief heterogeneity occurs whenever the marginal realist's valuation exceeds that of the marginal optimist (i.e., $\overline{\xi}_t^r > \overline{\xi}^{r,*}$ and $\overline{\xi}_t^o < \overline{\xi}^{o,*}$). Let q_t^i denote the quantity of coastal housing consumed by group i in period t,

[25] We also acknowledge existing literature on welfare implications of belief structure. For example, Brunnermeier, Simsek, and Xiong (2014) develop a welfare criterion, belief-neutral efficiency, in cases where beliefs are distorted and heterogeneous. However, a key difference from our work is that the future probabilities across the flood outcome are scientifically estimable rather than unknown.

which equals $q_t^o = \frac{\theta^o}{\Xi}(\Xi - \overline{\xi}_t^o)$ for optimists and $q_t^r = \frac{(1-\theta^o)}{\Xi}(\Xi - \overline{\xi}_t^r)$ for realists. The net loss in consumer surplus CS_t from coastal housing in period t due to belief heterogeneity is then given by:

$$\Delta W_t \equiv CS_t^* - CS_t = \int_{q^{*,o}}^{q_t^o} \left[\Xi - \frac{\Xi}{\theta^o} q \right] dq - \int_{q_t^r}^{q^{*,r}} \left[\Xi - \frac{\Xi}{(1-\theta^o)} q \right] dq \tag{29}$$

Figure 12 illustrates the evolution of the marginal coastal optimist's and realist's respective amenity values ($\overline{\xi}_t^o$ and $\overline{\xi}_t^r$) over time (right axis), as realists increasingly move out of coastal property markets (left axis).

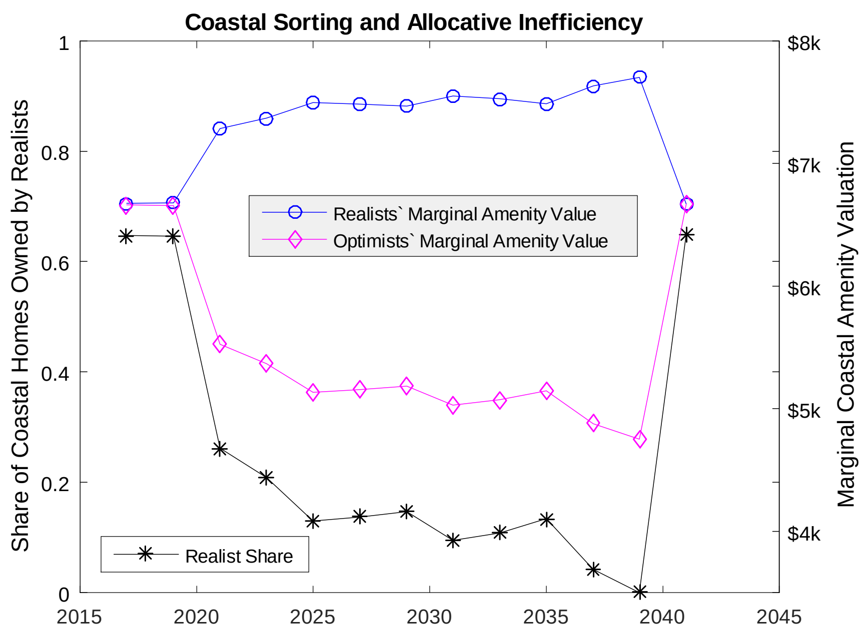

Figure 12

As the flood risk increases and beliefs start to diverge, an increasing number of realists are projected to move out of coastal markets. This prediction is in line both with our survey finding that coastal residents who are more concerned about flooding are also significantly more likely to intend to sell their homes within the next five years (Figure 5), and with BGL's empirical result that transaction volumes of vulnerable homes increased after the release of worsening sea level rise projections. In our model, the first realists to move are the ones with relatively lower amenity values for coastal living, so that the remaining coastal realists' amenity values increase (blue line with circles). In turn, the departing realists are replaced by optimists with lower amenity values (pink line with diamonds). Only once the policy reform at time T enforces the internalization of real risk rates do prices adjust so that realists return to coastal housing markets, restoring allocative efficiency.

Table 4 summarizes the allocative inefficiency costs in our target housing market on a per household basis, computed specifically as the present value of the flow costs (29) across the study period until policy reform. The benchmark costs are estimated at \$685 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 belief heterogeneity. For the whole of Bristol County, RI, the projected welfare costs thus amount to around \$13.2 million. Alternative assumptions for the maximum coastal amenity value (Ξ) - set at either our hedonic regression estimate (\$4.9k/yr, see Section 6.3), or at the 75th percentile of coastal residents in our survey (\$8.5k/yr) - do not materially affect this estimate due to the fact that higher losses for realists are partly offset by higher gains for optimists. In contrast, the share of coastal homes (k_1) naturally has a large effect on the allocative inefficiency. Finally, enacting flood insurance reform sooner than in the benchmark (2033 vs. 2043) naturally reduces the allocative inefficiency as well.

Table 4: Allocative Inefficiency Costs

Scenario	Per Household Net Costs	Scenario	Per Household Net Costs
Benchmark	\$685	k_1= 0.05	\$137
$\Xi = \$4.9k$	\$609	k_1= 0.20	\$862
$\Xi = \$8.5k$	\$648	T = 2035	\$374

6.3 Robustness and Extensions

This section presents a robustness analysis for the benchmark model. We first consider alternative flood risk scenarios. Figure 13 plots the projected evolution of coastal home prices for flood risk increases from 1% to 2%, 4% (benchmark), and 6% per year, comparing the homogeneous rational scenario with the benchmark optimist share of 35% in each case. Table 5 summarizes all sensitivity analysis results numerically. The extent to which current coastal housing prices are estimated to exceed fundamentals rises along with the future flood risk increase, up to 20% in the high risk scenario.

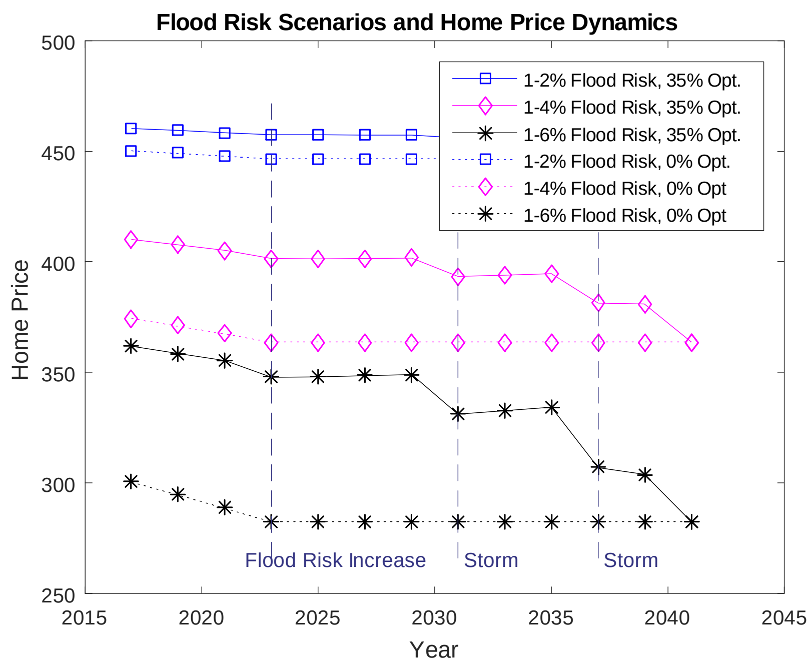

Figure 13

Our second sensitivity check introduces alternative assumptions for optimists' beliefs about the long-run risk rates enforced by policy as per (27). The results indicate that even optimists' beliefs about very long-run flood insurance policy changes can significantly affect coastal housing prices in the present. Expectations of long-run availability of cheap insurance can greatly inflate property prices relative to their fundamental value, leading to an estimated overvaluation of 25%. In contrast, if optimists expect to be forced to pay official risk rates eventually, overvaluation is significantly mitigated (2%).

Third, we consider sensitivity to a behavioral modification that allows optimists to "overreact" to flood events or the lack thereof. The motivation for this extension is that several empirical studies 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 the baseline Bayesian framework. We thus incorporate an overreaction parameter γ into agents' updating rules as follows:[26]

$$\begin{aligned}\widetilde{q}^{o}_{t+1}|_{\text{Flood}=1} &= \Pr(\pi^{H}|_{\text{Flood}=1}) = \frac{(\pi^{H}\cdot q^{o}_{t})\cdot(1+\gamma)}{\pi^{H}q^{o}_{t}+(1-q^{o}_{t})\pi^{L}} \\ \widetilde{q}^{o}_{t+1}|_{\text{Flood}=0} &= \Pr(\pi^{H}|_{\text{Flood}=0}) = \frac{((1-\pi^{H})\cdot q^{o}_{t})\cdot(1-\gamma)}{(1-\pi^{H})q^{o}_{t}+(1-q^{o}_{t})(1-\pi^{L})}\end{aligned} \tag{30}$$

Even a modest degree of overreaction ($\gamma = 10\%$) turns out to be sufficient for beliefs to revert back to baseline at a rate in line with these empirical studies (see Appendix Figure A2). While this overreaction increases the volatility of future coastal housing prices compared to rational Bayesian updating, it does not affect the estimated overvaluation or overall price decline *levels*, as shown in Table 5.

Another assumption which turns out not to affect the estimated level of coastal home price overvaluation is the number and timing of future flood events. Intuitively, this is because both the initial price and fundamental value depend only on *expectations* over flood events. The volatility of prices in the process of correcting to fundamentals does, however, depend on storm realizations, as they determine accumulated learning by the time policy reform is enacted. We also study sensitivity to the assumed timing of flood policy reform itself, which highlights an intuitive trade off: while faster reform could cut allocative inefficiency

[26] Gallagher (2014) formally compares the rational Bayesian model to a modification with a discounting parameter that weights older flood events less in agents' updating rules. Our model is not strictly comparable both as he focuses on a Beta-Bernoulli model and because we focus on learning in the context of changing flood risk and sea level rise. We therefore consider (30) as an analogous modified updating rule to match the empirical evidence.

Table 5: Sensitivity Analysis				
Scenario	Overvaluation	Future Price Change	Var($\%\Delta P$)	Re-scaled e^h
Benchmark	10%	-13%	2.4	n/a
High future flood risk π^H= 6%	20%	-28%	9.3	×
Low future lood risk π^H= 2%	2%	-3%	2.1	×
Long-run optimism $E_t^o[\pi_T^*] = E_t^o[\pi_T^o]$	25%	-28%	18.1	×
Long-run realism $E_t^o[\pi_T^*] = E_t^o[\pi_T^r]$	2%	-5%	0.1	×
Overreaction $\gamma = 10\%$	10%	-13%	3.7	n/a
Flood events: 2030 only	10%	-13%	5.6	n/a
Flood events: 2040 only	10%	-13%	5.4	n/a
Flood events: none	10%	-13%	7.9	n/a
Policy Reform $T = 2033$	10%	-13%	6.7	×
Share coastal $k_1 = 0.05$	10%	-13%	2.2	×
Share coastal $k_1 = 0.05$	12%	-15%	2.8	✓
Share coastal $k_1 = 0.20$	10%	-13%	2.5	×
Share coastal $k_1 = 0.20$	9%	-12%	2.1	✓
Discount factor $\beta = .97$	8%	-13%	2.1	×
Discount factor $\beta = .99$	11%	-12%	2.7	×

Re-scaling of own-home utility value e^h holds initial coastal home price constant at $410k.
Var($\%\Delta P$) refers to variance of year-to-year growth rates in coastal housing prices 2017-2043.

costs in half (Table 4), it would also triple price volatility by enforcing a correction over a shorter time horizon. Table 5 presents two further sensitivity checks. One, we vary the share of coastal housing above and below the benchmark value of $k_1 = 13.4\%$, with and without a re-scaling of the flow value of home living to match the initial observed median coastal housing price of $\$410k$. Two, we vary the utility discount factor above and below the benchmark value of $\beta = 0.98$. The estimated degree of overvaluation remains in the 8-12% range across these simulations.

Finally, we consider an additional 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*. Details are presented in the Appendix. 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.

6.4 Hedonic Estimation

This study relies in part on evidence from stated preference elicitation, a methodology with known shortcomings. For comparison, we thus present results from a hedonic analysis of housing prices in our empirical setting. We collect home sales transactions and characteristics data for Bristol County and North Smithfield, Rhode Island, from Tax Assessor records and merge these with a spatial layer to identify homes that are within 400 feet of the waterfront as well as in official NFIP-designated flood zones. The Appendix provides details on the data and estimation.

6.4.1 Coastal Amenity Value

We first consider robustness in our estimated coastal amenity value. The survey methodology enables us to ask respondents specifically about their valuation of the coastal amenity holding flood risk and other confounders constant. In contrast, 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 3. The estimated coastal home premium is around +23% and generally precisely estimated, as shown in Table A2. Given the median coastal home price in the data ($424k), at a real interest rate of 5%, this estimate corresponds to an annual coastal value of $4,876. For comparison, the survey results imply an annualized average coastal value of $6,720 for the median coastal home price in our sample ($410). While these figures are not strictly comparable, we cannot disentangle how much of the gap is due to structural differences (e.g., marginal versus average coastal buyer valuation) versus methodological biases in stated preference elicitation (e.g., hypothetical bias). We address this concern through a sensitivity check replacing the survey-based estimate of Ξ in the model with the hedonic regression results. The results (Table 6) reveal that the extent of overvaluation is either larger (17%) or unchanged (10%) depending on whether the flow value of housing is re-scaled to match the initial coastal home price in the data.[27]

Table 6: Hedonic Estimate of Amenity Value

Scenario	Overvaluation	Future Price Change	Var($\%\Delta P$)	Re-scaled e^h
Benchmark	10%	-13%	2.38	n/a
Hedonic $\Xi = \$4.9k$	17%	-23.2%	7.14	×
Hedonic $\Xi = \$4.9k$	10%	-13.2%	2.51	✓

6.4.2 Flood Risk Capitalization

The second use of the hedonic analysis is to provide direct empirical evidence on the capitalization of flood risks in our empirical setting, connecting back to the basic question of whether housing price data support the use of a heterogeneous agent model as developed in this paper. First, we fail to detect a significant negative effect of FEMA flood zone status on housing prices (while controlling for close proximity to the coast), in line with both a number of other empirical studies and the models' predictions, as described in Sections 2 and 3. Second, the time horizon of our data enables us to gauge changes in the flood risk premium over time. As described in Section 3, the homogeneous rational beliefs model would predict that the announcement of climate change should have lead to an immediate (absolute value) increase in the flood risk penalty, followed by a continual increase as sea level rise draws nearer. Bernstein, Gustafson, and Lewis (2018) fail to detect such a decline

[27] A ceteris paribus decrease in the maximum coastal amenity value Ξ (from the benchmark to the hedonic results) lowers the predicted 2017 coastal home price from \$410k to \$206k, so that a given overvaluation amount appears as a larger percentage of the initial price. Re-scaling the flow home ownership value e^h to once again match the initial coastal home price of \$410 returns the overvaluation to the benchmark magnitude of 10%.

for owner-occupied housing in a nation-wide analysis for 2007-2016. While our data cover only our empirical setting (Bristol County, Rhode Island), they include a longer time horizon (1970-2017) featuring many historic climate news milestones. Figure 14 plots the estimated hedonic flood zone premium across five year periods over this time horizon. (Estimation details are presented in the Appendix.)

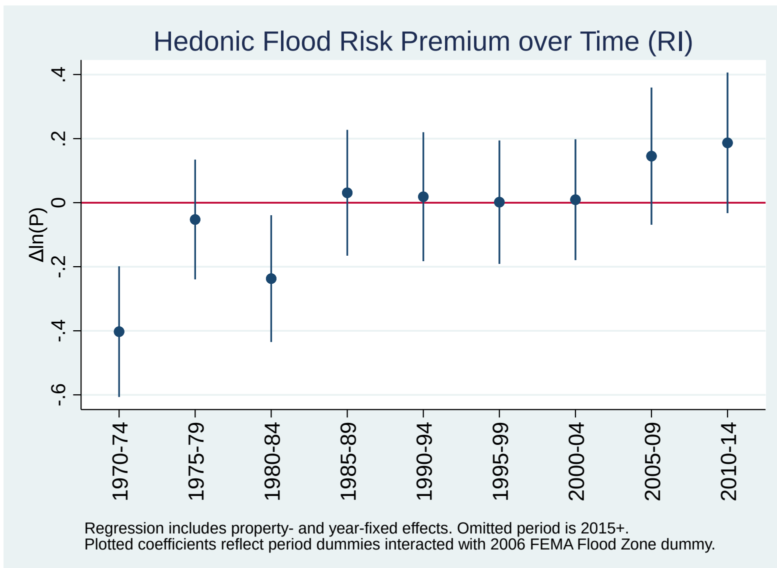

Figure 14

We fail to detect the pattern predicted by the homogeneous rational beliefs model in our setting.[28] Of course, these estimates are subject to numerous caveats both conceptually (see Section 3) and econometrically (see Appendix), and provide only suggestive evidence. Nonetheless, they are in line with both the varied findings of the empirical literature and the results of the model, which indicate that belief heterogeneity may be a critical factor preventing asset prices from accurately reflecting climatic risks in housing markets.

[28] In line with BGL, we do find that the flood risk premium appears to be more negative post-2014 compared to the 2005-2014 time period but that these differences are imprecisely estimated in the general sample dominated by owner-occupied housing. We also find that, over the longer time horizon in our sample, the current flood risk premium appears to be less negative than in the more distant past.

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., 2018), 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, 2017a), 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., Bernstein, Gustafson, Lewis, 2018).

This paper has explored the role of flood risk belief heterogeneity in accounting for these present and potential future pricing dynamics in coastal U.S. housing markets. We provide both theoretical and empirical evidence through the combination of (i) a dynamic housing market model allowing for heterogeneity in home types, consumer preferences, and flood risk beliefs, (ii) a field survey campaign eliciting belief distributions among waterfront and inland residents of coastal communities in Rhode Island, and (iii) supplementary evidence from both the prior empirical literature and a hedonic analysis of housing prices in our sample setting.

The main results are threefold. First, we find that allowing for belief heterogeneity enables our model to reconcile the mixed empirical evidence on flood risk penalties as driven by *sorting* and different resulting equilibria across markets that may vary in the distributions of beliefs and housing stock attributes.

Second, consistent with these theoretical predictions, the survey results indicate 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 flood risk projections under sea level rise, we estimate that coastal housing prices exceed fundamentals by 10% in our setting.

We moreover find that viewing current housing prices through the lens of a homogeneous rational beliefs framework may lead modelers to underestimate the outstanding coastal home price declines over the next 25 years by a factor of four. These results are robust to a range of robustness checks, but sensitive to the extent of future flood risk increases and households' long-run flood policy beliefs, highlighting the potential power of policy expectations to mitigate - or exacerbate - current inefficiencies. While our model can only capture welfare effects in the form of allocative inefficiency, devaluations in at-risk markets may also be a significant policy concern due to their potential effects on mortgage and credit markets. A formalizations and quantification of these impact mechanism would arguably be a highly interesting topic for future work.

While our analysis focuses on Rhode Island, coastal flood risks affect large areas of the United States. 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, household beliefs about these changes remain strongly heterogeneous, 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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8 Appendix

8.1 Tables and Figures

Table A1: Coastal Amenity Willingness-to-Pay

DBDC Estimation on WTP for Coastal Amenity

	Beta	Sigma
ln(Est. Home Market Value)	410.3***	
	(150.5)	
Coastal	339.5***	
	(96.34)	
Income	-0.000322	
	(0.766)	
Age	-3.412	
	(2.812)	
Number in Household	-27.72	
	(29.79)	
Education Index (1-9)	20.90	
	(19.89)	
Caucasian	207.4*	
	(125.7)	
Property Square Footage	-0.0149**	
	(0.00726)	
House # Rooms	24.50	
	(30.95)	
Constant	-2,358***	277.4***
	(857.9)	(59.82)
Observations	126	126

Reports results of double-bounded dichotomous choice estimation of WTP (non-coastal) or willingness to accept (coastal) for living within 400 feet of the waterfront. Starting bids randomized from $150, $250, and $350. Follow-up bids add/subtract $75. Standard errors in parentheses. (*** $p<0.01$, ** $p<0.05$, * $p<0.1$).

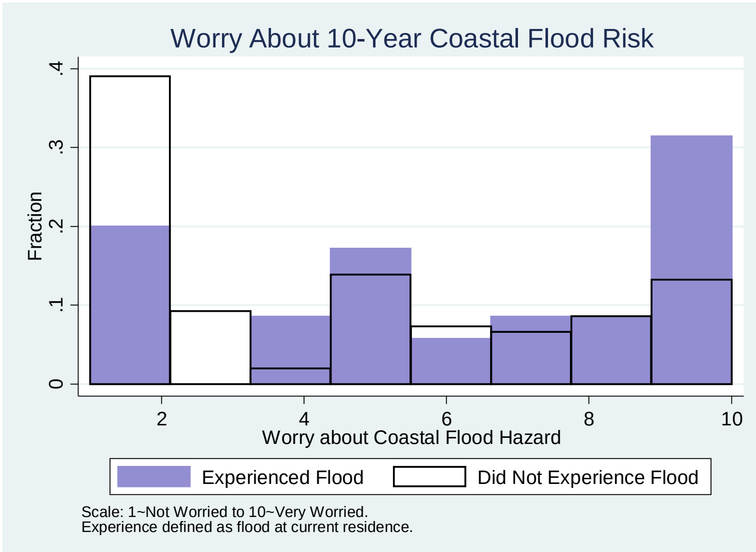

Figure A1

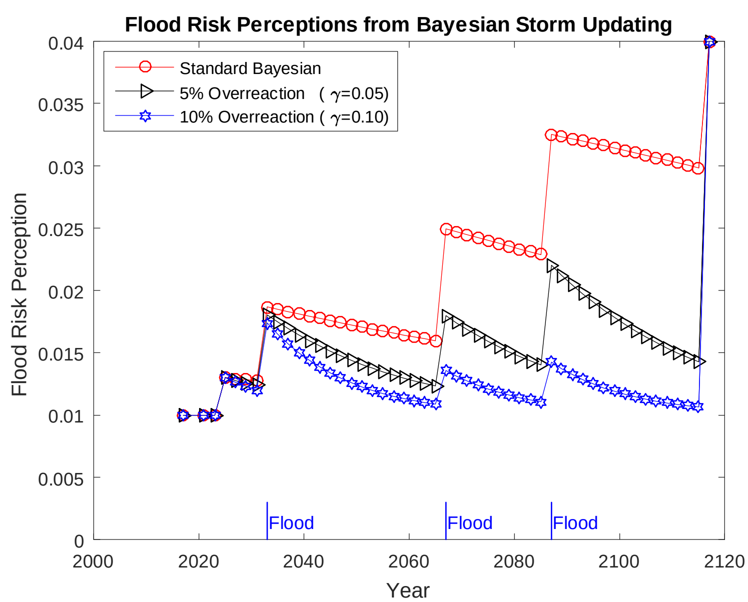

Figure A2

8.2 Ex-Post Rationalization vs. Ex-Ante Belief Heterogeneity

Our main analysis assumes that households' flood risk perceptions evolve principally based on the realization of flood events, or the lack thereof. One potential concern with interpreting observed flood risk belief heterogeneity in this way is that coastal residents could also be changing their beliefs *differentially* after moving to the coast in order to rationalize their sorting choice ex-post. This section presents an illustrative extension of the model to showcase the potential effects of ex-post rationalization. For ease of illustration, assume that the world starts in a neutral state where nobody has yet purchased or rented a home, and all optimists o initially have common flood risk belief π_0^o. The initial sorting in period 0 is thus the same as in the benchmark model.

We focus on the most interesting and empirically relevant case where both optimists and realists are initially in the coastal home market. In period 0, the market-clearing coastal home price P_0 equates both the marginal optimist's and realist's willingness to pay:

$$P_0^* = \beta(e^h + \overline{\xi_0^r} - \pi^r\delta + E_0^r[P_1]) = \beta(e^h + \overline{\xi_0^o} - \pi_0^o\delta + E_0^o[P_1]) \tag{31}$$

If no storm occurs in period 0, both coastal and non-coastal Bayesian learners update their flood risk beliefs downward. Importantly, however, coastal residents may further change their beliefs *differentially* in response to having moved to the coast (ex-post rationalization). Specifically, let $\pi_1^{o,C_{0,1}}$ denote the period 1 flood risk belief of optimists that lived on the coast from period 0 to 1 ($C_{0,1}$), and $\pi_1^{o,NC_{0,1}}$ analogously for optimists who did not live on the coast ($NC_{0,1}$). Beliefs evolve according to:

$$\pi^r > \underbrace{\pi_0^o > \pi_1^{o,NC_{0,1}}}_{\substack{\text{Bayesian}\\ \text{Updating}}} \underbrace{> \pi_1^{o,C_{0,1}}}_{\text{+Rationalization}} \tag{32}$$

Beliefs (32) imply the following changes. First, the coastal home price valuation of optimists already living on the coast has increased more than other agents', indicating that they will retain the highest willingness to pay and remain in their coastal homes. Consequently, measure $\frac{\theta^o}{\Xi}(\Xi - \overline{\xi^o}_0)$ of coastal homes remains occupied by their initial optimist residents. Second, the period 0 marginal optimist's contemporaneous coastal home price valuation has increased, i.e.: $[\overline{\xi_0^o} - \pi_1^{o,NC_{0,1}}\delta] > [\overline{\xi_0^o} - \pi_0^o\delta]$. In contrast, the marginal realist's contemporaneous valuation remains unchanged ($\overline{\xi_0^r} - \pi^r\delta$). While a full characterization of the period 1 equilibrium would require us to take a stance on the full evolution of all agent's future price expectations $E_1^r[P_2^{m_2}]$, $E_1^{o,NC_{0,1}}[P_2^{m_2}]$, $E_1^{o,C_{0,1}}[P_2^{m_2}], E_2^{o,NC_{0,2}}$, $[P_3^{m3}], E_2^{o,NC_{0,1};C_{1,2}}[P_3^{m_3}], ...$ including the extent to which each type of agent is aware of ex-post rationalization effects, how it colors their beliefs about others' beliefs, etc., a plausible scenario - in line with the structure of the baseline model - is that optimists' future price expectations at time 1 increase at least weakly more than realists' future price expectations in response to their updated beliefs (32): $E_1^{o,C_{0,1}}[P_2^{m_2}] \geq E_1^{o,NC_{0,1}}[P_2^{m_2}] \geq E_1^r[P_2^{m_2}] \geq E_0^r[P_1^{m_1}]$. In that case, we would expect the period 1 equilibrium to unfold as follows: some measure of non-coastal optimists' valuations now exceed those of coastal resident realists, leading the former to buy coastal homes from the latter. Importantly, the *marginal buyers* are now the previously non-coastal optimists, whereas the marginal sellers are the realists.[29] The equilibrium coastal home price in period 1 is thus determined by the interaction between these groups. More formally:

$$\begin{aligned} P_1^* &= \underbrace{\beta(e^h + \overline{\xi_1^r} - \pi^r\delta + E_1^r[P_2])}_{\text{Newly marginal coastal realists}} = \underbrace{\beta(e^h + \overline{\xi_1^o} - \pi_1^{o,NC_{0,1}}\delta + E_1^{o,NC_{0,1}}[P_2])}_{\text{Marginal new coastal Bayesians}} \\ &< \underbrace{\beta(e^h + \overline{\xi_0^o} - \pi_1^{o,C_{0,1}}\delta + E_1^{o,C_{0,1}}[P_2])}_{\text{Long-term coastal Bayesians}} \end{aligned} \tag{33}$$

With ex-post rationalization (or differential updating), the model thus predicts that long term coastal residents' valuations of their homes will exceed the market price of coastal homes being sold. However, as long as there are marginal buyers of coastal homes that hold inaccurate flood risk beliefs $\pi_1^{o,NC_{0,1}}$, the potential for mispricing remains robust.

Empirically, the key implication of (33) is that optimistic beliefs should be calibrated based on a sample representing marginal buyers, which may not correspond to the full sample. That is, if (long-term) coastal residents are more optimistic about flood risks than the marginal Bayesians whose beliefs pin down prices, we might be concerned that combining

[29] In the aftermath of a storm, coastal optimists could become marginal sellers as well, depending on how they update their beliefs.

survey responses from all residents leads to an overestimate of optimism compared to the relevant population. As noted in the main text, our survey results suggest that 30% of currently non-coastal residents are optimistic about coastal flood risks. We also find that *new movers* - defined as agents who moved from another town to their survey area within the past 3 years from other towns - exhibit a similar distribution including flood risk optimism, as shown in Figure A3. While the moving history questions were added to the survey late, thus limiting the sample size underlying Figure A3 to $n = 26$, the concept of out-of-town movers as having a 'fresh' distribution of flood risk beliefs is common in the literature (see, e.g., discussions in Gallagher, 2014).

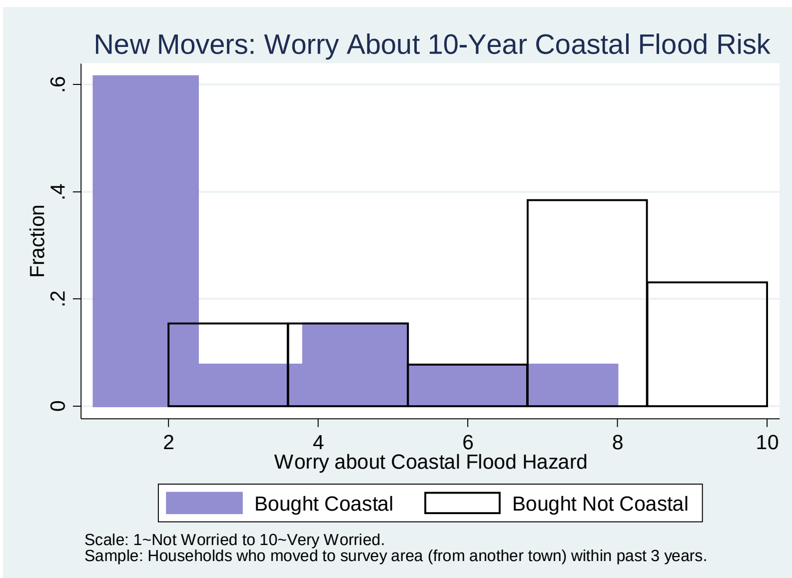

Figure A3

In sum, the potential marginal buyers for coastal properties thus appear likely to underestimate flood risks in our sample and empirical setting, regardless of whether beliefs of established coastal residents are additionally affected by ex-post rationalization.

8.3 Empirical Comparison: Hedonic Estimation

This section describes the dataset and estimation for Section 6.3. We scrape property data for the Rhode Island Bristol County towns of Barrington, Warren, and Bristol from Tax Assessor's records, including transactions histories and property characteristics from 2017. In addition, to allay concerns that potential homebuyers view Bristol County as a housing market, and therefore our control group of non-flood zone homes could be impacted through spillovers in housing market interactions, we also collect data for all of North Smithfield, Rhode Island, given that it has similar sociodemographic characteristics and proximity to Providence as Bristol Country. We locate buildings within a property using a GIS layer of all structures in Rhode Island originally compiled by the Rhode Island E-911 Uniform Emergency Telephone System and redistributed by the Rhode Island Geographic Information System (RIGIS, 2017). This layer geolocates all known structures in Rhode Island to the latitude and longitude of the center of the building. We obtain official flood map information from FEMA's Map Services Center and older flood maps from RIGIS. Finally, to map shorelines, we obtain the Rhode Island Continually Updated Shoreline Product from RIGIS (RIGIS, 2016). We add a 400 foot buffer to the shoreline in order to select coastal properties. In addition, we obtain the spatial extent of Superstorm Sandy surge inundation from STORMTOOLS (SAMP, 2017). We match individual property structures to their flood zone, coastal/non-coastal designation, and Sandy inundation status. We then match properties with Tax Assessor data including building structure information and the history of property transactions including sales price (which we inflation-adjust to 2015 $USD using the BLS Consumer Price Index) and deed type. In order to control for potentially confounding flood policy events, we also categorize property sales as before or after: the Biggert-Waters Act passage (July 6, 2012), the Homeowner Flood Insurance Affordability Act passage (March 21, 2014) and introduction (October 29, 2013).

We trim our transactions data to exclude the bottom and top 1% of annualized price changes between sales, and, for the recent analysis (2010-2016), observations for which the sales price is more than 50% below the 2017 tax assessor value, in order to remove non-arm's length deals. We also trim non-standard properties in terms of bedrooms (those with more than 10 bedrooms) and bathrooms so as to exclude apartment buildings, nursing homes, etc. We also drop observations where multiple deeds are recorded with different sales prices on the same date. Finally, we also consider a restriction to "Warranty" deed types, omitting deeds such as Quit Claims more likely to be associated with non-market sales.

We conduct two estimation exercises. The first focuses on recent post-crisis years (2010-2014) since several important variables are only available for the past decade or 2017 (e.g., property characteristics, tax assessor values, active flood maps, etc.). The second focuses on a longer time horizon (1970-2017) but has to use a fixed effects specification and is subject to more measurement error, as described below.

First, we estimate the following specification for 2010-2014:

$$lnP_{it} = \beta_0 + \gamma_i X_i + \delta c_i + \beta_1 f_i + \beta_2 BW_{it} + \beta_3 f_i * BW_{it} + \alpha_c + \theta_t d_{Yt} + \varepsilon_{it} \tag{34}$$

Here, we regress the log of house sales price (2015 $USD) on a vector of home characteristics (X_i), an indicator for a coastal home (within 400 feet of the coastline; c_i), an indicator for being in a flood zone (f_i), an indicator for a house sold after the passage of the Biggert-Waters Act (and before its partial repeal in 2014; BW_{it}), the interaction between the flood zone and Biggert-Waters status ($f_i * BW_{it}$), as well as Census tract fixed effects (α_c) and year fixed effects (d_{Yt}). The first column presents results including property sales between 2010 and 2017 that were not directly impacted by Sandy and whose flood designation did not change over the time period. Columns (3)-(4) and (5) further restrict the sample to the time before the HFIAA was passed and introduced, respectively.

Table A2: Hedonic Home Price Estimation

Dependent Variable: Log(Real Sales Price) ($2015)					
	(1)	(2)	(3)	(4)	(5)
Land Area (Acres)	0.220***	0.256***	0.164**	0.254***	0.184**
	(0.0607)	(0.0400)	(0.0607)	(0.0648)	(0.0696)
Age	-0.00428***	-0.00371***	-0.00526***	-0.00336**	-0.00557***
	(0.000838)	(0.00101)	(0.00139)	(0.00106)	(0.00133)
Age^2	1.61e-05***	1.48e-05**	2.25e-05**	1.19e-05*	2.43e-05**
	(4.39e-06)	(6.06e-06)	(7.74e-06)	(5.72e-06)	(7.87e-06)
#Bathrooms	0.224***	0.239***	0.226***	0.243***	0.230***
	(0.0224)	(0.0175)	(0.0297)	(0.0232)	(0.0265)
#Bedrooms	-0.00219	0.0115	-0.0199	-0.00101	-0.0310
	(0.0265)	(0.0241)	(0.0331)	(0.0285)	(0.0360)
Coastal (w/in 400 feet)	0.229***	0.176***	0.242***	0.169**	0.229***
	(0.0672)	(0.0554)	(0.0681)	(0.0624)	(0.0602)
FEMA Flood zone	-0.0413	-0.0127	-0.0409	0.0152	-0.0346
	(0.0723)	(0.0742)	(0.0909)	(0.0965)	(0.0927)
During Biggert-Waters Act	0.104*	0.0683	0.0794**	0.0561	0.0782**
	(0.0538)	(0.0552)	(0.0312)	(0.0351)	(0.0299)
Flood zone*Biggert-Waters	-0.00924	-0.0500	-0.0582	-0.0728	-0.0378
	(0.0723)	(0.0638)	(0.0583)	(0.0871)	(0.0749)
Constant	12.36***	12.29***	12.36***	12.20***	12.48***
	(0.131)	(0.110)	(0.156)	(0.116)	(0.214)
Observations	2,328	1,838	955	686	1,040
R-squared	0.626	0.661	0.615	0.662	0.604
Adj.R-sq.	0.621	0.656	0.606	0.650	0.595
"Warranty" Deeds only		✓		✓	

Reports results of OLS regression of log(Real Sales Price) on indicated variables plus Census tract- and year fixed effects. Standard errors clustered at the census tract level and in parentheses.

Our second specification seeks to gauge changes in the flood zone premium over a longer time horizon (1970-2017). Here, we utilize a fixed effects specification (since we do not observe property characteristics in a panel) to utilize only price variation *within* properties over time to identify the treatment effects of interest.[30] We also restrict the specification to

[30] A remaining identification concern would be if flood zone properties are differentially likely to receive renovations than non-flood zone properties, which could bias our estimated flood zone coefficient trend *downward* (to be more negative over time). Since our central finding is the *absence* of such a downward trend, however, this potential source of bias is not a concern for spuriously driving our result. It should be noted that McCoy and Zhao (2018) find a positive effect of Hurricane Sandy on investment rates at damaged buildings inside but not outside the flood zone in New York City. Column (2) thus excludes all properties damaged by Hurricane Sandy to avoid this potential confounder in damage repairs. We also note that other time periods with large statewide flood events (e.g., 1980-85) we find differentially more *negative* flood risk premia, suggesting that differentially positive investment in flood zones is unlikely

"Warranty" deeds since we do not observe historical tax assessor valuations, and thus cannot control for non-arm's length sales based on a price-to-assessor-value criterion as above.

The second specification thus includes property fixed effects α_i, year dummies d_{Yt}, and flood zone dummies f_i interacted with five-year time period dummies $\delta_{i,\tau}$:

$$lnP_{it} = \beta_0 + \alpha_i + \theta_t d_{Yt} + \sum_{\tau=1970-74}^{2010-14} + \beta_3 f_i * \delta_{i,\tau} + \varepsilon_{it} \tag{35}$$

Table A3 shows the results of estimating (34). Column (1) is the benchmark; Column (2) clusters standard errors at the property level; Column (3) excludes properties affected by Hurricane Sandy, and Column (4) clusters standard errors at the Census tract level to allow for arbitrary correlations of shocks within Census tracts.

to be a significant confounder in our setting.

Table A3: Historical Hedonic Home Price Estimation

Dependent Variable: Log(Real Sales Price) ($2015)				
	(1)	(2)	(3)	(4)
Flood zone*1970-74	-0.403***	-0.403*	-0.411***	-0.411
	(0.104)	(0.218)	(0.103)	(0.379)
Flood zone*1975-79	-0.0525	-0.0525	-0.0610	-0.0610
	(0.0954)	(0.129)	(0.0945)	(0.201)
Flood zone*1980-84	-0.237**	-0.237	-0.245**	-0.245
	(0.101)	(0.168)	(0.100)	(0.141)
Flood zone*1985-89	0.0310	0.0310	0.0228	0.0228
	(0.100)	(0.116)	(0.0993)	(0.0938)
Flood zone*1990-94	0.0186	0.0186	0.0105	0.0105
	(0.103)	(0.139)	(0.102)	(0.126)
Flood zone*1995-99	0.00166	0.00166	-0.00546	-0.00546
	(0.0983)	(0.0900)	(0.0974)	(0.0527)
Flood zone*2000-04	0.00937	0.00937	0.00423	0.00423
	(0.0962)	(0.116)	(0.0954)	(0.109)
Flood zone*2005-09	0.145	0.145	0.137	0.137
	(0.109)	(0.127)	(0.108)	(0.122)
Flood zone*2010-14	0.187*	0.187	0.159	0.159
	(0.112)	(0.137)	(0.111)	(0.110)
Observations	7,032	7,032	6,720	6,718
R-squared	0.862	0.862	0.862	0.861
Adj.R-sq.	0.708	0.708	0.719	0.718
Property fixed effects?	✓	✓	✓	✓
Year fixed effects?	✓	✓	✓	✓
"Warranty" Deeds only	✓	✓	✓	✓
S.E. Clustering		Property		Census tract

Reports OLS regression of log(Real Sales Price) on indicated variables plus a constant for 1970-2017. Omitted category is Flood zone*2015+. Columns (3)-(4) omit buildings damaged by Hurricane Sandy.